Essays on Uncertainty and Temporary Employment

Thesis by

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Abstract

This dissertation examines uncertainty and temporary employment in the United Kingdom, a country affected by global economic shocks such as the Great Financial Crisis and COVID-19 but also uniquely characterised by exceptionally high uncertainty during the Brexit negotiations, and where temporary employment—defined as employment with a predetermined termination date—is a consistent feature of its labour market.

The dissertation begins by exploring the broader effects of uncertainty. The first chapter constructs industry division-specific microeconomic uncertainty measures for the UK and applies them within a panel vector autoregressive (VAR) framework to assess the impacts of uncertainty. The findings demonstrate that, despite being underutilised in the uncertainty literature due to a lack of disaggregated measures, panel VARs can provide evidence consistent with findings from the uncertainty literature that use aggregate data. Furthermore, they provide new insights into the heterogeneous effects of uncertainty. Specifically, the magnitude of investment decline following a microeconomic uncertainty shock varies significantly across divisions, even within the same industry. The analysis also reveals differences in debt dynamics between manufacturing and services industry divisions following a microeconomic uncertainty shock.

The dissertation then turns to the topic of temporary employment. Rather than providing an exhaustive overview of temporary employment in the UK, the second chapter complements the existing literature by focusing on underexplored areas, including reasons for temporary employment, gender differences, and geographical variations in trends and correlations with macroeconomic variables in the UK. Using probit regressions,

this chapter provides preliminary evidence suggesting that uncertainty is associated with a higher probability of individuals being in temporary employment.

Finally, the dissertation brings together the themes of uncertainty and temporary employment. The third chapter provides novel empirical evidence of the positive association between uncertainty and the size of temporary employment through a VAR model. To account for these empirical results, the chapter proceeds with a partial equilibrium model that isolates the role of uncertainty in shaping labour composition. Simulations from the model show that uncertainty shocks initially reduce the aggregate share of temporary labour, but firms in the aftermath of heightened uncertainty become more cautious and subsequently react by favouring temporary labour over permanent labour. This shift is attributed to the higher adjustment costs associated with permanent labour that make hiring and firing mistakes more costly for permanent than for temporary labour.

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I would also like to thank the Productivity Institute for funding my scholarship, which made this research possible.

Affidavit

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Chapter 0 Introduction

Why study uncertainty?

Uncertainty is akin to dense fog on an unfamiliar road. The path ahead may be perfectly straight and clear, or it could conceal a sharp, unexpected turn. What would a driver do when visibility is limited to just a few meters? Instinctively, they slow down, hesitate at intersections, and avoid sudden maneuvers to minimize the risk of an accident. The lack of visibility forces cautious, incremental adjustments rather than confident, decisive movement. Some may even choose to pull over and wait for clearer conditions or seek an alternative route unaffected by the fog.

While not everyone has faced such conditions on the road, the experience of uncertainty is universal. Uncertainty is a fundamental and pervasive feature of human existence; it shapes decisions at every level, and its impact particularly evident during high-profile events such as the 2008 Financial Crisis and the COVID-19 pandemic. Without accounting for uncertainty, empirical estimates may understate the persistence and severity of economic shocks and ultimately lead to suboptimal policy recommendations. It may be shocking to some observers that, despite its fundamental role in economic decisions, empirical analysis of the effects of uncertainty is a relatively recent development, having gained prominence only in the past two decades. As Bloom (2009) aptly notes: "*Despite the size and regularity of these second-moment (uncertainty) shocks, there is no model that analyzes their effects. This is surprising given the extensive literature on the impact of first-moment (levels) shocks. This leaves open a wide variety of questions on the impact of major macroeconomic shocks, since these typically have both a first- and a second-moment component.*" This observation highlights a critical gap in the literature.

Since Bloom's seminal work, research on uncertainty has expanded significantly, with a growing body of evidence documenting its effects on economic activity. Elevated uncertainty can dampen economic activity through multiple channels: firms delay costly and irreversible investments (see Carruth, Dickerson, & Henley, 2000, for a comprehensive review of the literature on investment under uncertainty); financial institutions raise risk premiums, further deterring investment and hiring (Arellano, Bai, & Kehoe, 2019; Christiano, Motto, & Rostagno, 2014; Gilchrist, Sim, & Zakrajšek, 2014); households postpone discretionary spending (Coibion, Georgarakos, Gorodnichenko, Kenny, & Weber, 2024); and economic agents' collective cautious behavior weakens the effectiveness of fiscal and monetary stimulus (Aastveit, Natvik, & Sola, 2017; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018). Moreover, economic uncertainty is not confined within national borders; it spills over internationally through trade and financial linkages, magnifying its global repercussions (Londono, Ma, & Wilson, 2024). While much of the literature has focused on uncertainty's impact on traditional economic indicators, emerging research explores its broader societal effects, such as its influence on inequality (see Theophilopoulou, 2022) and time use (see Cacciatore, Gnocchi, & Hauser, 2024). These studies converge on two key insights: first, uncertainty exerts nontrivial real effects, and second, its effects permeate diverse areas in shaping economic and social outcomes. Given its profound implications, advancing the understanding of uncertainty across all dimensions of economics is not only intellectually compelling but also practically vital for effective policymaking.

Why study temporary employment?

Temporary employment—characterized by contracts with a predetermined termination date—has become an increasingly prominent feature of modern labour markets. Over the past four decades, temporary employment has spiked in OECD countries, accompanied by a diversification of temporary employment arrangements including seasonal jobs, fixed-term contracts, agency work, apprenticeship agreements, and even self-employment schemes (Boeri & Garibaldi, 2024).

While the literature on temporary employment is extensive, several important dimensions remain underexplored. Key gaps include reasons for temporary employment, gender disparities, and geographical variations in trends and their correlations with macroeconomic variables. Additionally, some countries have received disproportionate attention in the literature. In particular, countries where temporary contracts are widespread, such as Italy and Spain, are frequently studied, whereas the United Kingdom has received comparatively less focus due to its relatively stable share of temporary employment, which has hovered between 5% to 6% for decades (Office of National Statistics, 2024c). However, this stability does not imply a lack of importance; despite its modest numerical representation, temporary employment serves as a barometer of labour market flexibility, encapsulates the evolving dynamics of contemporary work arrangements, and reflects employer strategies. Moreover, rather than being viewed as a benign feature of the UK labour market, temporary employment is often associated with terms such as "vulnerable employment" (Trade Union Congress, 2008), "precarious work" (Pósch, Scott, Cockbain, & Bradford, 2020), and "insecure work" (Florisson, 2024), highlighting widespread public concern over its socioeconomic implications. These concerns justify the need for further research into the determinants and consequences of temporary employment, particularly within the context of heightened uncertainty.

More importantly, why study uncertainty and temporary employment together?

The effects of uncertainty on aggregate employment is well documented, yet the heterogeneous effects of uncertainty, in this case, on temporary employment, is still relatively scarce, with Lotti and Viviano (2012) and Cao, Shao, and Silos (2021) being notable exceptions. Existing studies focusing on total employment may mask interesting and potentially distinct dynamics of permanent and temporary employment in response to uncertainty.

Examining the relationship between uncertainty and the prevalence of temporary employment provides insights into how firms adapt workforce composition under uncertainty. A key determinant of the prevalence of temporary employment is the strictness of employment protection legislation: high dismissal costs associated with permanent employees incentivise firms to favour temporary employees, which typically involve lower firing costs and greater operational flexibility. During periods of high uncertainty where firms face volatile demand and challenges in accurately forecasting demand, the high firing costs of permanent employees make it riskier to commit to employees on permanent contracts, as workforce adjustments become costly if market conditions worsen. Instead, temporary employment becomes relatively attractive as it enables firms to adjust labour inputs more frequently and at a lower cost. These uncertainty-driven shifts in workforce composition represent a potential channel through which uncertainty affects the broader economy.

Overview

This dissertation examines uncertainty and temporary employment in the UK. The first chapter addresses the limited availability of disaggregated measures of uncertainty and the underutilization of panel VARs in the uncertainty literature, despite their potential for capturing heterogeneous responses across industries. In this chapter, I construct industry division-specific microeconomic uncertainty measures for the UK, following the approach of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and Mohades, Piccillo, and Treibich (2024). Using firm-level balance sheet data from the Financial Analysis Made Easy (FAME) database spanning from 2003 to 2022, I define microeconomic uncertainty as the dispersion of firms' productivity shocks across 68 industry divisions.[1] The dispersion of firms' productivity shocks is a sensible measure of uncertainty because, in real business cycle (RBC) frameworks, total factor productivity (TFP) shocks play a pivotal role in driving fluctuations in output, investment, and employment; as these shocks become more dispersed, the range of plausible future outcomes widens, translating naturally into greater uncertainty for agents making consumption, investment, or hiring decisions.

Regression results indicate that these microeconomic uncertainty measures are countercyclical (particularly for non-services industries), consistent with the well-

[1] In the UK, economic activities are systematically categorized according to the UK Standard Industrial Classification (UK SIC). This classification features a hierarchical structure, beginning with Sections, and progressing through more specific levels: Divisions, Groups, Classes, and Subclasses. Each successive level provides greater detail. For example, Section C encompasses Manufacturing; within this section, Division 10 pertains to the Manufacture of Food Products; further, Group 10.1 specifies the Processing and Preserving of Meat, and Class 10.11 narrows this down to the Processing and Preserving of Meat specifically.

established finding in the literature that uncertainty tends to decline during economic expansions and increase during downturns (Bloom, 2014). They complement existing macroeconomic uncertainty indicators for the UK, such as those by Theophilopoulou (2022), Redl (2020), and Dibiasi and Sarferaz (2023), as well as the Economic Policy Uncertainty index by Baker, Bloom, and Davis (2016). Most importantly, the microeconomic uncertainty measures constructed in this chapter are straightforward to compute, utilize widely available firm-level balance sheet data, and can facilitate a granular analysis of the impact of uncertainty on micro-level decisions.

With this granular, industry division-specific measure of microeconomic uncertainty, I estimate a straightforward panel VAR model to examine the effects of microeconomic uncertainty on firm real decisions. The chapter shows that, despite being underutilised in the uncertainty literature due to a lack of disaggregated measures, the simplest forms of panel VAR, the pooled estimator and the random coefficients model estimated with Bayesian techniques, can provide evidence consistent with findings from the uncertainty literature that use aggregate data. Using the microeconomic uncertainty measures and the annual firm-level data from the FAME database, the results show that a one-standard-deviation microeconomic uncertainty shock is associated with a peak decline—observed approximately one year after the onset of the microeconomic uncertainty shock—of slightly more than 4% in turnover, over 5% in employment, and nearly 10% in investment. The results are robust to the use of an alternative microeconomic uncertainty measure, the inclusion of a macroeconomic uncertainty measure as an exogenous variable, and variations in hyperparameter values.

The use of panel VARs provides additional insights into the heterogeneous effects of uncertainty on investment dynamics and debt-related variables, particularly by comparing service industry divisions with manufacturing industry divisions. In a Bayesian panel VAR with random coefficients applied exclusively to manufacturing industry divisions, the magnitude of investment decline in response to a microeconomic uncertainty shock varies significantly across divisions—even within the same industry. This finding aligns with the existing literature on the heterogeneous impacts of uncertainty on investment, as documented by Guiso and Parigi (1999), Gulen and Ion (2016), and Panagiotidis and Printzis (2021). A separate Bayesian panel VAR with random coefficients for a subset of services industry divisions reveals that the decline in investment following a microeconomic uncertainty shock is more persistent in services industry divisions compared to manufacturing industry divisions—a somewhat counterintuitive result that contrasts with the existing literature (e.g., Londono, Ma, & Wilson, 2024; Mohades, Piccillo, & Treibich, 2024; Strobel, 2015). In terms of debt composition, most manufacturing industry divisions experience a larger decline in short-term debt relative to long-term debt following a microeconomic uncertainty shock; in contrast, service industry divisions exhibit a greater reduction in long-term debt relative to short-term debt, with long-term debt also taking longer to return to pre-shock levels.

The first chapter faces several limitations. First, the microeconomic uncertainty measures—constructed from the ex post dispersion in TFP—do not disentangle distinct sources of uncertainty. Second, reliance on a Cholesky decomposition for identification imposes strong assumptions about contemporaneous relationships that may not be theoretically justified, potentially biasing the impulse response estimates. Third, the panel VAR specifications used—namely the pooled and random coefficient models—do not allow for dynamic interdependencies or spillover effects across divisions, which could obscure important cross-sectional dynamics. Fourth, data constraints limit the scope of firm-level decisions analyzed, excluding potentially relevant outcomes such as R&D expenditure or hiring preferences (e.g., temporary versus permanent contracts). Lastly, while the chapter offers plausible interpretations for the observed patterns, these remain speculative; more formal modeling is needed to rigorously test the mechanisms underlying the differing responses across industry divisions.

The dissertation then turns to the topic of temporary employment. Although temporary employment represents a modest share of the UK labour market, it serves as an indicator of labour market flexibility, reflects evolving work arrangements, and reveals strategic preferences among employers. Rather than providing an exhaustive overview of temporary employment in the UK, the second chapter complements the existing literature by focusing on underexplored areas, including the reasons for temporary employment, gender differences, and geographical variations in trends and correlations with macroeconomic variables in the UK, using data from the UK Labour Force Surveys (LFS).

Exploratory analysis shows that although women consistently have higher rates of temporary employment than men, both rates tend to comove while exhibiting distinct patterns during periods of crisis: Following the 2008 Financial Crisis, the increase in temporary employment was driven primarily by men, whereas the post-COVID-19 rise was more pronounced among women—likely due to industry-specific uncertainty affecting male- and female-dominated industries differently. Data on reasons for temporary employment reveal that during crisis periods, more individuals cite being unable to find permanent employment than a preference against permanent employment. The data also show that historically temporary employment has been more voluntary for women and more involuntary for men; however, this gender gap has narrowed considerably since the pandemic. Regional variation in temporary employment across the UK is minimal, and no macroeconomic variable (GDP growth, unemployment, or job density) emerges as a strong and consistent correlate of temporary employment.

The second chapter also provides preliminary evidence suggesting that uncertainty is associated with a higher probability of being in temporary employment. Using LFS data from 1992 to 2018 and the macroeconomic uncertainty measure developed by Theophilopoulou (2022), I estimate a probit regression and find that a one-standard-deviation increase in lagged macroeconomic uncertainty is associated with a 0.2 percentage point increase in the probability of being in temporary employment. Although this value appears small, it is equivalent to a 3% increase given the unconditional probability of being in temporary employment is only 5.9%. However, this effect is considered small compared to what is found in the literature. Re-estimating the regression with macroeconomic uncertainty treated as a categorical variable to distinguish levels of uncertainty reveals a non-linear association between macroeconomic uncertainty and the probability of being in temporary employment. A heterogeneity analysis further indicates that the relationship between uncertainty and the likelihood of being in temporary employment varies across age groups, levels of educational attainment, marital status, and number of children.

The second chapter has several limitations. First, while it documents trends and demographic differences in temporary employment, it does not explore the underlying mechanisms driving these patterns. Second, although the probit regression framework identifies associations between macroeconomic uncertainty and the probability of being in temporary employment, it does not establish causality. Third, the analysis is confined to the employed population, excluding unemployed and inactive individuals; as a result, it cannot capture how uncertainty influences transitions across broader labour market states, nor account for potential selection bias. Fourth, while the chapter presents suggestive evidence of heterogeneity in responses to uncertainty across demographic groups, the analysis remains limited in scope and requires more detailed empirical investigation to validate and understand these patterns.

Finally, the dissertation brings together the themes of uncertainty and temporary employment to examine the impacts of the former on the latter. The third chapter contributes to the literature by examining how uncertainty affects permanent and temporary employment differently, acknowledging that the two types of labour entail distinct adjustment costs. Existing studies focusing on total employment may mask interesting and potentially distinct dynamics of permanent and temporary employment in response to uncertainty. Using a VAR model and macroeconomic uncertainty measures developed by Dibiasi and Sarferaz (2023), the chapter presents novel empirical evidence of a positive relationship between macroeconomic uncertainty and the size of temporary employment in the UK. Impulse response functions show that a one-standard-deviation increase in macroeconomic uncertainty results in a peak increase of approximately 0.5% in temporary employment—defined as the number of employees with temporary contracts—slightly after 8 quarters following the shock. Although the value appears small, uncertainty 4 standard deviations above its mean—a scenario observed in practice during crises in the UK such as the Great Recession and the COVID-19 pandemic—corresponds to an approximately 2% rise in temporary employment. This finding holds across alternative VAR specifications, different measures of uncertainty, and the inclusion of additional controls. The VAR results also show that heightened uncertainty is followed by a rise in the share of temporary employees who take up temporary employment in the first place because they fail to find permanent employment, alongside a decline in those who do *not* want permanent employment, consistent with the idea that firms respond to heightened uncertainty by reducing their demand for permanent employees, rather than households becoming more willing to accept temporary employment.

To account for these empirical results, the chapter proceeds with a partial equilibrium model that isolates the role of uncertainty in shaping labour composition. Specifically, I augment the firm's problem as in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), with two types of labour—permanent and temporary. In the UK, the classification of permanent and temporary labour is based on contract duration, with temporary labour generally employed on contracts lasting less than a year. However, in the model, contract duration is not explicitly incorporated; instead, the distinction is conceptualized through a trade-off between adjustment costs and destruction rates: permanent labour is characterized by higher adjustment costs but lower destruction rates (analogous to longer contract duration), while temporary labour features lower adjustment costs but higher destruction rates (similar to shorter contract duration). Although this abstraction is not ideal as it omits contract duration, it offers a simplified representation of real-world dynamics for the purposes of the analysis. Firms face exogenous processes for aggregate and idiosyncratic productivity, with innovations that vary over time. To manage the high dimensionality of the state space, the model abstracts from capital. The lack of UK-specific estimates for adjustment costs, wages and productivity of both permanent and temporary labour necessitates the calibration of these parameters. I also adopt a simulated method of moments (SMM) estimation procedure to obtain the values for parameters governing the uncertainty process, which have not been previously estimated for the UK in the literature.

The analysis finds that heightened uncertainty induces a leftward shift in the firing threshold and a rightward shift in the hiring threshold; this dual shift expands the range of inaction, irrespective of the type of labour. The mechanism driving this result stems from the presence of labour adjustment costs, which renders any errors in hiring or firing decisions prohibitively expensive. Consequently, firms exercise greater prudence in their labour-related choices. Simulations of the model further show that uncertainty shocks lead to a decline in the aggregate share of temporary labour—measured as temporary labour relative to total labour—on impact. While both permanent and temporary labour decrease, the reduction in temporary labour is more pronounced. This is attributed to temporary labour's higher attrition rate as well as lower adjustment costs, making it less costly and less "irreversible" for firms to dismiss temporary employees compared to permanent ones. Following the initial decline, the share of temporary labour experiences a rebound and overshoot during the recovery phase. As firms gradually recover from the uncertainty shock, they resume hiring but disproportionately increase their reliance on temporary labour. Although the rebound and overshoot is a feature of the partial equilibrium framework where the lack of price adjustments leads to exaggerated dynamics, more realistic simulations that combine uncertainty shocks with negative first-moment shocks—as recessions are often characterized by both types of shocks (Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018)—mitigate but do not eliminate the overshoot in the share of temporary labour during the recovery. This suggests that firms become more cautious in the aftermath of heightened uncertainty and react by favouring temporary labour over permanent labour, as the higher adjustment costs incurred by permanent labour makes hiring or firing mistakes of permanent labour costlier than that of temporary labour.

Sensitivity analysis confirms that the results are robust to alternative parameterizations. The analysis further highlights the distinct roles of adjustment costs: while fixed adjustment costs primarily drive the initial impact of uncertainty shocks, linear adjustment costs are critical in shaping firms' responses during the recovery phase, particularly in the dynamics of the share of temporary labour. Introducing a wage penalty and productivity difference between permanent and temporary labour—arguably a more realistic representation of labour market conditions—preserves the baseline dynamics of the share of temporary labour. Policy experiments reveal that wage subsidies targeted exclusively at permanent labour appear to be more effective than blanket subsidies for both types of labour in reducing the share of temporary labour during uncertainty shocks, as such targeted policies increase the relative attractiveness of permanent labour, the less "reversible" input.

The third chapter faces several limitations stemming from both the empirical VAR analysis and the partial equilibrium model. First, the VAR relies on Cholesky decomposition for identification, which imposes a recursive ordering of variables without strong theoretical justification for the timing restrictions between uncertainty and real activity. Second, the number of individuals in temporary employment is a stock variable and may not fully capture the dynamic effects of uncertainty. Third, the analysis is restricted to the UK only; including additional countries could provide comparative insights. On the other hand. the partial equilibrium model abstracts from capital and fails to account for interactions across multiple agents of the economy. Additionally, the model's conceptualisation of temporary and permanent labour—based on adjustment costs and destruction rates rather than contract duration—deviates from real-world definitions. Lastly, key parameters are calibrated rather than estimated due to limited data availability, which constrains the assessment of the uncertainty surrounding these parameter values.

Chapter 1 Microeconomic Uncertainty in the UK

1.1 Introduction

Recent events such as Brexit, trade wars, and the COVID-19 pandemic have heightened uncertainty, making it increasingly imperative for economists to understand its impacts. Elevated uncertainty—broadly defined as the increase in unpredictability of future economic conditions[1]—can depress economic activity through multiple channels: firms delay costly and irreversible investments; financial institutions increase risk premiums, further deterring investment and hiring; households defer discretionary spending; economic agents' collective cautious behavior weakens the effectiveness of fiscal and monetary stimulus.[2] Several studies provide evidence that higher uncertainty reduces income and consumption inequality and shifts time allocation by increasing housework while reducing market hours worked.[3] Economic uncertainty can also have international spillovers through trade linkages, further amplifying its global economic consequences.[4]

Despite the steady growth of the uncertainty literature over the past two decades, notable gaps persist. Specifically, there is a lack of disaggregated measures of uncertainty, which subsequently constrains exploration of the impacts of uncertainty across various cross-sectional dimensions. For instance, the absence of industry-specific uncertainty indicators hinders the investigation of how uncertainty disproportionately affects industries such as

[1]Uncertainty differs from risk in that the probabilities of different outcomes are often unknown or difficult to quantify (Knight, 1921).

[2]See Section 1.2 on the effects of uncertainty on investment, financial distortions, and demand. See Aastveit, Natvik, and Sola (2017) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) on the effects of uncertainty on policy effectiveness. Bloom (2014) reviews the broader literature.

[3]See Theophilopoulou (2022) on the distributional effects of uncertainty and Cacciatore, Gnocchi, and Hauser (2024) on the effects of uncertainty on time use.

[4]See Londono, Ma, and Wilson (2024) among others on the transmission of uncertainty across countries.

manufacturing, services, or agriculture, each of which has distinct capital structures, labor dynamics, and exposure to external shocks. Similarly, the lack of firm-level measures prevents an examination of how small versus large firms respond differently to uncertainty particularly in terms of investment, hiring, and financing decisions. The absence of regional uncertainty measures restricts the analysis of how localized uncertainty—driven by political events, natural disasters, or regional economic policy shifts—affects subnational economies. In short, the use of aggregate measures of uncertainty may mask significant heterogeneity.

Recent advancements in the literature aim to address this gap. Baker, Davis, and Levy (2022) quantify state-level economic policy uncertainty in the United States, demonstrating that the sources of uncertainty differ across states and evolve over time. Similarly, Shields and Tran (2023) develop a state-level uncertainty index using Google Trends search data and highlight that the process of aggregation, which averages out heterogeneity in how uncertainty propagates across states, overlooks key dynamics that drive economic activity at the aggregate level. Mohades, Piccillo, and Treibich (2024) decompose firms' sales volatility to construct uncertainty measures at aggregate, sectoral, and firm levels jointly, revealing that diverse firm traits yield notable heterogeneity, with the manufacturing sector exhibiting the highest levels of uncertainty among sectors.

Building on this literature, This chapter constructs industry division-specific microeconomic uncertainty measures for the United Kingdom and uses them to explore the impacts of microeconomic uncertainty within a panel vector autoregressive (VAR) framework. Using firm-level balance sheet data from the Financial Analysis Made Easy (FAME) database spanning from 2003 to 2022, I define microeconomic uncertainty as the dispersion of firms' productivity shocks across 68 industry divisions.[5] The dispersion of firms' productivity shocks is a sensible measure of uncertainty because, in real business cycle (RBC) frameworks, total factor productivity (TFP) shocks play a pivotal role in

[5]In the UK, economic activities are systematically categorized according to the UK Standard Industrial Classification (UK SIC). This classification features a hierarchical structure, beginning with Sections, and progressing through more specific levels: Divisions, Groups, Classes, and Subclasses. Each successive level provides greater detail. For example, Section C encompasses Manufacturing; within this section, Division 10 pertains to the Manufacture of Food Products; further, Group 10.1 specifies the Processing and Preserving of Meat, and Class 10.11 narrows this down to the Processing and Preserving of Meat specifically.

driving fluctuations in output, investment, and employment; as these shocks become more dispersed, the range of plausible future outcomes widens, translating naturally into greater uncertainty for agents making consumption, investment, or hiring decisions. With this granular, industry division-specific measure of microeconomic uncertainty, I estimate a straightforward panel VAR using Bayesian techniques to examine the effects of microeconomic uncertainty on firm real decisions. I find that panel VARs, despite being underutilized in the uncertainty literature due to the scarcity of disaggregated uncertainty measures, can replicate the impacts of uncertainty documented in existing literature and provide new insights into the heterogeneous effects of uncertainty.

This chapter makes three contributions to the literature. First, it constructs industry division-specific microeconomic uncertainty measures for the UK, following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and Mohades, Piccillo, and Treibich (2024). I use a subset comprising 45,783 firms with 10+ years of data from the FAME database from 2003 to 2022 to mitigate potential biases stemming from compositional changes, yielding a sample close to a half-million firm-year observations. Using firm-level total factor productivity (TFP) estimates derived by Tsoukalas, Ramanan, Tsafos, and Walsh (2024) following the approach of Ackerberg, Caves, and Frazer (2015), microeconomic uncertainty at the industry level is proxied by the cross-sectional dispersion of the residuals from a first-order autoregressive model of firm TFP. The dynamics of microeconomic uncertainty vary significantly across industry divisions, providing evidence that uncertainty need not be identical across industries. Regression results indicate that these microeconomic uncertainty measures are countercyclical (particularly for non-services industries), consistent with the well-established finding in the literature that uncertainty tends to decline during economic expansions and increase during downturns (Bloom, 2014). They complement existing macroeconomic uncertainty indicators for the UK, such as those by Theophilopoulou (2022), Redl (2020), and Dibiasi and Sarferaz (2023), as well as the Economic Policy Uncertainty index by Baker, Bloom, and Davis (2016). Most importantly, the microeconomic uncertainty measures constructed in this chapter are straightforward to compute, utilize widely available firm-level balance sheet data, and can facilitate a granular analysis of the impact of uncertainty on micro-level decisions.

Second, this chapter use panel VARs—a surprisingly underutilized VAR variant in the uncertainty literature—in exploring the effects of uncertainty, enabled by the disaggregated microeconomic uncertainty measures developed herein. Specifically, it demonstrates that the simplest forms of panel VAR, the pooled estimator and the random coefficients model estimated with Bayesian techniques, can provide evidence consistent with findings from the uncertainty literature that use aggregate data. Using the microeconomic uncertainty measure and the annual firm-level data from the FAME database, the results show that firm turnover, investment, and employment experience a statistically significant decline following a microeconomic uncertainty shock, in line with the findings in Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), Jurado, Ludvigson, and Ng (2015), Basu and Bundick (2017), and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015). Quantitatively, the estimated effects of a microeconomic uncertainty shock are non-trivial: a one-standard-deviation microeconomic uncertainty shock leads to a peak decline—observed approximately one year after the onset of the microeconomic uncertainty shock—of slightly more than 4% in turnover, over 5% in employment, and nearly 10% in investment. Even when the random coefficients model is used to account for cross-sectional heterogeneity, the overall dynamics across all industry divisions are as revealing as the aggregated dynamics modeled by a pooled estimator. The results are robust to the use of an alternative microeconomic uncertainty measure, the inclusion of a macroeconomic uncertainty measure as an exogenous variable, and variations in hyperparameter values.

Finally, the use of panel VARs provides additional insights into the heterogeneous effects of uncertainty on investment dynamics and debt-related variables, particularly by comparing service industry divisions with manufacturing industry divisions. Several notable observations emerge. First, in a Bayesian panel VAR with random coefficients applied exclusively to manufacturing industry divisions, the magnitude of investment decline following a microeconomic uncertainty shock varies significantly across divisions, even within the same industry. This finding aligns with the existing literature on the heterogeneous impacts of uncertainty on investment, as documented by Guiso and Parigi (1999), Gulen and Ion (2016), and Panagiotidis and Printzis (2021). Second, a Bayesian panel VAR with random coefficients for a subset of services industry divisions reveals that the decline in investment following a microeconomic uncertainty shock is more persistent in services industry divisions compared to manufacturing industry divisions. This finding is somewhat counterintuitive and diverges from the prevailing literature (e.g., Londono, Ma, & Wilson, 2024; Mohades, Piccillo, & Treibich, 2024; Strobel, 2015).

Third, both long-term and short-term debt decrease following a microeconomic uncertainty shock. However, the proportion of short-term debt relative to total debt initially declines for slightly over a year, then increases and overshoots for approximately another year before gradually returning to its pre-shock equilibrium. This pattern suggests that, immediately after the shock, firms temporarily shift their reliance toward long-term debt, likely as a precaution against refinancing risks (Alfaro, Bloom, & Lin, 2024). However, this trend reverses after about a year as firms increase their reliance on short-term debt instead. This chapter draws on existing literature to provide rudimentary explanations for these dynamics. Fourth, the Bayesian panel VAR analysis with random coefficients reveals differences in debt dynamics between manufacturing and services industry divisions. In manufacturing, most divisions experience a larger decline in short-term debt relative to long-term debt, but there are notable exceptions with some divisions reducing long-term debt more than short-term debt. For instance, the manufacture of food products shows a larger decline in long-term debt relative to short-term debt, whereas the opposite pattern is observed in the manufacture of beverages; the absence of consistent patterns underscores the need for further investigation into the specific characteristics of these divisions that may explain these differences. In contrast, services industry divisions exhibit a greater reduction in long-term debt relative to short-term debt, with long-term debt also taking longer to return to pre-shock levels. These findings are particularly noteworthy because existing literature tends to focus more on the effects of uncertainty on cash holdings under the precautionary savings motive (see, for instance, Fiori & Scoccianti, 2023; Sánchez & Yurdagul, 2013; Smietanka, Bloom, & Mizen, 2018), with debt often being overlooked. Given the relatively limited exploration of uncertainty's effects on debt dynamics in the literature, these findings highlight a compelling avenue for future research.

1.2 Literature Review

This section reviews the existing economic uncertainty measures in the literature and describes how these measures inform the construction of a microeconomic uncertainty measure for the UK in this chapter. Additionally, this section discusses the effects of uncertainty as documented in the literature as well as the widely-utilized VAR method in studying these effects, and identifies a notable gap in the literature concerning its application.

1.2.1 Uncertainty Measures

Two key considerations warrant attention. First, theoretical models frequently conceptualize uncertainty as a mean-preserving change in the second moment of a distribution;[6] for example, this can be represented by an anticipated increase in the volatility of technology, assuming the mean remains constant (Castelnuovo, 2023). Second, while uncertainty inherently pertains to expectations of future events, many empirical studies have used measures of realized volatility to approximate uncertainty (Castelnuovo, 2023). Given these considerations, this chapter approaches uncertainty as an increase in the cross-dispersion of firm TFP, analyzed using ex post firm balance sheet data.

The literature on economic uncertainty measures has traditionally relied heavily on aggregate data. Early work use stock price volatility as a proxy for uncertainty. For instance, Bloom (2009) and Bloom, Van Reenen, and Bond (2007) use stock market volatility as a proxy for uncertainty based on its positive correlation with firms' profit growth volatility and the dispersion across macro forecasters over their predictions for future gross domestic product (GDP). Stock market volatility as a proxy for uncertainty might be problematic as it captures only one dimension of uncertainty—financial market uncertainty—and may be influenced by factors beyond uncertainty, such as investor sentiment (Jurado, Ludvigson, & Ng, 2015; Redl, 2020). More recent work, while still relying on aggregate data, attempts to circumvent this issue by leveraging large datasets of macroeconomic and financial indicators to construct macroeconomic uncertainty indices. Jurado, Ludvigson,

[6]The assumption here is that agents know the probability distribution of the possible outcomes. This assumption is different from 'Knightian' uncertainty where the probability distribution generating the data is unknown (Knight, 1921).

and Ng (2015) pioneer this method and provide a macroeconomic uncertainty index for the US economy, which is now widely adopted. Although this approach offers a more comprehensive measure of uncertainty compared to stock market volatility, its data-intensive nature and methodological complexities hinder widespread replication across other economies.[7] Even more recent work attempts to capture uncertainty using less complex and data-intensive methods. For instance, Dibiasi and Sarferaz (2023) consider the initial releases of real GDP by statistical agencies (for instance, the Office of National Statistics in the UK) as forecasts of the final releases and their subsequent revisions as forecast errors, thereby constructing a macroeconomic uncertainty measure as the conditional volatility of the error associated with the unpredictable component within GDP growth revisions. This method shows promise as time series data of GDP and its revisions are available in most countries.

Text analysis has emerged as another popular method in the literature for computing uncertainty measures. Baker, Bloom, and Davis (2016) exemplify this approach by quantifying newspaper coverage of policy-related economic uncertainty based on the frequency of articles containing the words 'uncertainty' and 'economy'. Similarly, Ahir, Bloom, and Furceri (2022) measure quarterly Economist Intelligence Unit country reports coverage of economic uncertainty by the frequency of the word 'uncertainty'. This method has gained widespread adoption across many countries owing to its data timeliness and low replication costs. Furthermore, its versatility allows for the analysis of uncertainty in narrower categories such as the environment (Abiad & Qureshi, 2023; Dang, Nguyen, Lee, Nguyen, & Le, 2023; Gavriilidis, 2021) and monetary policy (Baker, Bloom, & Davis, 2016). However, the quality of the media[8] may influence the accuracy of resulting uncertainty measure: Białkowski, Dang, and Wei (2022) attribute the puzzling divergence between the market volatility index and economic policy uncertainty following the 2016 U.S. presidential election and the UK Brexit referendum to low-quality political signals.

The literature also features business surveys as a tool to measure economic uncertainty. Bachmann, Elstner, and Sims (2013) and Bachmann, Carstensen, Lautenbacher, and

[7]The exception is Londono, Ma, and Wilson (2024), who leverage the methodology developed by Jurado, Ludvigson, and Ng (2015) to construct real economic uncertainty measures for 39 countries.

[8]Usage of modern vocabulary such as 'fake news', 'half-truths', and 'alternative facts' are on the rise.

Schneider (2024) use business survey questions on managers expectations to measure uncertainty. Awano, Bloom, Dolby, Mizen, Riley, Senga, Van Reenen, Vyas, and Wales (2018) use business survey questions on managers expectations of UK GDP growth and the uncertainty around these expectations to measure firm-level uncertainty. Altig, Barrero, Bloom, Davis, Meyer, and Parker (2022) elicit subjective probability distributions from business executives about their firm outcomes at a one-year look-ahead horizon. These methods might reflect differences in opinions and optimism and not uncertainty (Mohades, Piccillo, & Treibich, 2024), and more importantly, survey questions on uncertainty are often created ad hoc: Bachmann, Carstensen, Lautenbacher, and Schneider (2024) designed and introduced an online module of quantitative questions in the German ifo Business Survey to elicit subjective firm uncertainty in 2012, and fielded an additional one-time special survey in 2018 with questions on how firms collect information and arrive at the views expressed in this uncertainty module. Similarly, the new British survey of business-level expectations used by Awano, Bloom, Dolby, Mizen, Riley, Senga, Van Reenen, Vyas, and Wales (2018) to quantify the uncertainty businesses have around these expectations was created during the Brexit negotiations.

A subset of research leverages firm-level balance sheet data for measuring economic uncertainty. Baum, Caglayan, Ozkan, and Talavera (2006) use the cross-sectional dispersion of asset holdings as a firm uncertainty indicator, while De Veirman and Levin (2018) extract firm-specific volatility using US firm sales data. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) measure the cross-sectional dispersion of TFP shocks from firm balance sheet data as a proxy for microeconomic uncertainty. Kozeniauskas, Orlik, and Veldkamp (2018) use the interquartile range of firm sales growth to represent micro uncertainty. More recently, Mohades, Piccillo, and Treibich (2024) extend upon existing literature, introducing sales volatility as a metric for measuring economic uncertainty at the firm, sector, and aggregate levels. While economic uncertainty measures derived from balance sheet data may not capture uncertainty surrounding business expectations comprehensively and do not fully reflect macroeconomic uncertainty, their primary advantage lies in firm balance sheet data are a resource widely available across economies.

I am now in position to discuss the available economic uncertainty measures for the UK. On macroeconomic uncertainty, Redl (2020) and Theophilopoulou (2022) adopt the method in Jurado, Ludvigson, and Ng (2015) to derive macroeconomic uncertainty measures for the UK. Notably, these studies utilize distinct combinations of macroeconomic and financial variables, as well as varying frequencies in their analyses. Additionally, Dibiasi and Sarferaz (2023) contribute to this domain by deriving a macroeconomic uncertainty measure for the UK within a broader sample of 39 countries, deriving uncertainty from revisions in data sourced from standardized national accounts. Smietanka, Bloom, and Mizen (2018) compute a macroeconomic uncertainty measure by calculating the square root of the average subjective individual variances of forecasters and incorporating the extent of their average disagreement, derived using data from the Survey of External Forecasters compiled by the Bank of England from professional forecasters. Text-based uncertainty measures are also available for the UK. Noteworthy examples include the Economic Policy Uncertainty index (Baker, Bloom, & Davis, 2016) and the World Uncertainty Index (Ahir, Bloom, & Furceri, 2022). Moving to survey-elicited uncertainty measures, Awano, Bloom, Dolby, Mizen, Riley, Senga, Van Reenen, Vyas, and Wales (2018) utilize the Management and Expectations Survey, a firm-level survey conducted jointly by the Office of National Statistics and the Economic Statistics Centre of Excellence (ESCoE), to gauge uncertainty. Similarly, Bloom, Bunn, Chen, Mizen, Smietanka, Thwaites, and Young (2018) leverage the Decision Maker Panel, a business survey collaboratively initiated by the Bank of England, Stanford University, and the University of Nottingham, to assess uncertainty stemming from Brexit and its consequences.

These econometrics-heavy macroeconomic uncertainty measures, text-based indices for various types of uncertainty, and ad-hoc survey-based microeconomic uncertainty measures have provided valuable insights for the UK but there remains a notable gap: the absence of a microeconomic uncertainty measure derived directly from firm-level balance sheet data. The microeconomic uncertainty measure presented in this chapter, though not perfect but nonetheless serves as a complement to the other available measures, is computed on three key principles: simplicity, accessibility, and versatility. Inspired by the work of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and Mohades, Piccillo, and Treibich (2024), this measure is straightforward to compute, utilizes widely available firm-level balance sheet data, and offers a more granular perspective on the relationship between uncertainty and firms' decision-making and performance in various areas.

1.2.2 The Effects of Uncertainty

Output

VARs are widely used by empirical macroeconomists to examine the impact of uncertainty, with output being one of the most frequently analyzed endogenous variables. Table 1.1 provides an overview of the uncertainty literature that employs VARs to investigate the effects of uncertainty on output. This literature predominantly relies on aggregate data, making use of variables such as industrial production and GDP as measures of output. In terms of uncertainty measures, researchers often utilize indicators derived from stock market volatility along with various macroeconomic and financial indicators. While the literature initially focused on the US, it has evolved to include more accessible uncertainty measures discussed in the previous subsection, allowing for cross-country evidence on the effect of uncertainty on output (see, for instance, Baker, Bloom, & Davis, 2016; Baker, Bloom, & Terry, 2023; Dibiasi & Sarferaz, 2023; Redl, 2020).

Table 1.1 reveals the types of VAR models used in the uncertainty literature. Classical VAR models estimated with a frequentist approach and shocks identified via Cholesky decomposition dominate the literature, with notable examples including Bloom (2009), Alexopoulos and Cohen (2009), Jurado, Ludvigson, and Ng (2015), and Basu and Bundick (2017). Cholesky decomposition, which assumes a recursive structure, helps identify the causal relationships between variables by imposing an order on the variables. However, there is no compelling theoretical justification for restricting the timing of the relationship between uncertainty and real activity (Ludvigson, Ma, & Ng, 2021). Recent work uses other VAR identification strategies to circumvent the shortcomings of recursive structures. For instance, Baker, Bloom, and Terry (2023) employ an IV-VAR by instrumenting uncertainty with disaster events. Meanwhile, Redl (2020) and Mumtaz and Zanetti (2013) use sign restrictions, and Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) rely on penalty functions for shock identification. More recent work push the boundaries further by modifying VARs to better answer the question of causality and the identification of exogenous variation in uncertainty. Ludvigson, Ma, and Ng (2021) impose "event constraints" (for instance, the identified financial uncertainty shocks must be large enough during the Global Financial Crisis) and "correlation constraints" (which require external instruments to generate additional inequality constraints to narrow the identified set) for shock identification. Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) exploit breaks in the unconditional volatility of macroeconomic variables to identify uncertainty shocks. Carriero, Clark, and Marcellino (2018) build a large, heteroskedastic VAR model in which the estimate of uncertainty is obtained from a joint model in which uncertainty affects the conditional mean and variances of each variable in the VAR, so there is no need to resort to recursive schemes to identify uncertainty shocks.[9] VARs augmented with additional restrictions to identify the structural shocks generally, though not always, necessitate Bayesian techniques. Finally, Baker, Bloom, and Davis (2016) and Baker, Bloom, and Terry (2023) use panel VARs to compute the average effects of uncertainty across multiple countries.

Across the various types of VARs used in the uncertainty literature summarized in Table 1.1, two key observations emerge. First, the literature consistently documents an adverse effect of uncertainty on output. Although Ludvigson, Ma, and Ng (2021) find that macroeconomic uncertainty is an endogenous response to output shocks, in contrast with the results in Carriero, Clark, and Marcellino (2018) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019), the authors also argue that macroeconomic uncertainty amplifies downturns caused by other shocks during recessions. Furthermore, recent work addressing the limitations of early uncertainty literature—such as Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015)'s introduction of a proxy VAR approach to mitigate measurement errors in Bloom (2009)'s VAR—appears to strengthen the credibility of the evidence on the adverse impacts of uncertainty on real activity. Therefore, for the VAR analysis in this chapter, it is reasonable to expect microeconomic uncertainty to trigger a decline in firm turnover. Second, panel VARs are underutilized in the uncertainty literature. Despite recent efforts to develop more advanced identification strategies to

[9]Most uncertainty measures are estimated in a preliminary step and then used in (often small-scaled) VARs (Creal & Wu, 2017). Carriero, Clark, and Marcellino (2018) point out that this practice may be problematic because the uncertainty around the uncertainty estimates is ignored in the second step, and small VAR models may lead to omitted variable bias when assessing the impacts of uncertainty.

address causality—an exciting avenue in its own right—there remains a gap in empirical macroeconomics regarding the heterogeneous effects of uncertainty. Mumtaz, Sunder-Plassmann, and Theophilopoulou (2018) using a factor augmented VAR (FAVAR) model demonstrate that there is a large degree of heterogeneity in the magnitude and the persistence of the response to uncertainty shocks across US states: states with a large share of manufacturing and construction industries, a larger share of small firms, and a less rigid labour market suffer more from uncertainty. More research is needed to explore the heterogeneous effects of uncertainty across regions, industries, firms, and even individuals. Panel VARs, which are essentially classical VARs enhanced with a cross-sectional dimension, offer a straightforward and convenient starting point for exploring the heterogeneous effects of uncertainty.

Employment

Employment, encompassing both the extensive margin (total employment, employment rate, and unemployment rate) and the intensive margin (hours worked), are commonly incorporated into VAR models alongside output to examine the impacts of uncertainty in the literature. The majority of studies listed in Table 1.1 include employment variables in their VAR analyses; these studies find a negative impact of uncertainty on employment. In addition, Leduc and Liu (2016), employing a classical Structural VAR (SVAR) estimated with Bayesian methods, demonstrates that uncertainty leads to a persistent increase in the unemployment rate.[10] In a Bayesian Markov-switching SVAR model, Netšunajev and Glass (2017) illustrate that demand uncertainty elevates unemployment, with the effect being more persistent in the Euro area but more pronounced in the US. Similarly, Choi and Loungani (2015), utilizing a classical SVAR framework, find that uncertainty raises unemployment, with sectoral uncertainty exhibiting a more lasting impact compared to aggregate uncertainty. Mumtaz (2018) employs a classical SVAR estimated with Bayesian methods, leveraging geographical variation of US-wide macroeconomic uncertainty in US states as an instrument for state-level uncertainty, and find a significant increase in unemployment due to uncertainty. Guglielminetti (2016), using a SVAR with shocks identified through long-run restrictions, observes that uncertainty leads to a decline in vacancies and the job finding rate. Caggiano, Castelnuovo, and Groshenny (2014) estimate

[10]Leduc and Liu (2016) highlight the role of the option value of waiting as a plausible mechanism to rationalize the negative impacts of uncertainty on employment in a search-and-matching framework. However, Den Haan, Freund, and Rendahl (2021) demonstrate that the standard SaM models must be modified with the assumptions of finite entrepreneurs and heterogeneous productivity to rationalize the effects of uncertainty shocks on job creation in terms of an option-value channel.

Authors	Output	Uncertainty	VAR and Identification	Bayesian	Effect	Economies
Bloom (2009)	IP	VXO	VAR, shocks identified with Cholesky decomposition	N	$\downarrow$	US
Alexopoulos and Cohen (2009)	IP	VXO, newspaper coverage	VAR, shocks identified with Cholesky decomposition	N	$\downarrow$	US
Jurado, Ludvigson, and Ng (2015)	IP	macroeconomic uncertainty measure derived from a panel of macro and financial indicators	VAR, shocks identified with Cholesky decomposition	N	$\downarrow$	US
Carriero, Marcellino, and Tornese (2023)	IP	*ala* Jurado, Ludvigson, and Ng (2015)	VAR, *ala* Jurado, Ludvigson, and Ng (2015) with 120 lags	Y	$\downarrow$	US
Ma and Samaniego (2019)	IP	uncertainty measure derived from forecast errors	VAR, shocks identified with Cholesky decomposition	N	$\downarrow$	US
Redl (2020)	GDP	*ala* Jurado, Ludvigson, and Ng (2015)	VAR, shocks identified with sign restrictions using elections	Y	$\downarrow$	11 economies (advanced)
Basu and Bundick (2017)	GDP	VXO	VAR, shocks identified with Cholesky decomposition	N	$\downarrow$	US
Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016)	IP	realized stock market volatility, VXO	VAR, shocks identified with penalty function	Y	$\downarrow$	US
Dibiasi and Sarferaz (2023)	GDP	macroeconomic uncertainty measure derived from data revisions in national accounts	VAR, shocks identified with Cholesky decomposition	Y	$\downarrow$	39 economies
Mumtaz and Zanetti (2013)	GDP growth	estimated volatility of monetary policy	VAR with stochastic volatility, shocks identified with sign restrictions	Y	$\downarrow$	US
Ludvigson, Ma, and Ng (2021)	IP	*ala* Jurado, Ludvigson, and Ng (2015)	VAR, shocks identified with event restrictions	N	$\downarrow$	US
Carriero, Clark, and Marcellino (2018)	IP	common component of volatilities of macroeconomic and financial variables	Large VAR, shocks identified through common component of time-varying volatilities	Y	$\downarrow$	US
Angelini, Bacchiocchi, Caggiano, and Fanelli (2019)	IP growth	common component of volatilities of macroeconomic and financial variables	VAR, shocks identified with volatility breaks	N	$\downarrow$	US
Baker, Bloom, and Davis (2016)	IP	EPU	Panel VAR, shocks identified with Cholesky decomposition	N	$\downarrow$	12 economies
Baker, Bloom, and Terry (2023)	GDP growth	stock market volatility	Panel VAR, shocks identified *ala* Ludvigson, Ma, and Ng (2021) and IV-VAR, with disaster events as instruments	N	$\downarrow$	58 economies

Table 1.1: The effects of uncertainty on output documented in the literature.

a non-linear (Smooth-Transition) VAR and find that the rise in unemployment is even higher than the result predicted by standard linear VARs.

Other studies have explored the impacts of uncertainty on employment (as well as other economic indicators) through approaches beyond VAR models. For instance, Handley and Li (2020) employ a novel measure of firm-level uncertainty derived from the analysis of mandatory reports filed with the U.S. Securities and Exchange Commission. Their panel regressions reveal that uncertainty significantly dampens employment growth rates. Furthermore, Kumar, Gorodnichenko, and Coibion (2023), in a randomized controlled trial, exploit exogenous variation in firms' perception of macroeconomic uncertainty and find that firms reduce employment in times of heightened uncertainty. These studies, alongside the VAR evidence described earlier, offer compelling evidence that microeconomic uncertainty is accompanied by a decline in employment level in the panel VAR examined in this chapter.

Investment

Very early work on investment under uncertainty, notably by Hartman (1972) and Abel (1983), suggests that increased uncertainty can boost investment. This is because a mean-preserving increase in price variance elevates the expected return on a marginal unit of capital when the marginal product of capital is convex in price.[11] However, investment decisions are characterized by their irreversible nature and the potential for postponement (Pindyck, 1990).[12] Subsequent work, including Bernanke (1983) and McDonald and Siegel (1986), introduces the concept of "real options," whereby firms prefer to "wait and see" rather than commit to costly actions with uncertain outcomes. This perspective, along with Abel and Eberly (1993)'s analysis of fixed investment costs and Bertola and Caballero (1990)'s examination of lumpy adjustment costs, establishes a negative relationship between uncertainty and investment. Carruth, Dickerson, and Henley (2000) provide a

[11] Assume the marginal product of capital, $f(P)$, depends on the price P of the output. If $f(P)$ is convex and $\mathbb{E}[P] = \mu$, it satisfies Jensen's Inequality: $f(\mathbb{E}[P]) \leq \mathbb{E}[f(P)]$, where $\mathbb{E}[f(P)]$ is the expected marginal product of capital. A mean-preserving increase in the variance of P implies that while the mean μ remains unchanged, the spread of the distribution of P around μ increases. When $f(P)$ is convex, the function's value at extreme points grows faster than at the mean. The expected marginal product of capital $\mathbb{E}[f(P)]$ is higher than $f(\mathbb{E}[P])$ or $f(\mu)$ because the convex function places more weight on the higher values that result from the increased variance in prices.

[12] Henry (1974) defines an irreversible decision as one that "significantly reduces for a long time the variety of choices that would be possible in the future." Hubbard (1994) characterizes postponements as "keeping one's options open."

comprehensive review of the early literature on investment under uncertainty.

Following the influential work *Investment under Uncertainty* by Dixit and Pindyck (1994), the literature on investment under uncertainty over the past three decades has evolved to cover three key areas. The first area is the propagation mechanisms. Bloom (2009) and Bloom, Van Reenen, and Bond (2007) use numerical method to solve a model with adjustment costs, irreversibility, and time-varying uncertainty to demonstrate the negative effects of uncertainty on investment. Saltari and Ticchi (2007) and Femminis (2019) focus on the role of risk aversion in explaining the investment-uncertainty relationship. Gilchrist, Sim, and Zakrajšek (2014), Christiano, Motto, and Rostagno (2014), and Arellano, Bai, and Kehoe (2019) emphasize the role of financial distortions in amplifying the adverse effects of uncertainty on investment. Nakamura (2002) presents another rationale: increased uncertainty lowers investment even in the absence of irreversibility if the lifetime of capital is shorter than the firm's planning horizon. Glover and Levine (2015) demonstrate how managerial compensation structures influence managers' investment responses to uncertainty shocks.

The second area focuses less on propagation mechanisms and more on innovative methods to provide new evidence of the effect of uncertainty on investment. Bond, Moessner, Mumtaz, and Syed (2005) and Meinen and Röhe (2017) utilize various macroeconomic and microeconomic uncertainty indicators to reassess the impact of uncertainty on investment. Julio and Yook (2012) and Jens (2017) leverage elections as an instrument for political uncertainty to investigate its effects on investment. Handley and Limao (2015) and Guceri and Albinowski (2021) use natural experiments involving policies such as subsidies and trade agreements to identify the causal effect of uncertainty on investment. Additionally, List and Haigh (2010) provide experimental evidence that agents' investment timing decisions are generally responsive to changes in payoff uncertainty. Investment under uncertainty in the natural resource industries also receives attention; for instance, Kellogg (2014) examines the impact of oil price volatility on oil drilling activities in Texas.

The third area addresses the heterogeneous impacts of uncertainty on investment. Ghosal and Loungani (2000) find that the negative impact of uncertainty on investment is significantly greater in industries dominated by small firms. Gulen and Ion (2016) demonstrate that the decline in investment due to uncertainty is more pronounced in firms with a higher degree of investment irreversibility and those more reliant on government spending, corroborating earlier findings by Guiso and Parigi (1999). Kang, Lee, and Ratti (2014) observe that policy uncertainty has no effect on the investment decisions of the largest firms. Similarly, Morikawa (2016) reports that manufacturing and small companies in Japan face higher business uncertainty compared to non-manufacturing and larger companies. Panagiotidis and Printzis (2021) explore the heterogeneity among sectors within a panel quantile estimation framework using Greek firms' balance sheets. They find that while uncertainty negatively affects investment at an aggregate level, this effect is more pronounced in smaller firms and when the firm's investment rate is relatively high. This chapter is most similar to Panagiotidis and Printzis (2021) but differs in two key ways: it employs panel VAR rather than panel quantile estimation, and it also examines how uncertainty is associated with variables other than investment.

Debt

Cash serves as a strategic tool to mitigate refinancing risks (Harford, Klasa, & Maxwell, 2014; Kim & Bettis, 2014). There is a growing literature examining the effects of uncertainty on cash holdings. Sánchez and Yurdagul (2013) find a significant correlation between cash holdings and aggregate uncertainty, while Cheng, Chiu, Hankins, and Stone (2018), using structural VARs, demonstrate that increased political and economic policy uncertainty leads to higher corporate cash holdings. Similarly, Baum, Caglayan, Ozkan, and Talavera (2006) show that macroeconomic volatility reduces the cross-sectional dispersion of firms' cash-to-asset ratios. Im, Park, and Zhao (2017) find that uncertainty, measured by the standard deviation of a firm's daily stock prices, increases cash holdings. Bernile, Bhagwat, and Rau (2017) document that CEOs who have witnessed extreme downside risks from disasters tend to adopt more conservative corporate policies, including increased cash holdings. In a similar vein, Fiori and Scoccianti (2023) find that subjective uncertainty increases cash holdings in Italian firms. Demir and Ersan (2017) show that economic policy uncertainty elevates firm cash holdings in BRIC countries. Smietanka, Bloom, and Mizen (2018) highlight a rise in cash holdings and a concurrent decrease in dividend payouts in the UK during periods of high uncertainty, even when interest rates are low.

On the other hand, the effects of uncertainty on debt—a related but often overlooked topic in the literature—warrant further attention. Harford, Klasa, and Maxwell (2014) demonstrate that the maturity of firms' long-term debt has shortened significantly, which can explain a substantial portion of the increase in cash holdings over time. Li and Su (2020) suggest that uncertainty can shift firms' preference towards short-term debt for two main reasons: first, uncertainty increases information asymmetry between debtors and creditors, prompting high-quality firms to use short-term debt to signal project quality to external lenders; second, uncertainty heightens the risk that firms might not maintain their commitment to their debt maturity structure. They support their arguments with evidence showing a negative effect of economic policy uncertainty on long-term debt and its proportion of total debt in four European countries. Conversely, Alfaro, Bloom, and Lin (2024) theoretically and empirically show that, while firms indeed save more cash to hedge against uncertainty shocks due to a precautionary saving motive, they reduce long-term debt *less* than short-term debt because short-term debt carries higher refinancing risk.[13] This chapter contributes to this emerging branch of literature by exploring the heterogeneous relationships between uncertainty and debt dynamics at different maturities.

1.3 Microeconomic Uncertainty in the UK

In this section, I outline the method used to estimate microeconomic uncertainty and evaluate its relationship with the business cycle.

1.3.1 Measuring Microeconomic Uncertainty

[13]An earlier version of the paper by Alfaro, Bloom, and Lin (2024) (prior to its publication in the *Journal of Political Economy*) offered a more detailed discussion of short-term versus long-term debt dynamics under uncertainty.

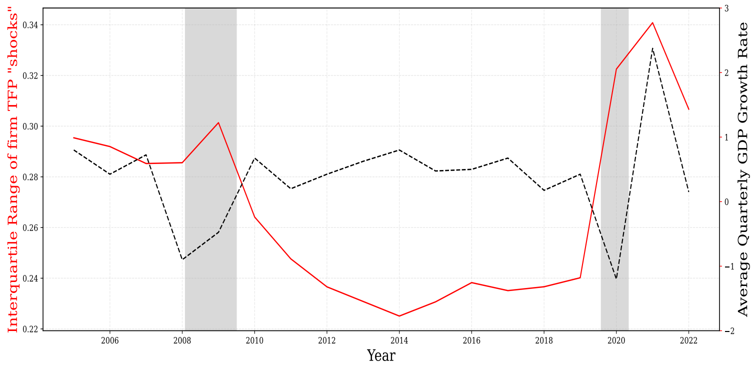

Figure 1.1: The dispersion of TFP 'shocks' increases during recessions. Shaded columns are the share of quarters in a recession within a year. The red solid line plots the interquartile range of firms' TFP 'shocks', while the black dotted line plots the average quarterly GDP growth rates.

Similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and Mohades, Piccillo, and Treibich (2024), I define microeconomic uncertainty as the cross-sectional dispersion of firm performance. This simple and straightforward definition allows for better understanding of how uncertainty affects firms at a granular level, capturing the variations in performance among different firms rather than relying on aggregate measures. To compute microeconomic uncertainty measures, I use annual firm-level data sourced from the Financial Analysis Made Easy (FAME) database. I focus on the subset comprising 45,783 firms with 10+ years of data from 2003 to 2022 to mitigate potential biases stemming from compositional changes, yielding a sample close to a half-million firm-year observations.

Using the firm-level TFP measures computed by Tsoukalas, Ramanan, Tsafos, and Walsh (2024) using the approach from Ackerberg, Caves, and Frazer (2015),[14] and following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I define TFP shocks as the residual from the first-order autoregressive equation of firm-level log TFP:

$$\log \hat{z}_{j,t} = \rho_1 \log \hat{z}_{j,t-1} + \mu_j + \lambda_t + e_{j,t}, \tag{1.1}$$

[14] Ackerberg, Caves, and Frazer (2015) (ACF) demonstrate that their estimation method outperforms the approaches proposed by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP). Both OP and LP assume that labour is a perfectly adjustable input. ACF argue that this assumption is too restrictive and leads to a collinearity problem in the first-stage regressions: when labour is a deterministic function of the set of variables that are nonparametrically conditioned on, there is no variation in labour left to identify its coefficient once this conditioning is performed. To overcome this issue, ACF allow labor choices to depend on unobserved productivity. Their approach involves a first-stage estimation where output is regressed on a polynomial function of capital, intermediate inputs, and labour, with the production function coefficients subsequently recovered in the second stage. Bournakis and Mallick (2018) establish that the estimation technique proposed by ACF provides the most plausible TFP estimates at the firm level for the UK.

where $z_{j,t}$ is firm j's idiosyncratic productivity at period t, μ_j a firm-level fixed effect that controls for permanent firm-level differences, and λ_t a year fixed effect that controls for factors that vary across years but are constant within each year. $e_{j,t}$, the residual from the equation, is the TFP shock, and microeconomic uncertainty is the cross-sectional dispersion of $e_{j,t}$.[15] Figure 1.1 plots the interquartile range (IQR) of this TFP shock: the TFP dispersion increases during the 2008 Financial Crisis as well as the COVID-19 pandemic.

How does the dispersion of TFP shocks compare to existing uncertainty measures for the UK? Figure 1.2 plots the IQR of TFP shocks alongside (i) the macroeconomic uncertainty measures by Dibiasi and Sarferaz (2023), (ii) the Economic Policy Uncertainty (EPU) index by Baker, Bloom, and Davis (2016), (iii) the macroeconomic uncertainty measures by Redl (2020), (iv) the financial uncertainty measures by Redl (2020), (v) the UK's World Uncertainty Index (WUI) by Ahir, Bloom, and Furceri (2022), and (vi) the conditional heteroskedasticity estimated via a GARCH(1,1) model for the percent change in the UK's quarterly aggregate labour productivity.[16] Since the IQR of TFP shocks is at annual frequency, it is inherently less capable of capturing the fluctuations seen in the other uncertainty measures, which are available at monthly or quarterly frequencies. Nevertheless, Figure 1.2 indicates that the IQR of TFP shocks comoves with the macroeconomic uncertainty measures of Dibiasi and Sarferaz (2023) and Redl (2020), as well as with the conditional heteroskedasticity of aggregate labour productivity. However, it fails to capture the sharp spike in the EPU index associated with Brexit and does not closely track the movements in the WUI. These observations suggest that while the IQR of TFP shocks—used here as a proxy for microeconomic uncertainty—reflects macroeconomic uncertainty but not specific episodes of heightened uncertainty such as Brexit.[17] Nonetheless, it appears to serve as a reasonable indicator of economic uncertainty.

[15]Campello, Kankanhalli, and Kim (2024) offer an excellent example of uncertainty: the Somali pirate attacks are an uncertainty shock to shipping activity because the attacks increase "the likelihood of both very negative (being attacked) and very positive (high profits from reduced competition) outcomes." Ergo, uncertainty can be treated as an increase in the dispersion of outcomes.

[16]The Appendix further describes these uncertainty indicators for the UK.

[17]This result should not be interpreted as evidence that microeconomic uncertainty was low during Brexit. The FAME data used to construct the microeconomic uncertainty measures in this chapter are not comprehensive enough to accurately capture the uncertainty experienced by firms during this period. The Decision Maker Panel (DMP) was specifically established to assess the microeconomic uncertainty surrounding Brexit. According to the DMP, Brexit was cited as one of the top three sources of uncertainty by approximately 40% of UK businesses in the two years following the 2016 referendum (Bloom, Bunn, Chen, Mizen, Smietanka, Thwaites, & Young, 2018).

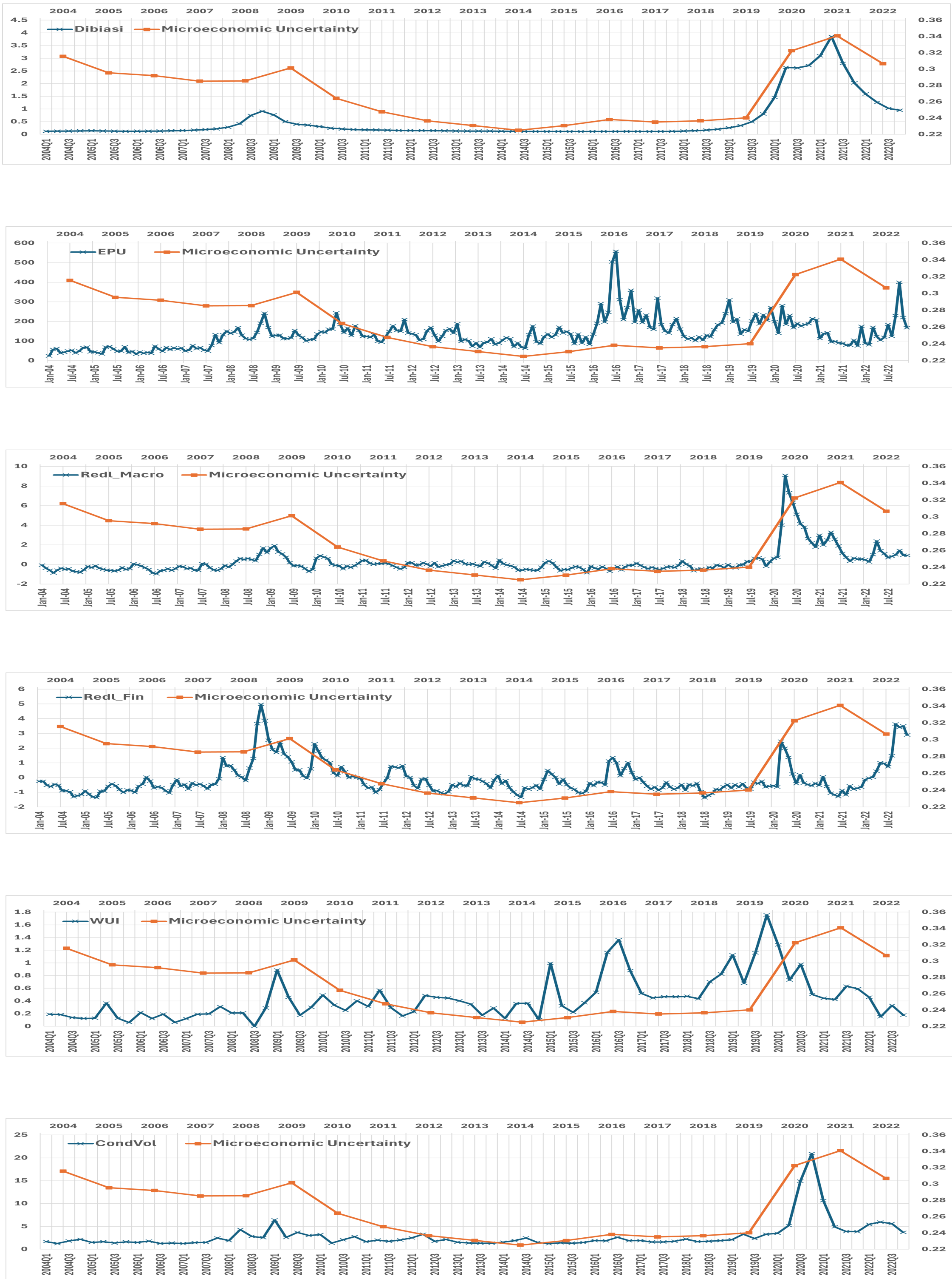

Figure 1.2: Annual microeconomic uncertainty (the IQR of TFP shocks) derived in this chapter with other uncertainty indicators for the UK from year 2004 to 2022. The first row presents quarterly macroeconomic uncertainty measures from Dibiasi and Sarferaz (2023). The second row displays the monthly Economic Policy Uncertainty Index from Baker, Bloom, and Davis (2016). The third and fourth rows show monthly macroeconomic and financial uncertainty measures, respectively, from Redl (2020). The fifth row presents the UK's monthly World Uncertainty Index from Ahir, Bloom, and Furceri (2022). The sixth row shows the conditional heteroskedasticity, estimated using a GARCH(1,1) model, for the percent change in the UK's (four-quarter moving average) aggregate labour productivity obtained from Office of National Statistics (2024g). For all rows, the left axis displays the respective uncertainty indicators, while the right axis the microeconomic uncertainty measures. Further details on these uncertainty indicators can be found in the Appendix.

1.3.2 Microeconomic Uncertainty and the Business Cycle

Figure 1.3 displays the distribution of firm-level TFP shocks in both non-crisis and crisis years within the FAME sample. There is a leftward shift in the distribution of firm TFP shocks during crisis years, indicating a decline in average firm TFP and a higher incidence of negative productivity shocks compared to non-crisis periods. Firm TFP shocks are also more dispersed in crisis years, suggesting that microeconomic uncertainty is countercyclical. This observation is consistent with the findings in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and Mohades, Piccillo, and Treibich (2024). Overall, Figure 1.3 suggests that crisis periods are not only characterized by a negative first-moment shock but also a positive second-moment shock to firm TFP.

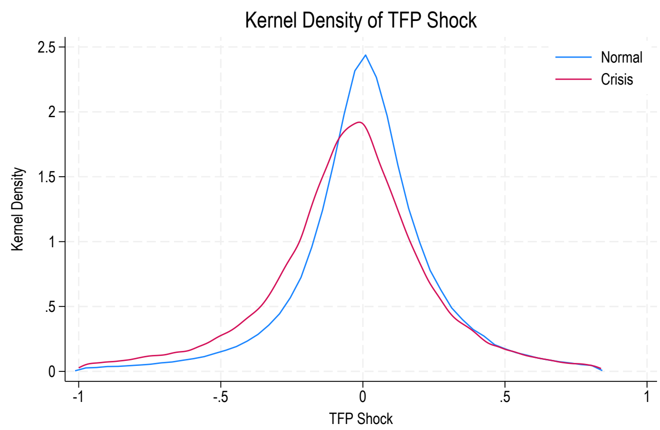

Figure 1.3: The distribution of firms' TFP shock in normal times and crisis periods (years 2008, 2009, 2020, and 2021).

Table 1.2 presents the relationship between the dispersion of TFP shocks and recessions. Here, following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I define recession as the number of quarters in a recession during that year using the GDP growth data from the ONS. For instance, this variable has a value of 0 in 2007 as the Great Recession has not yet started in the UK, and values of 1 and 0.5 respectively in 2008 and 2009 as the Great Recession lasted until 2009Q2. In column 1, I regress the cross-sectional standard deviation of firm-level TFP shocks on recessions. The coefficient is 0.108, which is significant at the 5% level. Since the mean of the dependent variable is 0.378, a year in recession is associated with a 28.57% increase in the dispersion of TFP shocks. Qualitatively, this result is similar to the findings in Bachmann and Bayer (2013) using German firm-level data, and Jurado, Ludvigson, and Ng (2015), Berger and Vavra (2015), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) using US data.

Therefore, the observed countercyclicality in micro-level dispersion is strikingly robust.

Quantitatively, although direct comparison between results obtained with different microdata is not possible, the increase in the dispersion of TFP shocks found in this chapter is twice higher than that documented in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The authors, based on US Census data, reveal that a year of recession corresponds to a 12.72% rise in TFP shock dispersion. Although a 28.57% surge in TFP shock dispersion might appear substantial, it is noteworthy to highlight Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)'s observation that their reported 12.72% increase significantly understates the rise in uncertainty during recessions due to a substantial portion of TFP dispersion being attributed to measurement error, a point proven in their Simulated Methods of Moments (SMM) estimation framework. Furthermore, the firm-level TFP measures in this chapter, sourced from Tsoukalas, Ramanan, Tsafos, and Walsh (2024), are estimated using the methodology introduced by Ackerberg, Caves, and Frazer (2015), which is a state-of-the-art production function estimation technique that addresses key identification issues and provides more consistent estimates compared to earlier methods. An alternative explanation for the disparity in the percentage increase may stem from differences in the sample period. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) analyze data spanning from 1972 to 2011, whereas my sample spans from 2003 to 2022. Naturally, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)'s regression encompass more recession episodes, whereas my recession episodes are only the 2008 Financial Crisis and the COVID-19 pandemic. The severity and unprecedented nature of these two recession episodes in my sample could plausibly account for the pronounced increase in microeconomic uncertainty observed in column 1.

As a robustness exercise, I use an outlier-robust measure of cross-sectional dispersion—the IQR of TFP shocks in column 2. The coefficient is 0.058, which is significant at the 10% level. Given that the mean of the IQR of TFP shocks is 0.270, the coefficient implies that a year in recession is associated with about 21.48% increase in the dispersion of TFP shocks. In column 3, I use the IQR of the firm-level turnover growth rather than TFP shocks as the dependent variable. Again I find a significant increase of this microeconomic uncertainty measure in recessions. Since recessions increase the dispersion of TFP shocks, recessions

	(1)	(2)	(3)	(4)
Dependent variable	S.D. of log(TFP) shock	IQR of log(TFP) shock	IQR of turnover growth	Overall uncertainty
Recession	0.108**	0.058*	0.058**	0.059**
	(0.040)	(0.030)	(0.022)	(0.026)
Mean of dep. var.	0.378	0.270	0.221	0.460
Frequency	Annual	Annual	Annual	Annual
Years	2003-2022	2003-2022	2003-2022	2003-2022
Observations	19	19	19	19
Underlying sample	417093	417093	417093	943036

Table 1.2: Microeconomic uncertainty in the UK. *Notes:* Each column reports an OLS regression point estimate (and standard error below in parenthesis) of a measure of microeconomic uncertainty on a recession indicator. Column 4, labeled "Overall uncertainty," refers to a microeconomic uncertainty measure estimated using GMM based on firm turnover, following Mohades, Piccillo, and Treibich (2024). The bottom panel reports the mean of the dependent variable. The sample is the population of firms with 10 years or more observations in the Financial Analysis Made Easy (FAME) dataset between 2003 to 2022 to reduce concerns over changing samples. All regressions include a time trend. Robust standard errors are applied in all columns. *** denotes 1% significance, ** 5% significance, and * 10% significance.

are often characterized as a negative first-moment shock and a positive second-moment shock (Fernández-Villaverde & Guerrón-Quintana, 2020). Figure 1.4 demonstrates the difference between TFP (first moment) shocks and uncertainty (second-moment) shocks.

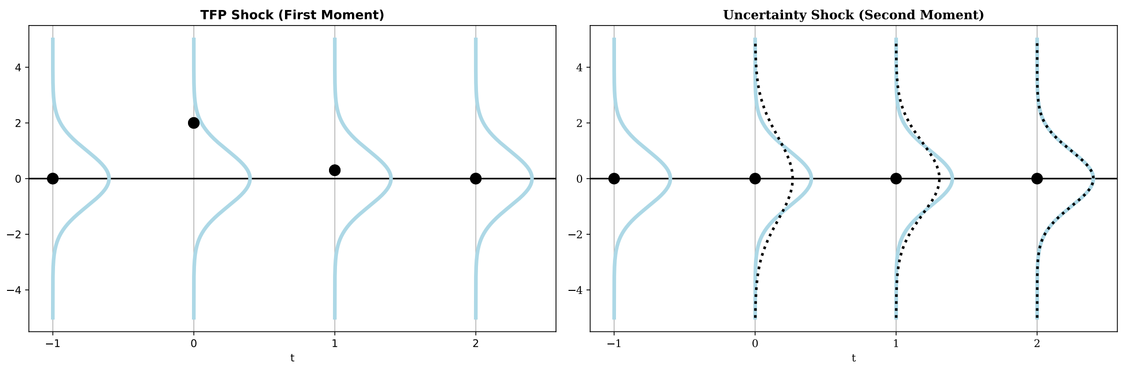

Figure 1.4: A graphical example of first moment versus second moment shocks. The left panel displays a TFP (first moment) shock while the right panel an uncertainty (second moment) shock hitting at period t=0. The horizontal axis represents time t, and the vertical axis captures the magnitude of the shocks. The blue solid lines represent a normal distribution, the black dots the level of productivity, and the black dotted lines the variance of productivity level. A TFP shock is an increase in the level of productivity, while an uncertainty shock is an increase in the dispersion of productivity without changes to its mean. Adapted from Cesa-Bianchi and Corugedo (2014).

As a further robustness check, I use the estimation method in Mohades, Piccillo, and Treibich (2024) to obtain an alternative microeconomic uncertainty measure. Following Mohades, Piccillo, and Treibich (2024), I estimate a dynamic panel from the FAME dataset using a Generalised Method of Moments (GMM) estimator pioneered by Arellano and

Bover (1995) and Blundell and Bond (1998): Instead of TFP, I now only need firm's turnover from the balance sheet data. I use the first lag of firm turnover as an instrument. Specifically, I use lagged differences as instruments for the level equation, alongside the moment conditions of lagged levels as instruments for the difference equation.[18] This methodology proves particularly adept for panel datasets characterized by limited time periods and many individual units (small T, large N), autocorrelation in the dependent variable, and potential heteroskedasticity within individual units' errors (Baltagi, 2008). Consequently, the estimator yields residuals uncorrelated with previously observed residuals, enabling the isolation of the inherently unpredictable component within the turnover process. The dispersion of the residuals, termed "Overall Uncertainty" by Mohades, Piccillo, and Treibich (2024), is used in column 4 of Table 1.2, where I regress this overall uncertainty measure on recessions. The coefficient is 0.059, which is significant at the 5% level. Given that the mean of the overall uncertainty measure is 0.460, a year in recession is associated with a 12.83% increase in the dispersion of firm TFP shock. Although this increase may appear more modest compared to the findings in Column 1, it nonetheless reaffirms the countercyclicality of microeconomic uncertainty.

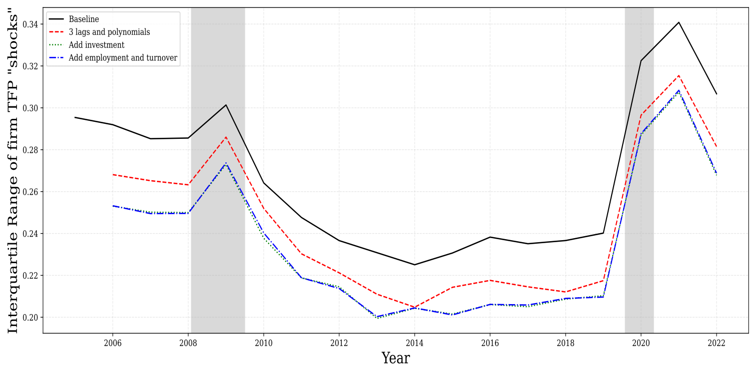

Figure 1.5: Different measures of TFP 'shocks' also exhibit greater dispersion during recessions. Shaded columns are the share of quarters in a recession within a year. The black solid line plots the interquartile range of firms' TFP 'shocks', which the TFP shocks are obtained by regressing on the first lag of log TFP (as in Figure 1.1). The red dotted line plots the interquartile range of firms' TFP 'shocks', which the TFP shocks are obtained by regressing log TFP on the first, second, and third lags of log TFP and their degree 5 polynomials. The green dotted line plots the interquartile range of firms' TFP 'shocks' from the previous specification but also includes the first, second, and third lags of investment rate and their degree 5 polynomials, while the blue dotted line plots interquartile range of firms' TFP 'shocks' using the previous specification but adding the first, second, and third lags of log employment and turnover as well as their degree 5 polynomials.

To confirm the robustness of the results in Table 1.2, I experiment with different specifications in the regressions. In the Appendix, I provide two additional analyses: Table 1.7 presents results using a balanced panel to address any potential sample changes,

[18] Section 1.A.7 in the Appendix describes the estimation method and plots the resulted uncertainty measures.

while Table 1.8 excludes data from the years 2021-2022 due to frequent revisions by FAME stemming from the COVID-19 pandemic. Both tables reaffirm the main conclusion that microuncertainty, represented by the dispersion of TFP shocks, exhibits a significant increase during recessions. In addition, I also augment the TFP forecast regressions (1) by incorporating additional firm-specific information as an attempt to withdraw true shocks to TFP from the perspectives of the firms. First, in contrast to the first-order autoregressive equation, I add an additional 2 lags and degree 5 polynomials. Next I also include investment (lags and polynomials) , as well as employment and sales (lags and polynomials) to control for forward looking investment and employment choices. Figure 1.5 plots the IQR of the TFP shocks for the baseline regression (1), as well as for the dispersion measures obtained by the three augmented regressions. As evident from Figure 1.5, the cyclical patterns of uncertainty remain largely unchanged.

1.4 Microeconomic Uncertainty at the Industry Division Level

The terms "industry" and "industry divisions" are defined slightly differently in this chapter. To define *industry divisions* within the data, I use the two-digit UK Standard Industrial Classification (SIC), which categorizes the sample into 68 distinct industry divisions. To identify broader *industries*, I re-sample the data using the 1-digit SIC. For instance, all firms with two-digit SIC codes ranging from 10 to 33 are classified as manufacturing firms (e.g., SIC 10 corresponds to the Manufacture of Food Products, while SIC 11 pertains to the Manufacture of Beverages). Similarly, firms with a first-digit identifier of either 5, 6, 7, 8, or 9 are grouped under the services industry.

The dispersion of TFP shocks in Section 1.3.1 provides an overall microeconomic uncertainty measure for the UK. To obtain industry division-specific microeconomic uncertainty measures, I modify Equation 1.1 to obtain:

$$\log \hat{z}_{j,t} = \rho_1 \log \hat{z}_{j,t-1} + \mu_j + \lambda_t + \alpha_{j,t} + e_{j,t}, \tag{1.2}$$

where again $z_{j,t}$ is firm idiosyncratic productivity, μ_j a firm-level fixed effect, and λ_t a year fixed effect. I add industrial common factor $\alpha_{j,t}$ as a control, in the spirit of Mohades, Piccillo, and Treibich (2024). To construct this industrial common factor, first I decide on a list of firm characteristics that distinctly define firms across different industry divisions. Details regarding the selection of firm characteristics are outlined in Section 1.A.6 in the Appendix. For *each* industry division, I run a principal component factor analysis based on the preselected firm characteristics to identify the firm-specific, time varying common factors in each division. The resultant values of common factors are then stacked into a single variable $\alpha_{j,t}$ and normalised so it follows a normal distribution.

To derive industry division-specific microeconomic uncertainty measures, I estimate Equation 1.2 separately for each industry division. The inclusion of $\alpha_{j,t}$ in Equation 1.2 controls for the variation in industry division-specific firm characteristics, resulting in 'cleaner' TFP shocks within each industry division. $\alpha_{j,t}$ also allows for the integration of an industry-specific control variable sourced directly from the primary dataset, eliminating the need for dependence on external or aggregated compilations of firms' data. The microeconomic uncertainty of each industry division is then calculated as the cross-sectional dispersion of $e_{j,t}$ within that industry division.

Figure 1.6 plots the industry-specific IQR of TFP shocks as a microeconomic uncertainty measure of a selected subset of manufacturing and services industry divisions. As evident from Figure 1.6, the dynamics of microeconomic uncertainty vary significantly across the industry divisions, providing evidence that uncertainty need not be identical across industry divisions. For instance, during the Global Financial Crisis, microeconomic uncertainty rose sharply in the manufacture of motor vehicles industry division, suggesting an increasing gap between thriving firms and those performing poorly within this industry division. However, microeconomic uncertainty in the manufacture of food products industry division was barely affected during the Crisis, suggesting that the firms in this industry division were affected more equally. Similarly, during the COVID-19 pandemic, microeconomic uncertainty in the legal and accounting industry division was less affected than the other services industry divisions. This finding is consistent with the results in the existing literature: Ma and Samaniego (2019) find that uncertainty shocks to different economic sectors generate different dynamics; Ozili and Arun (2023) find that the closure of mines and industries in China during the COVID-19 outbreak had a pronounced impact on the global manufacturing and mining sectors, whereas the services sector remained largely unaffected; Parast and Subramanian (2021) find that the manufacturing sector experiences greater levels of uncertainty compared to the services and mining sectors. In addition to the existing literature, Figure 1.6 demonstrates that even within the same industry, uncertainty might look very different across divisions. At this point, one may ask: are the seemingly noisy industry division-specific microeconomic uncertainty measures of any use? I answer this question in Section 1.5.

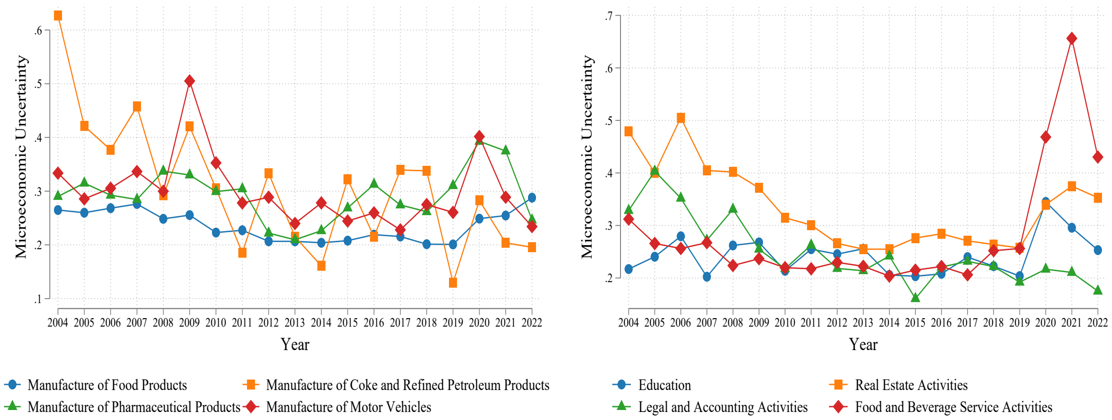

Figure 1.6: Microeconomic uncertainty—measured as the IQR of TFP shocks from the FAME sample—across selected manufacturing (left panel) and service (right panel) industry divisions over time.

In Table 1.3, I use the FAME dataset to examine the dispersion of TFP shocks within each SIC two-digit industry division-year cell to run panel regressions, with the interquartile range (IQR) of TFP shocks for all firms in each industry division (i)-year(t) cell as the dependent variable. The regression equation is given by

$$IQR_{i,t} = a_i + b_t + \beta \Delta y_{i,t}. \tag{1.3}$$

The independent variable ($\Delta y_{i,t}$) is the turnover growth rate in the industry division-year cell, with a full set of industry division (a_i) and year (b_t) dummies. Table 1.3 tests the countercyclicality of the within-industry dispersion of TFP shocks. Column 1 in Table 1.3 shows that across all industry divisions—-manufacturing, utilities, construction, and services—-the within-industry dispersion of TFP shocks increases during periods of slower industry growth, but the increase is not significant. This correlation is independent of the macroeconomic cycle, as the regression includes a comprehensive set of year and industry dummies. The result in column 1 diverges slightly from previous literature: Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) demonstrate a strong countercyclicality of within-industry dispersion of TFP shocks, but the authors focus solely on manufacturing industries. While Mohades, Piccillo, and Treibich (2024) include the services industries in their sample, they detect an occasional pro-cyclical pattern of uncertainty, akin to Jurado, Ludvigson, and Ng (2015). The lack of significance in the countercyclicality of the within-industry dispersion of TFP shocks in column 1 is neither unconventional nor unreasonable.[19] Pooling manufacturing and services industries together may also dilute the countercyclicality of uncertainty at the industry level because investment dispersion is more procyclical in manufacturing industries (Bachmann & Bayer, 2014), and consequently, higher investment dispersion may contribute to a higher dispersion in productivity. Thus, a stronger countercyclicality might be expected in manufacturing industries and a weaker countercyclicality in services industries. In addition, factors driving uncertainty differ across industries–in Bloom, Bunn, Chen, Mizen, Smietanka, Thwaites, and Young (2018), the majority of services industries do not consider the Brexit referendum as an important source of uncertainty. Therefore, the within-industry dispersion of TFP shocks might not exhibit a uniform countercyclical behavior.

Does the lack of statistical significance of the countercyclicality of uncertainty persist within groups of industries with similar characteristics? In column 2 of Table 1.3, I replicate the panel regression from column 1, but restrict the sample to non-services industries, which includes the utilities, construction, and manufacturing industries. Column 2 reveals that in non-services industries, the within-industry dispersion of TFP shocks increases during periods of slower industry growth, and the relationship is significant at the 5% level. This negative relationship between industry growth and the within-industry dispersion of TFP shocks remains robust when I focus solely on the manufacturing industry in column 3. Interestingly, in column 4, when I focus solely on services industry, I do not detect a

[19]Mohades, Piccillo, and Treibich (2024) highlight that not only the causal relationship between business cycles and uncertainty remains an open question, it is also difficult to assess business cycle features of uncertainty by considering either in isolation. Additionally, right-tail events also contribute to uncertainty measures, yet they do not necessarily signal adverse economic outcomes (Rossi & Sekhposyan, 2015).

	(1)	(2)	(3)	(4)	(5)
Dependent variable in all columns : IQR of firm TFP shocks within each industry–year cell					
Sample	All industries	Utilities, construction, manufacturing	Manufacturing	Services	Services excluding "recession-proof" industries
Industry turnover growth	-0.053	-0.115**	-0.126**	-0.052	-0.049
	(0.039)	(0.042)	(0.049)	(0.047)	(0.050)
Frequency	Annual	Annual	Annual	Annual	Annual
Years	2003-2022	2003-2022	2003-2022	2003-2022	2003-2022
Observations	1292	551	437	741	684
Underlying sample	414487	414487	414487	414487	414487

Table 1.3: Microeconomic uncertainty at the industry level in the UK. *Notes:* Each column reports the results from an industry-by-year OLS weighted panel regression. The sample is the 1292 industry-year cells of the population of firms with 10 years or more observations in the Financial Analysis Made Easy (FAME) dataset between 2003 to 2022. All regressions include a full set of industry and year fixed effects. In Column 5, "recession-proof" service industry divisions refer to education and human health activities. A complete list of industry divisions is provided in Section 1.A.1 of the Appendix. Standard errors clustered by industry are applied in all columns. *** denotes 1% significance, ** 5% significance, and * 10% significance.

significant relationship between industry growth and the within-industry dispersion of TFP shocks. Perhaps this lack of significance is attributed to industries less affected by the business cycle–the "recession-proof" industries? In column 5, I exclude education and human health activities from the services industry. Again, I fail to find a significant relationship. This finding suggests that the within-industry dispersion of TFP shocks does not comove with industry growth in all services industry divisions.

Table 1.3 raises the question of why the within-industry dispersion of shocks is higher during industry slowdowns in manufacturing industry but not in services industry. A possible explanation lies in the contrasting capital intensities of these industries: manufacturing industries inherently exhibit higher levels of capital intensity compared to services.[20] Consequently, during industry downturns, financially constrained firms within manufacturing industry must curtail capital investment to a greater extent than their less-constrained counterparts. This divergence in investment behavior contributes to

[20]The manufacturing industries are more capital intensive than the services industries (Fuchs, 1965; Szirmai & Verspagen, 2015). The service industries can be more knowledge-intensive, with capital equipment largely irrelevant in, for instance, law (Fuchs, Garicano, & Rayo, 2015). The manufacturing industries are also more tradable than the service industries; Gervais and Jensen (2019) find that tradable industries are more capital-intensive than non-tradable ones.

heightened dispersion in productivity outcomes within the manufacturing industry.

To conclude, measures of microeconomic uncertainty appear to be countercyclical (and especially so in non-services industries). Although the direction of causality between uncertainty and the business cycles is likely to go in both directions and difficult to disentangle, recent work has provided empirical evidence for the negative impacts of uncertainty on economic activity (see Section 1.2.2). Acknowledging the difficulty in identifying both causal directions, this chapter focuses solely on modeling the effects of uncertainty.

1.5 The Effects of Microeconomic Uncertainty: Evidence from a Panel VAR

This section offers an overview of panel VAR models and Bayesian methodologies, drawing heavily from Dieppe, Legrand, and Van Roye (2016) and Canova and Ciccarelli (2013). It also details the setup of the Bayesian panel VAR employed in this chapter and presents the results from the VAR analysis.

1.5.1 Panel VARs

Over four decades ago, Sims (1980) pioneered the vector autoregression (VAR) as a statistical tool to replace structural econometric models that heavily relied on often unsubstantiated theoretical assumptions for econometric identification (Christiano, 2012). VAR models are designed on the principle of letting the data inherently dictate its structure, using only minimal economic assumptions. This approach obviates the need for explicit theoretical stipulations about causal interdependencies among variables. Essentially, VAR models extend the univariate autoregressive model to multivariate contexts; all the variables in a VAR are treated symmetrically, that is, each variable is a linear function of past lags of itself and past lags of the other variables.

Panel VARs are a variant of VARs that incorporates a cross-sectional dimension. Let g represent endogenous variables, m exogenous variables, p lags, T periods, and N units or entities such as regions, countries, industries, firms, and individuals. The panel VAR model for unit i is given by:

$$y_{i,t} = \sum_{j=1}^{N} \sum_{k=1}^{p} A_{ij,t}^{k} y_{j,t-k} + F_{i,t} w_t + \varepsilon_{i,t}, \tag{1.4}$$

with: $y_{i,t} = \begin{pmatrix} y_{i1,t} \\ y_{i2,t} \\ \vdots \\ y_{ig,t} \end{pmatrix}$, $A_{ij,t}^{k} = \begin{pmatrix} a_{ij,11,t}^{k} & a_{ij,12,t}^{k} & \vdots & a_{ij,1g,t}^{k} \\ a_{ij,21,t}^{k} & a_{ij,22,t}^{k} & \vdots & a_{ij,2g,t}^{k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{ij,g1,t}^{k} & a_{ij,g2,t}^{k} & \vdots & a_{ij,gg,t}^{k} \end{pmatrix}$, $F_{i,t} = \begin{pmatrix} F_{i1,1,t} & F_{i1,2,t} & \vdots & F_{i1,m,t} \\ F_{i2,1,t} & F_{i2,2,t} & \vdots & F_{i2,m,t} \\ \vdots & \vdots & \ddots & \vdots \\ F_{ig,1,t} & F_{ig,2,t} & \vdots & F_{ig,m,t} \end{pmatrix}$,

$w_t = \begin{pmatrix} w_{1,t} \\ w_{2,t} \\ \vdots \\ w_{m,t} \end{pmatrix}$, and $\varepsilon_{i,t} = \begin{pmatrix} \varepsilon_{i1,t} \\ \varepsilon_{i2,t} \\ \vdots \\ \varepsilon_{ig,t} \end{pmatrix}$.

$y_{i,t}$ is a $g \times 1$ vector containing the g endogenous variables of unit i at time t, and $y_{ij,t}$ is the j^{th} endogenous variables of unit i. $A_{ij,t}^{k}$ is a $g \times g$ matrix of coefficients capturing the response of unit i to the k^{th} lag of unit j at time t. w_t is a $m \times 1$ vector of exogenous variables common to all units i, and $F_{i,t}$ is a $g \times m$ matrix reflecting the relationship between the endogenous variables and these exogenous variables. Lastly, $\varepsilon_{i,t}$ is a $g \times 1$ vector of residuals for the variables of unit i; it follows a multivariate normal distribution: $\varepsilon_{i,t} \sim \mathcal{N}(0, \Sigma_{ii,t})$. As the mean vector of the multivariate normal distribution is zero, $\Sigma_{ii,t}$ is equal to $\mathbb{E}(\varepsilon_{i,t}\varepsilon_{i,t}^{'})$, which yields a $g \times g$ symmetric positive definite variance-covariance matrix, with variance terms on the diagonal and covariance terms off diagonal. Assuming non-autocorrelation, that is, the residuals at different time points are uncorrelated, $\mathbb{E}(\varepsilon_{i,t}\varepsilon_{i,s}^{'}) = 0$ when $t \neq s$. Ergo, $\Sigma_{ii,t}$ captures all the necessary information about the variability and co-variability of the residuals at time t without any influence from residuals at other times.

Now, stacking over N units, the panel VAR model reformulates as:

$$y_t = \sum_{k=1}^{p} A_t^k y_{t-k} + F_t w_t + \varepsilon_t, \tag{1.5}$$

where y_t is a $Ng \times 1$ vector containing the g endogenous variables of N units at time t, A_t^k is a $Ng \times Ng$ matrix of coefficients capturing the response of N units to the k^{th} lag of N units at time t, F_t is a $Ng \times m$ matrix reflecting the relationship between the endogenous variables of N units and the exogenous variables, and ε_t is a $Ng \times 1$ vector of residuals. Since $\varepsilon_{i,t} \sim \mathcal{N}(0, \Sigma_{ii,t})$, ε_t also follows a multivariate normal distribution: $\varepsilon_t \sim \mathcal{N}(0, \Sigma_t)$. Again, given $\Sigma_t = \mathbb{E}(\varepsilon_t \varepsilon_t^{'})$, the assumption of non-autocorrelation implies that $\mathbb{E}(\varepsilon_t \varepsilon_s^{'}) = 0$ when $t \neq s$.

Inspection of Equation 1.4 and Equation 1.5 reveals four key features of panel VARs that set them apart from traditional VARs without a cross-sectional dimension. First, the model for unit i includes lags of all endogenous variables specific to unit i, as well as the lags of all endogenous variables across all other units. That is, $A_{ij,t}^k \neq 0$ when $i \neq j$. This is termed "dynamic interdependencies" in the literature. Second, $\varepsilon_{i,t}$ can be correlated across units. In other words, $\Sigma_{ij,t} \neq 0$ when $i \neq j$. This is known as "static interdependencies" in the literature. Third, the VAR coefficients and residual variances can be be unit-specific, meaning $A_{ik,t}^k \neq A_{jk,t}^k$, $F_{i,t} \neq F_{j,t}$, and $\Sigma_{ii,t} \neq \Sigma_{jj,t}$ when $i \neq j$. This is called "cross-subsectional heterogeneity" in the literature. Fourth, the VAR coefficients and residual variance-covariance matrices can also change over time, that is, $A_{ij,t}^k \neq A_{ij,s}^k$ and $\Sigma_{ij,t} \neq \Sigma_{ij,s}$ when $t \neq s$, representing dynamic heterogeneity. The most general form of panel VARs features these four properties, but it may prove too complex for generating precise estimates (Dieppe, Legrand, & Van Roye, 2016). In the next subsection, I describe two variants of panel VARs that relax some of the four properties.

1.5.2 The Bayesian Approach to Panel VARs

Pooled Estimator

The simplest form of Panel VAR is a pooled estimator, which relaxes all four properties.[21] Relaxing the first (dynamic interdependencies) and fourth (dynamic heterogeneity)

[21] It might be misleading to characterize the pooled estimator as the simplest form of panel VAR, as the relaxation of all four properties of panel VAR means that it is, in fact, *not* a panel VAR, although the approach requires a panel dataset.

properties implies that the coefficients are homogenous across units and time-invariant, so the units and time subscripts can be dropped from the $A^{k}_{ij,t}$ coefficient matrices in Equation 1.4, while relaxing the second (static interdependencies) and third (cross-subsectional heterogeneity) properties suggests that $\mathbb{E}(\varepsilon_{i,t}\varepsilon^{'}_{j,t}) = 0$ when $i \neq j$ and $\Sigma_{ii,t} = \Sigma_c \forall i$, with Σ_c representing the fact that the value is both time invariant and common to all units. In its most compact form,[22] a pooled estimator can be written as:

$$y = \bar{X}\beta + \varepsilon, \tag{1.6}$$

where y is a $NgT \times 1$ vector containing the g endogenous variables stacking over N units and T time periods, $\bar{X}$ a $NgT \times g(gp + m)$ matrices containing m exogenous variables and p lag values of g endogenous variables across N units and T time periods, β a $g(gp+m) \times 1$ vector of coefficients, and ε a $NgT \times 1$ vector of residuals. The residuals follow a normal distribution with a mean vector of zero and a covariance matrix $\bar{\Sigma} = \Sigma_c \otimes I_{NT}$, implying that the same covariance structure is assumed to be repeated identically and independently across different units and time periods. For inferences of the panel VAR, the objects of interest are therefore β and Σ_c.

I am now in position to describe the Bayesian approach in estimating β and Σ_c. The traditional, frequentist approach assumes "true" value of the parameter of interest exists, and econometricians strive to estimate this value. The Bayesian approach differs by assuming the parameter of interest is a random variable with an underlying probability distribution, and econometricians aim to identify this distribution to generate estimates for inferences. The identification of this distribution requires a posterior distribution—an updated distribution accounting for the prior information of the econometrician regarding the distribution of the parameter of interest, which is known as the prior distribution, as well as the information contained in the data, which represents the likelihood function. The Bayes rule is hence given by:

[22] I vectorise the pooled estimator, that is, for a coefficient matrix B which is $(gp + m) \times g$, I vectorise B to obtain β which is $g(gp + m) \times 1$. Bayesian analysis usually works with β rather than B, but one can of course use the equivalent B as well.

$$\pi(\theta|y) = \frac{f(y|\theta)\pi(\theta)}{f(y)} \propto f(y|\theta)\pi(\theta), \tag{1.7}$$

where $\pi(\theta|y)$ denotes the posterior distribution of θ conditional on the information in y, $f(y|\theta)$ the likelihood function, $\pi(\theta)$ the prior distribution, and $f(y)$ the data density which acts as a normalizing constant. In other words, the posterior distribution is the product of the likelihood function and the prior distribution, divided by the data density. Note that if there is more than one parameter of interest—for instance, β and Σ_c in a VAR, $\pi(\theta)$ represents the joint prior distribution for all the parameters considered simultaneously. By assuming independence between the parameters, which is common in Bayesian analysis, the joint distribution simply becomes a product of the individual distributions. Equation 1.7 can be formulated as $\pi(\theta|y) \propto f(y|\theta)\pi(\theta_1)\pi(\theta_2)...\pi(\theta_x)$ for a model with x parameters.

Estimating β and Σ_c using the Bayesian approach, that is, identifying the distribution of β and Σ_c, requires a likelihood function, the prior distribution of β, and the prior distribution of Σ_c. Given Equation 1.6 and the normal distribution of ε, the likelihood function is given by[23]

$$f(y|\beta, \Sigma_c) \propto |\bar{\Sigma}|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(y - \bar{X}\beta)'\bar{\Sigma}^{-1}(y - \bar{X}\beta)\right). \tag{1.8}$$

Adopting a normal-Wishart identification strategy, β follows a multivariate normal distribution with mean β_0 and covariance matrix $\Sigma_c \otimes \Phi_0$, with Φ_0 a diagonal matrix. The prior density is hence given by

$$\pi(\beta) \propto |\Sigma_c|^{-\frac{k}{2}} \exp\left[-\frac{1}{2}(\beta - \beta_0)'(\Sigma_c \otimes \Phi_0)^{-1}(\beta - \beta_0)\right], \tag{1.9}$$

[23]This section presents only the final equations of likelihood functions and prior densities. For a detailed step-by-step derivation, I refer readers to the excellent technical guide provided by Dieppe, Legrand, and Van Roye (2016).

with $k = g(gp + m)$ denoting the dimensionality of β. On the other hand, Σ_c follows an Inverse Wishart distribution with scale matrix S_0 that determines the scale and the inverse of the expected values of the covariance matrix Σ_c, and degree of freedom α_0 that represents the dispersion of the distribution. The prior density is hence given by

$$\pi(\Sigma_c) \propto |\Sigma_c|^{-\frac{\alpha_0+g+1}{2}} \exp\left[-\frac{1}{2} tr\{\Sigma_c^{-1} S_0\}\right]. \tag{1.10}$$

Equation 1.9 reveals that $\pi(\beta)$ depends on β_0 and Φ_0, while Equation 1.10 reveals that $\pi(\Sigma_c)$ depends on α_0 and S_0. These parameters are known as hyperparameters; they determine the prior distributions but do not directly formulate the posterior distribution. Econometricians can choose to provide values for these hyperparameters or treat them as random variables. Mathematical definitions of the hyperparameters are available in Section 1.A.8 in the Appendix.

Using Equation 1.7 and assuming independence between parameters of interest, the joint posterior distribution $\pi(\beta, \Sigma_c|y)$ is equal to the product of the likelihood function $f(y|\beta, \Sigma_c)$ and the prior densities $\pi(\beta)$ and $\pi(\Sigma_c)$. Integrating out Σ_c from the joint posterior distribution provides the marginal distribution of β, and vice versa.

Random Effect Panel VARs with Hierarchical Prior

A random effect panel VAR emerges when the third property (cross-subsectional heterogeneity) holds while the other properties are relaxed. Therefore, the random effect panel VAR is a richer model compared to the pooled estimator because the VAR coefficients are heterogeneous across units. In its most compact form, the random effect panel VAR is given by:

$$y_i = \bar{X}_i \beta_i + \varepsilon_i, \tag{1.11}$$

where y_i denotes a $gT \times 1$ vector containing the g endogenous variables stacking over T time periods of unit i, $\bar{X}_i$ a $gT \times g(gp + m)$ matrices containing m exogenous variables and

p lag values of g endogenous variables across T time periods of unit i, β_i a $g(gp+m)\times 1$ vector of coefficients, and ε_i a $gT \times 1$ vector of residuals. The residuals follow a normal distribution with a mean vector of zero and a covariance matrix $\bar{\Sigma}_i = \Sigma_i \otimes I_T$, implying that the same covariance structure is assumed to be repeated identically and independently across different time periods. The model assumes $\beta_i = b + b_i$, with b representing the fixed part of the coefficients across all units and b_i unit-specific random effects modeled as normally distributed with mean zero and covariance matrix Σ_b. It hence follows that $\beta_i \sim \mathcal{N}(b, \Sigma_b)$, meaning that the VAR coefficients are heterogeneous across units but are drawn from a distribution with similar mean and variance.

Under the Bayesian approach— specifically, the hierarchical prior identification strategy, [24] $\beta = (\beta_1, \beta_2, ...\beta_N)'$, $\Sigma = (\Sigma_1, \Sigma_2, ..., \Sigma_N)'$, b, and Σ_b are random variables. Bayesian econometricians aim to obtain the posterior distribution, that is, the distributions of β, Σ, b, and Σ_b. The identification process requires a likelihood function, and the prior distributions of β, Σ, b, and Σ_b. Slightly modifying Equation 1.8, the likelihood function is given by:

$$\pi(y|\beta,\Sigma) \propto \prod_{i=1}^{N} |\bar{\Sigma}_i|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(y_i - \bar{X}_i\beta_i)'(\bar{\Sigma}_i)^{-1}(y_i - \bar{X}_i\beta_i)\right). \tag{1.12}$$

Since $\beta_i \sim \mathcal{N}(b, \Sigma_b)$, the prior density of β writes as:

$$\pi(\beta|b,\Sigma_b) \propto \prod_{i=1}^{N} |\Sigma_b|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\beta_i - b)'(\Sigma_b)^{-1}(\beta_i - b)\right). \tag{1.13}$$

For simplicity, assume the prior density of b is a diffuse (improper) prior:[25]

[24] Another methodology is the Zeller and Hong prior, which Σ, b, and Σ_b are assumed to be known. The only parameter of interest is β.

[25] This prior is "diffuse" because it spreads the probability density very thinly over a wide range of values, implying little to no specific knowledge about the parameter's likely value. The term "improper" means that these priors do not meet the mathematical criteria of a probability distribution; specifically, they do not integrate to one over their entire range. In Bayesian inference, priors must usually be proper to ensure that the posterior distribution is also proper. However, using an improper prior can still result in a proper posterior distribution because the importance of the prior distribution diminishes as the sample size increases and the likelihood contributed by the data overwhelms the non-conformity of the prior (Gelman, Carlin, Stern, & Rubin, 1995).

$$\pi(b) \propto 1, \tag{1.14}$$

implying non-informative beliefs about b before any data are observed. Similarly, for convenience, the prior of Σ_b is assumed to correspond to a known covariance matrix Ω_b:

$$\Sigma_b = (\lambda_1 \otimes I_{g(gp+m)})\Omega_b, \tag{1.15}$$

where λ_1 denotes an overall tightness parameter controlling the overall strength of the prior beliefs imposed on the regression coefficients across all equations in the VAR model.[26] Definitions of λ_1 and Ω_b (and its subsequent hyperparameters) are available in Section 1.5.2 in the Appendix.

Finally, the prior distribution of Σ is assumed to take the form of a simple diffuse prior:

$$\pi(\Sigma) \propto \prod_{i=1}^{N} |\bar{\Sigma}_i|^{-\frac{g+1}{2}}. \tag{1.16}$$

Putting everything together, the joint posterior distribution is given by:

$$\pi(\beta, \Sigma, b, \Sigma_b | y) \propto \pi(y|\beta, \Sigma)\pi(\beta|b, \Sigma_b)\pi(b)\pi(\Sigma_b)\pi(\Sigma). \tag{1.17}$$

Integrating Equation 1.17 to obtain the marginal distributions of β, Σ, b, and Σ_b is challenging due to the high degree of interdependence among these parameters. A favored approach to circumvent this problem is the application of the Gibbs sampler, a type of Markov Chain Monte Carlo (MCMC) algorithm for generating a sequence of samples from

[26] A higher value of λ_1 results in greater shrinkage of the coefficients towards their prior means, effectively penalizing large coefficients. Conversely, a lower value implies less shrinkage, allowing the model more flexibility to fit the data.

the joint distribution of multiple variables. Essentially, this technique enables estimation of the distribution of variables when the joint distribution is complex and direct sampling is computationally prohibitive, but the conditional distributions of individual variables are easier to handle. The Gibbs sampler operates by iteratively updating each variable in a system, conditioning on the current values of all other variables. After a sufficient number of iterations, the distribution of the samples generated by the Gibbs sampler converges to the target joint distribution of all parameters of interest. Upon achieving convergence, the marginal distribution for each parameter can be extracted from the sequence of samples. Section 1.A.9 in the Appendix outlines the Gibbs sampler procedures.

1.5.3 Bayesian Panel VAR Setup

Panel VAR, as seen in Table 1.1, is surprisingly underutilized for exploring the effects of uncertainty. Panel VAR allows for the existence of potential unobserved individual heterogeneity across groups and over time, which can be particularly useful when examining how uncertainty affects various countries, regions, sectors, or firms differently (Canova & Ciccarelli, 2013). Understanding how uncertainty affects various groups of the economy can inform policy decisions aimed at mitigating its adverse effects or capitalizing on potential opportunities. In addition, panel VAR can accommodate large panel datasets with rich information on cross-sectional and time-series dimensions, enabling researchers to leverage comprehensive data sources to uncover the link between uncertainty and both macro- and microeconomic outcomes (Holtz-Eakin, Newey, & Rosen, 1988).

To address the existing gap in uncertainty literature, I choose a panel VAR framework to explore the effects of microeconomic uncertainty using industry-level data. The sample originates from the UK firm-level data in FAME, comprising 68 SIC two-digit industry divisions from 2005 to 2022.[27] Given industry divisions indexed $i = 1, \ldots, N$ and year $t = 1, \ldots, T$, I estimate a four-variable panel VAR model with 1 lag [28] as follows:

$$X_{i,t} = \gamma + BX_{i,t-1} + \varepsilon_{i,t}, \tag{1.18}$$

[27] I exclude industry divisions with insufficient observations to run Equation 1.2. Although firm-level data are available in FAME since 2003, due to the first-order autoregressive equation in Equation 1.1 as well as the entry of variables as first-differenced in the VAR, the sample for the Bayesian panel VAR starts from 2005.

[28] The lag order selection information criteria in Section 1.A.10 of the Appendix indicate that 1 lag is optimal for the Bayesian panel VAR.

where γ denotes a vector of constants, B a matrix of estimated coefficients, and $\varepsilon_{i,t}$ the error term. The vector $X_{i,t}$ consists of industry division turnover (deflated using industry division price deflators), [29] investment (in fixed assets for all firms in each industry division), employment (number of employees for all firms in each industry division), and a microeconomic uncertainty measure—IQR of TFP shocks for all firms in each industry division— constructed in Section 1.4. The uncertainty measure is placed last in the VAR, as in Jurado, Ludvigson, and Ng (2015). I place employment after investment in the VAR because Mecikovsky and Meier (2019) show that investment freeze as a result of uncertainty subsequently lowers labour demand, so uncertainty can affect labour demand even without labour adjustment frictions. The microeconomic uncertainty measure enters as first-differenced, while turnover, investment, and employment enter as log-differenced to ensure stationarity. The specified four-variable setup represents a most parsimonious model allowing for efficient estimation in light of the small number of observations (N=68, T = 18). Table 1.4 presents the summary statistics of the variables.

To further mitigate the small-sample problem I rely on Bayesian techniques to estimate Equation 1.18. Within the Bayesian VAR framework, model parameters are treated as random variables governed by underlying probability distributions (Doan, Litterman, & Sims, 1984; Litterman, 1981). Bayesian shrinkage incorporates prior beliefs about the model parameters and update these probability distributions conditional on the observed data, therefore shrinking parameter estimates towards benchmark values, which is useful particularly when the sample size is limited or the number of parameters to be estimated is large (Kilian & Lütkepohl, 2017). Specifically, following Canova and Ciccarelli (2013), I estimate a Bayesian panel VAR model to increase the accuracy of the estimation.[30][31] I use a Normal-Wishart prior distribution because it imposes fewer restrictions on the model—it assumes no prior knowledge about either the VAR coefficients or the variance-covariance matrix, in contrast to the Minnesota prior that assumes the variance-covariance matrix is known. I identify structural shocks through Cholesky decomposition and compute impulse responses based on 10,000 draws, with the initial 5,000 draws discarded as a

[29] The industry division deflators are available on the ONS website at https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/industrydeflators.

[30] I describe the hyperparameter values used in the estimation in the Appendix.

[31] The generalized method of moments (GMM) VAR framework by Love and Zicchino (2006) is also suitable for panels with a relatively short time dimension, but given that the sample used in this chapter is small, I use Bayesian panel VAR as the baseline approach.

burn-in sample.[32]

As the objective of this chapter is to estimate the average responses to uncertainty shocks using micro data and compare these findings with the established responses derived from macro data in the literature—I use the Bayesian panel VAR pooled estimator as well as random coefficients with a hierarchical prior. While larger datasets enable the modeling of complex static or dynamic heterogeneity within the Bayesian panel VAR framework contingent upon additional assumptions and priors (see Dieppe, Legrand, and Van Roye (2016) and Canova and Ciccarelli (2013)), such extension is beyond the scope of this chapter as the focus remains on inferring the average responses to uncertainty shocks. In the subsequent subsections, I explore heterogeneity across various industry division subsets with shared characteristics.

	N	Mean	SD	Min	Max
IQR of TFP shock	1224	-0.001	0.075	-0.580	0.696
SD of TFP shock	1224	-0.001	0.117	-0.759	0.882
Turnover	1224	-0.041	0.450	-3.646	2.015
Investment	1224	0.022	0.906	-8.034	5.666
Employment	1224	-0.036	0.409	-3.244	2.358

Table 1.4: Summary statistics of the variables used in the Bayesian panel VAR. Microeconomic uncertainty measures—the interquartile range (IQR) and standard deviation (SD) of TFP shocks—are first-differenced, while the remaining variables are log-differenced. The data are sourced from FAME, covering the period 2003 to 2022. In the Appendix, Section 1.A.2 provides additional descriptive graphs and Section 1.A.10 presents summary statistics for the variables without first-differencing.

1.5.4 Bayesian Panel VAR Analysis

Figure 1.7 displays the impulse response functions (IRFs) derived from the Bayesian panel VAR using a pooled estimator. The orange solid line indicates the median impulse response to a one-standard-deviation microeconomic uncertainty shock. Quantitatively, the effects of a microeconomic uncertainty shock prove non-trivial: a one-standard-deviation microeconomic uncertainty shock leads to a peak decline of slightly more than 4% in turnover, over 5% in employment, and nearly 10% in investment.[33] A subset of the literature demonstrates that uncertainty shocks have a very small impact on

[32] I use the MATLAB-based Bayesian Estimation, Analysis and Regression (BEAR) Toolbox developed by the European Central Bank (see Dieppe, Legrand, and Van Roye (2016)).

[33] With higher-frequency data, VARs can capture the gradual adjustments of economic variables to shocks, spreading the effects over several periods. When using annual data, however, these dynamics are condensed into a single period, leading to larger apparent responses.

macroeconomic variables, but the responses accumulate over time (e.g., Alessandri, Gazzani, & Vicondoa, 2023; Bonciani & Oh, 2019; Leduc & Liu, 2016), while another subset of the literature documents immediate and large impacts of uncertainty on economic activity (e.g., Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018). The results from the Bayesian panel VAR using a pooled estimator align with the latter: the decline in turnover, investment, and employment is substantial, with peak effects observed approximately one year after the onset of the microeconomic uncertainty shock. The magnitude of the decline in investment surpasses that of turnover and employment. In fact, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) using a dynamic general equilibrium model also observe a greater decline in investment than in output and labour following an uncertainty shock, hereby lending credibility to the IRFs derived from the Bayesian panel VAR analysis.

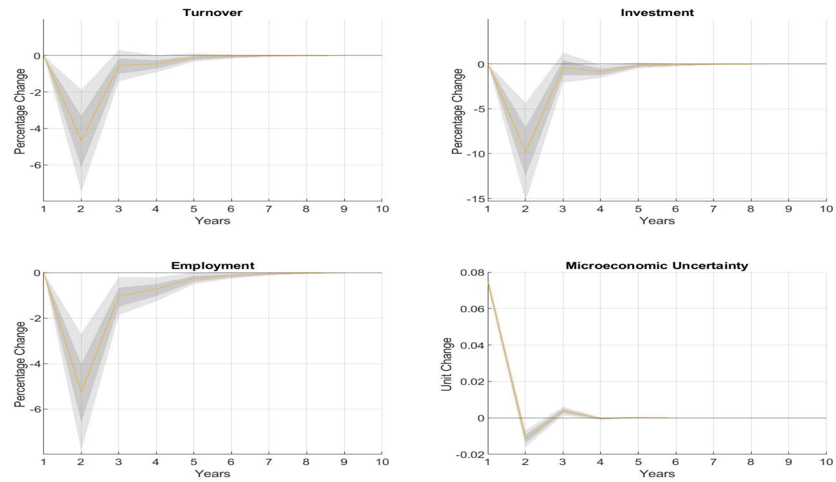

Figure 1.7: Impulse response functions of the Bayesian panel VAR using a pooled estimator. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The orange line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Qualitatively, the responses of the variables to the microeconomic uncertainty shock in the Bayesian panel VAR using a pooled estimator corroborate the findings regarding uncertainty shocks derived from aggregate data in the existing literature. The observed decline in turnover following the microeconomic uncertainty shock are in line with theory and the literature in Table 1.1, for instance, the decline in industrial production subsequent to a macroeconomic uncertainty shock (with the uncertainty measure constructed by a comprehensive set of macroeconomic and financial variables) in Jurado, Ludvigson, and Ng (2015), the decline in GDP following a macroeconomic uncertainty shock identified with close elections in Redl (2020), and the decline in output growth following a macroeconomic uncertainty shock proxied by natural disasters in Baker, Bloom, and Terry (2023). Similarly, the observed decline in employment following the microeconomic uncertainty shock resonates with the reduction in job creation in the wake of uncertainty in an economy with finite entrepreneurs and heterogeneous firm productivity in Den Haan, Freund, and Rendahl (2021), the contraction in employment in advanced economies following a macroeconomic uncertainty shock in Dibiasi and Sarferaz (2023), and uncertainty shocks as a driver of unemployment in Caggiano, Castelnuovo, and Groshenny (2014). The decline in turnover and employment following an uncertainty shock is intuitive: firms freezes hiring and delays investments as they are unsure about future demand (see, for instance, Kumar, Gorodnichenko, & Coibion, 2023), and households reduce (especially discretionary) spending due to precautionary saving motives (Coibion, Georgarakos, Gorodnichenko, Kenny, & Weber, 2024). The investment dynamics observed following a microeconomic uncertainty shock in the Bayesian panel VAR using a pooled estimator are also consistent with the expected patterns found in the literature. Generally, the literature suggests a significant decline in investment after an uncertainty shock, attributed to the "irreversibility effect," where firms opt to "wait and see" rather than commit to costly actions with uncertain outcomes (Bernanke, 1983; Bloom, Van Reenen, & Bond, 2007; Dixit & Pindyck, 1994), and to financial distortions (Arellano, Bai, & Kehoe, 2019; Christiano, Motto, & Rostagno, 2014; Gilchrist, Sim, & Zakrajšek, 2014).

In Figure 1.7, microeconomic uncertainty temporarily falls below its pre-shock level in the second period following the uncertainty shock in the first period. This pattern arises from the recursive ordering in the VAR model, where microeconomic uncertainty is ordered last. In the second period, the sharp contraction in turnover, investment, and employment—driven by firms' responses to the initial uncertainty shock—feeds back into uncertainty. The resulting drastic adjustments in investment and employment eliminate some sources of uncertainty and reduce future unpredictability, leading to a temporary overshooting correction where uncertainty dips below its pre-shock level. This temporary stabilization in turn improves expectations, prompting firms to restore output, investment, and employment, with these variables gradually returning to their pre-shock levels from the third period onward.

A subset of papers observes a 'drop and rebound' pattern in investment, employment, and productivity following an uncertainty shock, while this pattern is absent in other papers on uncertainty. Bloom (2009), who first documents this 'drop and rebound' pattern, explains that this pattern arises because uncertainty initially causes firms to temporarily pause their hiring and investment, but in the medium term, the increased volatility from the uncertainty shock leads to a volatility overshoot as firms respond to the heightened variance of productivity shocks, driving a medium-term overshoot and a longer-run return to trend. However, Figure 1.7 does not exhibit this "drop-and-rebound" pattern. Nonetheless, the results from the Bayesian panel VAR using a pooled estimator align closely with the broader findings in the uncertainty literature.

A natural question ensues: does the Bayesian panel VAR using random coefficients outperform the pooled estimator in generating effects of microeconomic uncertainty consistent with the literature? It is possible that the Bayesian panel VAR using random coefficients outperform the pooled estimator because the random coefficient model may address endogeneity and omitted variable bias more effectively than the pooled estimator by allowing unit-specific coefficients; the pooled estimator fails to capture unobserved heterogeneity, which might lead to biased estimates (Pesaran & Smith, 1995).[34] Another reason is that the random coefficient model may be using priors that better reflect the underlying structure of the data, leading to more informative estimates. Although direct comparison is not entirely feasible due to the use of different sets of hyperparameters, comparing the IRFs of both models can still be informative about the qualitative patterns of variable responses to a microeconomic uncertainty shock. Figure 1.8 presents the IRFs derived from the Bayesian panel VAR using random coefficients. Under a random coefficients model, the coefficients of the VAR will differ across units but are drawn from a distribution with similar mean and variance, so Figure 1.8 overlays the IRFs of all 68 industry divisions. Here, the individual coefficients are of little importance; we are interested in the overall dynamics of the variables for comparison with the results using the pooled estimator in Figure 1.7 .

[34] In pooled estimators, when T is small, lagged dependent variables bias results in downward biased coefficients but heterogeneity bias inflates coefficient estimates; in empirical applications it is challenging to judge the net effect on the coefficient estimates (Pesaran, Shin, & Smith, 1999).

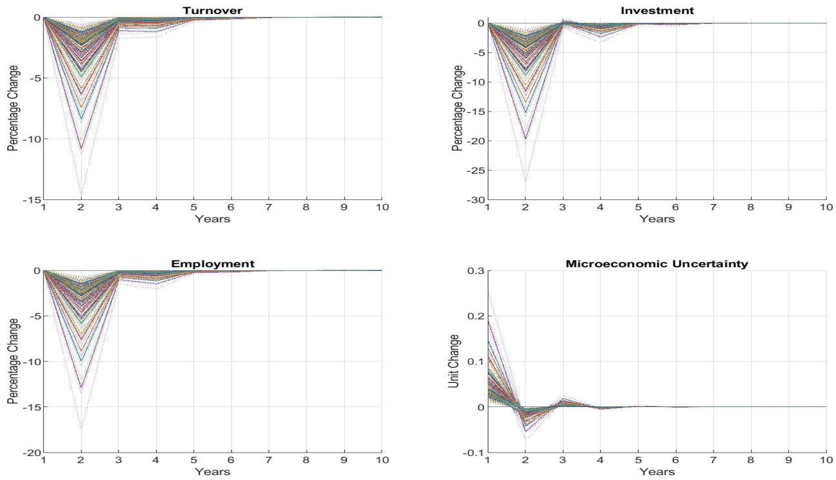

Figure 1.8: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Similar to the pooled estimator, the Bayesian panel VAR using random coefficients generates peak responses in the second period, with a statistically significant decline in all variables at the 95% confidence level. The advantage of the random coefficients approach lies in its ability to reveal heterogeneity in responses across the 68 industry divisions. As shown in Figure 1.8, the magnitude of a one-standard-deviation microeconomic uncertainty shock varies significantly across industry divisions, resulting in substantial variation in the declines of turnover, investment, and employment. This result highlights that while the effects of microeconomic uncertainty shocks are generally negative, their magnitudes differ across industry divisions. Thus, the answer to the question of whether the Bayesian panel VAR using random coefficients outperforms the pooled estimator in generating effects of microeconomic uncertainty consistent with the literature is: it depends. If one is satisfied with observing only a decline in output, employment, and investment to confirm alignment with theoretical expectations and the uncertainty literature, both the Bayesian panel VAR using the pooled estimator as well as random coefficients perform adequately. However, if one is interested in the heterogeneity of responses across industry divisions, the random coefficients model is better suited. Ultimately, model selection should be driven by methodology, not results. An econometrician's objective is to test which specification best fits the data. While comparing log marginal likelihood is a standard approach, this is not feasible for the Bayesian panel VAR with random coefficients due to the use of a diffuse prior. Therefore, the Bayesian Information Criterion (BIC) and Deviance Information Criterion (DIC) serve as alternatives. Indeed, the Bayesian panel VAR with random coefficients outperforms the pooled estimator in terms of both BIC and DIC values.[35]

Before making further conclusions, I conduct robustness checks on both models. Specifically, I use alternative hyperparameter values, include macroeconomic uncertainty as an exogenous variable, and replace the interquartile range with the standard deviation of TFP shocks as the microeconomic uncertainty measure.[36] First, does setting alternative hyperparameter values produce the same results in Figure 1.7 and Figure 1.8? The baseline Bayesian panel VAR using pooled estimator sets the overall tightness parameter, λ_1, to 0.1. This parameter controls the overall strength of the prior beliefs imposed on the regression coefficients across all equations in the VAR model. A higher value of λ_1 results in greater shrinkage of the coefficients towards their prior means, penalizing large coefficients. Conversely, a lower value of λ_1 implies less shrinkage, allowing the model more flexibility to fit the data. Testing both a reduction ($\lambda_1 = 0.05$ in Figure 1.27) and an increase ($\lambda_1 = 0.2$ Figure 1.26) in λ_1, I observe that these adjustments do not qualitatively alter the outcomes in Figure 1.7. The baseline Bayesian panel VAR using pooled estimator also sets the lag decay parameter, λ_3, to 1. This parameter adjusts the strength of the shrinkage applied to the coefficients of lags as they increase in order: essentially, it penalizes the impact of variables from earlier periods, under the assumption that more recent observations have a stronger predictive value than older ones. Higher λ_3 values cause a faster decay in the influence of successive lags, meaning that the model quickly discounts the importance of variables from more distant past periods, while lower λ_3 values result in a slower decay, suggesting that past values are still considered relevant. $\lambda_3 = 1$ suggests a linear decay in the influence of lagged terms, a neutral choice when no strong prior beliefs favor either rapid or slow decay. Variations in λ_3 ($\lambda_3 = 1.5$ in Figure 1.28 and $\lambda_3 = 2$ in Figure 1.29), aimed at accelerating the decay rate of influence from earlier periods, also fail to significantly affect the qualitative results in Figure 1.7.[37] Furthermore, simultaneous adjustments to both λ_1 and λ_3 ($\lambda_1 = 0.15$ and $\lambda_3 = 1.5$ in Figure 1.30) demonstrate that

[35]Section 1.A.10 in the Appendix provides further details on why log marginal likelihood cannot be computed for the random coefficients model, as well as the BIC and DIC comparisons between the two models.

[36]I also experiment with changing the Cholesky ordering in the Appendix.

[37]Testing λ_3 values below 1 might risk overfitting due to excessive weight on older lags.

while the dynamic responses of variables remain consistent as in Figure 1.7, the specific decline in investment loses significance at the 68% level. Collectively, these robustness checks suggest that while the tuning of hyperparameters λ_1 and λ_3 influences model sensitivity of a Bayesian panel VAR using pooled estimator, it does not fundamentally alter the directional effects observed following a microeconomic uncertainty shock.

For the Bayesian panel VAR using random coefficients, I test the model's sensitivity to alternative λ_2 and both s_0 and v_0 values.[38] λ_2 represents additional shrinkage applied specifically to the lags of variables other than the variable itself; this hyperparameter controls the extent to which the model penalizes the inclusion of lags from other variables, thus reduces the model's complexity and potential overfitting. A higher λ_2 value implies greater skepticism about the relevance of these cross-lags. I set λ_2 to 0.5 in the baseline Bayesian panel VAR using random coefficients, following Karlsson (2013). Setting a lower and higher λ_2 values (0.1 in Figure 1.33 and 0.6 in Figure 1.34 respectively) do not significantly change the qualitative outcomes observed in Figure 1.8. On the other hand, the residual variance in the context of Bayesian VAR models often assumes an Inverse Gamma (IG) prior distribution, and s_0 and v_0 represent respectively the shape parameter and the scale parameter. The choice of s_0 affects the tail behavior and concentration of the distribution around its mode; a higher s_0 generally results in tails that decay more quickly, meaning that extreme values become less probable. The scale parameter v_0 inversely affects how spread out the distribution is; a larger v_0 means a narrower spread since it appears in the denominator of the exponential part of the density function. I set s_0 and v_0 to 0.001 in the baseline Bayesian panel VAR using random coefficients to make the prior weakly informative, following Gelman (2006). Reassuringly, the qualitative results in Figure 1.8 remain the same when I set both s_0 and v_0 to a smaller value (0.0001 in Figure 1.35) and to a larger value (0.01 in Figure 1.36). Collectively, these robustness checks confirm the stability of the model's responses to parameter adjustments: following a microeconomic uncertainty shock, turnover, employment, and investment all experience a statistically significant decline.

[38] I do not use alternative values for λ_4 because this hyperparameter which controls the tightness on coefficients of exogenous variables (including constants) is frequently assign a value ranging from 100 to infinity to account for a lack of prior belief of exogenous variables (Dieppe, Legrand, & Van Roye, 2016). Setting $\lambda_4 = 100$ is a comfortable choice within the broader consensus of the field.

Second, I incorporate the UK's macroeconomic uncertainty measure by Dibiasi and Sarferaz (2023)[39] as an exogenous variable in both the Bayesian panel VAR using a pooled estimator and the one using random coefficients. Macroeconomic and microecnomic uncertainty tend to comove and potentially feed into each other (Bloom, 2014). The inclusion of macroeconomic uncertainty as an exogenous variable ensures that macroeconomic uncertainty is accounted for, so that the effects of microeconomic uncertainty on turnover, investment, and employment are not driven by macroeconomic uncertainty. Figure 1.25 and Figure 1.32 demonstrate that including macroeconomic uncertainty as an exogenous variable maintains the qualitative dynamics of the baseline results for either Bayesian panel VAR approach.

As a final robustness check, I replace the interquartile range (IQR) with the standard deviation (SD) of TFP shocks as a measure of microeconomic uncertainty. The difference between the two is that the former is outlier-robust, which is the preferred measure in this chapter. When the SD of TFP shocks is used, the Bayesian panel VAR with the pooled estimator generates declines in turnover, investment, and employment that are statistically significant at the 68% confidence level (but not at the 95% level) following a microeconomic uncertainty shock (Figure 1.31). Similarly, the Bayesian panel VAR using random coefficients (Figure 1.37) retains the qualitative dynamics of the baseline case, although the decline in the variables is statistically significant for a shorter period when the SD is used as the measure of microeconomic uncertainty. Putting all the robustness checks together, I conclude that the results of the Bayesian panel VAR using a pooled estimator and of the Bayesian panel VAR using random coefficients are robust to alternative specifications.

The implication here is that even when the average effect, not individual differences, across units is the focus of analysis—which is the primary objective of this study as I examine the capability of panel VARs using firm-level data to capture the effects of economic uncertainty documented in the literature—the random coefficients model can complement the pooled estimator model at providing insights into general trends consistent with the literature. Despite the random coefficients model accounting for cross-sectional heterogeneity, it maintains that the coefficients of the VAR are drawn from

[39]The macroeconomic uncertainty measure by Dibiasi and Sarferaz (2023) is available in quarterly frequency. I average it to obtain annual measures.

a distribution characterized by the same mean and variance. This approach ensures that, although coefficients may vary among industry divisions, the overall dynamics across all industry divisions are as revealing as the aggregated dynamics modeled by a pooled estimator. In the context of uncertainty, this implication is particularly exciting because the uncertainty literature heavily relies on aggregate data; the use of more granular data in the random coefficients framework now can provide meaningful insights without assuming homogeneity. Since the random coefficient model generates general effects of uncertainty consistent with the literature as shown in Figure 1.8, it can be used further to facilitate analysis of industry-specific responses. For example, the uncertainty shock in industry A might look different than the uncertainty shock in industry B. While industries A and B may both experience declines in employment following an uncertainty shock, the magnitude of the decline might be more pronounced in industry A due to industry-specific factors including greater dependence on global trade, higher regulatory burdens, or increased automation. I will use Bayesian VARs with random coefficients in the next subsections to further explore these differential responses to uncertainty shocks in distinct divisions of industries.

Non-services versus Services

Before analyzing the heterogeneous responses to uncertainty shocks across specific industry divisions, this subsection briefly compares the responses of non-services industries (manufacturing, utilities, and construction) with those of services industries using a pooled estimator.[40] Due to differences in, for instance, capital intensity, exposure to supply chain disruptions, and reliance on labour,[41] responses to uncertainty shocks may vary between non-services industry divisions and services industry divisions. The comparison highlights key differences between the two broad industry groups, providing a rationale for the subsequent focus on the role of industry division-specific factors in explaining the differential impact of uncertainty in the Bayesian VAR with random coefficients in the next subsection.

[40]The sample includes 68 industry divisions: 29 non-services industry divisions and 39 services industry divisions. A complete list of these divisions is provided in Section 1.5 of the Appendix.

[41]Charles, Hurst, and Schwartz (2019) highlight that the manufacturing industry in the US has experienced a sharp increase in capital intensity. Parast and Subramanian (2021) argue that supply chain disruptions elevate uncertainty in manufacturing firms through production bottlenecks.

Figure 1.9 illustrates the impulse responses of turnover, investment, and employment in non-services and services industry divisions following a microeconomic uncertainty shock. While the magnitude of the shock differs across groups, the shocks are standardized to a one-standard-deviation shock to allow for consistent comparison. Two key findings emerge from the figure. First, the declines in turnover and investment for non-services industry divisions are not statistically significant in the Bayesian panel VAR with a pooled estimator. This could be attributed to the smaller sample size of non-services divisions (29 divisions) relative to services divisions (39 divisions), which may reduce the statistical power of the pooled estimator. Additionally, there might be a greater heterogeneity in responses across non-services divisions (presented in Section 1.5.4); averaging responses across divisions increases the overall variance of the estimated impulse response functions, resulting in wider confidence intervals and a lack of statistical significance.

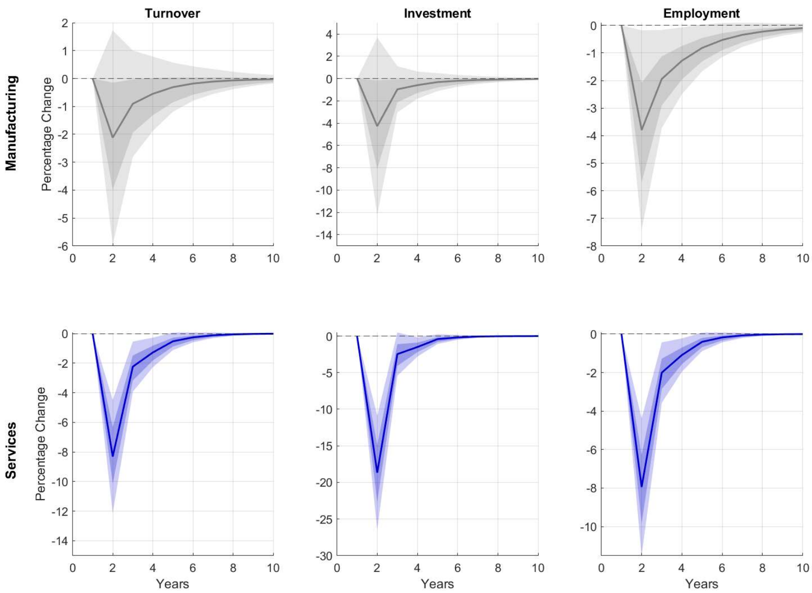

Figure 1.9: Impulse response functions of the Bayesian panel VAR using a pooled estimator for non-services and services industry divisions. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. In each plot, the black (purple) line denotes the median impulse response to the microeconomic uncertainty shock in the non-services (services) industry divisions. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Second, the declines in turnover, investment, and employment are more pronounced for the services industry compared to the non-services industry. This result contrasts with findings in prior literature. For instance, Londono, Ma, and Wilson (2024) analyze data from 39 countries and find that a one-standard-deviation increase in the foreign component of global real economic uncertainty leads to a decrease in retail sales that is nearly five times smaller than the corresponding decline in the tradable manufacturing sector, and this effect for retail sales is not statistically significant at any standard confidence level. Similarly, Strobel (2015), using a Generalized Autoregressive Conditional Heteroskedasticity-in-Mean (GARCH-M) model, shows that a hypothetical 50% increase in the conditional variance of profit growth or stock returns reduces expected quarterly profit by 29% in the manufacturing sector but only by 8% in the services sector, with statistical significance observed only for the manufacturing sector. It is important to acknowledge that while the variables examined in these studies and this study are related indicators of economic activity, they are not identical. The discrepancy between the findings here and those in the literature may also arise from the limitations of the pooled estimator. The pooled estimator could obscure underlying heterogeneity by averaging responses across divisions within each group. This could exaggerate the declines observed in the services industry if its divisions exhibit more consistent responses to uncertainty than the non-services divisions, where heterogeneity may dilute the average response. To address this limitation, the next subsection employs a Bayesian VAR with random coefficients to validate the observed differences in the magnitude of declines between the two groups. It also explores the differential responses of investment to uncertainty shocks across industry divisions, examining how the specific characteristics of these divisions may contribute to the varying responses to uncertainty.

Manufacturing

In this subsection, I run a Bayesian panel VAR with random coefficients on only manufacturing industry divisions, using specifications similar to the baseline random coefficients model. Studying manufacturing alone allows for a focused examination of within-industry heterogeneity, which might be diluted by aggregating data from less related industries such as services. For brevity, Figure 1.10 displays only the responses of investment to a microeconomic uncertainty shock across the different manufacturing industry divisions.[42]

Recall that the random coefficients model accounts for cross-sectional heterogeneity, meaning the magnitude of the microeconomic uncertainty shock varies for each industry

[42]A complete list of the industry division names is available at https://www.ons.gov.uk/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities. The specific industry divisions included in the sample are detailed in Section 1.A.1 of the Appendix.

division, but all are standardized to a one-standard-deviation shock. Using a one-standard-deviation microeconomic uncertainty shock facilitates a consistent comparison of each industry division's response to the shock. A quick glance at Figure 1.10 reveals that investment in each manufacturing industry division experiences a decline following a microeconomic uncertainty shock. This finding aligns with the results from the baseline Bayesian panel VAR with random coefficients depicted in Figure 1.8.

An interesting observation also emerges: the divisions experiencing the most substantial decline in investment is the manufacture of coke and refined petroleum products (division 19) and the manufacture of leather and related products (division 15). The former encompasses the transformation of crude petroleum and coal into usable products, as well as the manufacture of gases from petroleum refineries. A reason why this industry division experiences the greatest decline in investment due to microeconomic uncertainty compared to other manufacturing industry divisions might be the higher irreversibility of investments in natural resource industries compared to other industry divisions. Investments in natural resource industries are often studied in the context of uncertainty due to their highly irreversible nature, as highlighted in studies such as Hurn and Wright (1994), Moel and Tufano (2002), Dunne and Mu (2010), Kellogg (2014), and Dossani and Elder (2024). For instance, Kellogg (2014), examining the impact of expected future oil price volatility on oil well drilling in Texas, describes oil drilling as "a fully irreversible investment." Consequently, it is reasonable to infer that the manufacture of coke and refined petroleum products industry division is more susceptible to a decline in investment driven by uncertainty compared to other manufacturing industry divisions. Therefore, the greater decline in investment driven by uncertainty in the manufacture of coke and refined petroleum products industry division is not unreasonable. A second reason might be that financial distortions, as proposed by Gilchrist, Sim, and Zakrajšek (2014), Christiano, Motto, and Rostagno (2014), and Arellano, Bai, and Kehoe (2019), can disproportionately affect natural resource industries because these industries often require substantial capital expenditures that are difficult to reverse. This heightened sensitivity to financial distortions exacerbates the decline in investment in the manufacture of coke and refined petroleum products industry division relative to other manufacturing industry divisions where investments might be more flexible and less capital-intensive. These interpretations remain speculative and are offered as preliminary reflections rather than definitive conclusions.

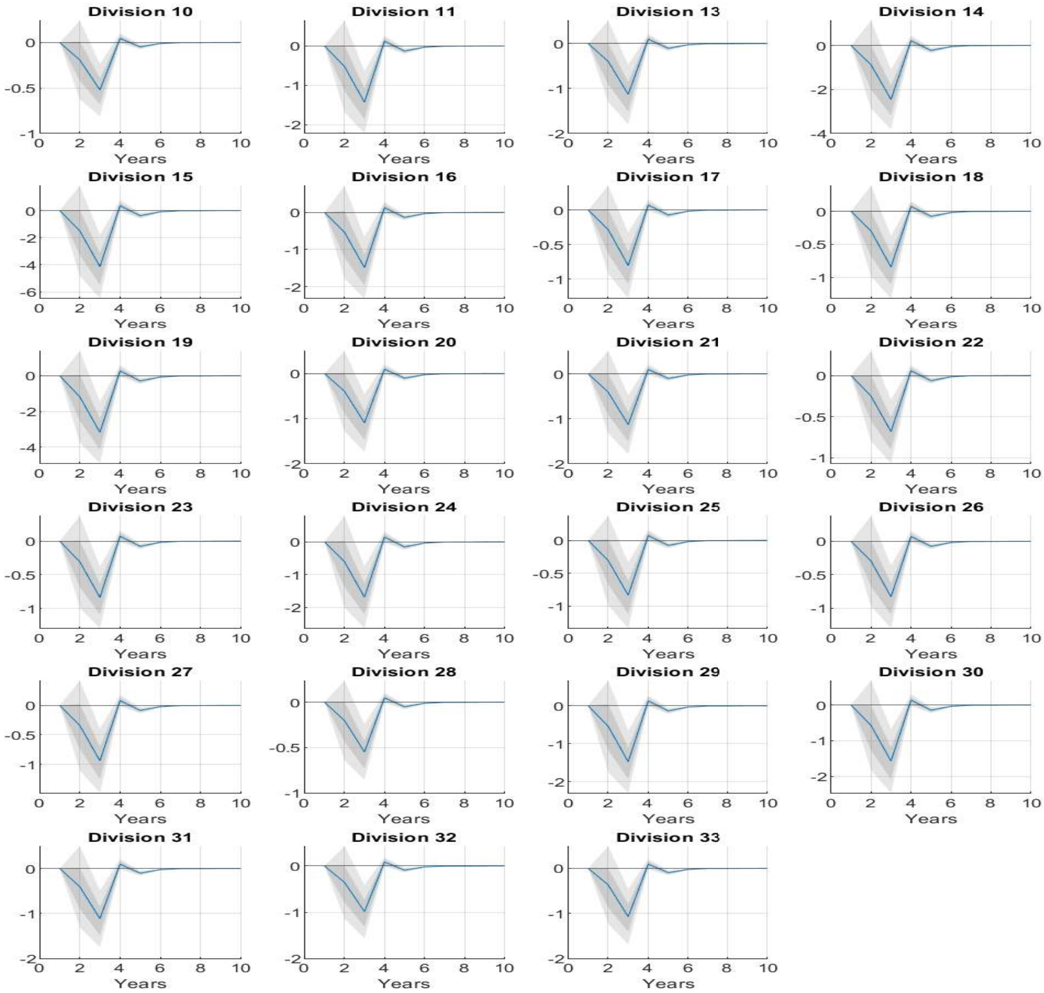

Figure 1.10: Impulse response functions of the Bayesian panel VAR using random coefficients for manufacturing industry divisions. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. In each plot, the blue line denotes the median impulse response of investment to the microeconomic uncertainty shock while the vertical axis measures the responses in percent. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets. Full names of the manufacturing industry divisions are listed in Appendix 1.A.1.

The manufacture of leather and related products industry (Division 15) experiences the largest decline in investment following a microeconomic uncertainty shock compared to other manufacturing divisions. This may be attributed to the discretionary nature of leather products, which are often non-essential goods such as luxury accessories. During periods of heightened uncertainty, consumers typically cut back on discretionary spending (Alfaro & Park, 2020; Coibion, Georgarakos, Gorodnichenko, Kenny, & Weber, 2024; Georgarakos & Kenny, 2022), leading to a significant drop in demand for such products. As a result, firms in this industry division face greater exposure to demand shocks, making them more vulnerable to investment declines during high uncertainty. Additionally, the industry division's reliance on discretionary spending may lead lenders to perceive it as higher risk, further constraining access to financing and amplifying the decline in investment. Consequently, this industry division might be particularly sensitive to uncertainty-induced declines in investment relative to other manufacturing industry divisions. Again, the potential mechanisms outlined remain speculative, and more detailed analysis would be needed to substantiate them.

Meanwhile, the manufacturing industry divisions with the smallest decline in investment during a microeconomic uncertainty shock are the manufacture of food products (division 10) and the manufacture of machinery and equipment (division 28). What explains this resilience? First, it is intuitive that food is a basic necessity, and its demand remains stable even during economic downturns. Ludvigson, Ma, and Ng (2021) show that macroeconomic uncertainty can amplify recessions even if it does not directly cause them. If investment is an endogenous response to output shocks, stable demand for food products (Marioni, Rincon-Aznar, Aitken, Kapur, Smith, & Beckert, 2022) helps explain why investment in the manufacture of food products industry division declines less than in other manufacturing industry divisions. Perhaps, this stability in demand suggests that firms in the manufacture of food products industry division might experience a shorter 'wait-and-see' period during times of heightened uncertainty. It is important to note that, while plausible, this explanation remain speculative and have not been tested within the current analysis.

Explaining the smaller decline in investment in the manufacture of machinery and equipment industry division is more challenging. The real options channel, typically invoked to explain investment postponement in the face of (partially) irreversible investments, does not offer a complete account in this context, particularly given the industry division's capital intensity. One may speculate that this industry division operates on longer investment horizons and displays a smaller sensitivity to transient uncertainty compared to other relatively less capital-intensive manufacturing industry divisions. Drawing from Nakamura (2002), who posits that heightened uncertainty can impede investment even without irreversibility if the capital's lifetime is shorter than the firm's planning horizon, it stands to reason that the capital's lifespan in this industry division may indeed surpass that of others. After all, the pace of technological change in machinery and equipment can be slower compared to industries such as IT. Another contributing factor might be that firms in the manufacture of machinery and equipment industry division face less information asymmetry due to their size, resulting in less financial distortions. This factor partially mitigates the decline in investment due to uncertainty amplified by financial distortions. These explanations, however, remain rudimentary and are not intended as definitive causal explanations.

The objective of this subsection is to examine any potential heterogeneity in investment responses to a microeconomic uncertainty shock in the manufacturing industry. Panel VAR framework, typically underutilized in the uncertainty literature, can yield new and surprisingly intuitive insights on the heterogeneous impacts of uncertainty. While the underlying reasons for this heterogeneity lie beyond the scope of this chapter, they undoubtedly present a promising avenue for future research.

Services

In this subsection, I analyze a subset of services industry divisions by running a Bayesian panel VAR with random coefficients, following specifications akin to the baseline random coefficients model.[43] The objective is to investigate heterogeneity within the services industry. For brevity, Figure 1.11 illustrates only the responses of investment to a microeconomic uncertainty shock across the selected industry divisions. The magnitude of the microeconomic uncertainty shock varies for each industry division, but all are standardized to a one-standard-deviation shock. Using a one-standard-deviation uncertainty shock facilitates a consistent comparison of each industry division's response to the shock.

Figure 1.11 reveals that, qualitatively, investment in the services industry divisions behaves differently following a microeconomic uncertainty shock compared to the manufacturing industry divisions discussed in Section 1.5.4. Specifically, investment in

[43]Specifically, this subset includes divisions from Section L (Real Estate Activities), M (Professional, Scientific, and Technical Activities), and N (Administrative and Support Service Activities). These divisions were selected based on the assumption that they likely share a distribution with similar mean and variance, as the panel VAR model with random coefficients assumes heterogeneity across units but draws coefficients from a distribution with a similar mean and variance. Veterinary activities (division 75) and travel agency, tour operator, and other reservation services (division 79) are excluded due to their distinct nature compared to the other service industries.

the services industry divisions declines significantly at the 95% confidence level but takes longer to return to its pre-shock levels. In other words, the decline is more persistent. This finding is somewhat counterintuitive, as investments in services industry divisions are typically less capital-intensive, suggesting that service-oriented firms have greater flexibility to adjust their investment plans quickly. The literature also documents a smaller effect of uncertainty on the services industry compared to the manufacturing industry (e.g., Londono, Ma, & Wilson, 2024; Strobel, 2015). Several factors may account for this discrepancy. First, investments in the services industry often involve intangible assets. Uncertainty may disproportionately affects these investments, as their returns are harder to quantify compared to the tangible assets typical of manufacturing (Ma & Samaniego, 2019; Van Criekingen, Bloch, & Eklund, 2022). Second, while manufacturing firms might need to commit to investments in physical capital and production processes to sustain operations, service firms can more easily delay investment decisions without immediate operational consequences. Third, services industry mostly cater to local markets. If uncertainty persists in a particular region or country, investment recovery in services may be slower compared to manufacturing, which can potentially benefit from export demand. These factors offer rudimentary explanations; further research is needed to better understand the mechanisms driving the observed differences in investment responses between the services and manufacturing industries.

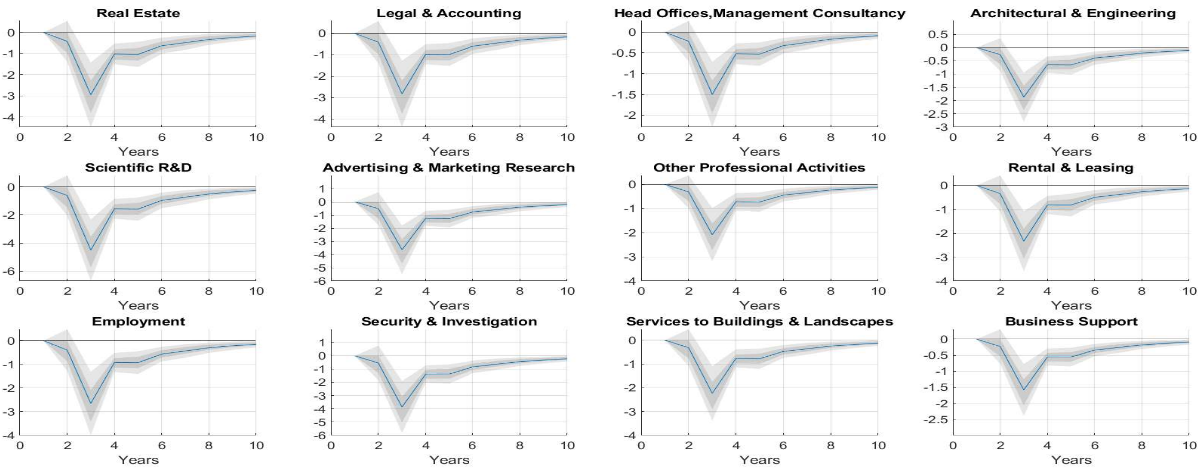

Figure 1.11: Impulse response functions of the Bayesian panel VAR using random coefficients for a subset of services industry divisions. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. In each plot, the blue line denotes the median impulse response of investment to the microeconomic uncertainty shock while the vertical axis measures the responses in percent. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Quantitatively, focusing on the magnitude of peak decline, an interesting observation arises. The services industry divisions with the smallest decline in investment (slightly more or less than 2%) following a microeconomic uncertainty shock are head offices and management consultancy activities, architectural and engineering activities, and business support activities. The microeconomic uncertainty shock exerts a moderate negative effect on investment (more than 2% but less than 3%) in divisions such as real estate activities, rental and leasing activities, legal and accounting activities, and employment activities. The largest adverse effect on investment (more than 3%) occurs in scientific research and development (R&D), advertising and marketing research, and security and investigation activities. One possible explanation for the difference relates to demand. Recall that the residual in Equation 1.1 combines both TFP and demand shocks (Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018). Additionally, since investment is ordered after turnover in the Bayesian panel VAR, microeconomic uncertainty will affect turnover first, subsequently influencing investment. It appears that essential services industry divisions that are critical to the operations of other businesses, such as head office and management consultancy services and business support activities, are the least affected by microeconomic uncertainty. In contrast, services industry divisions that are more sensitive to economic cycles, such as real estate activities, rental and leasing activities, and employment activities, are moderately affected by microeconomic uncertainty. On the other hand, scientific R&D, advertising and marketing research, and security and investigation—suffering the greatest decline in investment following a microeconomic uncertainty shock—appear to be considered non-essential during periods of heightened uncertainty.

Similar to the findings in subsection 1.5.4 on the heterogeneity in investment responses to a microeconomic uncertainty shock in the manufacturing industry, running a panel VAR using a selected subset of services industry divisions can also generate insights that warrant further research. For instance, while the effects of uncertainty on R&D are well-documented in the literature (see, for instance, Bloom, Van Reenen, & Bond, 2007), there is less focus on the impacts of uncertainty on firm's demand for security. Security can be considered distinct from other types of investments and R&D. Given the essential nature of security and its perceived heightened importance during uncertain periods, firms are less likely to delay investments in security measures. Instead, they may even accelerate these investments to mitigate risks associated with uncertainty. However, the findings in this chapter suggest the security and investigation industry division suffers a greater fall in demand during uncertainty that is amplified during economic downturns. The underlying reasons for this observation, as well as for the overall heterogeneity in investment responses, remain beyond the scope of this chapter but present a promising avenue for future research.

1.5.5 What About Debt?

This subsection investigates the relationship between microeconomic uncertainty and debt dynamics. In particular, it examines the liquidity ratio,[44] short-term debt (obligations due within one year), long-term debt (obligations due beyond one year), and total debt (the sum of short-term and long-term debt).[45]

Figure 1.12 presents the distribution of the debt-related variables within the FAME sample spanning from 2004 to 2022. The top left panel of Figure 1.12 reveals a notable rightward shift in the mode of the liquidity ratio distribution for UK firms, indicating a consistent year-over-year increase in the median liquidity ratio throughout the observed period. This upward trend in liquidity ratios suggests an increased accumulation of liquid assets and a decreased dependence on debt. This observation aligns with the findings of Smietanka, Bloom, and Mizen (2018), who, using an unbalanced panel of UK firms' balance sheets from Bloomberg covering the period from 1998 to 2015, document a post-2008 Financial Crisis decline in investment and dividends coupled with an increase in unproductive cash holdings. Such trends underscore a strategic shift towards financial prudence in the face of economic uncertainty. The distribution of the liquidity ratio in 2022 exhibits a long right tail, meaning that a subset of firms holds exceptionally high liquidity ratios. Such skewness may reflect differential uncertainty exposures and precautionary behaviors across firms following the COVID-19 pandemic.

The top right, bottom left, and bottom right panels of Figure 1.12 depict the distributions

[44]The FAME database defines the liquidity ratio as $\frac{\text{current assets - (stocks + work-in-progress)}}{\text{current liabilities}}$. This ratio assesses a company's ability to meet short-term obligations using its short-term assets.

[45]Antoniou, Guney, and Paudyal (2006) point out that certain companies treat the recurring elements of their short-term debt as long-term debt on their balance sheets, and firms can also use creative accounting techniques to lower their reported debt and modify its classification. As a result, it is challenging to accurately measure long-term and short-term debts. In this chapter, the FAME database classifies the maturity of debts based on whether the obligations are due within one year.

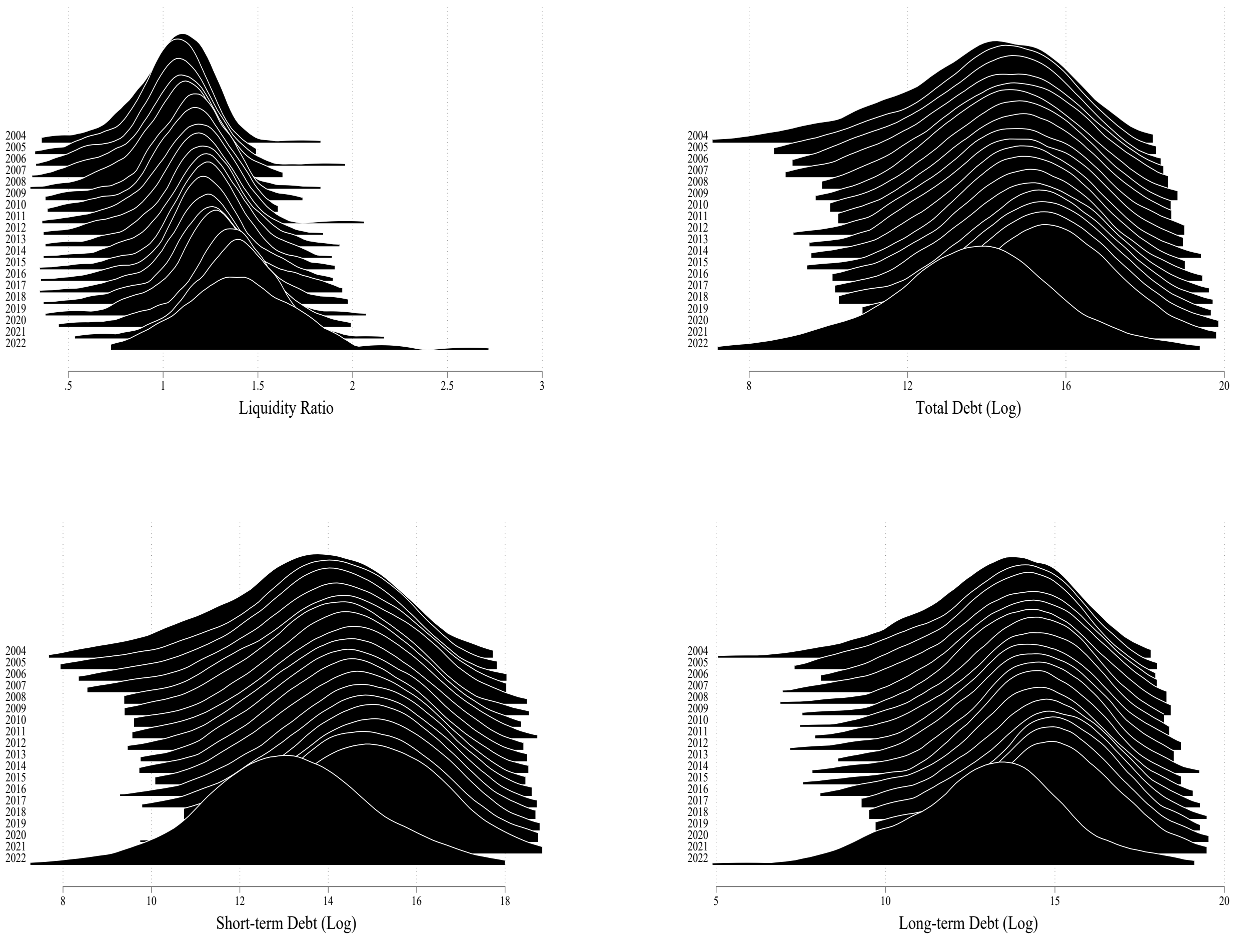

Figure 1.12: Distribution of UK firms' liquidity ratio, total debt, short-term debt, and long-term debt from 2004 to 2022 in the FAME sample.

of total debt, short-term debt, and long-term debt, respectively, over the sample period. A common observation across all three panels is a pronounced left tail in the distributions in 2022, suggesting that a greater proportion of firms reduce their debt levels in the post-pandemic recovery. This trend may be linked to heightened uncertainty, as reflected in Figure 1.1, which shows a spike in microeconomic uncertainty during the COVID-19 pandemic. The increased likelihood of financial distress during uncertain times likely drives firms to adopt more conservative debt strategies (Almeida & Philippon, 2007).[46] To investigate this further, I now incorporate these variables into a Bayesian panel VAR model. The ordering of the variables in the VAR is as follows: {turnover, *debt*, investment, employment, microeconomic uncertainty}, where *debt* is either long-term debt, short-term debt, total debt, or $\frac{\text{short-term debt}}{\text{total debt}}$.[47] Each debt-related variable is included *separately* in

[46] "If you cannot sleep at night because of debt worries, reduce your debt until you can." Patrick (1978) offers this advice to farmers facing greater uncertainty in prices and yields in the 1970s, but it applies as well to firms facing heightened uncertainty today.

[47] The conventional notation for debt maturity in the literature is typically expressed as $\frac{\text{long-term debt}}{\text{total debt}}$.

the Bayesian panel VAR using random coefficients with the baseline specifications detailed in Section 1.5.3. To ensure stationarity, the microeconomic uncertainty variable enters the model in first differences, while the remaining variables including the *debt* variables enter in logged differences. The specifications are consistent with the baseline Bayesian panel VAR with random coefficients.

Figure 1.13 presents the IRFs of each debt-related variable in response to a microeconomic uncertainty shock. For brevity, the responses of other variables are omitted, and only the 95% credible intervals are shown. The responses of the 68 industry divisions are overlaid to derive the aggregate responses in debt.[48] The first row of Figure 1.13 illustrates that both long-term and short-term debt decrease following a microeconomic uncertainty shock. This finding is broadly consistent with the responses of real variables such as employment and investment observed in Section 1.5: As firms scale back production and capital investment in response to uncertainty, they also simultaneously curtail the sources that finance these activities. While the literature specifically addressing the impact of uncertainty on debt is limited, broader research on the effects of uncertainty provides useful theories for interpreting these results. First, through the real options channel, firms delay hiring and investment when uncertainty rises (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018), hence reducing their need for external financing. This is consistent with the baseline results in Figure 1.8, which show that microeconomic uncertainty leads to reductions in both employment and investment. Second, heightened uncertainty exacerbates financial frictions (Arellano, Bai, & Kehoe, 2019; Christiano, Motto, & Rostagno, 2014; Gilchrist, Sim, & Zakrajšek, 2014), increasing the cost of raising external equity and issuing new debt. With uncertainty, it becomes more difficult for creditors to accurately assess a firm's value and risk profile (Datta, Doan, & Iskandar-Datta, 2019), further raising the cost of external financing. Third, if cash and debt are treated as financing substitutes, increased uncertainty may lead to precautionary savings (Almeida, Campello, & Weisbach, 2004; Opler, Pinkowitz, Stulz, & Williamson, 1999), as firms hoard more cash and consequently rely less on debt.[49] To

However, in this chapter, I use $\frac{\text{short-term debt}}{\text{total debt}}$ because it is more intuitive for interpreting the results, as will become evident in the following paragraph.

[48] Figure 1.13 focuses on the aggregate dynamics of debt variables in response to a microeconomic uncertainty shock, rather than the responses of individual industry divisions. Therefore, the industry divisions are not labeled in Figure 1.13. A comparison of magnitude is conducted separately for manufacturing and services industry divisions following the discussion of aggregate dynamics.

[49] Bates, Kahle, and Stulz (2009) provide empirical support for this view, documenting an increase in cash

further investigate this, an ideal approach would be to examine whether the VAR results hold across groups of firms with varying levels of cash holdings.[50] However, the data used in this chapter, sourced from Tsoukalas, Ramanan, Tsafos, and Walsh (2024), do not include cash-related variables. Downloading cash-related data separately from FAME is not feasible due to differences in data vintages. As a result, testing this hypothesis is beyond the scope of this analysis.

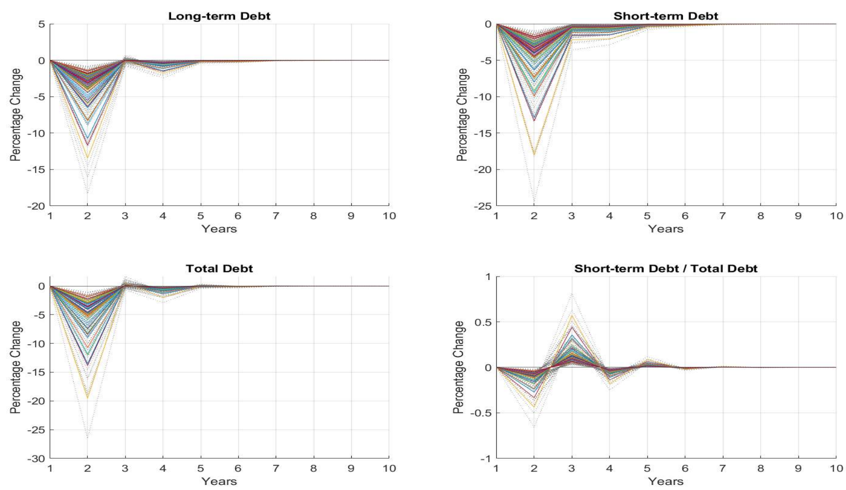

Figure 1.13: Impulse response functions of debt-related variables in the Bayesian panel VAR using random coefficients. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

The response of the $\frac{\text{short-term debt}}{\text{total debt}}$ ratio to a microeconomic uncertainty shock is particularly noteworthy. Although both long-term and short-term debt decline following the shock, the bottom right panel of Figure 1.13 provides additional insights into the evolution of the proportion of short-term debt relative to total debt. Following a microeconomic uncertainty shock, the $\frac{\text{short-term debt}}{\text{total debt}}$ ratio initially declines for slightly over a year, then increases and overshoots for approximately another year, before gradually returning to its pre-shock level. This pattern suggests that, immediately after the shock, firms shift their reliance toward long-term debt, but this trend reverses after about a year before eventually follows a declining path to the pre-shock equilibrium.

holdings and a corresponding decrease in net debt among U.S. firms between 1980 and 2006.

[50] Denis and Sibilkov (2010) show that constrained firms benefit from greater cash holdings as a response to costly external financing.

Alfaro, Bloom, and Lin (2024) theoretically and empirically show that, while firms indeed save more cash to hedge against uncertainty shocks due to a precautionary saving motive, they reduce long-term debt less than short-term debt because the latter carries higher refinancing risk. Does the response of the $\frac{\text{short-term debt}}{\text{total debt}}$ ratio to a microeconomic uncertainty shock in this chapter contradict the findings by Alfaro, Bloom, and Lin (2024)? Not entirely. Li and Su (2020) propose several reasons explaining how uncertainty can reduce debt maturity. First, uncertainty worsens the agency cost problem, potentially increasing the reliance on short-term debt to mitigate underinvestment (Myers, 1977). Second, uncertainty also exacerbates information asymmetry between borrowers and lenders (Nagar, Schoenfeld, & Wellman, 2019), prompting high-quality firms to use short-term debt as a signaling mechanism for the quality of their projects (Flannery, 1986). Third, uncertainty raises the risk of firms failing to commit to their current debt structures. As Brunnermeier and Oehmke (2013) demonstrate, a lack of commitment to debt maturity can result in excessively short maturities. Short-term debt often reflects short-term financing needs rather than long-term capital structure decisions (Korajczyk & Levy, 2003). The bottom right panel of Figure 1.13 suggests that, while uncertainty may initially prompt firms to rely less on short-term debt,[51] firms may subsequently face increasing liquidity constraints in the aftermath of uncertainty; to meet these immediate financing needs, they may increase reliance on short-term debt, causing the observed rebound and overshoot in the $\frac{\text{short-term debt}}{\text{total debt}}$ ratio. As uncertainty subsides, firms transition toward a declining path in this ratio. Thus, the argument proposed by Alfaro, Bloom, and Lin (2024) and Li and Su (2020) can help reconcile the observed pattern in the $\frac{\text{short-term debt}}{\text{total debt}}$ ratio.

Next, I conduct the Bayesian panel VAR analysis with random coefficients separately for the manufacturing industry divisions and a subset of services industry divisions. For each subset, I maintain the baseline ordering of the variables. The VAR is first run with long-term debt as the *debt* variable, and then repeated with short-term debt. Figure 1.14 presents the IRFs of long-term debt and short-term debt in response to a one-standard-

[51] The rise in cash holdings during periods of heightened uncertainty, as documented in the literature, can reduce firms' reliance on short-term debt. This hypothesis could be tested by segmenting firms based on their cash-to-assets ratio and comparing the VAR results. However, due to the absence of cash-related variables in the dataset used in this chapter, this analysis is not feasible. Downloading cash-related data separately from FAME is not ideal due to differences in data vintages. I leave this hypothesis for future research.

deviation microeconomic uncertainty shock within the manufacturing industry divisions, overlaid for comparison. Figure 1.15 displays the corresponding IRFs for the services industry divisions.

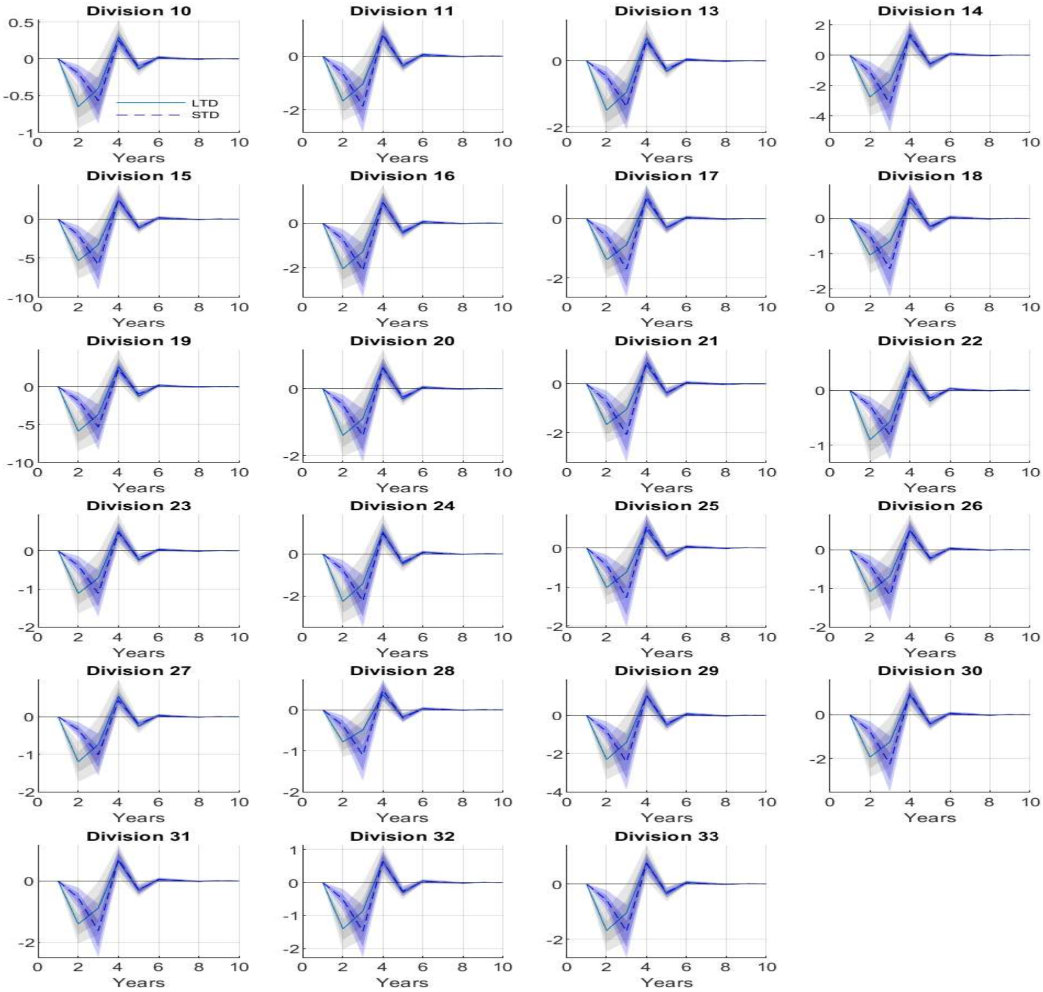

Figure 1.14: Impulse response functions of debt-related variables in the Bayesian panel VAR using random coefficients for manufacturing industry divisions. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. In each plot, the solid (dashed) line denotes the median impulse response of long (short) term debt to the microeconomic uncertainty shock while the vertical axis measures the responses in percent. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets. Full names of the manufacturing industry divisions are listed in Appendix 1.A.1.

Figure 1.14 reveals significant heterogeneity in the magnitude of debt responses across manufacturing industry divisions following a microeconomic uncertainty shock. While most divisions experience a larger decline in short-term debt compared to long-term debt, consistent with Alfaro, Bloom, and Lin (2024)'s argument that high uncertainty disproportionately affects short-term debt due to its higher liquidation risk, there are notable exceptions. Some divisions exhibit nearly identical declines in both types of debt, while others experience a greater reduction in long-term debt than in short-term debt.

For instance, the manufacture of food products (division 10) shows a slightly larger decline in long-term debt relative to short-term debt, whereas the opposite pattern is observed in the manufacture of beverages (division 11). These findings suggest that while Alfaro, Bloom, and Lin (2024)'s argument is useful in justifying firms' disproportionate decrease in short-term debt during uncertainty, it does not fully account for the variation in debt responses across manufacturing industry divisions. The lack of consistent patterns indicates that further research is needed to investigate the specific characteristics of these industry divisions, such as capital intensity, asset structure, and innovation density, that may explain why some divisions disproportionately reduce long-term debt more than short-term debt, in contrast to other manufacturing industry divisions.

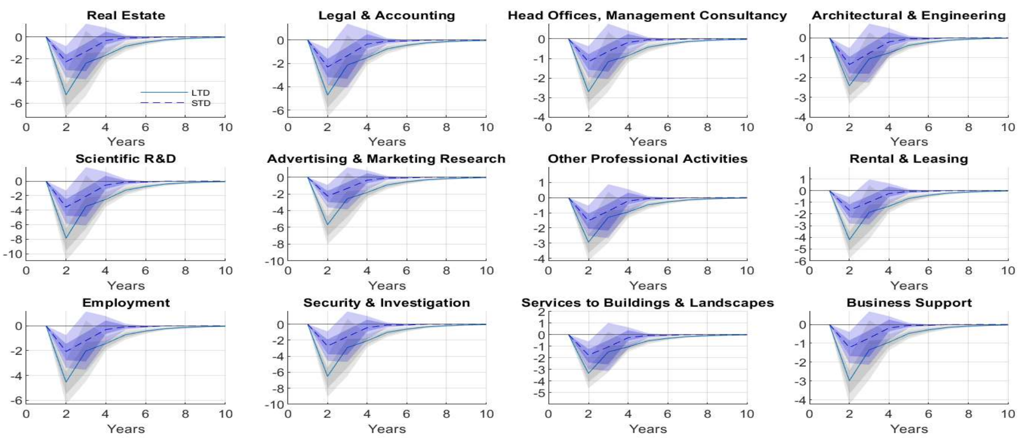

Figure 1.15: Impulse response functions of debt-related variables in the Bayesian panel VAR using random coefficients for a subset of services industry divisions. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. In each plot, the solid (dashed) line denotes the median impulse response of long (short) term debt to the microeconomic uncertainty shock while the vertical axis measures the responses in percent. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Figure 1.15 shows that services industry divisions also display considerable variation in debt responses, but with a greater reduction in long-term debt relative to short-term debt. Furthermore, long-term debt takes longer to return to its pre-shock level following an uncertainty shock. The difference is important because Alfaro, Bloom, and Lin (2024)'s argument—that firms reduce short-term debt more than long-term debt during uncertainty due to the higher refinancing risk of short-term debt[52]—overlooks the purpose of debt across industries. Manufacturing industry divisions tend to have higher innovation density,[53] which means they have a greater need for long-term debt financing. In contrast,

[52]An earlier version of the paper by Alfaro, Bloom, and Lin (2024) (prior to its publication in the *Journal of Political Economy*) offered a more detailed discussion of short-term versus long-term debt dynamics under uncertainty.

[53]Li and Su (2020), following Lerner, Sorensen, and Strömberg (2011), use patent data to proxy the

the services industry divisions are typically less capital-intensive and, consequently, has a lower demand for long-term debt. This difference may explain why services firms reduce long-term debt more aggressively in response to uncertainty. Another potential explanation lies in the asset composition of the services industry divisions. Services industry divisions often involve intangible assets, whose values are harder to quantify as collateral compared to the tangible assets typical of manufacturing (Ma & Samaniego, 2019; Van Criekingen, Bloch, & Eklund, 2022). This makes long-term debt in the services sector more vulnerable to uncertainty, as uncertainty exacerbates information asymmetries between borrowers and lenders (Nagar, Schoenfeld, & Wellman, 2019). Consequently, uncertainty may disproportionately affect long-term debt in services industry divisions. Exploring the heterogeneity across industry divisions can illuminate the justifications proposed by Li and Su (2020) regarding commitment flexibility and Alfaro, Bloom, and Lin (2024) concerning liquidation risk even further. Given the relatively limited exploration of uncertainty's effects on debt dynamics within the literature, these findings present a compelling avenue for further research.

A final observation from Figure 1.14 and Figure 1.15 highlights that while debt variables in the manufacturing industry divisions rebound and overshoot their pre-shock levels after an initial decline, this overshoot is absent in the services industry divisions. It is possible that firms in the manufacturing industry divisions need to rebuild inventories and scale up production to meet pent-up demand (Bloom, 2009), creating a surge in borrowing. Manufacturing industry divisions requires substantial debt financing due to its capital intensity; as uncertainty subsides, firms in manufacturing industry divisions resume borrowing to restart operations and reinvest in delayed projects, driving the rebound and overshoot in debt. In addition, the availability of tangible assets provides collateral that may facilitate access to credit markets, further amplifying the debt rebound and overshoot. In contrast, firms in services industry divisions typically rely less on physical inventory or large-scale production processes, reducing their need for significant borrowing during recovery, which leads to a more muted rebound in debt and no overshoot. Furthermore, firms in services industry divisions may face greater borrowing constraints due to a lack of tangible assets, dampening the likelihood of an overshoot. These differences underscore the role of industry-specific factors in shaping debt dynamics during and after uncertainty

need for long-term debt with innovation intensity and find that manufacturing sectors are generally more innovation-intensive than service sectors.

shocks. While this analysis offers novel suggestive evidence and plausible explanations, it remains preliminary. The discussion remains exploratory, and the proposed explanations serve more as starting points for further inquiry than as fully substantiated arguments. Examining the underlying mechanisms in greater detail is beyond the scope of this analysis but represents an important avenue for future research.

1.6 Conclusion

The lack of disaggregated uncertainty measures limits the exploration of the impacts of uncertainty across various cross-sectional dimensions. For instance, the absence of industry-specific uncertainty indicators hinders the investigation of how uncertainty disproportionately affects industries such as manufacturing, services, or agriculture, each of which has distinct capital structures, labor dynamics, and exposure to external shocks. Similarly, the lack of firm-level measures prevents an examination of how small versus large firms respond differently to uncertainty particularly in terms of investment, hiring, and financing decisions. The absence of regional uncertainty measures restricts the analysis of how localized uncertainty—driven by political events, natural disasters, or regional economic shifts—affects subnational economies. Recent advancements in the literature aim to address these gaps: Baker, Davis, and Levy (2022) quantify state-level economic policy uncertainty in the United States, demonstrating that the sources of uncertainty differ across states and evolve over time; Mohades, Piccillo, and Treibich (2024) decompose firms' sales volatility to construct uncertainty measures at aggregate, sectoral, and firm levels jointly, revealing that diverse firm traits yield notable heterogeneity, with the manufacturing sector exhibiting the highest levels of uncertainty among sectors. Building on this literature, this chapter uses firm-level balance sheet data to construct microeconomic uncertainty measures for 68 industry divisions in the UK. The advantage of using firm-level balance sheet data lies in its widespread availability, and employing the cross-sectional dispersion of firms' TFP shocks as a proxy for microeconomic uncertainty is computationally straightforward. With this measure, I estimate a simple panel VAR using Bayesian techniques to examine how firm decisions vary with microeconomic uncertainty, offering new insights into the cross-industry variation in responses to uncertainty.

I find that panel VARs, despite being underutilized in the uncertainty literature due to the scarcity of disaggregated uncertainty measures, can provide evidence consistent with findings from the uncertainty literature that use aggregate data and provide new insights into the heterogeneous effects of uncertainty. Specifically, results from the simplest forms of panel VAR, the pooled estimator and the random coefficients model estimated with Bayesian techniques, demonstrate that firm turnover, investment, and employment experience statistically significant declines following a microeconomic uncertainty shock. Moreover, this chapter documents several intriguing heterogeneous effects of microeconomic uncertainty. First, the magnitude of investment decline following a microeconomic uncertainty shock varies across divisions even within the same industry. Second, the decline in investment following a microeconomic uncertainty shock is more persistent in services industry divisions compared to manufacturing industry divisions. Third, while most manufacturing industry divisions experience a larger decline in short-term debt relative to long-term debt, services industry divisions exhibit a greater reduction in long-term debt relative to short-term debt, with long-term debt also taking longer to return to pre-shock levels.

The Bayesian panel VAR analysis presented in this chapter is not without limitations. First, the microeconomic uncertainty measure constructed in this chapter is far from perfect. Recall that this measure is the dispersion of TFP. Since TFP is driven by technology *and* demand dynamics, the microeconomic uncertainty measure does not distinguish between the different sources of uncertainty, such as technology, policy, or other types. More importantly, the interpretation of results when using the microeconomic uncertainty measure constructed in this chapter involves inherent ambiguity. For instance, if a significant effect of a microeconomic uncertainty shock is observed in industry division A but not in industry division B, it is difficult to determine whether this difference arises because industry division A is genuinely more sensitive to microeconomic uncertainty, or because the microeconomic uncertainty measure serves as a better proxy for the actual uncertainty faced by industry division A compared to industry division B. Unfortunately, the current framework does not allow for disentangling these possibilities. It is also important to note that this measure is constructed from ex post data realizations as opposed to ex ante data (expectations). While many empirical studies have used measures of realized volatility to approximate uncertainty, the conclusions drawn from using ex post data versus ex ante data can differ significantly (Berger, Dew-Becker, & Giglio, 2020). Moreover, the dispersion in firms' productivity is only one dimension of microeconomic uncertainty. Other firm-level variables, such as asset holdings (Baum, Caglayan, Ozkan, & Talavera, 2006) and sales (De Veirman & Levin, 2018; Kozeniauskas, Orlik, & Veldkamp, 2018; Mohades, Piccillo, & Treibich, 2024), can also be used to compute microeconomic uncertainty. Despite these limitations, the microeconomic uncertainty measure can be seen as a complement to the various macroeconomic uncertainty measures available for the UK. As Bloom (2014) aptly states: "Given this broad definition of uncertainty, [...] there is no perfect measure but instead a broad range of proxies."

Second, recent literature has highlighted limitations in using Cholesky decomposition for shock identification. Cholesky decomposition assumes a recursive structure, identifying causal relationships by imposing an order on the variables and hence assuming that some shocks have zero contemporaneous effect on certain endogenous variables. However, there is no compelling theoretical justification for restricting the timing of the relationship between uncertainty and real activity (Carriero, Clark, & Marcellino, 2018; Ludvigson, Ma, & Ng, 2021). As described in Table 1.1, there are alternative VAR identification strategies that can address the shortcomings of recursive structures. The primary aim of this chapter is to evaluate the viability of using panel VARs with firm-level balance sheet data to replicate the effects of (microeconomic) uncertainty documented in the literature. Given this humble objective, it is reasonable to start with the simplest identification scheme such as the Cholesky decomposition. It would certainly be interesting in the future to apply the more advanced identification strategies listed in Table 1.1 within a panel VAR framework to improve credibility.

Third, this chapter presents only the two most straightforward variants of panel VARs that do not allow for direct dynamic interactions between units. Specifically, the pooled estimator relaxes all four properties (cross-sectional heterogeneity, static interdependencies, dynamic interdependencies, and dynamic heterogeneity), while the random coefficient model relaxes all but maintains cross-sectional heterogeneity. A model that does not relax the static interdependencies property can capture contemporaneous relationships between units in the panel, allowing for the analysis of spillover effects.

A model that maintains dynamic interdependencies is better suited to capture time-lagged influences between units, which is crucial for understanding how past shocks propagate over time across different units. Additionally, a model that features dynamic heterogeneity can account for the possibility that dynamic coefficients may evolve over time, a consideration that is increasingly important in modern macroeconomic methodologies (Dieppe, Legrand, & Van Roye, 2016). The exploration of other panel VAR variants is beyond the scope of this chapter, as the primary aim is to test the viability of the simplest forms of panel VARs in capturing the effects of microeconomic uncertainty. In the future, I hope to investigate the effects of microeconomic uncertainty using panel VARs that allow for direct dynamic interactions between units.

Fourth, this chapter explores the relationship between microeconomic uncertainty and a limited set of firm decisions, within the bounds of available data.[54] Expanding the scope of the Bayesian panel VAR analysis to include other firm decisions would be highly valuable. For instance, examining the impact of microeconomic uncertainty on R&D expenditure could provide insights comparable to those documented in the literature (see, for example, Bloom, Van Reenen, & Bond, 2007). It would also be intriguing to investigate whether microeconomic uncertainty influences firms' preferences for temporary over permanent employment, given the lower adjustment costs associated with temporary hires.[55] These are promising avenues for future research on how uncertainty affects various firm decisions using a panel VAR framework with more granular data.

Finally, this chapter offers some intuitive yet speculative and unverified explanations for the findings from the Bayesian panel VAR analysis. While these explanations provide a starting point, a more rigorous and formal investigation is necessary to fully understand the observed dynamics. For instance, further research is required to examine why certain industry divisions experience a greater decline in investment following a microeconomic uncertainty shock compared to others. Similarly, it is crucial to investigate why the decline in investment is more persistent in services industry divisions relative to manufacturing

[54]For example, in the FAME database, R&D data are only available for publicly quoted firms, resulting in numerous missing observations. Additionally, FAME's firm-level balance sheet data lack detailed information on corporate governance practices such as executive compensation and risk management strategies. They also do not differentiate between permanent and temporary employees.

[55]The impacts of uncertainty on temporary employment are explored in Chapter 3.

industry divisions, and why services industry divisions exhibit a greater reduction in long-term debt relative to short-term debt, whereas the opposite pattern is observed in manufacturing industry divisions.

1.A Appendix

1.A.1 List of Industry Divisions

Division	Description	Division	Description
10	Manufacture of food products	11	Manufacture of beverages
13	Manufacture of textiles	14	Manufacture of wearing apparel
15	Manufacture of leather and related products	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products	18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products	20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products	24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment	26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment	28	Manufacture of machinery and equipment nec
29	Manufacture of motor vehicles, trailers and semi-trailers	30	Manufacture of other transport equipment
31	Manufacture of furniture	32	Other manufacturing
33	Repair and installation of machinery and equipment	35	Electricity, gas, steam and air conditioning supply
38	Waste collection, treatment and disposal activities; materials recovery	39	Remediation activities and other waste management services
41	Construction of buildings	42	Civil engineering
43	Specialised construction activities	45	Wholesale and retail trade and repair of motor vehicles and motorcycles
46	Wholesale trade, except of motor vehicles and motorcycles	47	Retail trade, except of motor vehicles and motorcycles
49	Land transport and transport via pipelines	50	Water transport
51	Air transport	52	Warehousing and support activities for transportation
53	Postal and courier activities	55	Accommodation
56	Food and beverage service activities	58	Publishing activities
59	Motion picture, video and television programme production, sound recording and music publishing activities	61	Telecommunications
62	Computer programming, consultancy and related activities	63	Information service activities
68	Real estate activities	69	Legal and accounting activities
70	Activities of head offices; management consultancy activities	71	Architectural and engineering activities; technical testing and analysis
72	Scientific research and development	73	Advertising and market research
74	Other professional, scientific and technical activities	75	Veterinary activities
77	Rental and leasing activities	78	Employment activities
79	Travel agency, tour operator and other reservation service and related activities	80	Security and investigation activities
81	Services to buildings and landscape activities	82	Office administrative, office support and other business support activities
85	Education	86	Human health activities
87	Residential care activities	90	Creative, arts and entertainment activities
91	Libraries, archives, museums and other cultural activities	92	Gambling and betting activities
93	Sports activities and amusement and recreation activities	94	Activities of membership organisations
95	Repair of computers and personal and household goods	96	Other personal service activities

Table 1.5: UK Standard Industrial Classification (SIC) by industry divisions. Some industry divisions are excluded in the sample due to missing or insufficient observations in the FAME data.

1.A.2 Descriptive Graphs

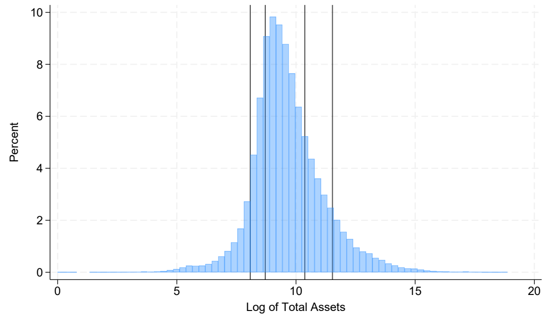

Figure 1.16: The distribution of total assets and 10th, 25th, 75th, and 90th percentiles.

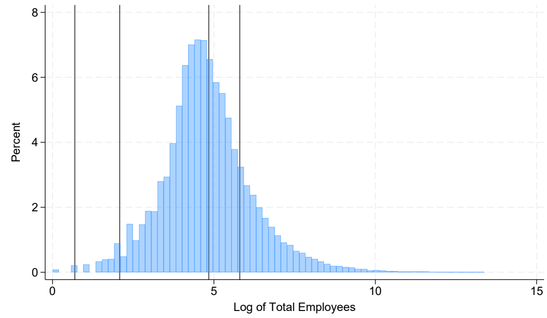

Figure 1.17: The distribution of total employees and 10th, 25th, 75th, and 90th percentiles.

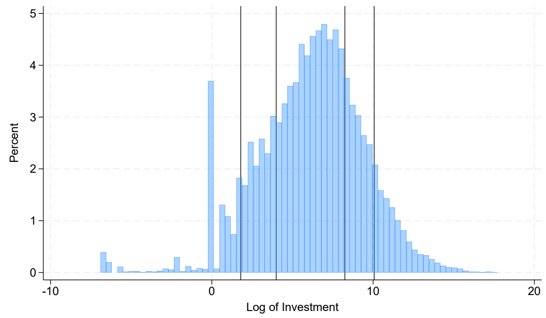

Figure 1.18: The distribution of investment and 10th, 25th, 75th, and 90th percentiles.

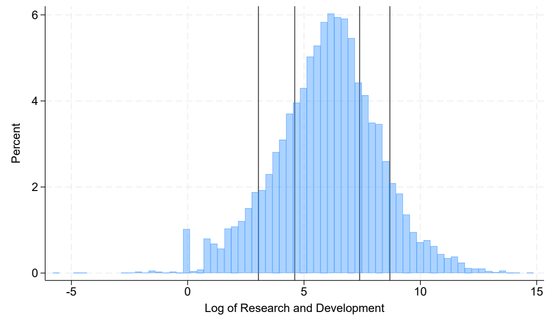

Figure 1.19: The distribution of research and development (R&D) and 10th, 25th, 75th, and 90th percentiles.

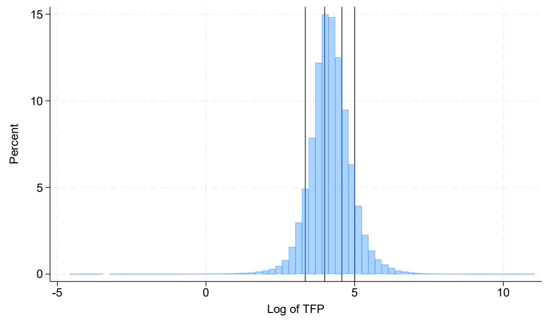

Figure 1.20: The distribution of TFP and 10th, 25th, 75th, and 90th percentiles.

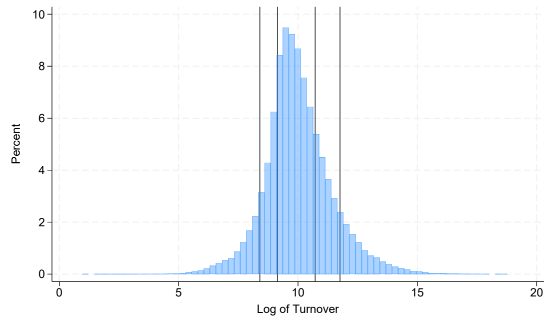

Figure 1.21: The distribution of turnover and 10th, 25th, 75th, and 90th percentiles.

1.A.3 Existing Uncertainty Indicators for the UK

Microeconomic uncertainty is plotted alongside existing uncertainty indicators for the UK in Figure 1.2. This section briefly describes these uncertainty indicators.

The macroeconomic uncertainty measures by Dibiasi and Sarferaz (2023) defines macroeconomic uncertainty as the conditional volatility of unforecastable deviations in GDP, based on releases published by the Office for National Statistics (ONS). A detailed description of this measure is provided in Chapter 3. The macroeconomic and financial uncertainty measures by Redl (2020), following the methodology of Jurado, Ludvigson, and Ng (2015), capture uncertainty as the conditional variance of the unanticipated component common to a broad array of macroeconomic and financial variables. The Economic Policy Uncertainty (EPU) Index by Baker, Bloom, and Davis (2016) quantifies policy-induced economic uncertainty by tracking the frequency of newspaper articles referencing economic policy uncertainty through text analysis. Similarly, the UK's World Uncertainty Index (WUI) by Ahir, Bloom, and Furceri (2022) is based on text mining of the Economist Intelligence Unit's country reports. The estimated heteroskedasticity presented in Figure 1.2 is derived from the quarterly labor productivity data published by the ONS. Given that this series is inherently jumpy, I apply a four-quarter moving average to smooth out fluctuations and identify underlying trends. Subsequently, I use a GARCH(1,1) model to estimate the conditional heteroskedasticity of the percent change in this smoothed series, following an approach similar to that of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). This conditional heteroskedasticity is illustrated in Figure 1.2.

1.A.4 Higher Moments

	(1)	(2)	(3)
Dependent variable	S.D. of log(TFP) shock	Skewness of log(TFP) shock	Kurtosis of log(TFP) shock
Recession	0.108**	-1.349***	1.072
	(0.040)	(0.448)	(3.614)
Mean of dep. var.	0.378	-1.941	32.003
Frequency	Annual	Annual	Annual
Years	2003-2022	2003-2022	2003-2022
Observations	19	19	19
Underlying sample	417093	417093	417093

Table 1.6: Microuncertainty in the UK. *Notes:* Each column reports an OLS regression point estimate (and standard error below in parenthesis) of a measure of uncertainty on a recession indicator. The bottom panel reports the mean of the dependent variable. The sample is the population of firms with 10 years or more observations in the Financial Analysis Made Easy (FAME) dataset between 2003 to 2022 to reduce concerns over changing samples. All regressions include a time trend. Robust standard errors are applied in all columns. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Do recessions also affect the higher moments of the productivity distribution? In column 2, I investigate the coefficient of the skewness of TFP shocks throughout the economic cycle and uncover a significant correlation. This finding resonates with the work of Guvenen, Ozkan, and Song (2014), who observe an increase in left-skewness for personal income growth during recessions, albeit without a concomitant rise in the variance of idiosyncratic income shocks. Column 2 also highlights the "bad news principle" in Bernanke (1983) and how the economy displays self-reinforcing episodes of high uncertainty and low activity (Fajgelbaum, Schaal, & Taschereau-Dumouchel, 2017; Jeon, 2022). Furthermore, the negative correlation in column 2 is as expected, because recessions are associated with higher microeconomic uncertainty (column 1), which, in turn, fosters a more negatively skewed growth distribution (Jovanovic & Ma, 2022). Interestingly, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) fail to find a significant correlation between recessions and the skewness of TFP shocks using US Census data. Nonetheless, they underscore the drop in the left tail as the principal driver of recessions in their model. Nevertheless, in contrast to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), column 2 suggests that recessions at the microeconomic level also constitute a negative third-moment shock. However, this distinction holds relatively less importance given that the primary focus of this chapter lies in examining the effects of positive second-moment ("uncertainty") shocks. In column 3, I examine the coefficient of the kurtosis of TFP shocks throughout the economic cycle and do not find a significant correlation. The lack of a significant correlation implies that recessions are not associated with changes in the kurtosis of TFP shocks. Thus far, the literature does not identify recessions as fourth moment shocks.[56]

1.A.5 Robustness

	(1)	(2)	(3)	(4)	(5)
Dependent variable	S.D. of log(TFP) shock	Skewness of log(TFP) shock	Kurtosis of log(TFP) shock	IQR of log(TFP) shock	IQR of turnover growth
Recession	0.121**	-1.290***	-2.704	0.074	0.076**
	(0.052)	(0.386)	(5.350)	(0.045)	(0.028)
Mean of dep. var.	0.367	-1.965	32.472	0.258	0.028
Frequency	Annual	Annual	Annual	Annual	Annual
Years	2003-2022	2003-2022	2003-2022	2003-2022	2003-2022
Observations	19	19	19	19	19
Underlying sample	376706	376706	376706	376706	376706

Table 1.7: Microuncertainty in the UK (balanced panel). *Notes:* Each column reports an OLS regression point estimate (and standard error below in parenthesis) of a measure of uncertainty on a recession indicator. The bottom panel reports the mean of the dependent variable. The sample is a balanced panel of firms in the Financial Analysis Made Easy (FAME) dataset between 2003 to 2022 to reduce concerns over changing samples. All regressions include a time trend. Robust standard errors are applied in all columns. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

[56] Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) also do not find a significant correlation between recessions and the kurtosis of TFP shocks. Jovanovic and Ma (2022) focus on the second and third moments of the growth distribution.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	S.D. of log(TFP) shock	Skewness of log(TFP) shock	Kurtosis of log(TFP) shock	IQR of log(TFP) shock	IQR of turnover growth
Recession	0.111**	-1.547***	3.048	0.059*	0.076**
	(0.053)	(0.807)	(3.514)	(0.031)	(0.028)
Mean of dep. var.	0.372	-2.028	33.724	0.265	0.208
Frequency	Annual	Annual	Annual	Annual	Annual
Years	2003-2020	2003-2020	2003-2020	2003-2020	2003-2020
Observations	17	17	17	17	17
Underlying sample	377627	377627	377627	377627	377627

Table 1.8: Microuncertainty in the UK, excluding year 2021 and 2022. *Notes:* Each column reports an OLS regression point estimate (and standard error below in parenthesis) of a measure of uncertainty on a recession indicator. The bottom panel reports the mean of the dependent variable. The sample is the population of firms with 10 years or more observations in the Financial Analysis Made Easy (FAME) dataset between 2003 to 2020 to reduce concerns over changing samples. All regressions include a time trend. Robust standard errors are applied in all columns. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

1.A.6 Construction of Common Factor

I adopt the method in Mohades, Piccillo, and Treibich (2024) to construct industrial common factor for Equation 1.2. In the simplest sense, the method derives from firms' balance sheet a list of firms' characteristics, and summarizes firms' data into one component that explains the comovement and covariation in that data-rich environment for each industry. I direct interested readers to Mohades, Piccillo, and Treibich (2024) concerning the method.

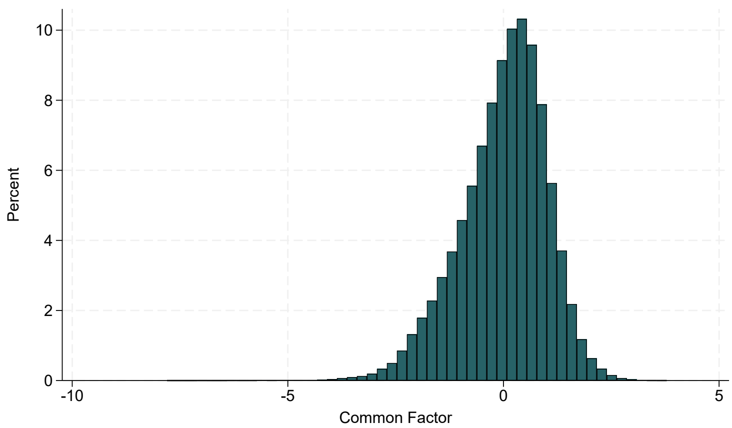

Figure 1.22: The distribution of industrial common factor.

The initial step involves the identification of variables that capture commonalities at the industry division level, with a focus on ordering them for broad applicability across international datasets while minimizing missing values within the FAME dataset. I select

20 variables, and the order of the variables that I use is {age, total assets, liquidity ratio, turnover, number of employees, tangible assets, fixed assets, long term liabilities, asset cover, investments, cost of sales, working capital per employee, return on shareholders' funds, return on capital employed, return on total assets, net income, operating profit, profit before taxation, retain profit, and remuneration}. Subsequently, I conduct a principal component analysis to construct a common factor using all time series data for all firms.

Next, I sequentially remove one variable from the end of the list and perform principal component analysis to generate a factor variable. Within each iteration, I assess the correlation with the initial factor variable and penalise this correlation by the number of variables added to the factor variable construction in every iteration. This straightforward Bayesian-like penalizing algorithm leads to the identification of two optimal variables—age and total assets—which demonstrate the highest correlation without succumbing to the curse of dimensionality. I derive the resulting common factors within industry divisions by running principal component analyses for each industry divisions. Figure 1.22 shows the distribution of the industrial common factor: values near zero indicate firms with close-to-average attributes in their industry division at specific times. Conversely, extreme values in the right and left tails—significantly deviating from zero—highlight firms experiencing atypical conditions far from the expected norms in their industry division. Finally, I stack these values into a single variable, $\alpha_{j,t}$, which is now ready to be used in Equation 1.2.

1.A.7 Overall Uncertainty Measure

I estimate a dynamic panel of the form:

$$\log S_{j,t} = \rho_1 \log S_{j,t-1} + \mu_j + \lambda_t + e_{j,t}, \tag{1.19}$$

where $S_{j,t}$ refers to turnover of firm i at period t, μ_j firm fixed effects, λ_t time fixed effects, and $e_{j,t}$ the residuals. The firm and time fixed effects may be correlated with the lagged dependent variable. Therefore, following Mohades, Piccillo, and Treibich (2024), I employ a Generalized Method of Moments (GMM) estimator, utilizing the first lag of the log of turnover as an instrument. This approach leverages lagged differences as instruments for the level equation and uses lagged levels for the difference equation. Compared to the baseline Equation 1.1 , the GMM estimator is robust to heteroscedasticity—it generates residuals uncorrelated with past residuals, thus capturing the truly unpredictable component of the turnover process. The standard deviation of the resulting $e_{j,t}$ is termed 'Overall Uncertainty'. Figure 1.23 plots this Overall Uncertainty measure.

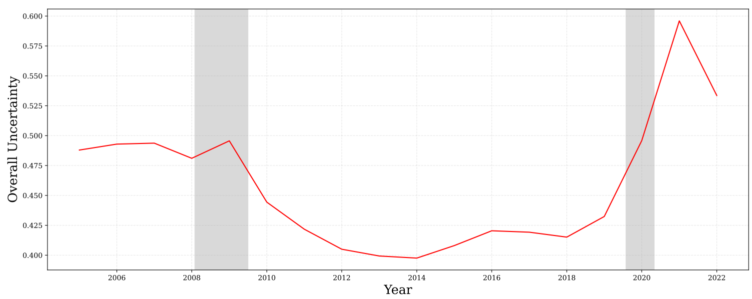

Figure 1.23: Overall Uncertainty measures. Shaded columns are the share of quarters in a recession within a year.

1.A.8 Hyperparameters

Pooled Estimator

In Section 1.5.2, the prior distribution β for a pooled estimator depends on β_0 and Φ_0. I follow the strategy proposed by Litterman (1986) in determining β_0 by seting the value 1 for own first lag coefficients and 0 for cross variable and exogenous coefficients. According to Dieppe, Legrand, and Van Roye (2016), this strategy is due to two assumptions: One, unit roots are observed in most macroeconomic variables, so it is reasonable to believe that each endogenous variable presents a unit root in its first own lag. Two, without prior belief about exogenous variables, a conservative approach is to assume these variables do not systematically influence the endogenous variables and set their coefficients to zero.

The variance-covariance matrix of β is $\Sigma_c \otimes \Phi_0$, where Σ_c contains variable-specific variances; the variance of variable x is estimated by pooling the samples for variable x across N units and then estimating an autoregressive model over this pooled series. Φ_0 is a $(gp+m) \times (gp+m)$ diagonal matrix containing the variances of parameters relating endogenous variables to their own and cross lags as well as parameters related to exogenous variables. Following Karlsson (2013), for parameters in β relating endogenous variables to their own and cross lags, define the variance as $(\frac{1}{\sigma_j^2})(\frac{\lambda_1}{l^{\lambda_3}})^2$, where σ_j^2 is the unknown residual variance of variable j, λ_1 a hyperparameter controlling overall tightness, λ_3 a hyperparameter implementing the decay of influence for more distant lags, and l the lag considered by the coefficient. For parameters related to exogenous variables, define the variance as $(\lambda_1\lambda_4)^2$, where λ_4 is a variance parameter. [57] It is easier to illustrate $\Sigma_c \otimes \Phi_0$ with an example. For a VAR with 2 endogenous variables, 2 lags, no exogenous variable, and an assumed diagonal Σ_c, $\Sigma_c \otimes \Phi_0$ writes as:

$$\Sigma_c \otimes \Phi_0 = \begin{pmatrix} (\lambda_1)^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & (\frac{\sigma_1^2}{\sigma_2^2})(\lambda_1)^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & (\frac{\lambda_1}{2^{\lambda^3}})^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & (\frac{\sigma_1^2}{\sigma_2^2})(\frac{\lambda_1}{2^{\lambda_3}})^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & (\frac{\sigma_2^2}{\sigma_1^2})(\lambda_1)^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & (\lambda_1)^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & (\frac{\sigma_2^2}{\sigma_1^2})(\frac{\lambda_1}{2^{\lambda_3}})^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & (\frac{\lambda_1}{2^{\lambda^3}})^2 \end{pmatrix}, \tag{1.20}$$

with

$$\Sigma_c = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix} \tag{1.21}$$

and

$$\Phi_0 = \begin{pmatrix} (\frac{1}{\sigma_1^2})(\lambda_1)^2 & 0 & 0 & 0 \\ 0 & (\frac{1}{\sigma_2^2})(\lambda_1)^2 & 0 & 0 \\ 0 & 0 & (\frac{1}{\sigma_1^2})(\frac{\lambda_1}{2^{\lambda_3}})^2 & 0 \\ 0 & 0 & 0 & (\frac{1}{\sigma_2^2})(\frac{\lambda_1}{2^{\lambda_3}})^2 \end{pmatrix}. \tag{1.22}$$

In the literature, λ_1 is often set to 0.1 to enforce moderate shrinkage on the coefficients

[57]Again, without prior belief of exogenous variables, λ_4 usually takes a large value.

of the contemporaneous endogenous variables; λ_3, which modulates the decay rate of influence for higher-order lags, is generally configured at values such as 1 or 2; λ_4, which controls the tightness on coefficients of exogenous variables, is frequently assigned a value ranging from 100 to effectively infinity to account for a lack of prior belief of exogenous variables (Dieppe, Legrand, & Van Roye, 2016). In alignment with these established norms, I set $\lambda_1 = 0.1$, $\lambda_3 = 1$, and $\lambda_4 = 100$ for my Bayesian Panel VAR analysis, thereby situating my hyperparameter choices within the broader consensus of the field.

The prior distribution of $\pi(\Sigma_c)$ of a pooled estimator is an inverse Wishart distribution with scale matrix S_0 and degree of freedom α_0. Following Karlsson (2013), α_0 is defined as

$$\alpha_0 = g + 2, \tag{1.23}$$

and S_0 is defined as

$$S_0 = (\alpha_0 - g - 1) \begin{pmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \sigma_g^2 \end{pmatrix}, \tag{1.24}$$

with the variance of variable x estimated by pooling the samples for variable x across N units and then estimating an autoregressive model over this pooled series. Also, since $\pi(\Sigma_c)$ follows an inverse Wishart distribution, it follows that $E(\Sigma_c) = \frac{S_0}{\alpha_0 - g - 1}$.

Random Coefficient Model

In Section 1.5.2, the covariance matrix Σ_b is assumed to correspond to a known covariance matrix Ω_b. Essentially, this form corresponds to the Minnesota prior covariance matrix: the variance of parameters in β relating endogenous variables to their own lags is given by $(\frac{1}{l^{\lambda_3}})^2$; the variance of parameters in β related to cross-lag coefficients is given by $(\frac{\sigma_i^2}{\sigma_j^2})(\frac{\lambda_2}{l^{\lambda_3}})^2$; the variance for exogenous variables is given by $\sigma_i^2(\lambda_4)^2$. The definitions of l, λ_3, and λ_4

are similar to that in Section 1.A.8, while λ_2 is a cross-variable specific variance parameter. The values I use for λ_3 and λ_4 are also similar to that in Section 1.A.8, while for λ_2, I set it to 0.5. One may notice the absence of λ_1, the overall tightness parameter, and assume that the hyperparameter has been normalized to one. This is not the case—recall that in Section 1.5.2, Σ_b is defined as $\Sigma_b = (\lambda_1 \otimes I_{g(gp+m)})\Omega_b$. By adopting this form, we can treat λ_1 as a random variable, so determining the prior distribution of only λ_1 can effectively determines the prior distribution of Σ_b since Ω_b is assumed to be known.

λ_1 affects the degree of information sharing across units. $\lambda_1 = 0$ implies that all β_is are equal to b, hence the estimate is simply the pooled estimator. A higher λ_1 allows coefficients to differ more across units. $\lambda_1 \to \infty$ implies that b becomes uninformative and there is no sharing of information applied between units. According to Dieppe, Legrand, and Van Roye (2016), a classic choice for the prior distribution of λ_1 is an inverse Gamma distribution: $\lambda_1 \sim IG(\frac{s_0}{2}, \frac{v_0}{2})$, where $\frac{s_0}{2}$ and $\frac{v_0}{2}$ are the shape and scale of the distribution respectively. Following Gelman (2006), I set low values for s_0 and v_0 (0.001 for both hyperparameters) to make the prior weakly informative.

1.A.9 Gibbs Sampling for the Random Coefficient Model

Algorithm for the hierarchical prior:

1. Fix the initial values $\beta^{(0)}$, $b^{(0)}$, $\Sigma_b^{(0)}$, and $\Sigma^{(0)}$. $\beta^{(0)} = \{\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_N\}$ is the OLS estimates. $b^{(0)}$ is simply given by $\frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i$. Since $\Sigma_b = (\lambda_1 \otimes I_{g(gp+m)})\Omega_b$, $\lambda_1^{(0)}$ is set to 0.01 so that $\Sigma_b^{(0)}$ corresponds to the Ω_0 matrix from the Minnesota prior. $\Sigma^0 = \{\hat{\Sigma}_1, \hat{\Sigma}_2, \ldots, \hat{\Sigma}_N\}$ is the residuals from the OLS estimates.

2. At iteration 1, determine the conditional distribution $f(b|\beta^{(0)}, \Sigma_b^{(0)}, \Sigma^{(0)})$. Obtain a draw b^1 from this distribution.

3. At iteration 1, determine the conditional distribution $f(\lambda_1|b^{(1)}, \beta^{(0)}, \Sigma^{(0)})$. Obtain a draw $\lambda_1^{(1)}$ from this distribution. Then, obtain $\Sigma_b^{(1)} = (\lambda_1^{(1)} \otimes I_{g(gp+m)})\Omega_b$.

4. At iteration 1, determine the conditional distribution $f(\beta|b^{(1)}, \Sigma_b^{(1)}, \Sigma^{(0)})$. Obtain a

draw $\beta^{(1)}$ from this distribution.

5. At iteration 1, determine the conditional distribution $f(\Sigma|b^{(1)}, \Sigma_b^{(1)}, \beta^{(1)})$. Obtain a draw $\Sigma^{(1)}$ from this distribution. This marks the end of iteration 1. Repeat the process until:

6. At iteration n, determine the conditional distribution $f(b|\beta^{(n-1)}, \Sigma_b^{(n-1)}, \Sigma^{(n-1)})$. Obtain a draw b^n from this distribution.

7. At iteration n, determine the conditional distribution $f(\lambda_1|b^{(n)}, \beta^{(n-1)}, \Sigma^{(n-1)})$. Obtain a draw $\lambda_1^{(n)}$ from this distribution. Then, obtain $\Sigma_b^{(n)} = (\lambda_1^{(n)} \otimes I_{g(gp+m)})\Omega_b$.

8. At iteration n, determine the conditional distribution $f(\beta|b^{(n)}, \Sigma_b^{(n)}, \Sigma^{(n-1)})$. Obtain a draw $\beta^{(n)}$ from this distribution.

9. At iteration n, determine the conditional distribution $f(\Sigma|b^{(n)}, \Sigma_b^{(n)}, \beta^{(n)})$. Obtain a draw $\Sigma^{(n)}$ from this distribution.

10. Discard the initial segment of the sample generated by the algorithm (burn-in sample). This is because the initial values of the parameters may not be representative of the target distributions; the chain needs cycles of iterations to converge to the stationary distribution from which proper sampling is desired. The burn-in period allows the chain to move past the transient effects of the initial conditions. Only the samples generated after this burn-in period are used for estimating the posterior distribution. This concludes the process.

1.A.10 Panel VAR Specifications

Lag Order Selection

Lags	Log-likelihood	AIC	BIC	HQIC
1	-123.091	16.834	17.814	16.931
2	-115.303	18.913	20.651	19.002
3	-110.033	22.307	24.059	21.578
4	-104.629	26.186	27.765	24.374
5	-99.083	30.662	31.817	27.416

Table 1.9: Lag order selection information criteria for the baseline model.

Summary Statistics

	N	Mean	SD	Min	Max
IQR of TFP shock	1224	0.283	0.094	0.086	1.085
SD of TFP shock	1224	0.362	0.118	0.115	1.149
Log(turnover)	1224	16.346	1.451	11.039	20.017
Log(investment)	1224	13.571	2.142	3.999	18.223
Log(employment)	1224	11.114	1.391	6.436	14.942

Table 1.10: Summary statistics of the variables used in the Bayesian panel VAR. The data are sourced from FAME, covering the period 2003 to 2022. All variables are presented without first differenced.

Identification Scheme: Cholesky Decomposition

This section draws from Hamilton (2020) to explain Cholesky decomposition in a less formal manner. Cholesky decomposition is used to identify structural shocks in the Bayesian panel VAR in this chapter. Specifically, the technique decomposes a positive-definite matrix into a lower triangular matrix and its transpose. Let ϵ_t be a vector of reduced-form residuals in a VAR model and Σ their covariance matrix. The reduced-form shocks ϵ_t are usually correlated, so it is not possible to interpret them directly as structural shocks. To identify the structural shocks, assume that $u_t = L\epsilon_t$, where u_t is a vector of structural shocks assumed to be uncorrelated and with unit variance, and L the matrix that maps reduced-form shocks to their structural counterparts. Therefore, Σ can be written as:

$$\Sigma = \mathbb{E}[u_t u_t'] = \mathbb{E}[(L\epsilon_t)(L\epsilon_t)'] = L\mathbb{E}[\epsilon_t \epsilon_t']L' = L\Sigma_\epsilon L' = LL', \tag{1.25}$$

with Σ_ϵ a diagonal matrix. The identification problem simply reduces to finding L that satisfies $\Sigma = LL'$. By assuming that some shocks have zero contemporaneous effect on some of the endogenous variables—determined by the ordering of the variables in the VAR—L becomes a lower triangular matrix. Since Σ in a VAR is positive semi-definite, we can use Cholesky decomposition to write $\Sigma = PP'$, where P is a lower triangular matrix. Given $\Sigma = PP'$ and $\Sigma = LL'$ together, as well as the fact that both P and L are lower triangular matrices, it must follow that $L = P$.

Log Marginal Likelihood, Bayesian Information Criterion (BIC), and Deviance Information Criterion (DIC)

This section draws from Dieppe, Legrand, and Van Roye (2016) in explaining why it is not possible to compute the log marginal likelihood for the Bayesian VAR with random coefficients in this chapter. Let the marginal density of a given model be

$$m(y) = \int f(y|\theta)\pi(\theta)d\theta, \tag{1.26}$$

where $f(y|\theta)$ represents the likelihood function, $\pi(\theta)$ the prior distribution of θ, and $\theta = \beta, \Sigma$. Recall that β and Σ are independent. Therefore, the marginal density can be written as

$$m(y) = \iint f(y|\theta)\pi(\beta)\pi(\Sigma)d\beta d\Sigma. \tag{1.27}$$

In this chapter, the $\pi(\Sigma)$ in the Bayesian panel VAR with random coefficients is a diffuse improper prior. This prior does not integrate to one, so only its kernel is known: $\pi(\Sigma) \propto |\Sigma|^{-\frac{n+1}{2}}$, where n is the number of endogenous variables. As a result, deriving the marginal likelihood is not possible since the full proper prior $\pi(\Sigma)$ is needed.

This chapter employs two commonly used model selection criteria, the Bayesian Information Criterion (BIC) and Deviance Information Criterion (DIC), to compare the performance of the baseline pooled estimator and the random coefficients model. These metrics, while simpler and potentially second-best compared to the log marginal likelihood, offer a practical approach for balancing model fit and complexity. The MATLAB codes used to compute the BIC and DIC are taken from Koop and Korobilis (2016). For the baseline pooled estimator and the random coefficients model, as shown in Figure 1.7 and Figure 1.8, the respective BIC values are 5.138×10^5 and 5.126×10^5; these high values are due to the large sample size and the number of parameters involved. Meanwhile, the DIC values are -2.386 and -9.295, respectively. Based on both BIC and DIC, the random coefficients model outperforms the pooled estimator.

1.A.11 Bayesian Panel VAR with Pooled Estimator: Robustness Checks

Ordering Microeconomic Uncertainty First

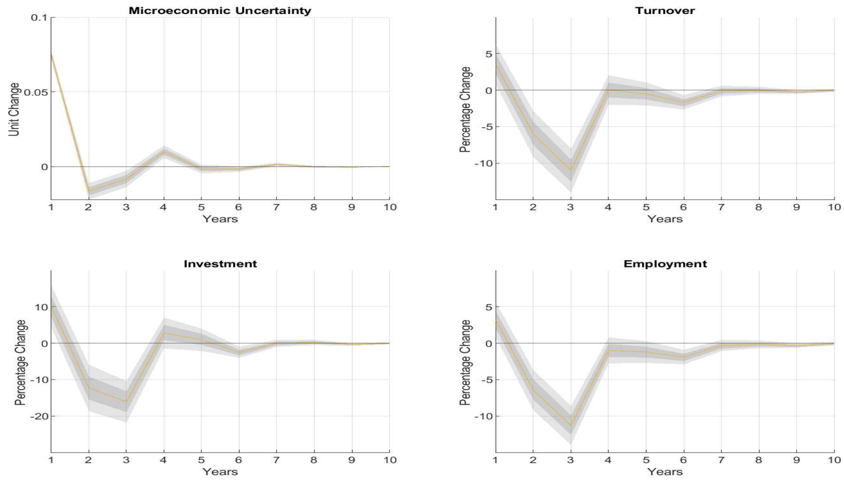

Figure 1.24: Impulse response functions of the Bayesian panel VAR using a pooled estimator, ordering microeconomic uncertainty first.A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The orange line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Including Macroeconomic Uncertainty as Exogenous Variable

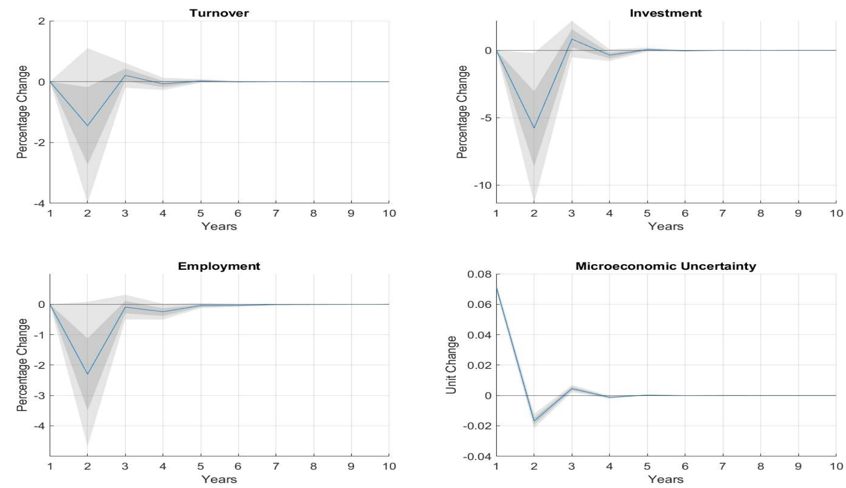

Figure 1.25: Impulse response functions of the Bayesian panel VAR using a pooled estimator, with macroeconomic uncertainty as an exogenous variable. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The blue line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Setting Overall Tightness Hyperparameter (λ_1) to 0.2

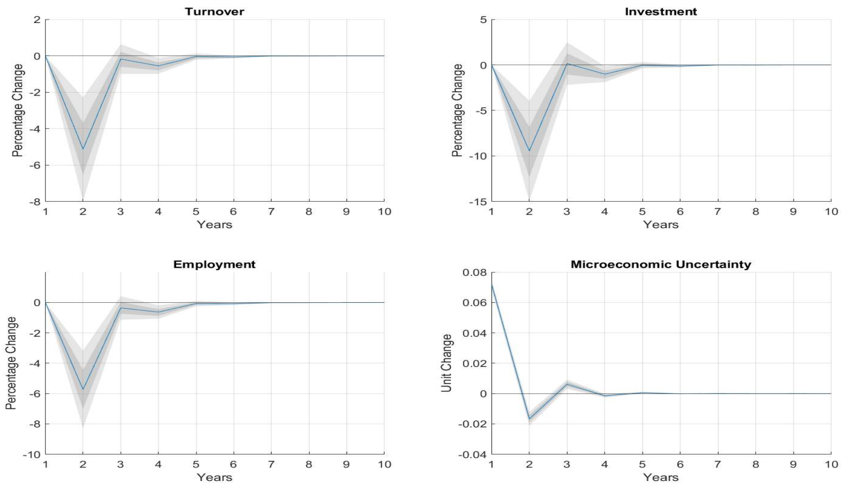

Figure 1.26: Impulse response functions of the Bayesian panel VAR using a pooled estimator, setting the overall tightness parameter $\lambda_1 = 0.2$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The blue line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areaa represent 68-percent and 95-percent credible sets.

Setting Overall Tightness Hyperparameter (λ_1) to 0.05

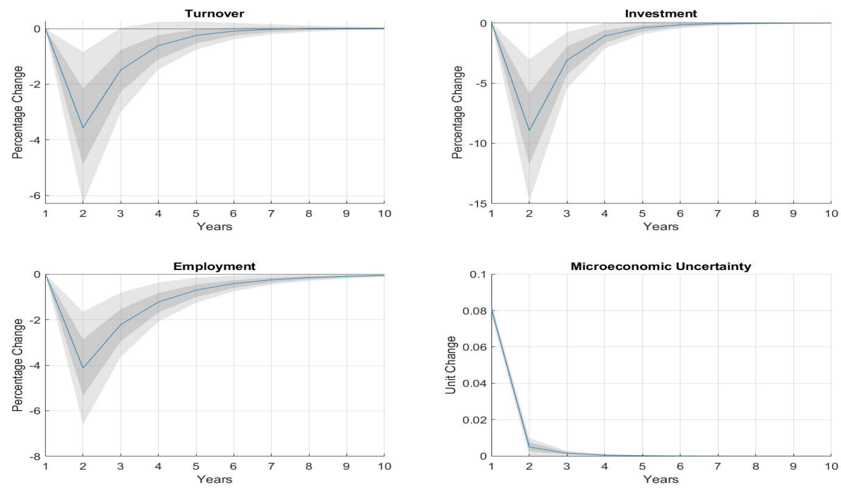

Figure 1.27: Impulse response functions of the Bayesian panel VAR using a pooled estimator, setting the overall tightness parameter $\lambda_1 = 0.05$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The blue line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Setting Lag Decay Hyperparameter (λ_3) to 1.5

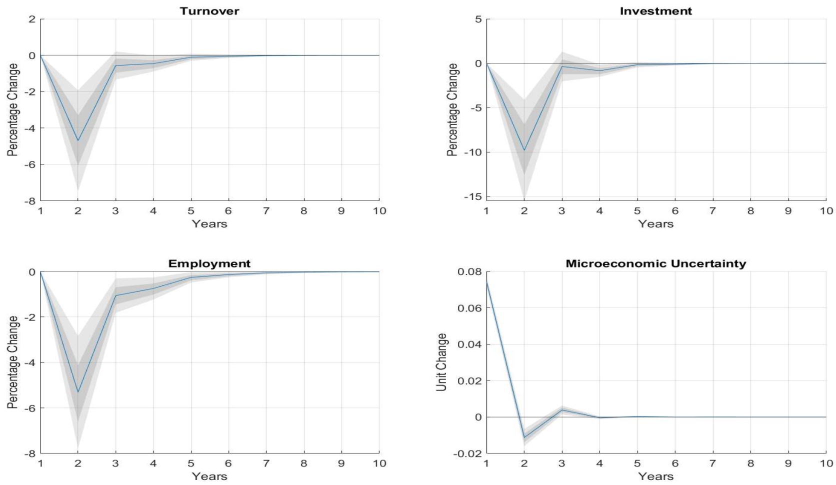

Figure 1.28: Impulse response functions of the Bayesian panel VAR using a pooled estimator, setting the lag decay parameter $\lambda_3 = 1.5$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The blue line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areaa represent 68-percent and 95-percent credible sets.

Setting Lag Decay Hyperparameter (λ_3) to 2

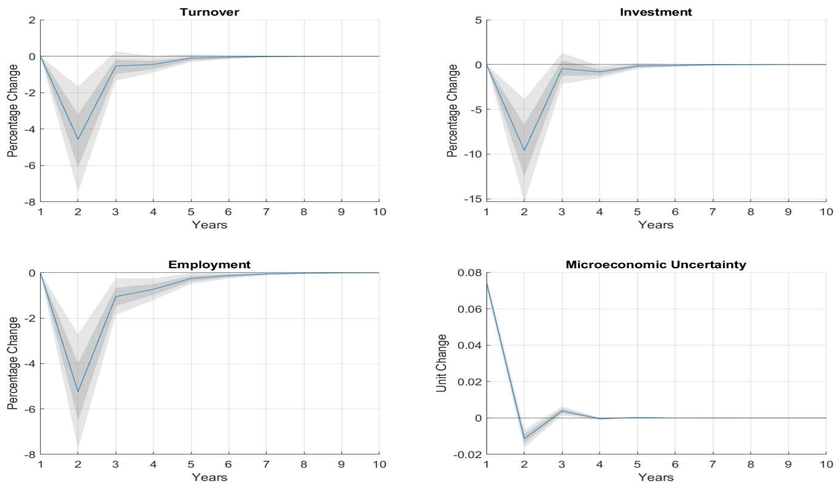

Figure 1.29: Impulse response functions of the Bayesian panel VAR using a pooled estimator, setting the lag decay parameter $\lambda_3 = 2$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The blue line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Setting Overall Tightness Hyperparameter (λ_1) to 0.15 and Lag Decay Hyperparameter (λ_3) to 1.5

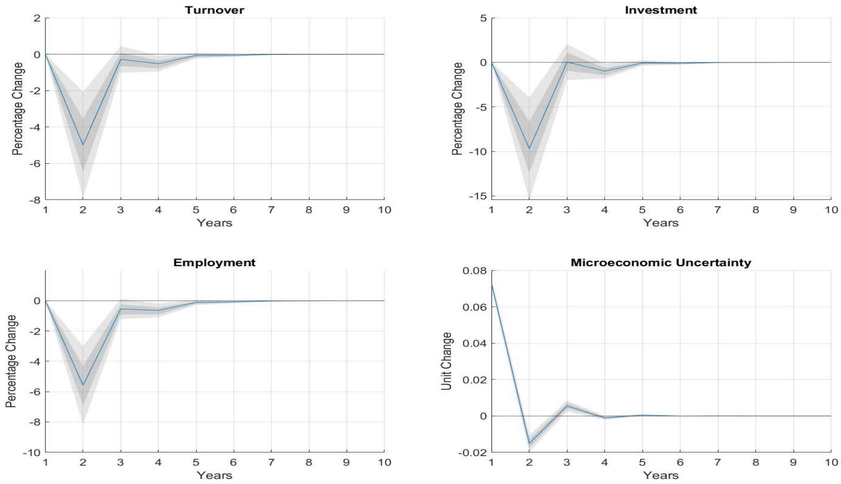

Figure 1.30: Impulse response functions of the Bayesian panel VAR using a pooled estimator, setting the overall tightness parameter $\lambda_1 = 0.15$ and lag decay parameter $\lambda_3 = 1.5$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The blue line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

Using Standard Deviation of TFP Shocks as A Measure of Microeconomic Uncertainty

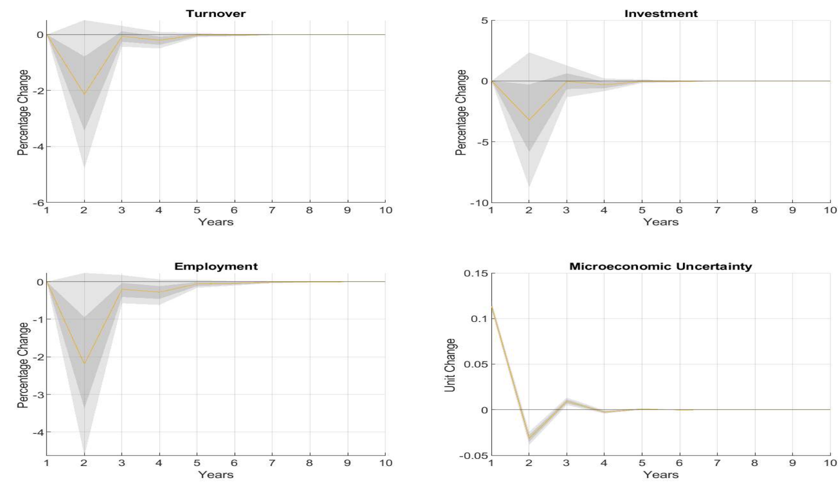

Figure 1.31: Impulse response functions of the Bayesian panel VAR using a pooled estimator, replacing the interquartile range of productivity shocks with the standard deviation of productivity shocks as the microeconomic uncertainty measure. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. The orange line denotes the median impulse response to the microeconomic uncertainty shock. The darker and lighter shaded areas represent 68-percent and 95-percent credible sets.

1.A.12 Bayesian Panel VAR with Random Coefficients: Robustness Checks

Including Macroeconomic Uncertainty as Exogenous Variable

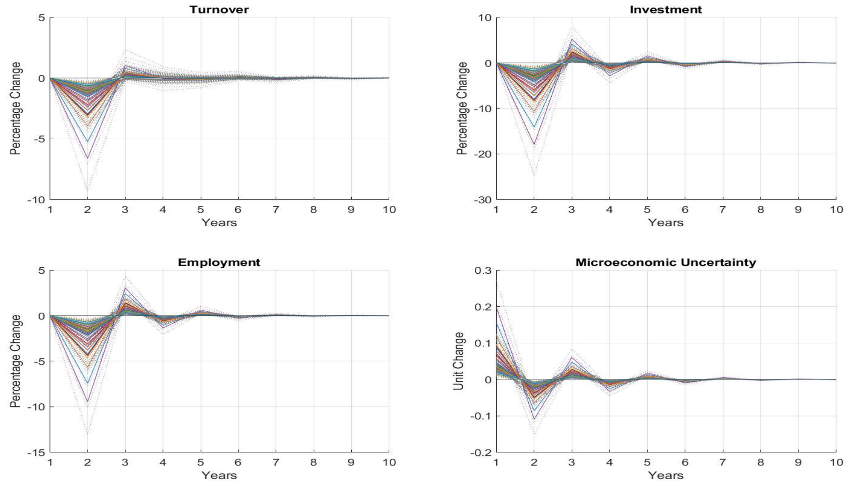

Figure 1.32: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions, with macroeconomic uncertainty as an exogenous variable. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Setting Cross-variable Weighting Parameter, λ_2, to 0.1

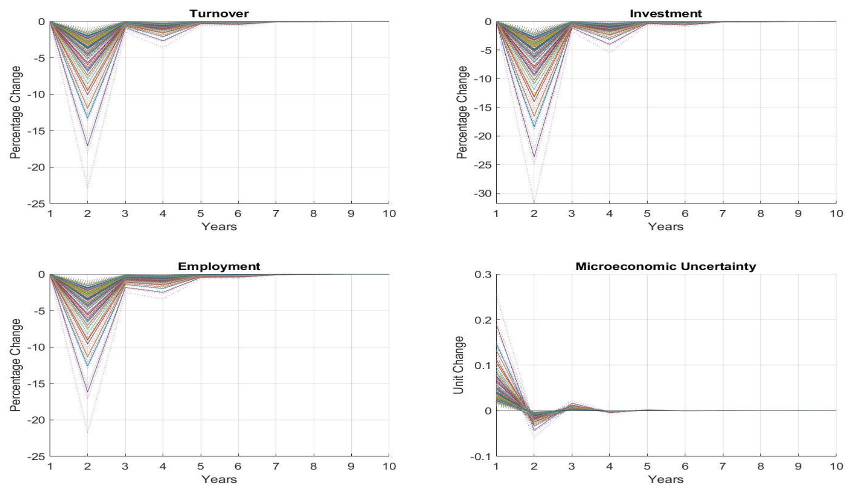

Figure 1.33: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions, setting the cross-variable weighting parameter $\lambda_2 = 0.1$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Setting Cross-variable Weighting Parameter, λ_2, to 0.6

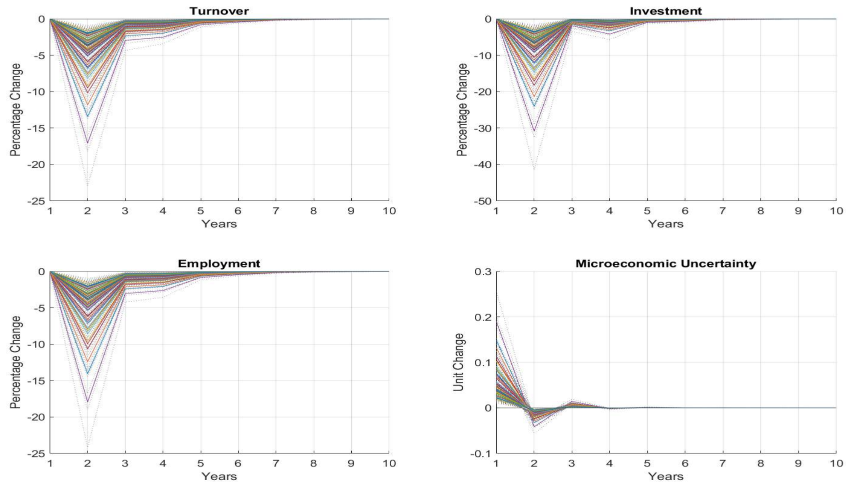

Figure 1.34: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions, setting the cross-variable weighting parameter $\lambda_2 = 0.6$. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Setting the Inverse Gamma Shape and Scale on Overall Tightness Parameters, s_0 and v_0 , to 0.0001

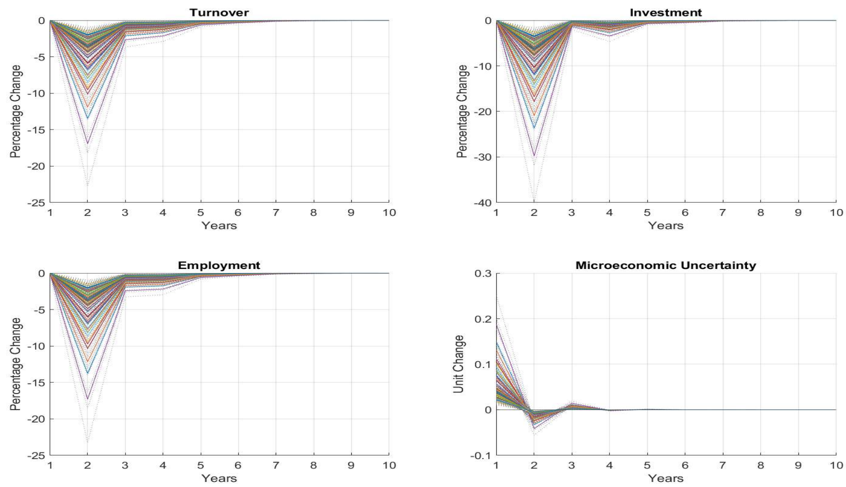

Figure 1.35: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions, setting the Inverse Gamma shape and scale on overall tightness parameters s_0 and v_0 to 0.0001. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Setting the Inverse Gamma Shape and Scale on Overall Tightness Parameters, s_0 and v_0 , to 0.01

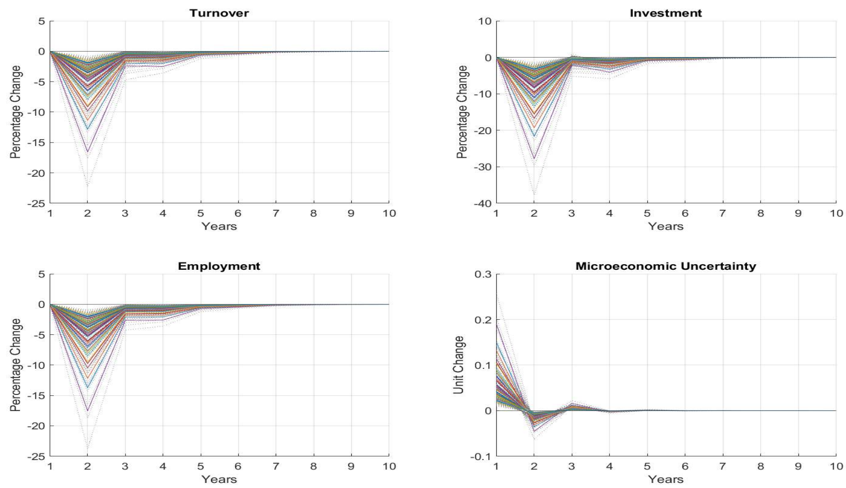

Figure 1.36: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions, setting the Inverse Gamma shape and scale on overall tightness parameters s_0 and v_0 to 0.01. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Using Standard Deviation of TFP Shocks as A Measure of Microeconomic Uncertainty

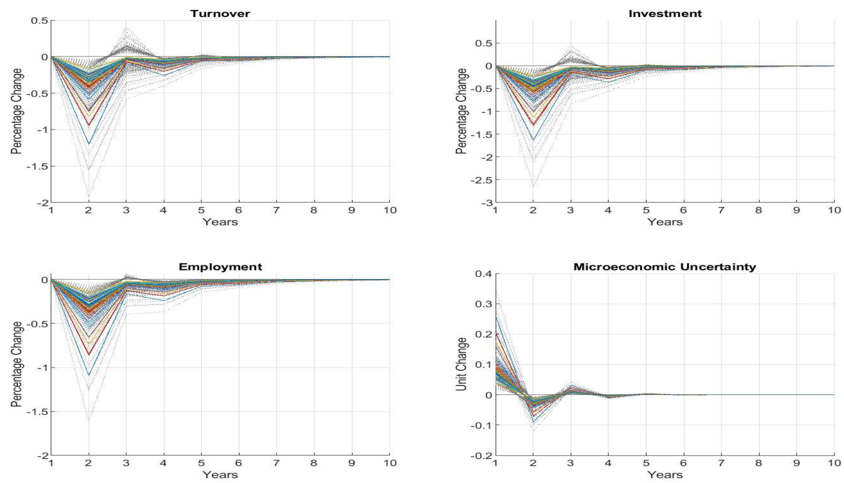

Figure 1.37: Impulse response functions of the Bayesian panel VAR using random coefficients, overlaid for all 68 industry divisions, replacing the IQR of productivity shocks with the standard deviation of productivity shocks as the microeconomic uncertainty measure. A one-standard-deviation microeconomic uncertainty shock is imposed in the year labelled 1. Each colored line represents the median impulse response for a specific industry division, though individual lines are not labelled, as the aim is not to identify specific industries but to examine common response patterns across divisions. The dotted lines represent 95-percent credible sets; however, due to the overlaying of all 68 industry divisions, the credible sets largely overlap and are therefore not clearly distinguishable. The 68-percent credible sets are not presented for brevity.

Chapter 2 Temporary Employment in the UK

2.1 Introduction

Temporary employment refers to work arrangements in which salary and wage earners are engaged for a predetermined, limited duration. Across OECD countries, temporary employment encompasses various forms, including fixed-term contracts, agency temping, seasonal jobs, internships, and apprenticeship agreements. Since the early 1980s, the share of temporary employment in total dependent employment has surged on average by 30% in OECD countries, and in some countries, more than one in four contracts have a fixed duration (Boeri & Garibaldi, 2024). The United Kingdom is *not* one of them. The share of temporary employment in total employment in the UK has remained remarkably stable, consistently hovering between 5% to 6% for almost two decades (Office of National Statistics, 2024c). As a result, while countries with widespread temporary employment, such as Italy and Spain, have attracted significant academic attention, the UK has received comparatively less focus, largely due to the relative stability of its share of temporary employment.

Despite its modest numerical representation, temporary employment in the UK is far from trivial. Temporary employment serves as a barometer of labour market flexibility, encapsulates the evolving dynamics of contemporary work arrangements, and reflects employer strategies. It has been linked to both positive and negative labour market outcomes: on one hand, it facilitates job creation by providing firms with greater flexibility (Boeri & Garibaldi, 2007; Daruich, Di Addario, & Saggio, 2023; Faccini, 2014) and providing pathways into work for some groups of workers (de Graaf-Zijl, Van den Berg, & Heyma, 2011; García-Pérez, Marinescu, & Vall Castello, 2019; Heinrich, Mueser, &

Troske, 2005); on the other, it is associated with job insecurity (Blanchard & Landier, 2002; Clark & Postel-Vinay, 2009; Dawson, Veliziotis, & Hopkins, 2017), lower job satisfaction (Booth, Francesconi, & Frank, 2002; Kauhanen & Nätti, 2015), and adverse effects on productivity (Cappellari, Dell'Aringa, & Leonardi, 2012; Damiani, Pompei, & Ricci, 2011; Hijzen, Mondauto, & Scarpetta, 2017). As such, temporary employment features prominently in policy discussions surrounding labour market duality and labour precarity. Moreover, temporary employment in the UK is not merely a neutral feature of the labour market but is often framed in terms of "vulnerable employment" (Trade Union Congress, 2008), "precarious work" (Pósch, Scott, Cockbain, & Bradford, 2020), and "insecure work" (Florisson, 2024), highlighting widespread public concern over its socioeconomic implications. These concerns have intensified in the wake of major economic shocks, including the 2008 Financial Crisis, Brexit, and the COVID-19 pandemic, all of which have heightened uncertainty. Understanding the determinants and consequences of temporary employment, particularly within the context of economic uncertainty, can yield valuable and new insights into how the labour market adapts to economic fluctuations.

This chapter achieves two primary objectives. First, it offers new perspectives of temporary employment in the UK. Work on temporary employment in the UK including Casey (1987), Forde and Slater (2001), Booth, Francesconi, and Frank (2002), and Forde and Slater (2005), primarily addresses the regulations governing various types of temporary employment, general overviews, characteristics of individuals in temporary employment, and the consequences of such employment.[1] Rather than providing a comprehensive overview of temporary employment in the UK, this chapter intends to complement the existing literature by focusing on the reasons for temporary employment, gender differences, and geographical variations in trends and correlations with macroeconomic variables in the UK—areas that have been underexplored. The UK Labour Force Surveys (LFS) specifically ask respondents in temporary employment to identify their reasons for such arrangements, but less is known in the literature about whether these reasons differ by type of temporary employment. Additionally, while trends and reasons in temporary employment may vary across genders, existing literature often overlooks these distinctions. Geographical disparities in temporary employment within the UK also have not been adequately addressed in the current literature. Using the

[1] Section 2.A.3 in the Appendix provides a further summary of the literature on temporary employment in the UK.

LFS data covering the period from 1992 to 2023, this chapter uncovers novel facts on the evolution of the reasons cited for temporary employment, gender differences in temporary employment trends, and geographical variations in temporary employment within the UK.

Second, this chapter provides preliminary evidence that higher macroeconomic uncertainty is associated with a greater likelihood of temporary employment. As early as the late 1980s, Casey (1987) emphasizes the importance of studying involuntary temporary employment—where individuals engage in temporary employment because they have no alternative. In recent years, temporary employment has often been described as vulnerable (Trade Union Congress, 2008), precarious (Pósch, Scott, Cockbain, & Bradford, 2020), or insecure (Florisson, 2024), underscoring the notion that many individuals are in temporary employment involuntarily. This chapter contributes to the discussion of 'involuntary' temporary employment by proposing that periods of increased macroeconomic uncertainty are linked to a higher probability of individuals being in temporary employment: firms may prefer temporary contracts over permanent ones due to the lower costs of reversing these decisions during periods of heightened uncertainty. As a result, workers may find themselves forced into temporary employment despite a preference for permanent positions.

To test the relationship between macroeconomic uncertainty and the probability of being in temporary employment in the UK, I run a probit regression using LFS data and the macroeconomic uncertainty measure from Theophilopoulou (2022) from 1992 to 2018. In this context, the probability of temporary employment specifically refers to the likelihood that an employed individual holds a temporary rather than a permanent position, rather than the probability of being in temporary employment relative to all possible labor market states, including unemployment or inactivity. This distinction matters because the analysis is conducted on a sample of *employed* individuals; unemployed and inactive individuals are excluded from the sample. Therefore, the results do not speak to the overall likelihood of employment versus non-employment, but rather to the composition of employment between temporary and permanent contracts.[2] Two noteworthy observations emerge.

[2]This sample restriction also introduces a form of selection bias. For instance, heightened uncertainty could influence both the probability of being employed *at all* and the type of employment obtained, but the current analysis cannot capture the former effect. Consequently, the results should be interpreted as

First, macroeconomic uncertainty is positively associated with the probability of being in temporary employment. A one-standard-deviation increase in macroeconomic uncertainty from a year prior yields an approximately 0.2 percentage point rise in the probability of being in temporary employment. While this value appears small, it is nontrivial given the relatively low unconditional probability of being in temporary employment in the UK. Second, the positive marginal association peaks when using the macroeconomic uncertainty measure from two years prior as the regressor, but subsequently diminishes when using lagged macroeconomic uncertainty measures from earlier periods (3, 4, and 5 years ago), hinting that more distant spikes in uncertainty appear to play a smaller role in estimating the probability of being in temporary employment.

Although the estimated marginal association between macroeconomic uncertainty and the probability of being in temporary employment is small, it raises the question of whether the relationship may be non-linear. I re-estimate the regression with macroeconomic uncertainty treated as a categorical variable to distinguish the levels of uncertainty. Specifically, I classify macroeconomic uncertainty into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). A consistent pattern emerges across all lag periods: compared to very low macroeconomic uncertainty, low, moderate, high, and very high levels of uncertainty exhibit a statistically significant and positive correlation with the probability of being in temporary employment. Notably, moderate and high levels of uncertainty display the highest coefficients, indicating that these levels are more important predictors of temporary employment probability. Simple macroeconomic reasoning might explain this finding: when faced with a small uncertainty shock, firms may recover more quickly and begin hiring again sooner, perhaps opting for temporary contracts over permanent ones, thus increasing the probability of temporary employment. Conversely, a larger uncertainty shock might prompt firms to lay off more temporary employees, as they are easier to dismiss (Cao, Shao, & Silos, 2021), and take longer to resume hiring (Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Den Haan, Freund, & Rendahl, 2021; Schaal, 2017). This delay in rehiring could result in a smaller proportion of individuals being in temporary employment. Therefore, the results underscore that the severity of macroeconomic uncertainty matters in predicting an

conditional associations within the employed population.

individual's probability of being in temporary employment. These findings remain robust across a different categorization method for the macroeconomic uncertainty measure and the inclusion of additional control variables.

Leveraging the probit regression results, this chapter provides a brief analysis of the heterogeneity in the relationship between macroeconomic uncertainty and the probability of being in temporary employment. The analysis reveals that more highly educated individuals exhibit greater sensitivity to changes in macroeconomic uncertainty in their probability of being in temporary employment. Additionally, the effect of macroeconomic uncertainty varies by gender and family status: women with children are predicted to experience a higher probability of temporary employment as macroeconomic uncertainty rises, and this likelihood increases with the number of children. However, these findings should be interpreted with caution as the analysis is restricted to employed individuals; this sample limitation introduces potential selection bias, which may influence the observed relationships. While these findings are interesting in their own right, further research is required to empirically validate these patterns and to uncover the underlying mechanisms driving these observations.

The remainder of this chapter is organized as follows. Section 2.2 reviews the institutional and societal context, recent trends, and geographical variations of temporary employment in the UK. Section 2.3 describes the data and presents the regression analysis testing the relationship between macroeconomic uncertainty and the probability of being in temporary employment. Section 2.4 explores the heterogeneity in the relationship between macroeconomic uncertainty and the probability of being in temporary employment. Section 2.5 summarizes the findings, discusses the limitations of the analysis, and proposes avenues for future research.

2.2 Overview of Temporary Employment in the UK

This section reviews the institutional and societal context, recent trends, and geographical variations of temporary employment in the UK.

The International Labour Organization (2016) defines temporary employment as a form of work where workers are hired for a predetermined and limited duration, encompassing fixed-term contracts, project- or task-based assignments, seasonal roles, casual work, and day labour. Contrary to French and German labour laws, British labour law does not differentiate between temporary and permanent statuses within employment relationships (Casey, 1987). In the UK, an employee[3] is in temporary employment if they have a fixed-period contract, or are doing agency temping, casual work, seasonal work, or other forms of temporary work. According to the UK Government (2022), a fixed-term contract pertains to individuals with an employment agreement that concludes on a predetermined date or upon the fulfillment of a specific task; agency temping involves individuals holding contracts with agencies including recruitment agencies, yet providing temporary services to a hirer; casual work entails sporadic engagements with specific businesses, where neither party is obligated to offer or accept work consistently;[4] seasonal employment entails fulfilling business needs during particular periods, notably prevalent in agricultural sectors.

In the UK, the legislative framework governing temporary employment is anchored by two critical statutes. The Fixed-term Employees (Prevention of Less Favourable Treatment) Regulations 2002, enacted on October 1, 2002, prescribe that individuals under fixed-term contracts should not face discriminatory treatment in comparison to their permanent counterparts concerning service qualification periods, training opportunities, and prospects for securing permanent positions within the organization (UK Government, 2002). Similarly, the Agency Workers Regulations 2010, enforced since October 1, 2011, ensure that after 12 weeks of employment, agency workers receive equal treatment in terms of remuneration, annual leave, and working hours compared to full-time permanent employees performing similar work (UK Government, 2010). Regarding employment

[3]In the UK, a distinction is made between employees and workers. A person is typically classified as a 'worker' if they engage in work or services under a contract, whether written or unwritten, in exchange for compensation, whether monetary or in kind, with limited delegation rights, subject to the employer's provision of work throughout the contract duration, and are not operating under their own limited company where the 'employer' functions as a customer or client. (UK Government, 2022) While all employees fall under the category of workers, employees possess additional rights and responsibilities not afforded to non-employee workers, including protection against unfair dismissal and entitlement to request flexible working arrangements (UK Government, 2022).

[4]Casual work contracts usually use terms such as 'casual', 'freelance', 'zero hours', or 'as required'.

protection legislation, the UK has relatively lenient employment protection legislation for both permanent and temporary employment. As depicted in Figure 2.1, the UK, measured by the OECD's Strictness of Employment Protection Indicators,[5] is the third most lenient among G7 countries in 2019 for regular contracts. Notably, the employment protection legislation for temporary contracts in the UK is even less stringent than that for regular contracts. Although the UK is among the few countries achieving convergence in termination costs across contract types (OECD, 2014),[6] there is limited judicial review of contract terminations due to the low degree of employment protection.[7] Additionally, there is no legal cap on the number of renewals for fixed-term contracts, and the maximum cumulative duration of successive fixed-term contracts is set at four years—exceeding the legal limits in most OECD countries (OECD, 2014).

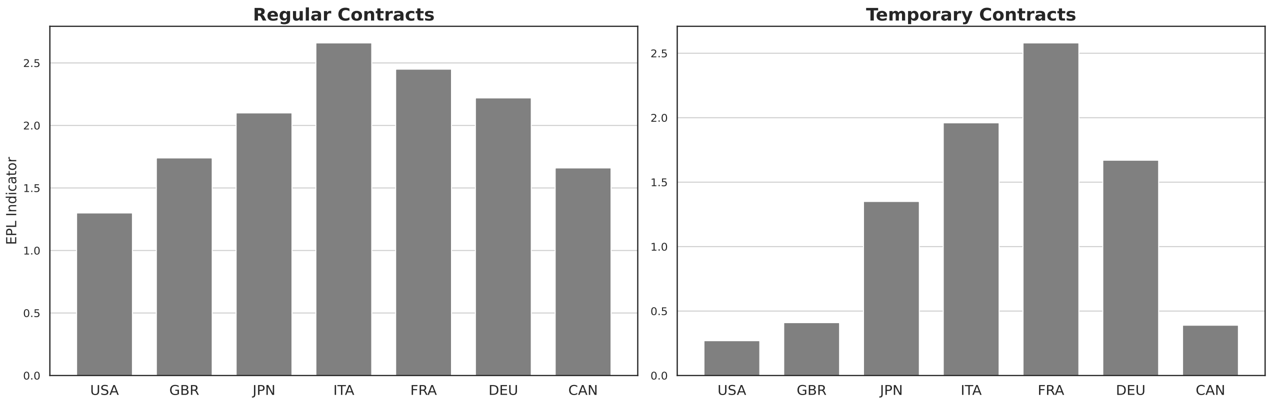

Figure 2.1: The OECD's Strictness of Employment Protection Legislation Indicators in 2019. *Notes:* The left panel depicts the strictness of employment protection legislation in regular contracts for the United States (USA), the United Kingdom (GBR), Japan (JPN), Italy (ITA), France (FRA), Germany (DEU), and Canada (CAN) , while the right panel depicts these countries' strictness of employment protection legislation in temporary contracts. Data range from 0 to 6 with higher scores representing stricter regulation. *Source:* OECD Employment and Labour Market Statistics (2019).

Due to the limited definition of temporary employment and its association with lenient employment protection, temporary employment in the UK is often framed and studied within broader conceptual terms, often imbued with negative connotations. Temporary employment in the UK is commonly characterized as a form of 'vulnerable employment'

[5]The OECD's Strictness of Employment Protection Indicators assess various dimensions including the procedural hurdles employers encounter when initiating dismissals, the mandated notice periods, severance pay, and the overall difficulty of terminating employment. (OECD, 2013)

[6]All workers are covered by unfair dismissal rules if they have tenure of at least one year, while employees on fixed-term contract also share the same rights to redundancy pay as regular employees (OECD, 2014). However, the definition of "unfair dismissal" remains a subject of debate (OECD, 2014).

[7]The enforcement of employment protection legislation (EPL) in the UK depends on individual complaints, as judicial review is not extensive (OECD, 2014). Although potential claimants are identifiable and can respond to perceived unfair terminations, breaches concerning temporary contract hiring practices are more challenging to detect (Muñoz-Bullón, 2004).

because, for example, temporary agency workers may legally receive lower wages than their permanent counterparts for identical roles, and they typically lack equivalent rights to workplace benefits such as sick pay, paid holidays, or pension contributions (Trade Union Congress, 2008). Temporary employment is also considered as a subset of ’precarious work’ in the UK, reflecting concerns that individuals on temporary contracts may be more vulnerable to breaches of labour market rules and regulations (Pósch, Scott, Cockbain, & Bradford, 2020). In addition, some classified temporary employment as ’insecure work’ in the UK due to the inherent contractual instability faced by temporary employees (Florisson, 2024).

Existing literature predominantly discusses how temporary employment can contribute to lowering unemployment (see, for instance, Faccini, 2014), with less emphasis on the comovement between the two, and even less on the reverse relationship. Figure 2.2 and Figure 2.3 present the trends in the unemployment rate and the overall proportion of employed individuals in temporary employment, as well as the proportions of employed men and women in temporary employment in the UK from 1992Q2 to 2023Q4. Following an increase in temporary employment in the early 1990s,[8] temporary employment begins to move in tandem with unemployment.[9] This pattern aligns with findings by Kahn (2010), who shows that European policies encouraging the creation of temporary jobs increase temporary employment, particularly during periods of high unemployment.[10] Several explanations could account for this observation. Intuitively, high unemployment intensifies competition for jobs, prompting individuals to accept temporary positions they might otherwise decline in more favorable economic conditions. Assuming households generally prefer permanent to temporary employment, and temporary employment to unemployment,[11] higher unemployment may reduce households’ resistance to temporary employment. Furthermore, when the available labour pool expands with high unemployment, employers are more likely to use temporary contracts to screen workers for permanent positions (Engellandt & Riphahn, 2005; Faccini, 2014; Portugal &

[8]Many OECD countries observe an increase in temporary employment during the 1990s due to partial labour market reforms (OECD, 2014).

[9]This observation does not imply that the share of temporary employment is as a whole countercyclical. Figure 2.24 in the Appendix demonstrates a downward trend in temporary employment during periods of stagnant GDP growth, particularly from 2000 until the 2008 Financial Crisis and again from 2015 until the onset of the COVID-19 pandemic.

[10]Holmlund and Storrie (2002) also attribute the rise in temporary employment in Sweden during the 1990s to recession.

[11]This assumption is plausible, as studies such as Blanchard and Landier (2002), Hijzen, Mondauto, and Scarpetta (2017), García-Pérez, Marinescu, and Vall Castello (2019) and others document negative impacts of temporary employment on household earnings and welfare.

Varejão, 2022). Although this chapter does not delve into the underlying reasons for this observation, it later introduces economic uncertainty to provide a more comprehensive understanding of the phenomenon.

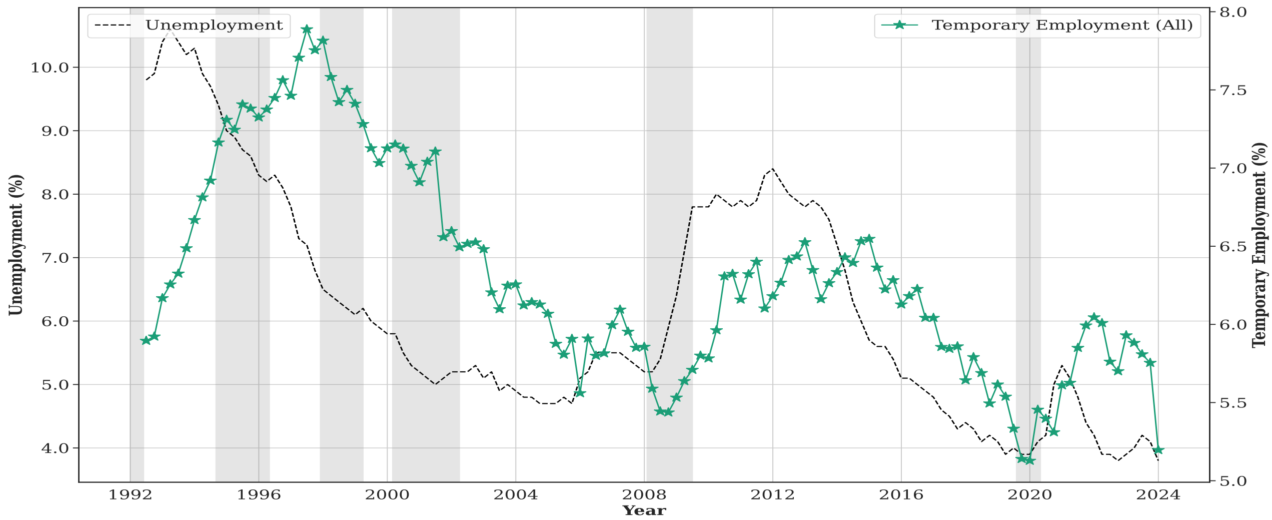

Figure 2.2: Unemployment rate (dotted line) and overall proportion of employed individuals in temporary employment (solid line with * symbols) from 1992Q2 to 2023Q4. *Notes:* The left vertical axis displays the unemployment rate in percent, while the right vertical axis the proportion of employed individuals in temporary employment in percent. The horizontal axis shows the time period in years. The shaded areas represent recessionary periods in the UK. *Source:* Office of National Statistics (2024b, 2024c).

The proportions of employed men and women in temporary employment reveal notable trends undocumented in previous literature. Figure 2.3 shows that the rate of temporary employment is consistently higher for women than for men, but both rates tend to comove. More interestingly, the overall proportion of employed individuals in temporary employment rises following the 2008 Financial Crisis, and this increase is driven primarily by men. During this period, the proportion of employed women in temporary employment remains relatively stable. However, in the aftermath of the COVID-19 pandemic, the overall proportion of employed individuals in temporary employment unsurprisingly increases again, but this time it features a more pronounced rise for women compared to men. These differences may stem from the unique nature of each crisis and their uneven effects on various industries through uncertainty. Treating uncertainty, in the simplest sense, as an increase in the dispersion of outcomes,[12] industries most affected by the 2008 Financial Crisis experience heightened uncertainty, leading firms to

[12] An increase in the dispersion of outcomes signifies that potential future states of the economy are more varied and less predictable. Under such conditions, the probability of experiencing extreme outcomes, whether positive or negative, escalates. Consider the finance industry during the 2008 Financial Crisis: firms faced heightened uncertainty, as the risk of incurring losses increased, yet there was also an elevated potential for profits for those that could navigate through the crisis while competitors exited the market. Similarly, the healthcare industry during the COVID-19 pandemic encountered increased uncertainty. Although there was a clear rise in demand for healthcare services, the magnitude and duration of this surge were uncertain.

favour temporary employment over permanent employment due to the lower adjustment costs associated with the former.[13] Notably, these industries are predominantly male-dominated.[14] Conversely, the COVID-19 pandemic likely increases uncertainty relatively more in industries such as healthcare which are dominated by women, resulting in firms offering more temporary contracts to new hires in these industries. Consequently, the patterns of rising temporary employment among men and women differ between the two crises. However, it is important to note that these explanations are speculative and may not be fully warranted by the available evidence.

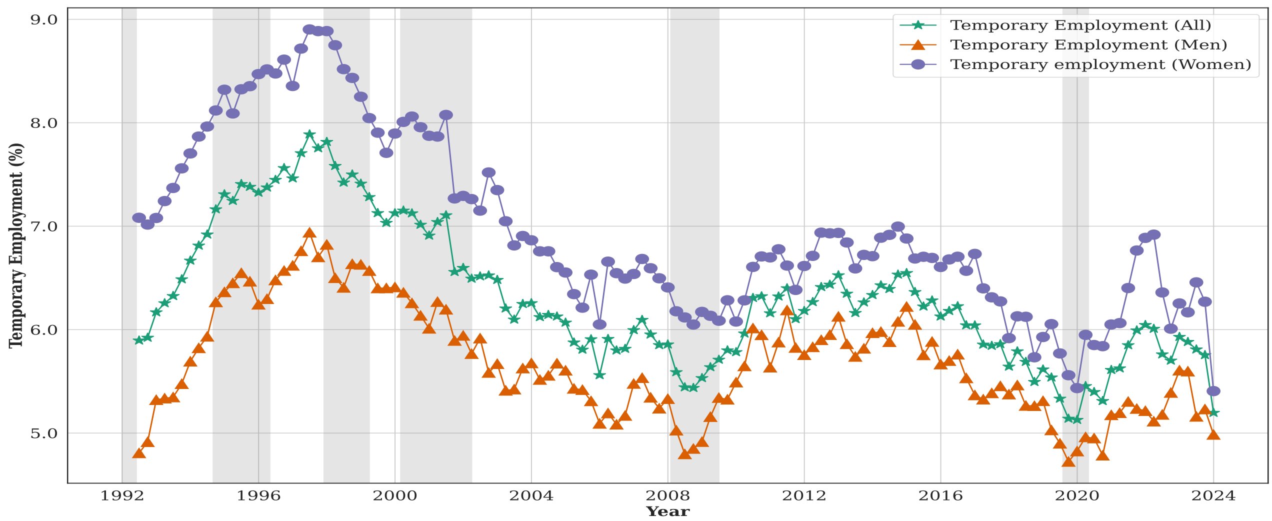

Figure 2.3: Employed individuals in temporary employment. *Notes:* The figure plots the overall proportion of employed individuals in temporary employment (solid line with * symbols), proportion of employed men in temporary employment (solid line with ▲ symbols), and proportion of employed women in temporary employment (solid line with • symbols) from 1992Q2 to 2023Q4. The left vertical axis displays the proportion of employed individuals in temporary employment in percent. The horizontal axis shows the time period in years. The shaded areas represent recessionary periods in the UK. *Source:* Office of National Statistics (2024c).

Before exploring further gender differences in temporary employment trends, this chapter first examines the underlying reasons for temporary employment. Figure 2.4 displays the unemployment rate alongside the reasons cited for temporary employment. Notably, the proportion of individuals in temporary employment citing a contract with a training period remains stable over time.[15] Prior to 2000, the proportion citing they could not to find permanent employment exceeds those indicating a preference against

[13]Section 2.3.1 discusses the reasons why uncertainty may prompt employers to shift their preference to temporary employment.

[14]Using data from the LFS, Section 2.A.4 in the Appendix plots the proportion of women employed in each industry. As shown in Figure 2.25, although the banking and finance industry is not dominated by a single sex, finance-dependent industries, particularly manufacturing and construction, are heavily dominated by men. Conversely, the public administration, education and health industry is dominated by women.

[15]Temporary employment contracts that include periods of training are commonly associated with, for instance, apprenticeships and internships.

permanent employment, corresponding with a dramatic rise in temporary employment during this period, as illustrated in Figure 2.2. This surge is not isolated but occurred concurrently across other advanced economies, marking a period of increasing popularity for temporary employment (Zijl, 2006). Post-2000, until the onset of the 2008 Financial Crisis, fewer cite they could not find permanent employment compared to those did not want permanent employment. However, following the financial crisis, this trend reverses significantly, with a greater proportion citing they could not find permanent employment. Although aggregate data are able to isolate neither labour supply nor demand, the observed discrepancy may be suggestive of both a negative perception of temporary employment among workers and a potential decline in demand for permanent employees during downturns. The gap re-emerges in the wake of the COVID-19 pandemic, yet, intriguingly, the duration of this gap is markedly shorter compared to the post-2008 period.

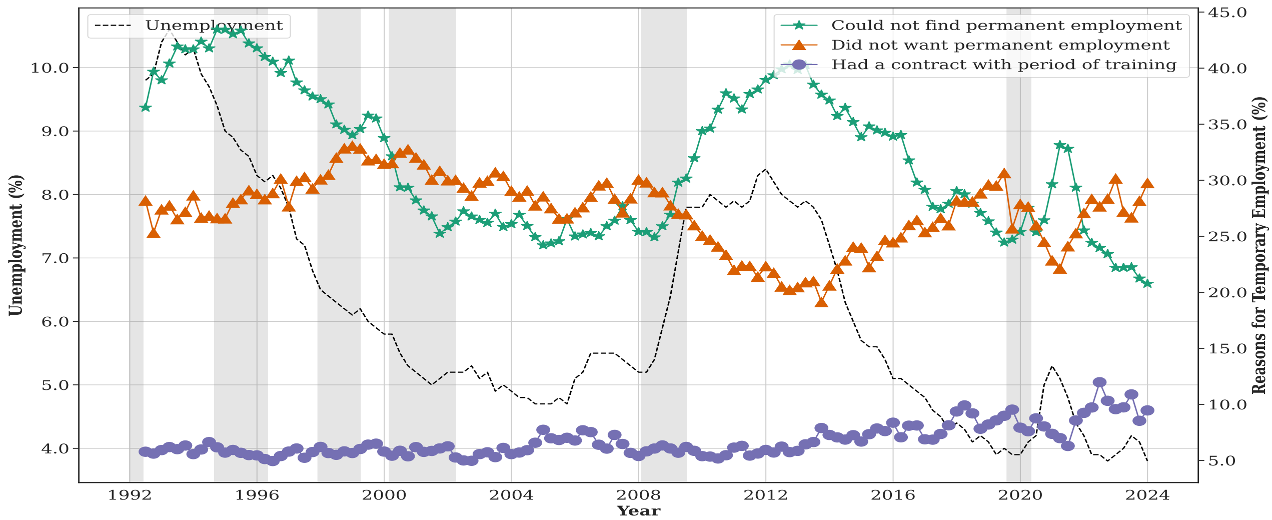

Figure 2.4: Unemployment and reasons for temporary employment. *Notes:* The figure plots the unemployment rate (dotted line), proportion of individuals in temporary employment who could not find permanent employment (solid line with * symbols), proportion of individuals in temporary employment who did not want permanent employment (solid line with ▲ symbols), and proportion of individuals in temporary employment who had a contract with training (solid line with • symbols) from 1992Q2 to 2023Q4. The left vertical axis displays the unemployment rate in percent, while the right vertical axis the proportion of individuals in temporary employment for respective reasons. The horizontal axis shows the time period in years. The shaded areas represent recessionary periods in the UK. *Source:* Office of National Statistics (2024c).

Why? The significant increase in unemployment following the 2008 Financial Crisis, in contrast to the COVID-19 pandemic, as illustrated in Figure 2.2, indicates a slower job market recovery during the former period, potentially due to a cautious business climate reluctant to commit to permanent hiring (Cao, Shao, & Silos, 2021).[16] Since

[16]Economic crises might have heterogeneous effects across industries. Appendix 2.A.6 illustrates how the time series of vacancies for permanent and temporary positions evolve distinctly across various industries,

the 2008 crisis primarily originated within the financial industry, it leads to a severe and prolonged economic downturn characterized by significant contractions in credit availability, consumer spending, and business investment (See, among others, Gorton, 2010; Ivashina & Scharfstein, 2010; Reinhart & Rogoff, 2009). Consequently, the recovery is sluggish, necessitated by the need for extensive financial system restructuring (Acharya, Philippon, Richardson, & Roubini, 2009; Ellis, Haldane, & Moshirian, 2014; Hanson, Kashyap, & Stein, 2011). Conversely, one can argue that the economic impact of the COVID-19 pandemic, while involving spikes of uncertainty and initially severe (Brodeur, Gray, Islam, & Bhuiyan, 2021),[17] is largely driven by external health crises rather than inherent economic weaknesses. The transition to remote work (Aksoy, Barrero, Bloom, Davis, Dolls, & Zarate, 2022; Barrero, Bloom, & Davis, 2021) and rapid adoption of new technologies (Leduc & Liu, 2019) facilitate a quicker employment recovery. In addition, the UK government's financial intervention in the banking sector[18] in response to the 2008 Financial Crisis leads to cutbacks in public spending (Emmerson & Tetlow, 2015), which could adversely affect job creation and economic growth. However, during the pandemic, there is significant fiscal expansion with unprecedented government support for wages through, for instance, furlough schemes (Spencer, Stuart, Forde, & McLachlan, 2023). This policy not only safeguards jobs but also alleviates the urgency for individuals to seek employment and accept temporary employment. Consequently, the duration of the gap between the proportion of employed individuals in temporary employment unable to find permanent employment and those not desiring permanent employment appears shorter following the COVID-19 pandemic than after the 2008 Financial Crisis. However, it is important to emphasize that these interpretations are conjectural and extend beyond what the current evidence can substantiate.

Figure 2.5 displays the proportions of reasons for temporary employment cited by individuals in the UK from 1992Q2 to 2023Q4, disaggregated by sex. The data reveal a pronounced gender disparity in the motivations for temporary employment. Specifically, a larger proportion of women than men in temporary positions reported a preference for non-permanent employment, while more men in temporary employment cited they

highlighting the differential impact of uncertainty on industry-specific labour markets.

[17]Bloom, Bunn, Mizen, Smietanka, and Thwaites (2023) find that despite large pandemic effects, UK firms' post-Covid forecasts imply minimal lasting impact on aggregate TFP.

[18]The Office for Budget Responsibility (OBR) estimates that, as of 2018, the interventions cost the public £23 billion. (Mor, 2018)

could not find permanent employment. This suggests that temporary employment is predominantly involuntary for men, whereas women are more likely to engage in temporary employment by choice.[19]

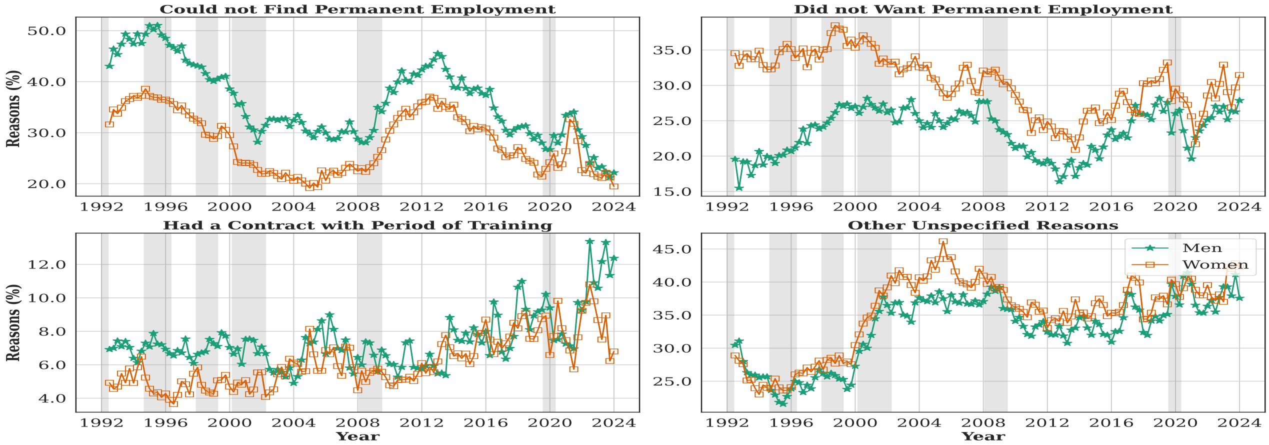

Figure 2.5: Reasons for temporary employment by gender. *Notes:* The figure plots the proportion of individuals in temporary employment by reasons for temporary employment from 1992Q2 to 2023Q4 in the UK. The vertical axes displays the proportion of individuals in temporary employment in percent and the horizontal axes displays the time period in years. The solid line with □ symbols plots the trend for women, and the solid line with * symbols for men. The shaded areas represent recessionary periods in the UK. *Source:* Office of National Statistics (2024c).

Another notable observation from Figure 2.5 is the narrowing gap in the motivations for temporary employment between men and women, which has largely converged in the period following the COVID-19 pandemic. This convergence is observed across all reasons for temporary employment, with the exception of contracts involving a training period.[20] For example, while historically a higher proportion of men cite failure to find permanent employment as their reason for accepting temporary employment compared to women, this disparity has significantly diminished post-pandemic. The proportions of men and women unable to find permanent employment have become markedly similar, indicating an alignment in their motivations for engaging in temporary employment. This convergence also suggests that traditional gender roles may no longer hold strong predictive power in explaining recent temporary employment choices. Further empirical

[19]Historical societal expectations often position men as primary earners, which may lead them to prioritize job security (and hence permanent employment) as a means to fulfill their perceived role as family providers (Bertrand, Cortés, Olivetti, & Pan, 2016). Conversely, women might seek flexibility (and hence temporary employment) to accommodate work and family care responsibilities. Using data derived from the British Household Panel Survey (1991–2009) and Understanding Society (2009–2022), Section 2.A.5 in the Appendix indicates that gender beliefs among men do not differ between those in permanent versus temporary employment. In contrast, women in temporary employment exhibit slightly more conservative gender beliefs compared to their counterparts in permanent employment.

[20]Contracts involving a training period is not a popular reason for temporary employment, with less than 10% of individuals in temporary employment citing it as the reason for temporary employment in most years, as seen in Figure 2.5 .

investigation is warranted to explore the drivers behind this convergence and to ascertain whether these changes reflect broader shifts in societal norms or labour market dynamics.

An additional observation from Figure 2.5 is that a significant proportion of individuals, regardless of gender, provides unspecified reasons for their temporary employment. The LFS does not require respondents to provide detailed explanations for these reasons, limiting the depth of analysis possible from the existing data. However, given that these unspecified reasons account for a considerable share, there is substantial potential for future research to uncover valuable insights. Understanding these undisclosed motivations could illuminate broader labour sentiment towards temporary employment and potentially reveal more about how firms engage with labour contracts in possibly subtle and strategic ways. This avenue of research could shed light on the underlying dynamics that drive temporary employment beyond the standard categories currently captured by the LFS.

2.2.1 Geographical Differences

Research exploring geographical differences in temporary employment within the UK has been notably scarce. Figure 2.6 illustrates the regional disparities in the proportion of employed individuals in temporary employment across 12 UK regions, with a focus on years 2000, 2010, and 2020 due to space constraints. Darker shades on the map indicate regions with higher rates of temporary employment. Consistent with Figure 2.2, the proportion of employed individuals in temporary employment is higher in 2000, but exhibits lower and more stable rates in 2010 and 2020. Notably, regional variations in temporary employment are more pronounced in 2000 than in 2020; over time, these differences have significantly narrowed, currently presenting minimal variation, approximately around a 2 percentage point difference. Throughout this twenty-year span, London has consistently displayed one of the highest proportions of temporary employment, a predictable finding due to its role as the economic center of the country. Beyond London, no other region consistently shows higher temporary employment rates compared to their counterparts. Geographical variations in temporary employment across the UK hence do not appear to yield significant insights.

Figure 2.6: Geographical variations in temporary employment. *Notes:* Graduated color maps depicting geographical variations in the proportion (in percent) of employed individuals in temporary employment in 2000, 2010, and 2020 within the UK. The maps categorize the 12 UK regions (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East, London, South East, South West, Wales, Scotland, and Northern Ireland) into four distinct shades, with the darkest shade representing regions with the highest rates of temporary employment and the lightest indicating the lowest rates in each respective year. *Source:* Office of National Statistics (2024f).

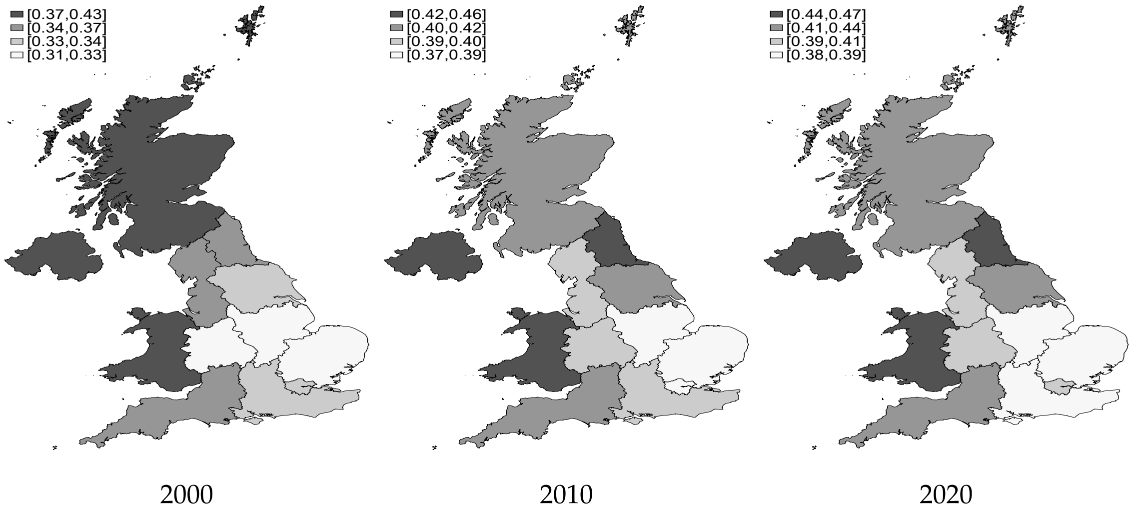

Figure 2.7: Regional distribution of industries with a high share of temporary employment. *Notes:* Graduated color maps depicting geographical variations in the density of industries (measured using the number of employed individuals) with a high share of temporary employment in 2000, 2010, and 2020 within the UK. The industries classified as having a high share of temporary employment include agriculture, forestry, and fishing (SIC 1), public administration, education, and health (SIC 8), and other services (SIC 9); further details are provided in Section 2.A.7 in the Appendix. The maps categorize the 12 UK regions (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East, London, South East, South West, Wales, Scotland, and Northern Ireland) into four distinct shades, with the darkest shade representing regions with the highest density of SIC 1, 8, and 9 industries, and the lightest indicating the lowest density in each respective year. *Source:* Office of National Statistics (2024f).

One possible driver for regional differences in temporary employment is industrial composition. Section 2.A.7 in the Appendix shows that certain industries, such as agriculture, forestry, and fishing (SIC 1), public administration, education, and health (SIC 8), and other services (SIC 9), consistently exhibit higher shares of temporary employment. Regions where these industries are more concentrated may naturally experience higher levels of temporary employment. Figure 2.7 suggests that industrial composition aligns with some regional differences in temporary employment, but not consistently across all regions. For instance, although London has one of the highest rates of temporary employment, it does not have a particularly high concentration of these industries that exhibit higher shares of temporary employment. This implies that while industrial composition may offer some explanatory power, it does not fully account for geographical disparities in temporary employment. Other factors, such as regional labour market conditions and economic disparities, may also contribute to these variations.

This subsection briefly examines the correlations between temporary employment and key macroeconomic indicators across the 12 UK regions utilizing quarterly data spanning from 1992Q2 to 2023Q4. The objective is to determine the extent to which standard economic measures correlate with temporary employment, and whether these correlations exhibit consistency across all regions. Figure 2.8 illustrates the correlation between GDP growth and temporary employment, providing insights into how economic expansions or contractions influence temporary employment. Figure 2.9 illustrates the correlation between unemployment and temporary employment, which may reveal counter-cyclical trends associated with economic downturns. Figure 2.10 illustrates the correlation between job density—a measure of employment concentration—and temporary employment.

Figure 2.8, Figure 2.9, and Figure 2.10 demonstrate that across all 12 UK regions temporary employment exhibits a positive correlation with both GDP growth and unemployment, while showing a negative correlation with job density. The positive correlation between temporary employment and GDP growth as well as unemployment can be attributed to the cyclical nature of economic expansions when firms face increased demand: to rapidly scale up operations and capitalize on favorable market conditions, firms might resort to hiring temporary workers (Foote & Folta, 2002). This strategy enables firms to respond to fluctuating economic conditions without the encumbrance of long-term labour commitments. Also, better economic conditions may motivate a more diverse demographic—including students, retirees, and caregivers—to engage in the labour market (Brückner & Pappa, 2012), perhaps temporarily as they seek to exploit the advantageous economic conditions without the long-term commitment associated with permanent employment. Conversely, the negative correlation between temporary employment and job density suggests that regions with higher job concentration tend to have a lower proportion of temporary employment. High job concentration often reflects stronger economic conditions, which may give firms the confidence to invest in permanent employees. The negative correlation may also indicate that temporary employment are less attractive in denser job markets, where firms might be more inclined to offer permanent positions as a strategy to attract new hires when there are more jobs available in the area.

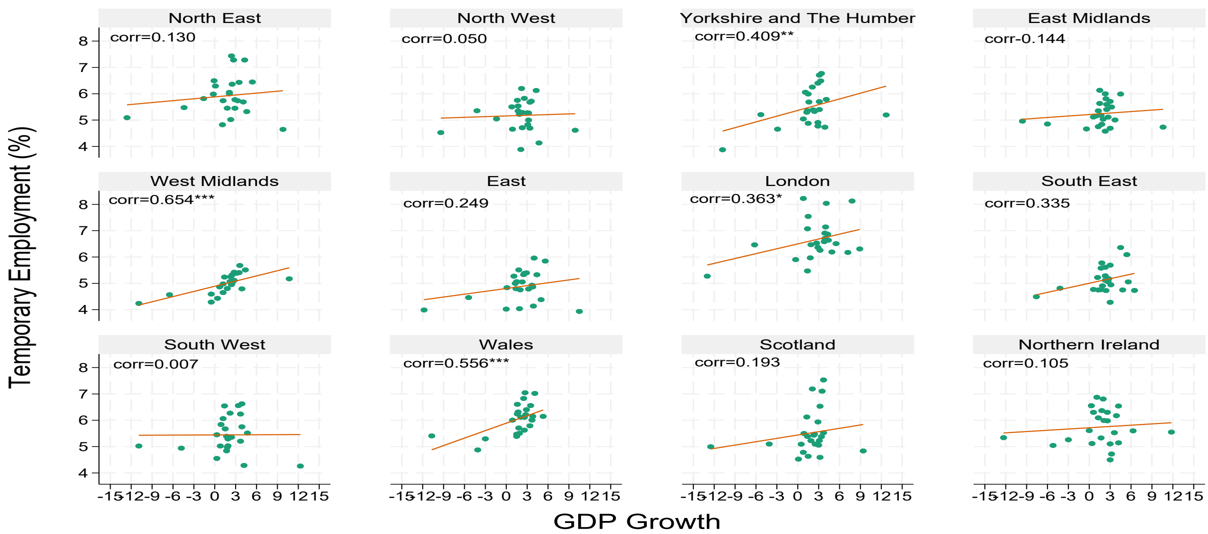

Figure 2.8: Correlation between GDP growth and temporary employment. *Notes:* The figure plots the correlation between GDP growth and the proportion of employed individuals in temporary employment using quarterly data from 1992Q2 to 2023Q4 for 12 UK regions. GDP growth data are sourced from the UK Census, while temporary employment data come from the Labour Force Survey (LFS). The vertical axes represent the proportion of employed individuals in temporary employment, expressed as a percentage, while the horizontal axes depict GDP growth, also in percentage terms. Solid straight lines indicate the lines of best fit for the data points. Each panel displays the correlation coefficient between these two variables at the top left. *** denotes 1% significance, ** 5% significance, and * 10% significance. *Source:* Office of National Statistics (2001, 2011, 2021, 2024f).

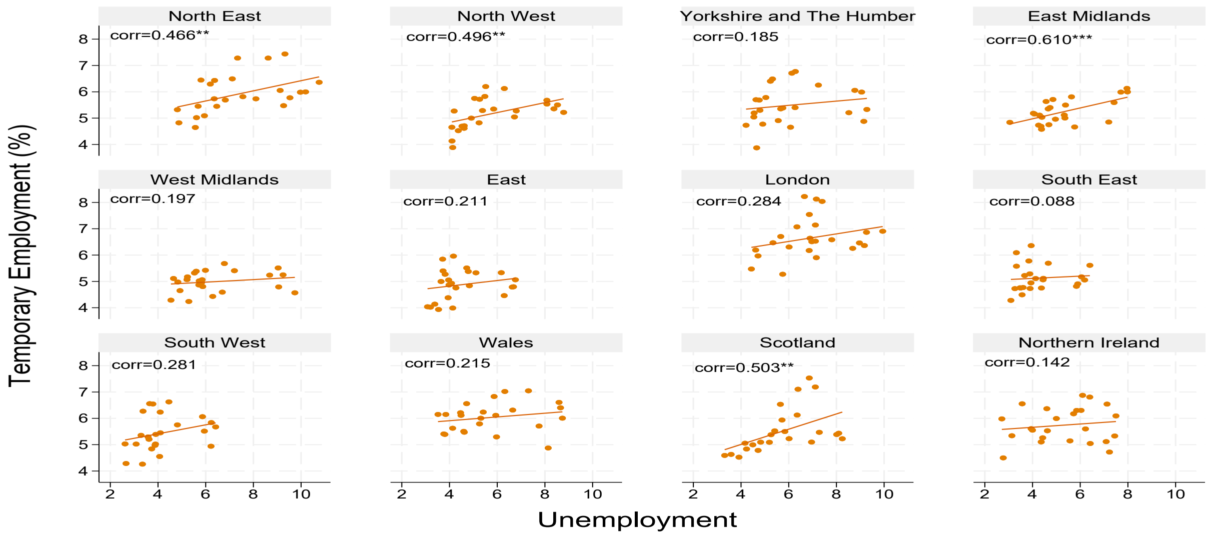

Figure 2.9: Correlation between unemployment and temporary employment. *Notes:* The figure plots the correlation between unemployment and the proportion of employed individuals in temporary employment using quarterly data from 1992Q2 to 2023Q4 for 12 UK regions. Unemployment data are sourced from the UK Census, while temporary employment data come from the Labour Force Survey (LFS). The vertical axes represent the proportion of employed individuals in temporary employment, expressed as a percentage, while the horizontal axes depict unemployment rate, also in percentage terms. Solid straight lines indicate the lines of best fit for the data points. Each panel displays the correlation coefficient between these two variables at the top left. *** denotes 1% significance, ** 5% significance, and * 10% significance. *Source:* Office of National Statistics (2001, 2011, 2021, 2024f).

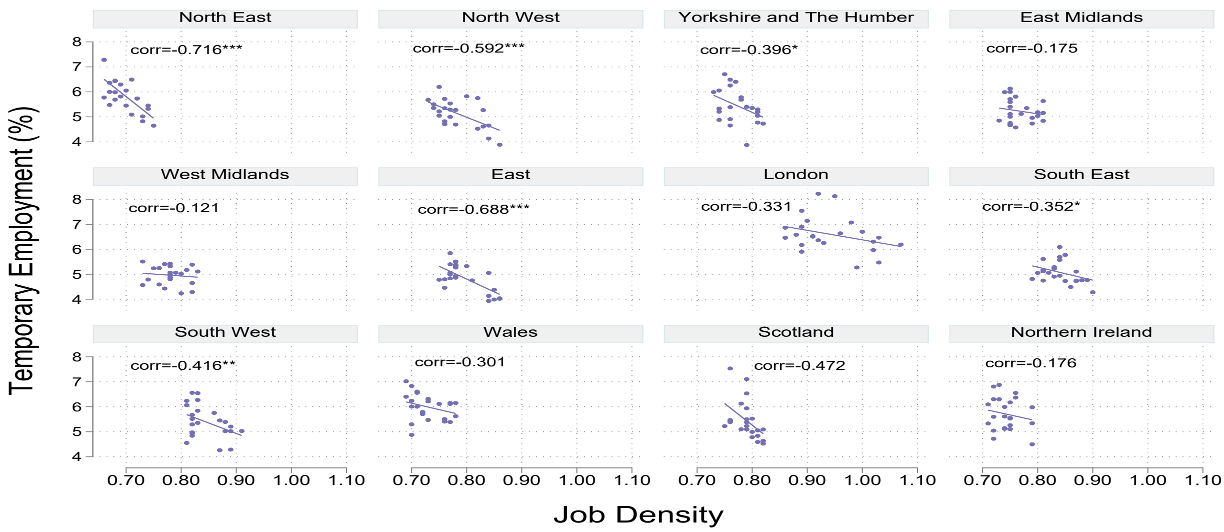

Figure 2.10: Correlation between job density and temporary employment. *Notes:* The figure plots the correlation between job density and the proportion of employed individuals in temporary employment using quarterly data from 1992Q2 to 2023Q4 for 12 UK regions. Here, job density is defined as the number of jobs divided by the resident population aged 16-64 in that area. Job density data are sourced from the UK Census, while temporary employment data come from the Labour Force Survey (LFS). The vertical axes represent the proportion of employed individuals in temporary employment, expressed as a percentage, while the horizontal axes depict job density. Solid straight lines indicate the lines of best fit for the data points. Each panel displays the correlation coefficient between these two variables at the top left. *** denotes 1% significance, ** 5% significance, and * 10% significance. *Source:* Office of National Statistics (2001, 2011, 2021, 2024f).

However, from Figure 2.8, Figure 2.9, and Figure 2.10, no single macroeconomic variable emerges as the most statistically significant correlate of temporary employment. Notably, the significance of these correlations varies by region. For instance, in Wales, GDP growth demonstrates a significant correlation with temporary employment, whereas unemployment rate and job density do not exhibit similar statistical significance. Conversely, in the North East, it is unemployment rate that shows a significant correlation with temporary employment, but not GDP growth or job density. Other localized factors might contribute to this lack of uniform, definite patterns across the regions. However, given that regional differences in temporary employment appear small and have diminished over time, further research into this aspect may have limited value.

2.3 Uncertainty and Temporary Employment

Evidence in Section 2.2 suggests that temporary employment increases during both the 2008 Financial Crisis as well as the COVID-19 pandemic, which are periods characterized by heightened uncertainty. In this section, I propose potential reasons why uncertainty may be associated with an increase in temporary employment. I also describe the macroeconomic uncertainty measure used in this chapter and provide summary statistics of variables obtained from the LFS data.

2.3.1 Why Might Firms Prefer Temporary Contracts When Uncertainty Increases?

Similar to Chapter 1 and following Castelnuovo (2023), this chapter defines uncertainty as a mean-preserving expected change in the second moment of a distribution. For example, uncertainty rises when the expected volatility of a technological process increases, while the mean of the process remains unchanged. After examining the comovements of temporary employment with macroeconomic variables in the previous section, this chapter suggests that heightened uncertainty may prompt firms to favour temporary contracts over permanent ones when addressing vacancies. Stylized facts about uncertainty and its effects support this hypothesis, as detailed below:

Adjustment Costs

According to Hamermesh and Pfann (1996), labour adjustment costs encompass search and hiring expenses (such as posting vacancies, screening, and processing new employees), production disruptions (where existing employees spend time training new hires and adjusting to the departure of colleagues), and firing costs (including severance pay and administrative expenses related to worker outflow). Temporary labour are associated with lower adjustment costs due to several factors. Recruitment through temporary work agencies—not uncommon in the UK—minimizes advertising and search costs for the employers.[21] Moreover, temporary employees have limited entitlement to severance pay compared to permanent employees, further lowering adjustment costs. Goux, Maurin, and Pauchet (2001), by measuring the entry and exit rates for both types of employment between 1988 and 1992 in French firms, provide evidence that adjusting the number of temporary workers is less costly than adjusting the number of regular workers.

It is these adjustment costs that play a crucial role in shifting firms' preferences toward temporary contracts over permanent ones during periods of uncertainty. Lower adjustment costs make decisions related to temporary employees less costly and hence more "reversible" than those related to permanent employees. The irreversible nature and potential postponement of investment decisions introduce the concept of "real options," where firms prefer to "wait and see" rather than commit to costly actions with uncertain outcomes (Bernanke, 1983; Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Bloom, Van Reenen, & Bond, 2007; Dixit & Pindyck, 1994; McDonald & Siegel, 1986). In the context of labour investment decisions, uncertainty increases the value of the option to defer hiring permanent employees and the option to terminate temporary employees (Foote & Folta, 2002). During uncertainty, firms are more inclined to dismiss temporary labour due to their lower firing costs and to defer hiring permanent labour in favor of temporary ones when addressing a vacancy, as temporary hires involve lower costs both at entry and exit. Consequently, uncertainty may be associated with an increase

[21] Additionally, temporary employees typically receive less training from employers: Booth, Francesconi, and Frank (2002) provide evidence for the UK, while similar findings are reported by Albert, García-Serrano, and Hernanz (2005) for Spain, Sauermann (2006) for Germany, Forrier and Sels (2003) for Belgium, Wallette (2005) for Sweden, and Adolfsson, Baranowska-Rataj, and Lundmark (2022) for several European countries. Poulissen, De Grip, Fouarge, and Künn-Nelen (2023) provide experimental evidence that employers are less inclined to invest in training for temporary workers compared to permanent workers. In this context, temporary employees are less 'costly' than permanent employees.

in temporary employment.

Match Quality

Cao, Shao, and Silos (2021) propose that uncertainty increases temporary employment when match quality determines contract choice. Firms prefer to offer permanent contracts (which come with higher wages) to high-quality labour to avoid losing a high-quality match and temporary contracts to lower-quality labour. Under increased uncertainty where there is a higher dispersion of outcomes, low-quality matches are more affected by the increase in upside risk, while high-quality matches are more impacted by the increase in downside risk. Consequently, higher uncertainty raises the value of temporary employment and reduces the appeal of permanent employment, leading to a higher proportion of temporary job offers. The authors further substantiate the asymmetric impact of uncertainty on contract types in Canada using a search-and-matching model that incorporates endogenous hiring, firing, and promotion.

Work Effort

If individuals view temporary employment as stepping stones toward permanent positions, they are likely to make additional efforts to demonstrate their value. Engellandt and Riphahn (2005), using the Swiss Labour Force Survey, find that temporary workers are 60 percent more likely to work unpaid overtime compared to their permanent counterparts. Similarly, Geary (1992) reports that fixed-term workers in three large US electronic firms were the first to volunteer for overtime.

Booth, Francesconi, and Frank (2002) provide evidence that fixed-term contracts are a stepping stone to permanent employment in the UK. Following the line of reasoning aforementioned, individuals in temporary employment in the UK may be more inclined to work overtime.[22] This willingness to work overtime reduces the need for frequent hiring and firing to adjust the workforce during periods of uncertainty. Consequently, this flexibility provided by temporary employment can decrease turnover and adjustment costs,[23] making temporary employment more attractive to firms during uncertain times.

[22]It is important to also note that Booth, Francesconi, and Frank (2002) find temporary employees experience lower job satisfaction compared to their permanent counterparts.

[23]The literature, however, documents that temporary employment *increases* turnover. For instance, Blanchard and Landier (2002) show that a partial reform of employment protection in France, which allowed firms to hire workers on fixed-term contracts, led to a substantial rise in turnover, with workers

Monitoring

Monitoring costs can be partially offset by hiring more productive workers (Oi, 1990). If match quality determines contract choice, firms may prefer offering permanent contracts to more productive workers and temporary contracts to less productive workers. However, during periods of heightened uncertainty, firms are more cautious; they may choose to wait-and-see by delaying commitments to costly and irreversible decisions (Bernanke, 1983; Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Bloom, Van Reenen, & Bond, 2007; Dixit & Pindyck, 1994; McDonald & Siegel, 1986). This approach suggests that firms are increasing monitoring efforts to mitigate risks associated with uncertain outcomes. Increased monitoring may, in turn, reduce the reliance on permanent contracts as a mechanism to prevent shirking, since closer oversight ensures that temporary workers maintain the required productivity levels. Consequently, as uncertainty rises and firms intensify monitoring, firms might be more incline to offer temporary contracts rather than permanent ones when addressing vacancies.

This chapter does not attempt to definitively prove each of the proposed reasons why uncertainty may lead firms to favour temporary employment. Some hypotheses are admittedly more plausible than others: the adjustment costs hypothesis is particularly compelling, as adjustment costs are frequently cited as a key element of irreversibility in the context of uncertainty. Additionally, the match quality hypothesis has been substantiated by Cao, Shao, and Silos (2021). In contrast, the work effort hypothesis cannot be validated without comprehensive data on labour work effort for different contract types. The monitoring hypothesis, while conceptually interesting, may appear speculative and is challenging to test empirically. This chapter focuses on providing preliminary evidence of the association between uncertainty and temporary employment rather than evaluating the relative plausibility of each hypothesis. In Chapter 3, adjustment costs will be featured in a partial equilibrium model to further explore the effects of uncertainty on temporary employment.

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being worse off cycling through multiple spells of unemployment.

2.3.2 Choice of Macroeconomic Uncertainty Measure

To quantify uncertainty, I use the UK's macroeconomic uncertainty index constructed by Theophilopoulou (2022), which is available from 1971Q1 to 2018Q1. The author follows closely the methodology described in Jurado, Ludvigson, and Ng (2015). The measure is constructed from an extensive array of macroeconomic and financial indicators (64 UK and world time series). It is not related to the structure of theoretical models and emphasizes the evolution of the unpredictable component of each variable. Jurado, Ludvigson, and Ng (2015) posit that an increase in these unpredictable components signifies a decline in predictability and hence an increase in uncertainty.

Here, I briefly summarize the model in Jurado, Ludvigson, and Ng (2015). Define the h period ahead uncertainty $(U_{jt}(h))$ of the variable $y_{jt} \in Y_t = (y_{1t}...y_{Nyt})'$ as

$$U_{jt}(h) = \sqrt{E\left[y_{jt+h} - (Ey_{jt+h} \mid I_t)\right]^2 \mid I_t}, \tag{2.1}$$

where I_t is the information set available to agents at period t. $U_{jt}(h)$ is the conditional volatility of the nonforecastable component of the future value of the series; when the expectation today on the forecast error, $y_{jt+h} - (Ey_{jt+h} \mid I_t)$ increases, the uncertainty rises as well. The crucial feature of this measure is that the whole forecastable component of the variable y_j has been removed before obtaining its conditional volatility. The final measure of macroeconomic uncertainty is constructed using a weighted average of the uncertainty for each variable for period t:

$$U_t(h) = p \lim_{Ny \to \infty} \sum_{j=1}^{Ny} w_j U_{jt}(h), \tag{2.2}$$

where w_j are aggregation weights for the uncertainty of each variable y_j. Since a large number of variables are used, this measure takes the common variation across all variables in the sample. I refer interested readers to the online appendix in Theophilopoulou (2022) for the complete list of variables employed by the author to construct the macroeconomic uncertainty measure of the UK.

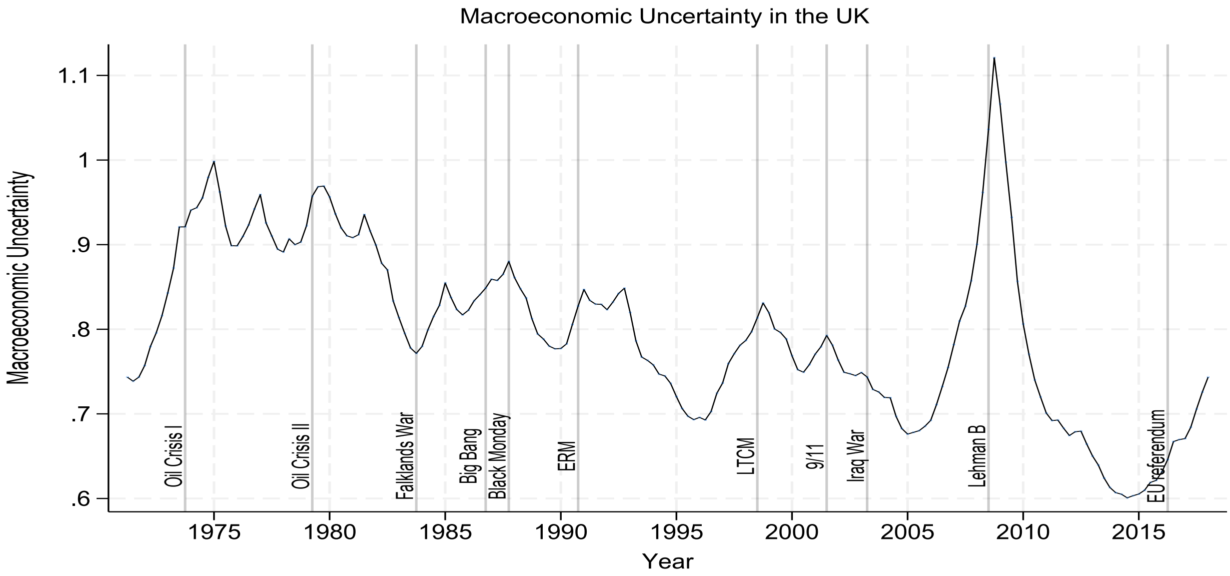

Figure 2.11: Macroeconomic uncertainty in the UK spanning the period from 1971Q1 to 2018Q1. *Notes:* The vertical lines plot the major events in the UK. The horizontal axis denotes time in years, while the vertical axis quantifies macroeconomic uncertainty. Summary statistics for the dataset analyzed in this chapter, covering 1992Q2 to 2018Q1, are as follows: mean = 0.745, standard deviation = 0.095, minimum = 0.601, and maximum = 1.121. *Source:* Theophilopoulou (2022).

Figure 2.11 presents the quarterly macroeconomic uncertainty measure ($h = 4$) spanning the period from 1971Q1 to 2018Q1. Macroeconomic uncertainty increases following major political and economic events. It rises sharply during the 2008 Financial Crisis, and seems to rise again following the 2016 EU referendum.

2.3.3 LFS Data

I use the Labour Force Surveys (LFS) data collected by the Office of National Statistics (ONS). The LFS collects information on the employment circumstances of a representative sample in the UK and provides the country's official measures of employment every quarter. In the LFS, the respondents are asked whether their employment is temporary in nature. If their employment is indeed temporary, they are then asked about the ways in which their employment is temporary, the reason they take up temporary employment, and the length of temporary employment. The data in the sample cover the period from 1992: Q2 to 2018 : Q1,[24] with a focus on individuals aged between 18 and 64 that are in paid employment only at the time of the survey, resulting in a total of about 4.5 million

[24]The analysis is until 2018: Q1 only because the macroeconomic uncertainty measure by Theophilopoulou (2022) is available only until this date.

observations. I link the macroeconomic uncertainty data from Theophilopoulou (2022) with the LFS data using the respondents' survey date.

Table 2.1 presents the statistical description of the sample characteristics. The average age of the participants is approximately 40 years. Predominantly, the sample comprises individuals born in the UK and identified as white. Regarding educational attainment, about half of the sample possesses at least a GCE A Level or an equivalent qualification. Approximately 6% of the sample is in temporary employment, mirroring the proportions observed in aggregate data from the ONS. The data reveal that a greater proportion of women than men is in temporary employment.[25] In terms of family demographics, more than half of the sample is married and approximately the same proportion is childless. Additionally, approximately 50% of the sample is a head of household, but there exists a pronounced gender disparity in line with social norms: over 80% of men assuming this role compared to fewer than 20% of women.

Table 2.1 also reveals the distribution of the sample across various industries and occupations. Notably, up to 30% of the sample is employed in the public administration, education, and health industry. Almost half of the women in the sample is employed within this industry, compared to a significantly lower proportion of men. Conversely, about a quarter of the men are employed in the manufacturing industry, whereas fewer than 10% of women work in this industry. The most minimal gender discrepancy is observed in the banking and finance industry. There are also marked gender differences in terms of occupations: a majority of men predominate in managerial and skilled trades occupations, while women are disproportionately represented in administrative and service-related occupations.

[25] As Casey (1987) observes, the proportion of women in temporary employment exceeds that of men, a trend attributable to the positive correlation between temporary employment and part-time employment. Women are statistically more inclined to partake in part-time employment compared to men, contributing to their higher representation in temporary employment.

	All	Men	Women
Sociodemographics			
Age	39.79(11.95)	39.87(12.06)	39.71(11.84)
Born in the UK	90.18%	90.09%	90.26%
White	93.43%	93.23%	93.62%
Highest Qualifications			
Degree or equivalent	21.28%	21.98%	20.59%
Higher education	10.86%	9.88%	11.83%
GCE A Level or equivalent	23.92%	29.17%	18.76%
GCSE or equivalent	21.58%	17.36%	25.75%
Other qualifications	11.69%	12.11%	11.28%
No qualifications	10.63%	9.47%	11.77%
Employment			
In temporary employment	5.90%	5.16%	6.63%
Family Demographics			
Married	58.12%	59.71%	56.55%
Household head	51.38%	83.36%	19.89%
Without child	56.85%	57.63%	56.08%
Has 1 child	19.09%	17.84%	20.32%
Has 2 children	17.98%	17.94%	18.02%
Has 3 or more children	6.06%	6.58%	5.56%
Standard Industrial Classification			
Agriculture, forestry, and fishing	0.74%	1.05%	0.42%
Energy and water	1.6%	2.52%	0.7%
Manufacturing	16.17%	23.6%	8.85%
Construction	5.16%	8.77%	1.62%
Distribution, hotels and restaurants	18.79%	16.81%	20.75%
Transport and communication	7.29%	10.73%	3.9%
Banking and finance	14.72%	14.79%	14.65%
Public admin, education and health	30.87%	17.57%	43.98%
Other services	4.62%	4.13%	5.09%
Standard Occupational Classification			
Managers, directors, and senior officials	13.65%	17.81%	9.55%
Professional occupations	13.83%	14.33%	13.33%
Associate prof and tech occupations	12.38%	12.09%	12.67%
Administrative occupations	14.83%	6.38%	23.15%
Skilled trades occupations	9.08%	16.29%	1.97%
Service occupations	9.83%	4.54%	15.04%
Sales occupations	8.08%	4.93%	11.18%
Process, plant and machine operatives	8.22%	13.53%	2.99%
Elementary occupations	10.07%	10.05%	10.08%
Observations	4,561,523	2,263,266	2,298,257

Notes: The table features percentages for categorical variables and mean (standard deviation) for continuous variables. *Source:* Office of National Statistics (2024f).

Table 2.1: Individual characteristics.

2.3.4 Control Variables

The initial regression analysis explores the association between the control variables and the probability of being in temporary employment, using a weighted probit model with robust standard errors defined as follows:

$$Temp_{i,t} = \beta_x X_{i,t} + \varepsilon_{i,t}, \tag{2.3}$$

where the dependent variable $Temp_{i,t}$ represents the probability of individual i to be in temporary employment at period t. The independent variables $X_{i,t}$ encompasses a range of sociodemographic factors such as age, sex, country of birth, ethnicity, and education, as well as family demographic characteristics such as marital status, fertility, and household roles. Industry and occupational categories are also included in $X_{i,t}$. $\varepsilon_{i,t}$ is the error term, capturing unobserved influences on the probability to be in temporary employment.

Figure 2.12 displays the initial results. The first column of each figure illustrates the results of the overall initial regression. Subsequent columns segregate these results by sex, with the second column detailing outcomes for men and the third for women. The results indicate a positive association between temporary employment and specific demographic groups: new entrants to the labour force (under 30 years of age), near-retirees (60 years and older), individuals not born in the UK, and those not identified as white, suggesting a higher propensity for temporary employment among these groups. This association is in line with previous studies focusing on these types of variables.[26] Additionally, individuals with a degree or equivalent qualification exhibit a greater likelihood of temporary employment compared to those with other or no qualifications. Conversely, there is a negative association between temporary employment and being the head of a household or married, indicating that those in such categories are less likely to engage in temporary employment. Having children correlates negatively with temporary employment among men, yet positively among women, underscoring potential divergent impacts of familial responsibilities on employment trends.

[26] Section 2.A.3 in the Appendix summarizes the findings from previous studies on temporary employment in the UK.

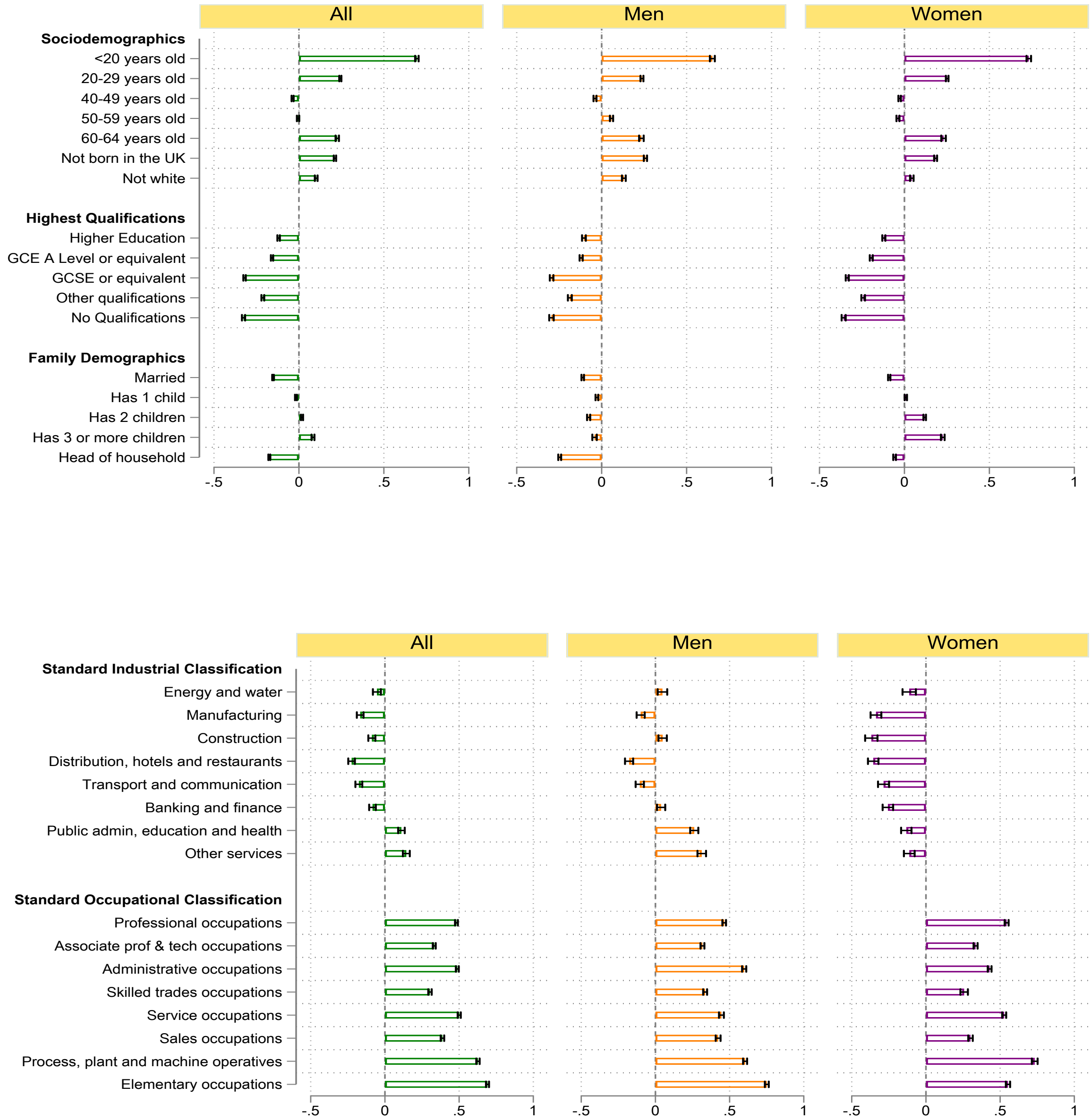

Figure 2.12: Probit regressions of temporary employment on control variables. *Notes:* Point estimates (end of bars) along with their 95% confidence intervals (line intervals) are displayed. Base categories: Aged 30-39 years old; Is born in the UK; Is white; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. Tables containing the regression coefficient numbers are available in Table 2.6 and Table 2.7 in the Appendix.

Intuitively, as evident in Figure 2.12, individuals in the agriculture, forestry, and fishing industry exhibit a greater likelihood of temporary employment compared to their counterparts in all other industries, except for the public admin, education, and health industry and industry involving other services.[27][28] However, while men in the public admin, education and health industry and other services industry are more likely to be in temporary employment compared to their counterparts in the agriculture, forestry, and fishing industry, this is not the case for women. On the other hand, individuals in managerial occupations exhibit a lower likelihood of temporary employment compared to other types of occupations, with this trend consistent across sexes.

In the subsequent subsection, I include these control variables when regressing temporary employment on macroeconomic uncertainty.

2.3.5 Regression Analysis: Uncertainty and the Probability of Temporary Employment

This subsection presents the probit regression examining the relationship between macroeconomic uncertainty and the probability of being in temporary employment and runs robustness checks testing the stability of this relationship.

Baseline Results

The first baseline regression, a slight modification of Equation 2.3, is specified as follows:

$$Temp_{i,t} = \beta_u UNCERT_{t-j} + \beta_x X_{i,t} + \varepsilon_{i,t}, \tag{2.4}$$

where again the dependent variable $Temp_{i,t}$ represents the probability of individual i to be in temporary employment at period t. The term $X_{i,t}$ encompasses a range of control variables detailed in Section 2.3.4. These controls account for a wide range of sociodemographic factors, including age, sex, country of birth, ethnicity, and educational attainment, family demographic characteristics such as marital status, fertility, and

[27]The 'other services' industry includes activities of membership organisations, repair of computers and personal and household goods, and other personal service activities such as washing of textile and fur products. More details of industry categorization are available on the ONS website at https://www.ons.gov.uk/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities.

[28]Appendix 2.A.7 presents a brief discussion on how industrial differences in temporary employment might be relevant for the effects of uncertainty at the aggregate level.

household roles, as well as industry and occupational classifications. The variable $UNCERT_{t-j}$ denotes quarterly macroeconomic uncertainty at period $t-j$, with $j \in \{4, 8, 12, 16, 20\}$, reflecting lags of 1 year, 2 years, 3 years, 4 years, and 5 years, respectively.[29] Thus, Equation 2.4 is estimated separately for each specified lag of macroeconomic uncertainty. $\varepsilon_{i,t}$ is the error term, capturing unobserved influences on the probability of being in temporary employment.

Figure 2.13 illustrates the marginal effect estimates from the probit regression indicating the association between macroeconomic uncertainty and the probability of being in temporary employment. Three noteworthy observations emerge. First, irrespective of the number of lags, the association between macroeconomic uncertainty and temporary employment probability is positive. A one-unit increase[30] in macroeconomic uncertainty from a year prior correlates with an increase of just under 1.8 percentage points in the probability of being in temporary employment. Translating this to a one-standard-deviation increase in macroeconomic uncertainty from a year prior yields an approximately 0.2 percentage point rise in the probability of being in temporary employment. Although this value appears small, it is equivalent to a 3% increase given the unconditional probability of being in temporary employment, as shown in Table 2.1, is only 5.9%.

However, this effect is considered small compared to what is found in the literature. Lotti and Viviano (2012) by estimating a fixed effect model using firms' expected demand volatility as a measure of uncertainty between 1999 and 2010, find that moving from the 10^{th} to the 90^{th} percentile of the uncertainty distribution increases the share of temporary workers in total workforce in Italy by approximately 12.5%. Scaling my results accordingly to facilitate comparison, if a one-standard-deviation increase in macroeconomic uncertainty from the previous year leads to a 0.2 percentage point rise in the probability of temporary employment, as shown in Figure 2.13, then moving

[29] Current macroeconomic uncertainty (j=0) is not considered in the regression because labour market frictions, workers' resistance towards temporary employment, and even firms' habit formation in contract choice might impede the immediate response in temporary employment to changes in uncertainty. In fact, Leduc and Liu (2016) show that the peak increase in unemployment following an uncertainty shock occurs about 1.5 years from the impact period.

[30] It is important to note that a one-unit increase in macroeconomic uncertainty is substantial: throughout the period from 1992Q2 to 2018Q1, the macroeconomic uncertainty measure predominantly remained below 1, only slightly exceeding 1.1 during the 2008 Financial Crisis.

from the 10^{th} to the 90^{th} percentile of uncertainty is associated with a 7.31% increase in the probability of temporary employment. Similarly, Cao, Shao, and Silos (2021), using a search and matching model calibrated to the Canadian economy, find that a 7.1% increase in uncertainty raises an unemployed individual's probability of finding temporary employment by approximately 6.25%. In contrast, again applying a proportional scaling to my results, a 7.1% increase in uncertainty would correspond to only a 1.89% increase in the probability of temporary employment. While differences in estimates may stem from variations in methodology, sample composition, and economic context, the 0.2 percentage point increase in the probability of temporary employment following a one-standard-deviation rise in macroeconomic uncertainty—equivalent to a 3% increase given the unconditional probability of being in temporary employment is 5.9%—places my estimates on the lower end relative to prior findings.

Second, the positive correlation peaks when macroeconomic uncertainty measure 2 years ago is used as the regressor. This result hints that very recent macroeconomic uncertainty has a smaller association with the probability of being in temporary employment. This is unsurprising: labour market frictions, workers' resistance towards temporary employment (discussed further in Chapter 3), and even firms' habit formation in contract choice may prevent the immediate realization of the change in probability of being in temporary employment following an increase in macroeconomic uncertainty. I provide further evidence of the peak effect of macroeconomic uncertainty on temporary employment in Chapter 3.

Third, although the analysis reveals that the positive correlation between macroeconomic uncertainty and the probability of being in temporary employment peaks when the uncertainty measure from two years prior is used as the regressor, it subsequently diminishes when using lagged macroeconomic uncertainty measures from earlier periods (3, 4, and 5 years ago) in separate regressions. In essence, more distant spikes in uncertainty appear to play a smaller role in estimating the probability of being in temporary employment.

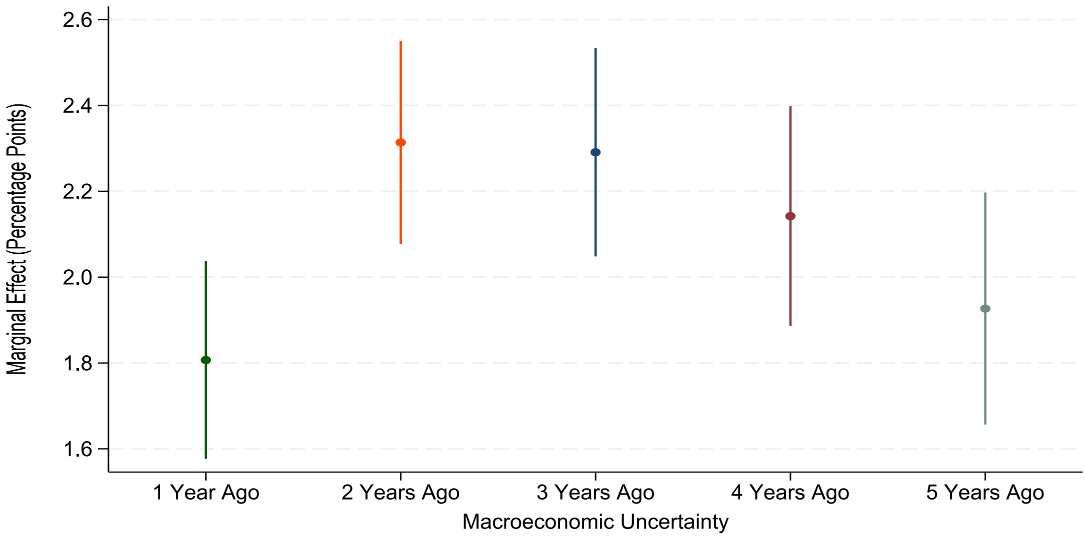

Figure 2.13: Marginal effects of lagged macroeconomic uncertainty on the probability of being in temporary employment in a weighted probit regression with robust standard errors. *Notes:* The horizontal axis represents respective regressors which are macroeconomic uncertainty from 1 to 5 years ago while the vertical axis plots the marginal effects of lagged macroeconomic uncertainty (in percentage points) on the probability of being in temporary employment. Point estimates (dots) along with their 95% confidence intervals (lines) are displayed. Base categories: Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. A table containing the regression coefficient numbers is available in Table 2.2.

Figure 2.13 presents the marginal effect estimates of overall lagged macroeconomic uncertainty on the probability of being in temporary employment without differentiating between varying levels of macroeconomic uncertainty. Notably, the estimated association appears strongest when macroeconomic uncertainty from two years prior is considered. However, it is possible that very high levels of macroeconomic uncertainty may not be associated with the same probability of being in temporary employment as very low levels. Perhaps there are non-linear patterns in the relationship between macroeconomic uncertainty and the probability of being in temporary employment. To explore this question further, I re-estimate the regression in Equation 2.4, treating macroeconomic uncertainty as a categorical variable. Specifically, I classify macroeconomic uncertainty into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above).

Figure 2.14 displays the estimated marginal effects from the probit regression where macroeconomic uncertainty is entered as a categorical variable, highlighting the association

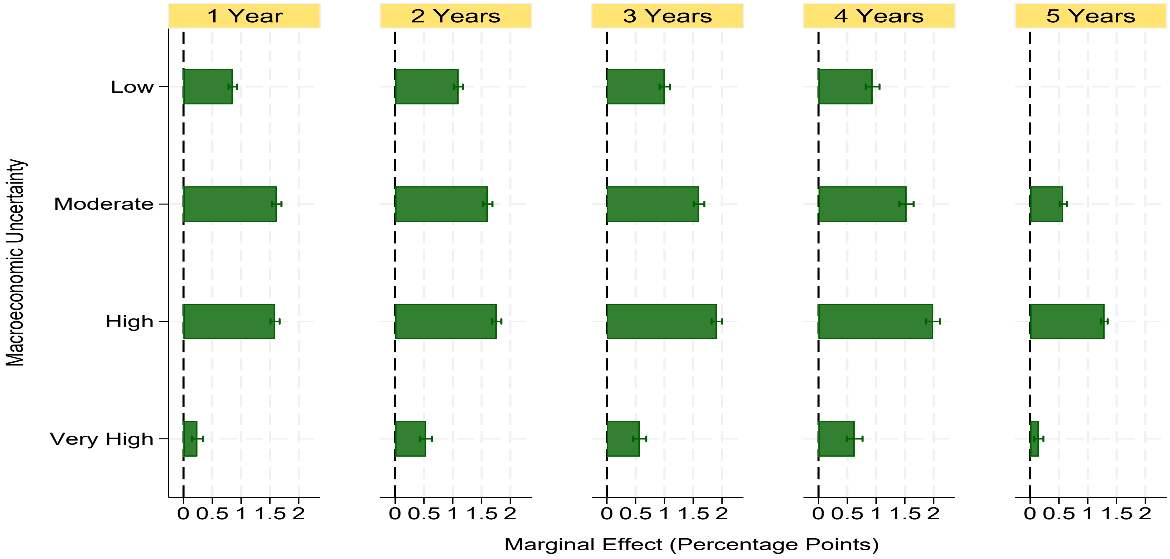

Figure 2.14: Marginal effects (in percentage points) of macroeconomic uncertainty on the probability of being in temporary employment, treating macroeconomic uncertainty as a categorical variable. *Notes:* Macroeconomic uncertainty are classified into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). Point estimates (end of bars) along with their 95% confidence intervals (line intervals) are displayed. Base categories: Is experiencing very low macroeconomic uncertainty; Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. Note that in the last column where macroeconomic uncertainty 5 years ago is used as the regressor, the base macroeconomic uncertainty category is low instead of very low macroeconomic uncertainty, as the macroeconomic uncertainty 5 years ago do not contain very low (10^{th} percentile and below) values. A table containing the regression coefficient numbers is available in Table 2.3.

between different uncertainty levels and the probability of being in temporary employment. The base category corresponds to very low macroeconomic uncertainty (10^{th} percentile and below), except when using macroeconomic uncertainty from five years prior as the regressor (in this case, the base category is low instead of very low macroeconomic uncertainty as the macroeconomic uncertainty 5 years ago does not contain values in the very low (10^{th} percentile and below) range). A consistent pattern emerges regardless of the lag period considered: compared to very low macroeconomic uncertainty, low, moderate, high, and very high levels of macroeconomic uncertainty exhibit a statistically significant and positive correlation with the probability of being in temporary employment. Notably, moderate and high levels of macroeconomic uncertainty display the highest correlations, indicating that these levels of macroeconomic uncertainty are more important predictors of the probability of being in temporary employment. For example, when macroeconomic uncertainty 2 years prior is used as the regressor, the probability of being in temporary employment is at least 1.5% percentage points higher during moderate and high levels of macroeconomic uncertainty as compared to the base category of very low macroeconomic uncertainty. Interestingly, the marginal effect estimates of very high macroeconomic uncertainty is the smallest, which seems counterintuitive given that the base category is very low macroeconomic uncertainty. However, simple reasoning might explain such finding: When faced with a small uncertainty shock, firms may recover more quickly and begin hiring again sooner, perhaps opting for temporary contracts over permanent ones, thus increasing the probability of temporary employment. Conversely, a larger uncertainty shock might prompt firms to lay off more temporary employees as they are easier to dismiss (Cao, Shao, & Silos, 2021), and take longer to resume hiring (Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Den Haan, Freund, & Rendahl, 2021; Schaal, 2017). This delay in rehiring could result in a smaller proportion of individuals being in temporary employment. Therefore, Figure 2.14 underscores that the severity of macroeconomic uncertainty matters in predicting an individual's probability of being in temporary employment.

Robustness

Readers may have concerns about the robustness of the probit regressions presented in the previous subsection, particularly in relation to the categorization of macroeconomic uncertainty levels and the regression specification itself. One key concern is that the baseline categorization (very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above)) might capture extreme values, potentially skewing the regression results and misrepresenting the true correlation. To address this issue, I recategorized the macroeconomic uncertainty measures into five equal bins: very low (below 20^{th} percentile), low (20^{th}–39^{th} percentile), moderate (40^{th}–59^{th} percentile), high (60^{th}–79^{th} percentile), and very high (80^{th} percentile and above). This equal binning ensures a more balanced distribution of observations across categories, thereby enhancing the reliability of the regression analysis.

Figure 2.15 presents the estimated marginal effects obtained from the probit regression after recategorizing macroeconomic uncertainty into five equal bins, illustrating the association between different levels of macroeconomic uncertainty and the probability of being in temporary employment. The figure confirms the pattern observed in Figure 2.14, where moderate and high levels of macroeconomic uncertainty (bins 3 and 4) exhibit the highest marginal effect estimates, indicating that these levels are the most significant predictors of the probability of being in temporary employment. However, unlike in Figure 2.14. the smallest marginal effect estimates (with the base category being very low macroeconomic uncertainty) does not correspond to the very high macroeconomic uncertainty (bin 5) in the recategorized data when macroeconomic uncertainty 4 and 5 years prior are used as the regressors. This discrepancy arises because the equal binning approach reduces the influence of extreme values by distributing more observations into the very high macroeconomic uncertainty category, thus providing a more balanced analysis. Therefore, the findings from the equal binning approach do not conflict with the original results; rather, they complement the original results by mitigating the effect of outliers.

The next robustness check addresses the specification of the baseline probit regression by adding more control variables to better capture potential confounding factors. Figure 2.16 presents the marginal effects obtained from probit regressions with these additional controls, focusing on the case where macroeconomic uncertainty from two years ago is used as the regressor. First, I control for lagged GDP growth[31] as adverse economic conditions often coincide with high macroeconomic uncertainty (Basu & Bundick, 2017; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Jurado, Ludvigson, & Ng, 2015; Leduc & Liu, 2016). An increase in the probability of being in temporary employment might thus reflect agents' responses to poor economic conditions rather than to an uncertain future. By controlling for GDP growth, the model aims to account for its potential influence when examining the association between macroeconomic uncertainty and the probability of being in temporary employment. In the second robustness check, I control for a binary variable indicating whether the individual is working full or part-time, since temporary employment is often associated with part-time work (Booth, Francesconi, & Frank, 2002). In the third robustness check, I control for health status as individuals with health conditions might be more likely to opt for temporary employment, potentially confounding the baseline results. In the final robustness check, I incorporate all control variables, including lagged GDP growth, the full/part-time indicator, and health status.

[31]The lags of GDP growth correspond to the lags of macroeconomic uncertainty. For instance, if macroeconomic uncertainty 2 years ago is used as the regressor, then GDP growth 2 years ago is included as an additional control.

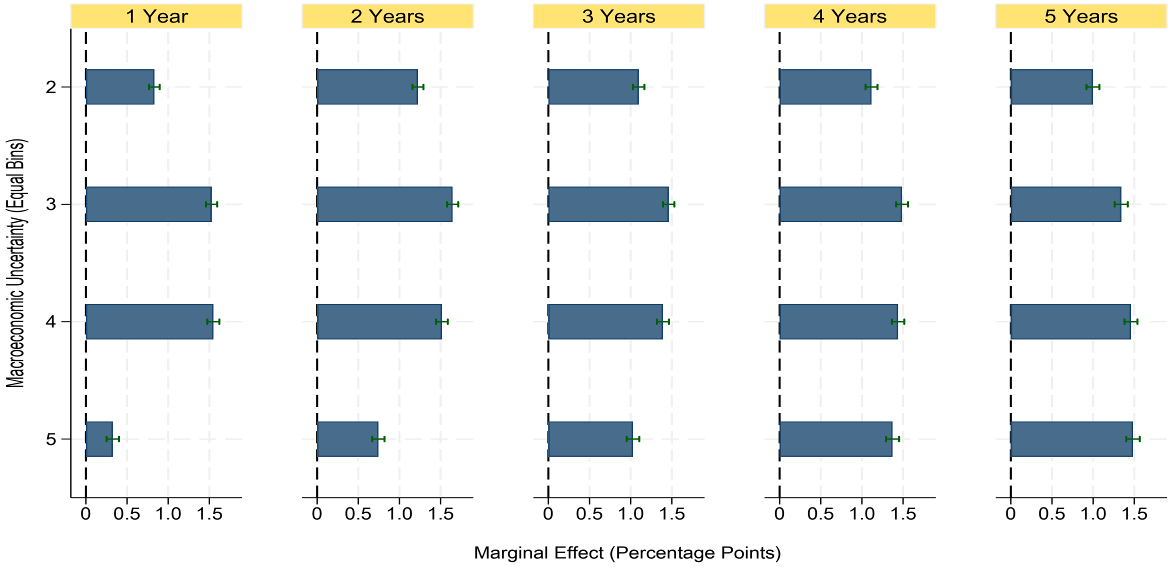

Figure 2.15: Marginal effects (in percentage points) of macroeconomic uncertainty on the probability of being in temporary employment. *Notes:* Here, I categorize macroeconomic uncertainty into 5 equal bins (bin 1: very low (below 20^{th} percentile), bin 2: low (20^{th}–39^{th} percentile),bin 3: moderate (40^{th}–59^{th} percentile), bin 4: high (60^{th}–79^{th} percentile), and bin 5: very high (80^{th} percentile and above). Point estimates (end of bars) along with their 95% confidence intervals (line intervals) are displayed. Base categories: Is experiencing very low macroeconomic uncertainty; Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. A table containing the regression coefficient numbers is available in Table 2.4.

The addition of these control variables in Figure 2.16 confirms the robustness of the non-linear effect observed in the baseline results: moderate and high levels of macroeconomic uncertainty exhibit the highest marginal effects (with very low macroeconomic uncertainty as the base category), indicating that these levels are more significant predictors of the probability of being in temporary employment. In other words, the severity of macroeconomic uncertainty matters in predicting the probability of being in temporary employment. This pattern may reflect the idea that when macroeconomic uncertainty increases, firms may prefer temporary contracts over permanent ones due to their lower reversal costs.[32] However, when uncertainty reaches very high levels, although firms are more likely to opt for temporary contracts, firms might also respond by dismissing even more temporary employees than permanent ones, as the former are easier to lay off. During periods of heightened uncertainty, firms may adopt a "wait and see" approach,[33] delaying hiring altogether. As a result, the increase in the overall proportion of temporary employees in the labour market is smaller when macroeconomic uncertainty is very high.

[32]This hypothesis is explored further in Chapter 3.

[33]See, for instance, Bernanke (1983), McDonald and Siegel (1986), Pindyck (1990), Dixit and Pindyck (1994), Bloom, Van Reenen, and Bond (2007), Bachmann, Elstner, and Sims (2013), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) for the "irreversibility effect", where firms opt to "wait and see" rather than commit to costly actions with uncertain outcomes.

Nonetheless, these explanations should be interpreted with caution, as the data do not allow for causal inference or direct observation of firms' decision-making processes.

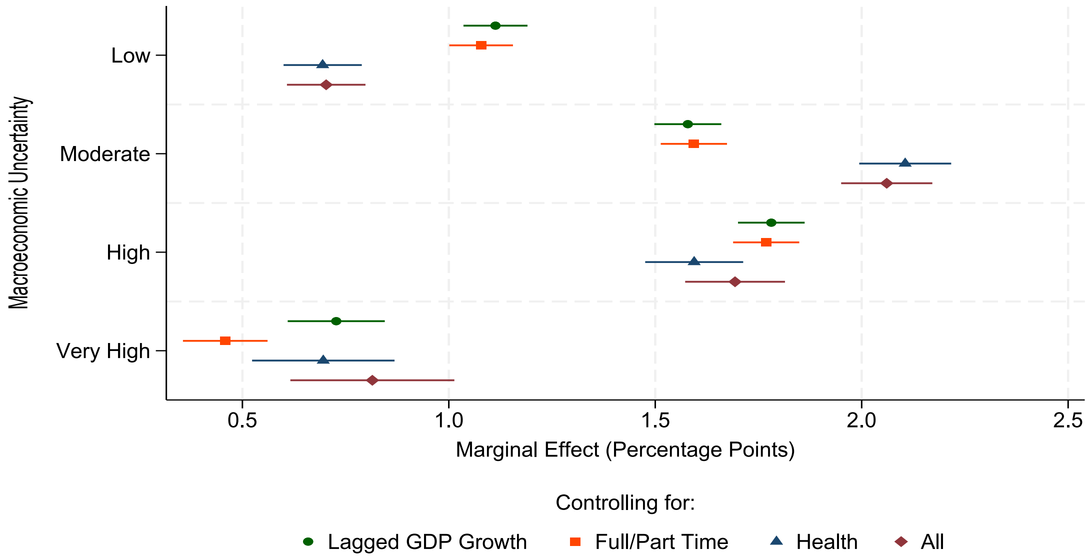

Figure 2.16: Marginal effects of macroeconomic uncertainty on the probability of being in temporary employment, with additional control variables. *Notes:* The vertical axis represents macroeconomic uncertainty from 2 years ago (base level is very low macroeconomic uncertainty) while the horizontal axis plots the marginal effects (in percentage points). Point estimates (dots) along with their 95% confidence intervals (lines) are displayed. Base categories: Is experiencing very low macroeconomic uncertainty; Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. A table containing the regression coefficient numbers is available in Table 2.5.

2.4 Heterogeneity Analysis

This section examines how individual characteristics mediate the relationship between macroeconomic uncertainty and the likelihood of temporary employment. Specifically, it investigates how the relationship between macroeconomic uncertainty and the likelihood of being in temporary employment varies across different age groups, levels of educational attainment, marital status, and number of children. The analysis includes a gender perspective, exploring the association between macroeconomic uncertainty and the probability of temporary employment for both men and women. Since, as demonstrated in the previous section, positive marginal effect peaks when using the macroeconomic uncertainty measure from two years prior as the regressor, for brevity the heterogeneous analysis in this section focus on the case where macroeconomic uncertainty from two years ago is used as the regressor. Similar to the baseline probit regression, macroeconomic uncertainty is also categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above).

It is important to emphasize that the interpretations offered here are intended to be illustrative, rather than definitive, as the analysis identifies statistical associations rather than causal relationships. Moreover, the focus on employed individuals introduces selection bias, which may affect the observed patterns across groups.

2.4.1 Age

The literature documents that the incidence of temporary employment varies across age groups (see OECD, 2014). Figure 2.17 verifies this pattern, revealing similar trends for both men and women. In this figure, each age group's probability of temporary employment is compared to the base group of individuals aged 30-39. For all levels of macroeconomic uncertainty, those under 20 exhibit the highest probability of temporary employment. This is expected, as many individuals in this group are still in education and are more likely to take on casual or seasonal jobs.[34] Similarly, individuals aged 60 and above also show a higher probability of temporary employment compared to the 30-39 age group, likely because they are nearing or have entered retirement and are less inclined towards permanent employment.

Individuals aged 20-29 also exhibit a higher probability of temporary employment compared to the base group of 30-39 years old, regardless of the level of macroeconomic uncertainty. This is partly due to some individuals in this age group pursuing higher education and unable to pursue permanent employment. However, this observation also suggests a "stepping stone" effect of temporary employment in the UK, as highlighted by Booth, Francesconi, and Frank (2002). Individuals aged 20-29, who are new entrants to the labour market, appear to transition to permanent employment after exiting this age group. Figure 2.17 illustrates that the probability of temporary employment stabilizes for individuals between 30 and 60 years old, with little variation among those in their 30s, 40s, and 50s. This indicates that, holding macroeconomic uncertainty and other factors constant, individuals experience minimal changes in the probability of temporary

[34]Using data from the European Labour Force Survey (EU LFS), Nunez and Livanos (2015) find that 42% of young European workers are temporary employees by choice.

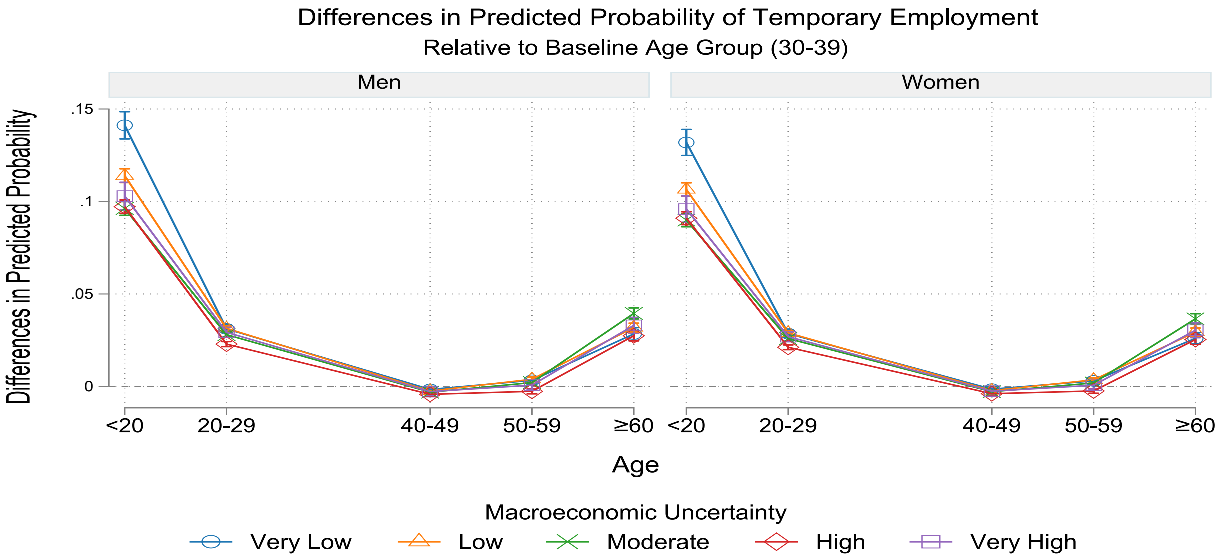

Figure 2.17: Differences in predicted probability of temporary employment by age group across levels of macroeconomic uncertainty. *Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). This figure presents differences in the predicted probability of being in temporary employment by age group for men and women, based on estimates from baseline probit regressions where macroeconomic uncertainty two years prior is included as a regressor. The differences are computed relative to the baseline age group (30–39 years old) across all levels of macroeconomic uncertainty. The horizontal axis represents age groups, while the vertical axis measures the difference in predicted probabilities relative to the baseline. Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to the 30–39 age group. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

employment throughout their 30s to 60s. However, these interpretations should be treated as tentative, as the analysis does not track individual transitions or establish causal mechanisms and is subject to selection bias due to its focus on the employed population.

How does the probability of being in temporary employment change across varying levels of macroeconomic uncertainty for each age group? Figure 2.18 illustrates the difference in predicted probabilities of being in temporary employment between different levels of macroeconomic uncertainty with the baseline being very low macroeconomic uncertainty, for each age group. Notably, the age group under 20 displays anomalous results compared to other age groups. Specifically, compared to very low macroeconomic uncertainty, the probability of being in temporary employment is lower at higher levels of macroeconomic uncertainty (except for the high level of macroeconomic uncertainty). Perhaps, when macroeconomic uncertainty is very low, job opportunities, including temporary positions, are more readily available to individuals under 20, leading to a higher probability of temporary employment. As uncertainty increases, these less experienced individuals in temporary roles might be among the first to be dismissed. Additionally, these young individuals often engage in temporary employment in sectors such as retail and hospitality, which might be more vulnerable to economic fluctuations. Consequently, at higher levels of macroeconomic uncertainty, the proportion of temporary employment among employed individuals under 20 appears to be lower than in periods of very low level of macroeconomic uncertainty. These findings are in contrast with Caggese, Cuñat, and Metzger (2024), who find that younger, less skilled, and less tenured workers in Swedish firms benefit from lower firing rates during high uncertainty. It is crucial to note that the sample size for the age group under 20 in this chapter is considerably smaller than for other age groups, suggesting that these results should be interpreted with caution.

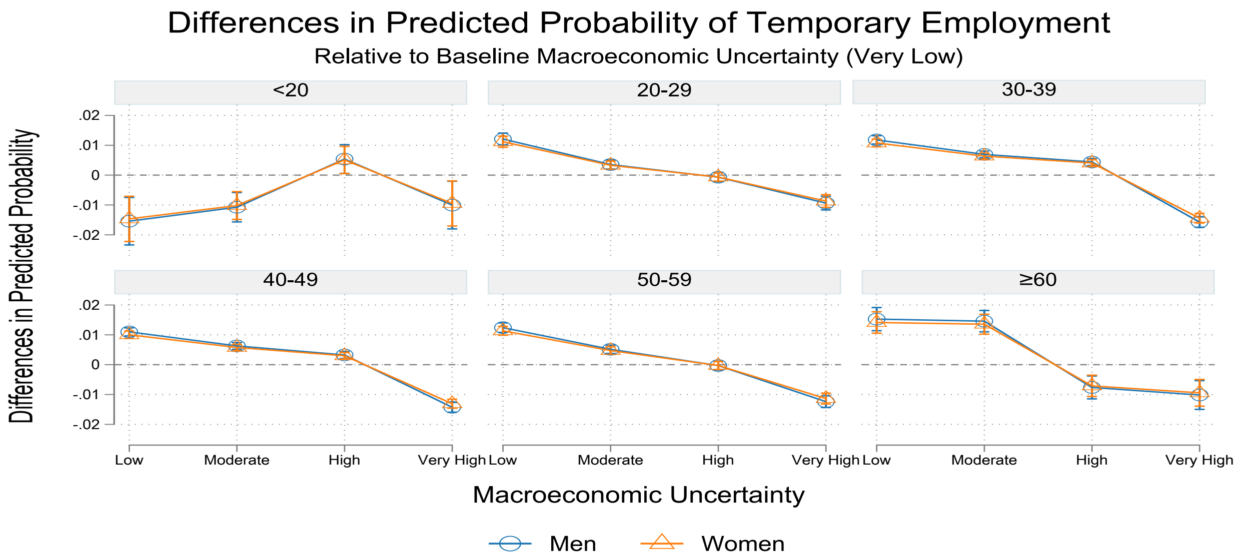

Figure 2.18: Differences in predicted probability of temporary employment by macroeconomic uncertainty across all age groups. *Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). This figure presents differences in the predicted probability of being in temporary employment in each age group for men and women, based on estimates from baseline probit regressions where macroeconomic uncertainty two years prior is included as a regressor. The differences are computed relative to the baseline macroeconomic uncertainty level (very low) within each age group. The horizontal axis represents macroeconomic uncertainty levels, while the vertical axis measures the difference in predicted probabilities relative to the baseline. Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to periods of very low macroeconomic uncertainty. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

The 20-29, 30-39, 40-49, and 50-59 age groups exhibit patterns consistent with baseline results. First, as macroeconomic uncertainty increases, the probability of being in temporary employment initially rises but the rate of increase diminishes at higher levels of uncertainty, creating a downward-sloping curve. Second, when macroeconomic uncertainty is very high, the likelihood of temporary employment is actually lower compared to periods of very low macroeconomic uncertainty. Again, one possible explanation for this pattern—albeit speculative—is that initially, firms may dismiss temporary employees because they are relatively easier to be dismissed. However, as firms adjust to increased uncertainty, they may prefer temporary employees when addressing vacancies, given their lower adjustment costs compared to permanent employees.[35] Consequently, the probability of temporary employment rises with modest increases in macroeconomic uncertainty. In contrast, when macroeconomic uncertainty becomes more severe, firms' recovery times lengthen, which may lead to prolonged hiring delays and sustained dismissals of temporary employees. This combination results in a lower proportion of individuals in temporary employment among all employed individuals. Therefore, under very high macroeconomic uncertainty, the impact of hiring delays is stronger as the option value of waiting is greater (Schaal, 2017), reducing the probability of being in temporary employment compared to periods of very low macroeconomic uncertainty.

The 60 and above age group mirrors the baseline results but also exhibits some unique patterns. Compared to periods of very low macroeconomic uncertainty, the probability of being in temporary employment is higher during low and moderate levels of macroeconomic uncertainty. However, the difference between low and moderate macroeconomic uncertainty levels is minimal, indicating that individuals aged 60 and above do not experience significant changes in temporary employment probability between these two levels of uncertainty. When macroeconomic uncertainty is high or very high, the probability of temporary employment for those aged 60 and above falls below that observed during periods of very low uncertainty. This contrasts with the 30-39 and 40-49 age groups, where the probability of temporary employment remains higher even under high macroeconomic uncertainty. One possible, though speculative, explanation is that those over 60 might opt out of the labour force entirely when uncertainty is high, avoiding even temporary employment (assumedly the preferred form of employment by firms during heightened uncertainty). Bilenkisi (2024) finds that uncertainty-induced

[35] Caggese, Cuñat, and Metzger (2024) show that a rise in firm-level uncertainty increases relatively more the hiring of workers that are cheaper to hire and to train.

discouragement effect causes households to reduce both labour supply and search intensity; given that the 60 and above age group is approaching retirement, it is not surprising that this discouragement effect may be even stronger for this group. While such a mechanism could contribute to the observed patterns, it is important to interpret these associations cautiously, as the analysis does not directly observe labour market exits and does not allow for causal inference.

2.4.2 Education

How does the probability of being in temporary employment differ across varying levels of macroeconomic uncertainty for each highest educational qualification group? Figure 2.19 illustrates the differences in predicted probabilities of temporary employment across different levels of macroeconomic uncertainty, using very low uncertainty as the baseline, for each highest educational qualification group. Again, macroeconomic uncertainty from two years prior is used as the regressor. The results reveal no discernible gender differences, and all educational attainment groups exhibit patterns consistent with the baseline results: First, as macroeconomic uncertainty increases, the probability of being in temporary employment initially rises, but the rate of increase diminishes at higher levels of uncertainty, forming a downward-sloping curve. Second, when macroeconomic uncertainty is very high, the likelihood of temporary employment is actually lower compared to periods of very low uncertainty.

Most interestingly, the steepness of the downward-sloping curve in the difference in predicted probability of temporary employment compared to the baseline of very low macroeconomic uncertainty varies by educational attainment. For individuals with a degree, the probability of temporary employment increases with rising macroeconomic uncertainty, but the rate of increase slows at higher macroeconomic uncertainty levels. Conversely, for individuals without any qualifications, the increase in the probability of temporary employment is minimal across different levels of macroeconomic uncertainty, except when macroeconomic uncertainty is very high (potentially due to prolonged hiring delays and sustained dismissals of temporary employees, similar to other groups). These patterns may suggest greater responsiveness among higher-educated individuals to macroeconomic uncertainty in terms of temporary employment likelihood, though this interpretation is speculative and subject to selection bias, as the analysis includes only employed individuals.

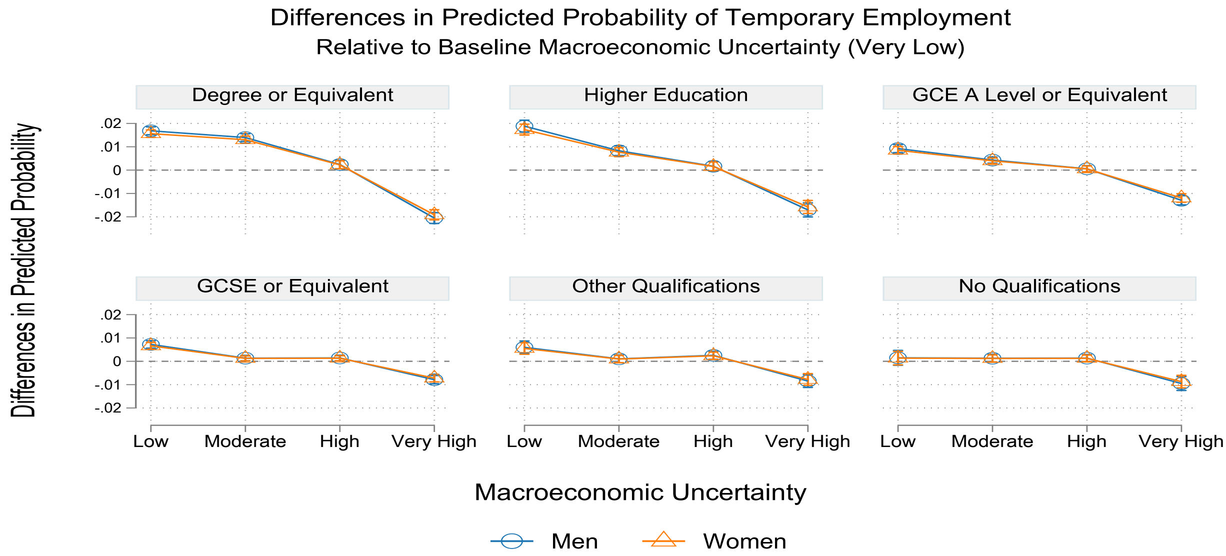

Figure 2.19: Differences in predicted probability of temporary employment by macroeconomic uncertainty across all highest educational attainment groups. *Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). The graph compares the predicted probabilities of being in temporary employment for men and women, derived from baseline probit regressions using macroeconomic uncertainty two years prior as the regressor, against the baseline macroeconomic uncertainty level (very low macroeconomic uncertainty) across all highest educational attainment groups. Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. The horizontal axis represents different levels of macroeconomic uncertainty, while the vertical axis shows the differences in predicted probabilities relative to the baseline macroeconomic uncertainty level (very low). A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to periods of very low macroeconomic uncertainty. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

Why are more highly educated individuals exhibit greater sensitivity to changes in macroeconomic uncertainty in their probability of temporary employment? Several tentative explanations, drawn from the discussion in Section 2.3.1, may offer some insights.

First, the difference might relate to differences in adjustment costs. Highly educated individuals might incur higher labour adjustment costs because the time and resources spent acquiring advanced qualifications need to be compensated. These higher adjustment costs make decisions regarding permanent employees more costly and less "reversible" than those related to temporary employees. As a result, firms may prefer to hire higher educated individuals as temporary employees during heightened uncertainty. Second, the match quality hypothesis proposed by Cao, Shao, and Silos (2021) may offer a potential framework. Assume that higher educated individuals represent high-quality labour, while less educated individuals low-quality labour. Firms prefer to offer permanent contracts to high-quality labour to retain these valuable matches and temporary contracts to lower-quality labour. When macroeconomic uncertainty increases, the dispersion of outcomes widens. According to the hypothesis, low-quality matches are more affected by increased upside risk, while high-quality matches are more impacted by increased downside risk. Consequently, higher uncertainty raises the relative value of temporary jobs while reducing the appeal of permanent jobs, leading firms to offer more temporary positions to highly educated individuals. Another reason why more highly educated individuals are more sensitive to changes in macroeconomic uncertainty in their probability of temporary employment may be because highly educated individuals, compared to their less educated counterparts, are likely to be in employment where higher salary expectations are common (Deming, 2023). During periods of economic uncertainty, firms may struggle to maintain these expectations and, in response, may increasingly rely on temporary contracts to moderate salary expectations while maintaining workforce flexibility. However, it is important to note that the nature of the analysis—being associative rather than causal and subject to selection bias—limits the strength of the interpretations offered.

2.4.3 Marital Status

Figure 2.20 illustrates the difference in predicted probabilities of being in temporary employment between married and unmarried individuals for both men and women for all levels of macroeconomic uncertainty, using macroeconomic uncertainty from two years prior as the regressor. As anticipated, married individuals, both men and women, are consistently less likely to be in temporary employment across all levels of macroeconomic uncertainty. This might be attributed to intrahousehold insurance (See e.g. Blundell, Pistaferri, & Saporta-Eksten, 2016; Mincer, 1962) which permits longer job searches and reduces the necessity for married individuals to accept temporary employment, assuming temporary employment is less desirable than permanent employment.[36] However, when macroeconomic uncertainty increases (up to high, but not very high, levels), the difference in predicted probabilities of being in temporary employment between married and unmarried individuals narrows.

[36]Booth, Francesconi, and Frank (2002) confirm the perception in the UK that temporary jobs are generally undesirable when compared to permanent employment.

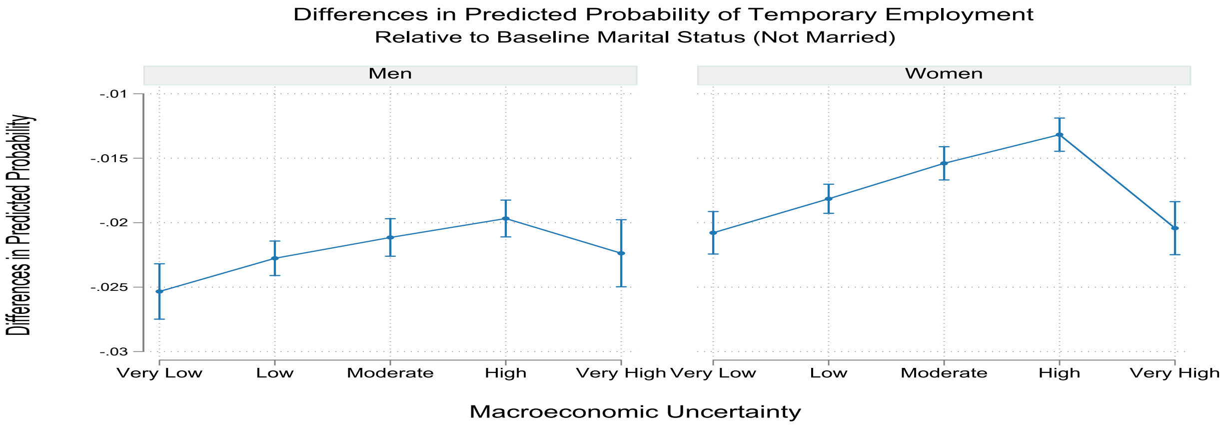

Figure 2.20: Differences in predicted probability of temporary employment between married and unmarried counterparts.*Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). The graph compares the predicted probabilities of being in temporary employment, derived from baseline probit regressions using macroeconomic uncertainty two years prior as the regressor, against the baseline marital status group (not married) across all levels of macroeconomic uncertainty. The horizontal axis represents different levels of macroeconomic uncertainty, while the vertical axis shows the differences in predicted probabilities relative to the baseline marital status group (not married). Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to the unmarried group. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

Figure 2.21 presents the differences in predicted probabilities of temporary employment across varying levels of macroeconomic uncertainty, with very low macroeconomic uncertainty serving as the baseline. Relative to the baseline, higher levels of macroeconomic uncertainty are associated with an increased likelihood of temporary employment. However, at the highest level of macroeconomic uncertainty (very high), the probability of temporary employment declines relative to the baseline. A particularly striking feature of Figure 2.21 is that this decline is steeper for women, especially married women.[37] Firms facing extreme uncertainty may prolong hiring delays and sustain dismissals of temporary employees because temporary employees are less costly to dismiss. If women are disproportionately employed in temporary positions, this would result in a sharper decline in the probability of temporary employment among women when uncertainty peaks. Married women may exhibit greater sensitivity to macroeconomic uncertainty, particularly if they have alternative household income sources. Faced with deteriorating job prospects, they may exit the labour force entirely rather than remain in temporary employment, further contributing to the observed decline in probability of temporary

[37]Note that Bertrand (2020) highlights the limited evidence of direct discrimination against women by employers. However, the existing literature has not explored the possibility of employers offering temporary contracts to women during periods of heightened uncertainty to mitigate potential higher adjustment costs compared to men.

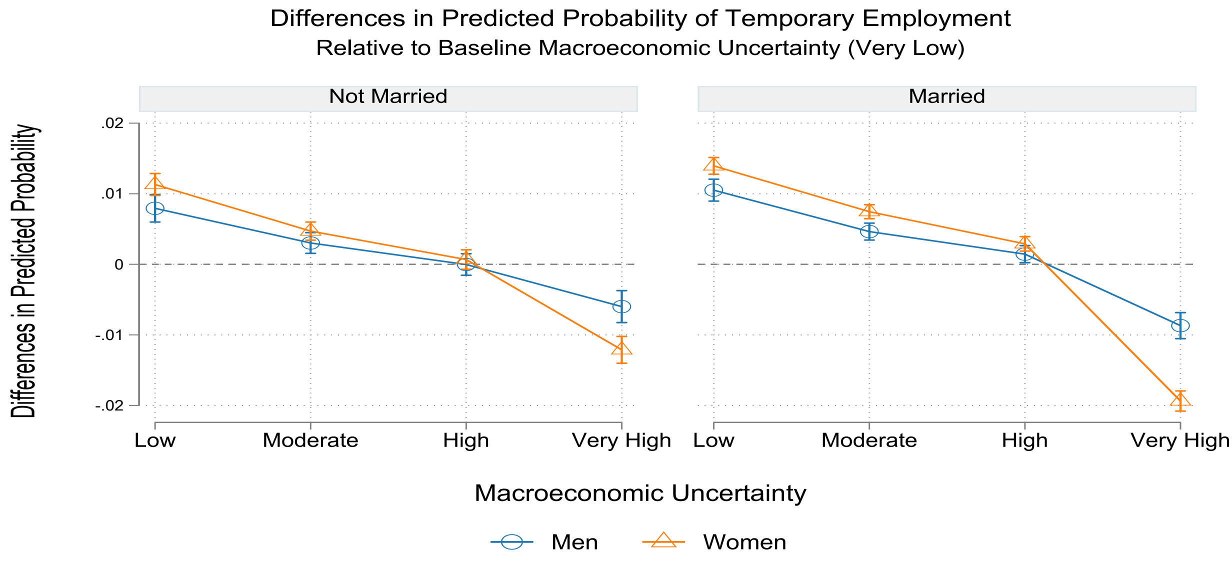

Figure 2.21: Differences in predicted probability of temporary employment by macroeconomic uncertainty for men and women. *Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). The graph compares the predicted probabilities of being in temporary employment, derived from baseline probit regressions using macroeconomic uncertainty two years prior as the regressor, against the baseline macroeconomic uncertainty level (very low macroeconomic uncertainty) for men and women. The horizontal axis represents different levels of macroeconomic uncertainty, while the vertical axis shows the differences in predicted probabilities relative to the baseline macroeconomic uncertainty level (very low). Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to periods of very low macroeconomic uncertainty. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

employment at very high levels of macroeconomic uncertainty. While these explanations are theoretically plausible, they remain hypothetical and may extend beyond what the current analysis can substantiate. Further empirical research is needed empirically validate these interpretations of the observed patterns.

2.4.4 Number of Children

Figure 2.22 illustrates the differences in predicted probabilities of temporary employment between individuals with at least one child and childless individuals for both men and women across all levels of macroeconomic uncertainty, using macroeconomic uncertainty from two years prior as the regressor. The figure reveals a stark gender disparity: men with at least one child generally experience a lower probability of temporary employment compared to childless men across all levels of macroeconomic uncertainty, whereas women with at least one child are predicted to experience a higher probability of

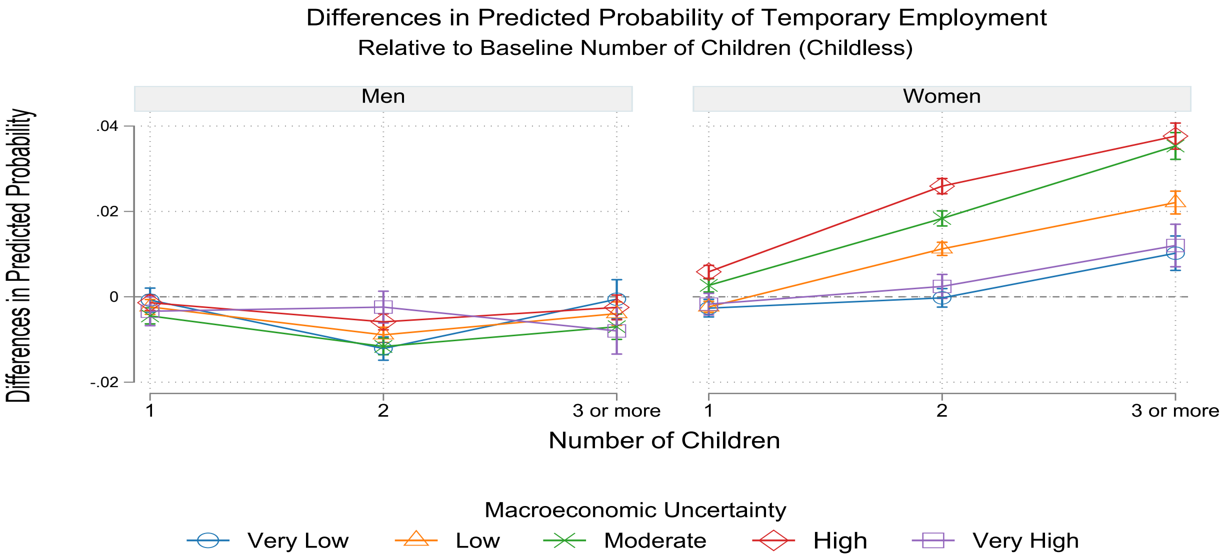

Figure 2.22: Differences in predicted probability of temporary employment between childless individuals and those with at least one child. *Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). The graph compares the predicted probabilities of being in temporary employment, derived from baseline probit regressions using macroeconomic uncertainty two years prior as the regressor, against the baseline group (childless) across all levels of macroeconomic uncertainty. The horizontal axis represents the number of children ("3" represents 3 and more children), while the vertical axis shows the differences in predicted probabilities relative to the baseline group (childless). Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to the childless group. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

temporary employment compared to childless women. Furthermore, this probability increases for women as the number of children increases. What can potentially explain this difference between men and women? The literature suggests gender norms[38] and gender discrimination might be at play. Traditional gender norms often dictate that men serve as the primary breadwinners (Bertrand, Cortés, Olivetti, & Pan, 2016), leading men with children to seek greater job security (and hence permanent employment) to provide for their families. Conversely, women are pressured to seek more flexibility (and hence temporary employment) to balance work and child-rearing responsibilities (Vandello, Hettinger, Bosson, & Siddiqi, 2013), with this need for flexibility becoming more pronounced as the number of children increases. Additionally, gender discrimination might play a role: men with children might benefit from the "fatherhood premium" in the form of more secure employment opportunities, while women with children face the "motherhood penalty" in the form of less secure employment opportunities (See, among

[38]Benabou and Tirole (2021) define norms as 'social sanctions or rewards'. Gender norms are characterized as societal expectations regarding the appropriate behavior for men and women. Bertrand (2020) writes: "Gender stereotypes are beliefs, shared by men and women, about what men and women should or ought to do (or how they should or ought to be). The prescriptive nature of gender stereotypes motivates men and women to adjust their self-view to what seems appropriate for their gender group."

others, Angelov, Johansson, & Lindahl, 2016; Bertrand, 2018; Goldin, Kerr, & Olivetti, 2022). Pinpointing the exact reasons for these disparities is beyond the scope of this chapter, but these gender perspectives are crucial for further research on temporary employment.

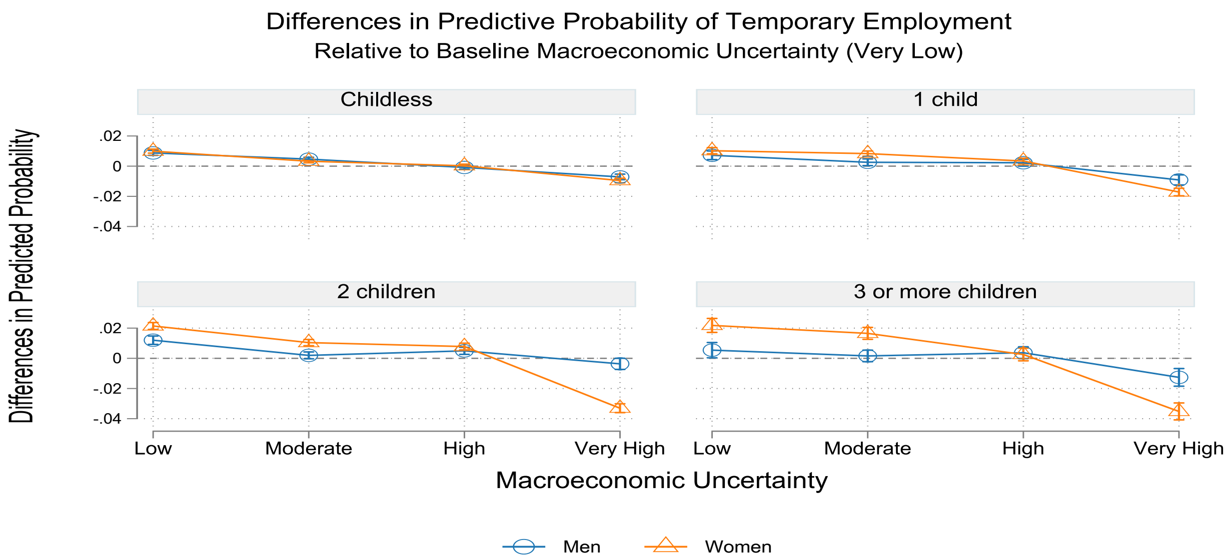

Figure 2.23: Differences in predicted probability of temporary employment by macroeconomic uncertainty by number of children. *Notes:* Similar to the baseline probit regression, macroeconomic uncertainty is categorized into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). The graph compares the predicted probabilities of being in temporary employment, derived from baseline probit regressions using macroeconomic uncertainty two years prior as the regressor, against the baseline macroeconomic uncertainty level (very low macroeconomic uncertainty) for men and women. The horizontal axis represents different levels of macroeconomic uncertainty, while the vertical axis shows the differences in predicted probabilities relative to the baseline macroeconomic uncertainty level (very low). Difference in point estimates (symbols) and their 95% confidence intervals (vertical error bars) are displayed. A positive (negative) value indicates a higher (lower) probability of being in temporary employment compared to periods of very low macroeconomic uncertainty. Confidence intervals provide an indication of statistical significance, with intervals crossing zero suggesting differences that may not be statistically distinguishable from the baseline.

Figure 2.23 illustrates the variations in predicted probabilities of temporary employment across different levels of macroeconomic uncertainty, using very low macroeconomic uncertainty as the baseline, and disaggregates the data by number of children. For men, the probability of temporary employment remains relatively insensitive to fluctuations in macroeconomic uncertainty, irrespective of the number of children. Among childless individuals, gender differences in probability of temporary employment are minimal. However, relative to the baseline macroeconomic uncertainty (very low), women—particularly those with two or more children—experience a higher likelihood of temporary employment than men when macroeconomic uncertainty rises, followed by a steeper decline when uncertainty reaches its highest levels. Without further research, it is difficult to pinpoint the exact reasons for these observations. Additionally, since the analysis includes only employed individuals, it is subject to selection bias, which limits the strength and generalizability of any interpretive claims. Nevertheless, the preliminary analysis suggests that the relationship between temporary employment and macroeconomic uncertainty varies between men and women. Understanding the underlying causes may require an exploration of gender roles, financial needs, and potential discrimination in the labour market.

2.5 Conclusion

This section summarizes the findings of this chapter, outlines the limitations of the analysis, and suggests avenues for future research.

First, this chapter documents trends, gender differences, and geographical variations in temporary employment in the UK. Many new questions emerge from these findings. For instance, the chapter shows that a higher proportion of individuals in temporary employment could not secure permanent employment compared to those who voluntarily chose temporary employment following the 2008 Financial Crisis and the COVID-19 pandemic. However, little is known about those who managed to secure permanent employment during these periods of heightened uncertainty. Do firms raise skill and experience requirements for permanent positions when uncertainty increases, effectively making permanent employment less accessible? Exploring how uncertainty affects the intricacies of labour contracts remains largely uncharted territory. This chapter also observes the convergence in motivations for temporary employment between men and women but does not investigate the underlying reasons for this trend. Additionally, it highlights the geographical variations in the strength of some macroeconomic variables (GDP growth, unemployment, and job density) as correlates of temporary employment but does not explore the specific characteristics of each UK region to explain these differences. These findings underscore promising avenues for future research.

Second, this chapter provides preliminary evidence that macroeconomic uncertainty is positively associated with the probability of temporary employment. Using LFS data and the macroeconomic uncertainty measure from Theophilopoulou (2022) from 1992Q2 to 2018Q1, I run a probit regression to explore the relationship between macroeconomic uncertainty and the probability of being in temporary employment in the UK. In this context, the probability of temporary employment specifically refers to the likelihood that an employed individual holds a temporary rather than a permanent position, rather than the probability of being in temporary employment relative to all possible labor market states, including unemployment or inactivity. This distinction matters because the analysis is conducted on a sample of *employed* individuals; unemployed and inactive individuals are excluded from the sample. Therefore, the results do not speak to the overall likelihood of employment versus non-employment, but rather to the composition of employment between temporary and permanent contracts. This sample restriction also naturally introduces a form of selection bias; the results should therefore be interpreted with caution. The findings from the probit model indicate a positive, albeit modest, marginal effect of macroeconomic uncertainty on the probability of temporary employment. When macroeconomic uncertainty is treated as a categorical variable, distinguishing between various levels of uncertainty, a consistent pattern emerges: higher levels of uncertainty are positively and statistically significantly correlated with the likelihood of temporary employment. Notably, moderate and high levels of uncertainty yield the highest marginal effects, underscoring their stronger predictive power for temporary employment. These results highlight that the intensity of macroeconomic uncertainty matters in predicting the probability of temporary employment. However, this chapter does not delve into the underlying mechanisms driving this relationship. Although it briefly discusses potential factors such as adjustment costs, match quality, work effort, and monitoring, these discussions remain speculative. Future research should rigorously test these factors to provide a more comprehensive understanding of the dynamics at play.

Third, it is important to note that the probit regression analysis in this chapter primarily captures correlations rather than establishing causal relationships. Probit regression estimates the probability of an outcome based on predictor variables and illustrates how these predictors are associated with changes in the probability of the outcome. However, it does not inherently account for potential endogeneity or other issues critical for establishing causality. Addressing causality is gaining traction in the literature: Baker, Bloom, and Terry (2023) instrument uncertainty with disaster events; Ludvigson, Ma, and Ng (2021), Angelini, Bacchiocchi, Caggiano, and Fanelli (2019), and Carriero, Clark, and Marcellino (2018) enhance econometric methods to improve the identification of exogenous variation in uncertainty. In future research, I aim to supplement the probit regression with additional empirical strategies such as instrumental variables to better address causality.

Fourth, this chapter briefly documents the heterogeneity in the probability of temporary employment as macroeconomic uncertainty increases. The analysis reveals that more highly educated individuals exhibit greater sensitivity to changes in macroeconomic uncertainty in their probability of being in temporary employment. Additionally, women with children are predicted to experience a higher probability of temporary employment as macroeconomic uncertainty rises, and this likelihood increases with the number of children.

Fifth, this chapter does not exhaust the topic of the effects of uncertainty on temporary employment. One intriguing area for future research is the use of vacancy data instead of aggregate data. The aggregate data on temporary employment used in this chapter conflates the forces of both labour supply and demand, providing limited insight into each. Vacancy data can isolate labour demand. Specifically, tracking vacancies for temporary versus permanent positions during periods of economic uncertainty can reveal firms' preferences in labour contracts when uncertainty rises. This approach is particularly compelling because vacancy data is available at very high frequencies (e.g., daily). When combined with high-frequency uncertainty measures (such as the daily Economic Policy Uncertainty (EPU) data by Baker, Bloom, and Davis (2016)), this method could add robustness to the analysis since the use of high-frequency data to explore the impact of uncertainty remains scarce in the literature. Utilizing vacancy data from sources such as Adzuna and Lightcast presents a promising avenue for understanding how uncertainty specifically affects labour demand for temporary employment.[39]

This chapter examines the relationship between macroeconomic uncertainty and

[39]The UK's vacancy data from Adzuna is available at no cost to researchers, whereas accessing the vacancy data from Lightcast requires a subscription fee. Both datasets include information on contract types (permanent or temporary).

the probability of temporary employment exclusively within the UK. Expanding this analysis to other countries could provide valuable comparative insights, particularly given the substantial cross-country differences in employment protection legislation, labour market institutions, and definitions of temporary employment. Such variations may influence the extent to which uncertainty affects temporary employment, highlighting the need for a broader international perspective. Additionally, it would be interesting to explore whether uncertainty-induced fluctuations in temporary employment influence immigration patterns in the UK. For example, a heightened demand for temporary employees during periods of elevated uncertainty may attract more migrant labour from neighboring countries rather than being met by domestic labour, who may be less willing to accept temporary contracts. These are promising avenues for future research on uncertainty and temporary employment.

2.A Appendix

2.A.1 Time Series Plot of Temporary Employment and GDP Growth

Figure 2.24: GDP growth and temporary employment. *Notes:* The figure plots the GDP (chained value measures, seasonally adjusted) quarter on quarter growth rate (dotted line) and overall proportion of employed individuals in temporary employment (solid line with * symbols) from 1992Q2 to 2023Q4. The left vertical axis displays the GDP growth rate in percent, while the right vertical axis the proportion of employed individuals in temporary employment in percent. The horizontal axis shows the time period in years. The shaded areas represent recessionary periods in the UK. *Source:* Office of National Statistics (2024c, 2024d).

2.A.2 Baseline Probit Regressions

Table 2.2: Macroeconomic Uncertainty and Temporary Employment: Probit Coefficients

	1 Year Ago	2 Years Ago	3 Years Ago	4 Years Ago	5 Years Ago
Macroeconomic Uncertainty	0.018***	0.023***	0.023***	0.021***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls for:	YES	YES	YES	YES	YES
Sociodemographics	YES	YES	YES	YES	YES
Family demographics	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES
Occupation	YES	YES	YES	YES	YES
Observations	4561523	4561523	4561523	4561523	4561523

Notes: Probit regressions with the probability of being in temporary employment as the dependent variable. Each column reports the coefficients using different lagged measures of macroeconomic uncertainty as regressors, specifically 1 year ago, 2 years ago, 3 years ago, 4 years ago, and 5 years ago. Robust standard errors are applied in all columns. Base categories: Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. All regressions include sociodemographics, family demographics, industry, and occupational controls. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table 2.3: Macroeconomic Uncertainty (Categorical) and Temporary Employment

	1 Year Ago	2 Years Ago	3 Years Ago	4 Years Ago	5 Years Ago
Macroeconomic uncertainty					
Base level	Very Low	Very Low	Very Low	Very Low	Low
Low	0.083***	0.107***	0.100***	0.095***	
	(0.004)	(0.004)	(0.005)	(0.007)	
Moderate	0.149***	0.152***	0.153***	0.149***	0.054***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.003)
High	0.147***	0.165***	0.179***	0.188***	0.115***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.003)
Very High	0.025***	0.055***	0.059***	0.065***	0.014***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.004)
Observations	4561523	4561523	4561523	4561523	4561523

Notes: Probit regressions with the probability of being in temporary employment as the dependent variable, treating macroeconomic uncertainty as a categorical variable. Macroeconomic uncertainty are classified into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). Each column reports the coefficients using different lagged measures of macroeconomic uncertainty as regressors, specifically 1 year ago, 2 years ago, 3 years ago, 4 years ago, and 5 years ago. Robust standard errors are applied in all columns. Base categories: Experienced very low macroeconomic uncertainty; Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. Note that in the last column where macroeconomic uncertainty 5 years ago is used as the regressor, the base macroeconomic uncertainty category is low instead of very low macroeconomic uncertainty, as the macroeconomic uncertainty 5 years ago do not contain very low (10^{th} percentile and below) values. All regressions include sociodemographics, family demographics, industry, and occupational controls. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table 2.4: Macroeconomic Uncertainty (Categorical, equal bins) and Temporary Employment

	1 Year Ago	2 Years Ago	3 Years Ago	4 Years Ago	5 Years Ago
Macroeconomic uncertainty					
Base level	1	1	1	1	1
2	0.078***	0.115***	0.104***	0.108***	0.097***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
3	0.138***	0.150***	0.135***	0.140***	0.128***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
4	0.139***	0.140***	0.129***	0.136***	0.138***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
5	0.032***	0.072***	0.098***	0.130***	0.140***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	4561523	4561523	4561523	4561523	4561523

Notes: Probit regressions with the probability of being in temporary employment as the dependent variable, treating macroeconomic uncertainty as a categorical variable. Macroeconomic uncertainty are classified into 5 equal bins (bin 1: very low (below 20^{th} percentile), bin 2: low (20^{th}–39^{th} percentile), moderate (40^{th}–59^{th} percentile), high (60^{th}–79^{th} percentile), and very high (80^{th} percentile and above). Each column reports the coefficients using different lagged measures of macroeconomic uncertainty as regressors, specifically 1 year ago, 2 years ago, 3 years ago, 4 years ago, and 5 years ago. Robust standard errors are applied in all columns. Base categories: Experienced very low macroeconomic uncertainty; Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. All regressions include sociodemographics, family demographics, industry, and occupational controls. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table 2.5: Macroeconomic Uncertainty and Temporary Employment, with Additional Controls

	GDP	Full/Part Time	Health	All
Macroeconomic uncertainty				
Base level	Very Low	Very Low	Very Low	Very Low
Low	0.109***	0.108***	0.068***	0.071***
	(0.004)	(0.004)	(0.005)	(0.005)
Moderate	0.150***	0.154***	0.188***	0.190***
	(0.004)	(0.004)	(0.005)	(0.005)
High	0.167***	0.170***	0.147***	0.160***
	(0.004)	(0.004)	(0.005)	(0.006)
Very High	0.073***	0.048***	0.068***	0.081***
	(0.006)	(0.005)	(0.008)	(0.010)
Observations	4561523	4560565	1740813	1740255

Notes: Probit regressions with the probability of being in temporary employment as the dependent variable and additional control variables. The regressor is macroeconomic uncertainty 2 years prior. Macroeconomic uncertainty are classified into five categories: very low (10^{th} percentile and below), low (11^{th}–39^{th} percentile), moderate (40^{th}–60^{th} percentile), high (61^{st}–89^{th} percentile), and very high (90^{th} percentile and above). Column 1 includes lagged GDP growth as an additional control, Column 2 a binary indicator for full-time or part-time employment, Column 3 incorporates a binary indicator for no health conditions versus at least one health condition, Column 4 all the aforementioned controls in the baseline probit regression presented in Section 2.3. Robust standard errors are applied in all columns. Base categories: Experienced very low macroeconomic uncertainty; Aged 30-39 years old; Is born in the UK; Is white; Is male; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. In Column 2, the base categories are expanded to include full-time employment. In Column 3, the base categories include individuals with no health conditions. Column 4 combines the base categories with full-time employment and no health conditions. All regressions include sociodemographics, family demographics, industry, and occupational controls. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table 2.6: Temporary Employment and Control Variables Only (Excluding Macroeconomic Uncertainty)

	All	Men	Women
Sociodemographics			
< 20 years old	0.694***	0.652***	0.732***
	(0.005)	(0.007)	(0.007)
20-29 years old	0.244***	0.237***	0.252***
	(0.003)	(0.004)	(0.004)
40-49 years old	-0.037***	-0.039***	-0.028***
	(0.003)	(0.005)	(0.004)
50-59 years old	-0.005	0.058***	-0.038***
	(0.003)	(0.005)	(0.005)
60-64 years old	0.226***	0.234***	0.230***
	(0.005)	(0.007)	(0.007)
Not born in the UK	0.212***	0.257***	0.183***
	(0.004)	(0.005)	(0.004)
Not white	0.102***	0.130***	0.043***
	(0.004)	(0.006)	(0.005)
Highest Qualifications			
Higher Education	-0.120***	-0.104***	-0.121***
	(0.004)	(0.006)	(0.005)
GCE A Level or equivalent	-0.158***	-0.121***	-0.195***
	(0.003)	(0.005)	(0.004)
GCSE or equivalent	-0.320***	-0.295***	-0.337***
	(0.004)	(0.005)	(0.005)
Other qualifications	-0.212***	-0.187***	-0.243***
	(0.004)	(0.006)	(0.005)
No Qualifications	-0.326***	-0.296***	-0.358***
	(0.005)	(0.007)	(0.006)
Family Demographics			
Married	-0.152***	-0.112***	-0.090***
	(0.002)	(0.004)	(0.003)
Has 1 child	-0.017***	-0.028***	0.008**
	(0.003)	(0.004)	(0.004)
Has 2 children	0.018***	-0.077***	0.119***
	(0.003)	(0.005)	(0.004)
Has 3 or more children	0.083***	-0.042***	0.226***
	(0.004)	(0.007)	(0.006)
Head of household	-0.174***	-0.247***	-0.058***
	(0.003)	(0.004)	(0.004)
Observations	4561523	2263266	2298257

Notes: Probit regressions with temporary employment as dependent variable. Base categories: Aged 30-39 years old; Is born in the UK; Is white; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table 2.7: Temporary Employment and Control Variables Only (Excluding Macroeconomic Uncertainty) Continued

	All	Men	Women
Standard Industrial Classification			
Energy and water	-0.054***	0.047***	-0.113***
	(0.014)	(0.016)	(0.023)
Manufacturing	-0.167***	-0.099***	-0.337***
	(0.011)	(0.014)	(0.019)
Construction	-0.088***	0.049***	-0.368***
	(0.012)	(0.014)	(0.021)
Distribution, hotels and restaurants	-0.225***	-0.178***	-0.355***
	(0.011)	(0.014)	(0.018)
Transport and communication	-0.176***	-0.106***	-0.286***
	(0.012)	(0.014)	(0.019)
Banking and finance	-0.084***	0.039***	-0.257***
	(0.011)	(0.014)	(0.018)
Public admin, education and health	0.111***	0.262***	-0.132***
	(0.011)	(0.014)	(0.018)
Other services	0.144***	0.312***	-0.112***
	(0.012)	(0.015)	(0.018)
Standard Occupational Classification			
Professional occupations	0.482***	0.463***	0.544***
	(0.005)	(0.006)	(0.007)
Associate prof & tech occupations	0.333***	0.317***	0.335***
	(0.005)	(0.007)	(0.007)
Administrative occupations	0.488***	0.598***	0.429***
	(0.005)	(0.007)	(0.007)
Skilled trades occupations	0.304***	0.335***	0.258***
	(0.006)	(0.007)	(0.013)
Service occupations	0.501***	0.445***	0.527***
	(0.005)	(0.008)	(0.007)
Sales occupations	0.388***	0.423***	0.300***
	(0.006)	(0.008)	(0.008)
Process, plant and machine operatives	0.627***	0.604***	0.733***
	(0.006)	(0.007)	(0.010)
Elementary occupations	0.691***	0.751***	0.553***
	(0.005)	(0.007)	(0.007)
Observations	4561523	2263266	2298257

Notes: Probit regressions with temporary employment as dependent variable. Base categories: Aged 30-39 years old; Is born in the UK; Is white; Has a degree or equivalent; Is not married; Is childless; Is not head of household; Works in the agriculture, forestry, and fishing industry; Works in managerial occupations. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

2.A.3 Selected Literature on Temporary Employment in the UK

Authors	UK only?	Topics/Findings
Stanworth and Druker (2006)	Y	Firms tend to react to periods of turbulence by increasing temporary labour.
Marx (2014)	N	Temporary workers, compared to permanent workers, show a higher demand for redistribution policies and stronger support for green and left-libertarian parties.
Lisi and Malo (2017)	N	Temporary employment negatively impacts productivity growth, with a more pronounced effect in skilled sectors.
Brown and Sessions (2003)	Y	Hourly wages for temporary workers are approximately 13% lower than those of permanent workers, even after adjusting for personal and job characteristics.
Comi and Grasseni (2012)	N	Workers with similar characteristics to permanent employees earn lower wages when employed on temporary contracts.
Leschke (2009)	N	Temporary employment is predominantly found among young and low-skilled workers, but the UK is an exception.
Pavlopoulos (2013)	N	A wage penalty exists for those entering the labor market with fixed-term contracts, with British females exhibiting a significant learning effect, particularly for those starting in temporary roles.
Casey (1987)	Y	Overview of temporary employment.
Forde and Slater (2005)	Y	Overview of agency work.
Forde and Slater (2001)	Y	Overview of temporary employment.
Booth, Francesconi, and Frank (2002)	Y	Temporary workers report lower job satisfaction, receive less training, and earn lower wages, though some evidence suggests fixed-term contracts can lead to permanent positions.
Giesecke and Groß (2004)	N	Temporary employment poses substantial socioeconomic risks in the UK.
Dawson, Veliziotis, and Hopkins (2017)	Y	Fixed-term employment contracts are associated with decreased individual well-being, primarily due to increased job insecurity.
Kahn (2007)	N	Employment protection legislation (EPL) increases the incidence of temporary employment, particularly among low-skilled workers, youth, native women, and immigrants.
Salvatori (2012)	Y	Firms facing unionization threats are not more likely to use temporary employment.
Lisi (2013)	N	The adoption of temporary contracts leads to decreased labor productivity.
Booth, Francesconi, and Frank (2003)	Y	Agency temping has the most significant negative effect on wages among all forms of temporary jobs. There is also a pay gap between permanent and temporary jobs.
Inanc (2018)	Y	When male partners experience temporary employment, it significantly lowers the psychological well-being and life satisfaction of their female partners.
Gash (2008)	N	In the UK, temporary workers have higher transition rates to permanent employment compared to France and Germany and lower transition rates to unemployment.
Gebel (2010)	N	Temporary contracts are linked to initial wage penalties that diminish over time and create cyclical patterns of temporary employment among tertiary graduates.
Högberg, Strandh, and Baranowska-Rataj (2019)	N	Stricter employment protection legislation (EPL) reduces transitions to permanent jobs, while partial deregulation with strict EPL for permanent contracts but weaker EPL for temporary contracts increases these transitions.

Table 2.8: Selected literature on temporary employment in the UK.

2.A.4 Which Industries Are Dominated by Women?

In Section 2.2, there is a rise in the proportion of employed individuals in temporary employment following both the 2008 Financial Crisis and the COVID-19 pandemic, though the demographic dynamics of this increase differ. Since industries most affected by each crisis may prompt firms to prefer hiring temporary employees over permanent ones, the gender composition of these industries hence may explain the different trends in temporary employment of men and women after the crises. Following the 2008 Financial Crisis, the increase in temporary employment was predominantly driven by men. This pattern is likely attributable to the crisis's roots in the banking and finance industries, generating heightened uncertainty across finance-dependent industries such as manufacturing and construction. Although the banking and finance industry is not dominated by a single gender, manufacturing and construction are heavily dominated by men, as shown in Figure 2.25. Conversely, in the wake of the COVID-19 pandemic, the proportion of temporary employment grew more markedly for women than men. This shift likely reflects the pandemic's disproportionate impact on public administration, education, and health—industries where women make up a large share of the workforce, as shown in Figure 2.25. Consequently, the patterns of rising temporary employment among men and women differ between the two crises.

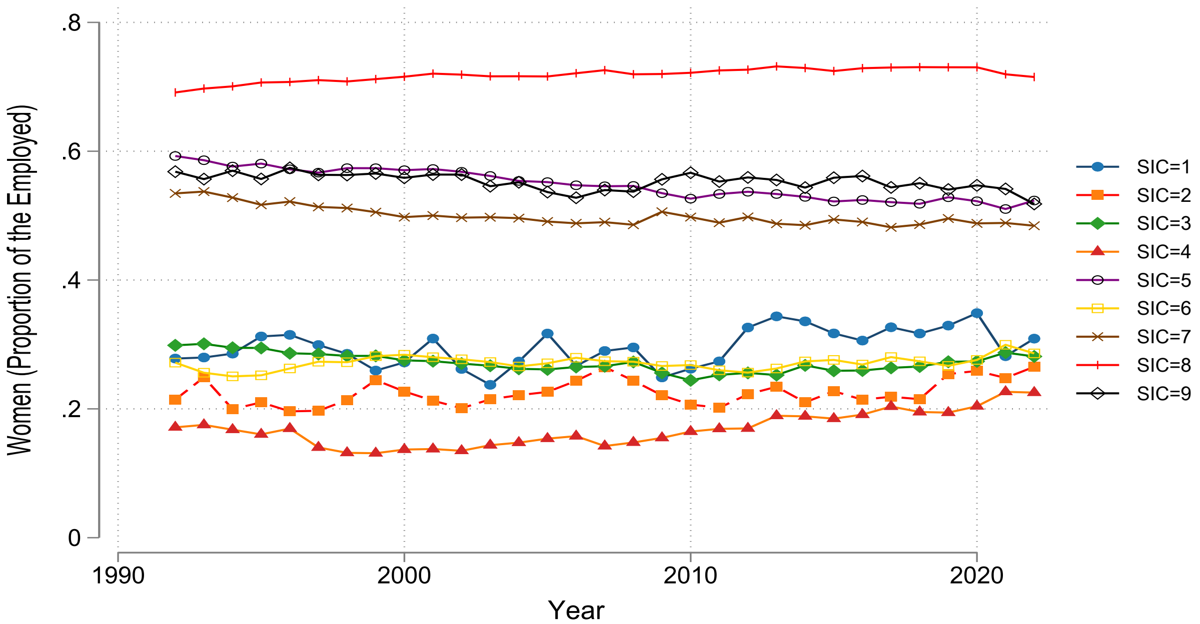

Figure 2.25: Proportion of women employed from 1992 to 2022, by industry. *Notes:* SIC is the shorthand notation for Standard Industrial Classification. SIC 1 = Agriculture, forestry and fishing; SIC 2 = Energy and water; SIC 3 = Manufacturing; SIC 4 = Construction; SIC 5 = Distribution, hotels and restaurants; SIC 6 = Transport and communication; SIC 7 = Banking and finance; SIC 8 = Public admin, education and health; SIC 9 = Other services. *Source:* Office of National Statistics (2024f)

2.A.5 Temporary Employment and Gender Norms

Using data from the British Household Panel Survey (1991–2009) and Understanding Society (2009–2021), I plot the responses to gender norm questions by employed individuals in both permanent and temporary employment. It appears that gender beliefs among men do not differ between those in permanent versus temporary employment. In contrast, women in temporary employment exhibit slightly more conservative gender beliefs compared to their counterparts in permanent employment.

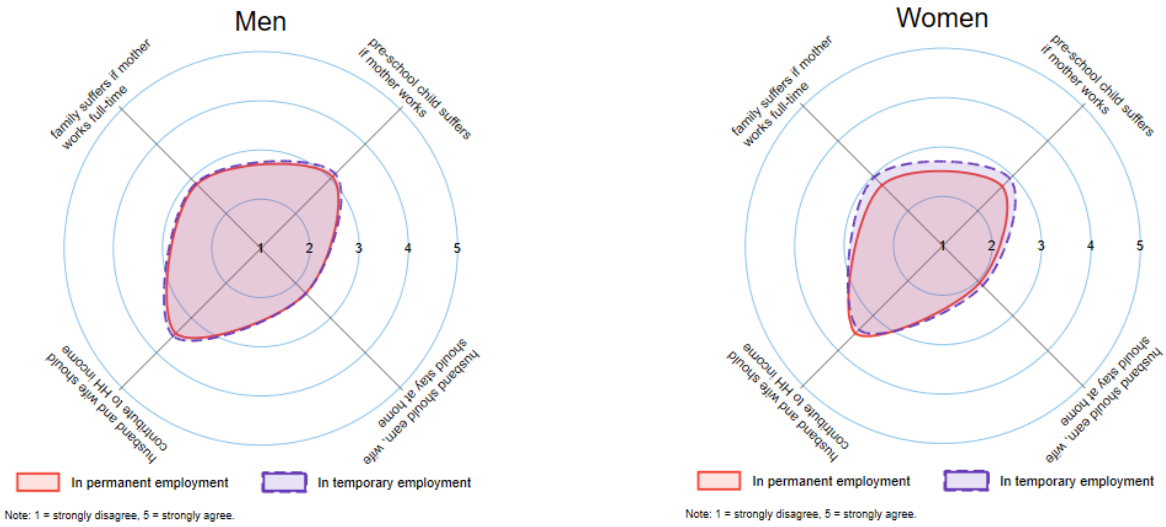

Figure 2.26: Spider plots of average responses to gender norms questions among employed individuals. *Notes:* The responses are rated on a scale from 1 (strongly disagree) to 5 (strongly agree). Solid lines represent average agreement levels for individuals in permanent employment, while dashed lines indicate responses for those in temporary employment. Data are derived from the British Household Panel Survey (1991–2009) and Understanding Society (2009–2021). The plots use cross-sectional data from these surveys, restricted to employed heterosexual couples, yielding a total sample of 941,396 individuals (94,698 couples). *Source:* Institute for Social and Economic Research (2022).

2.A.6 Uncertainty and Vacancies

I plot the total number of job vacancies using data from Adzuna (2022) from January 2017 to March 2022. While this period is relatively short, it captures two critical events characterized by heightened uncertainty: Brexit and the COVID-19 pandemic. Notably, only approximately 2% of the vacancies in the Adzuna dataset provide information on whether the position is permanent or temporary.[40] Despite this limitation, I plot the available data. Figures 2.27, 2.28, 2.29, and 2.30 reveal that during the Brexit negotiations

[40]Text analysis could potentially be used to extract information on job duration (i.e., 'permanent' or 'temporary') from the job description. However, this approach has proven challenging, as many job postings, particularly from temporary employment agencies, contain advertisements about the agencies (for instance, 'we offer both *permanent* and *temporary* positions') rather than specifying the nature of the advertised vacancy itself.

and the aftermath of the COVID-19 pandemic, the evolution of permanent and temporary employment differs across industries, suggesting that crisis-induced uncertainty may have heterogeneous effects on industries, possibly reflecting variations in how these industries respond to shocks.

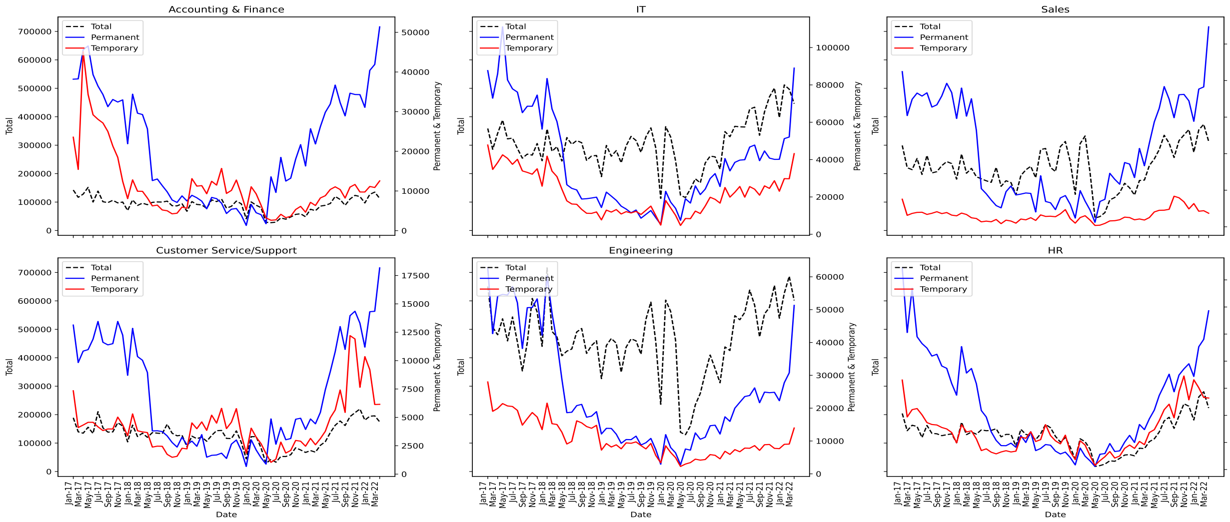

Figure 2.27: Monthly vacancies by industries in the UK, from January 2017 to March 2022. *Source:* Adzuna (2022).

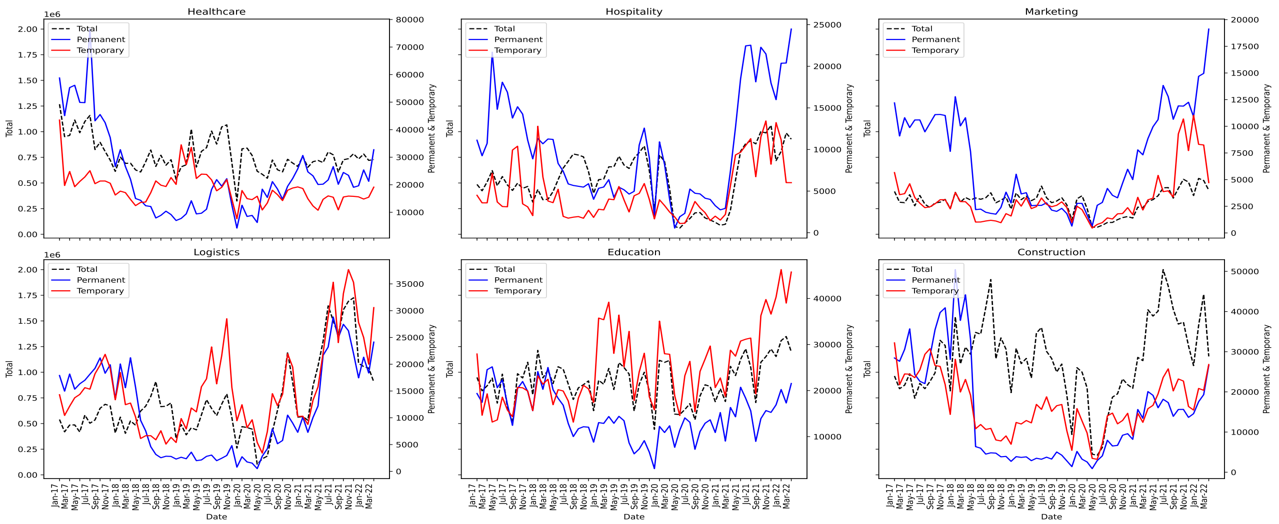

Figure 2.28: Monthly vacancies by industries in the UK, from January 2017 to March 2022, continued. *Source:* Adzuna (2022).

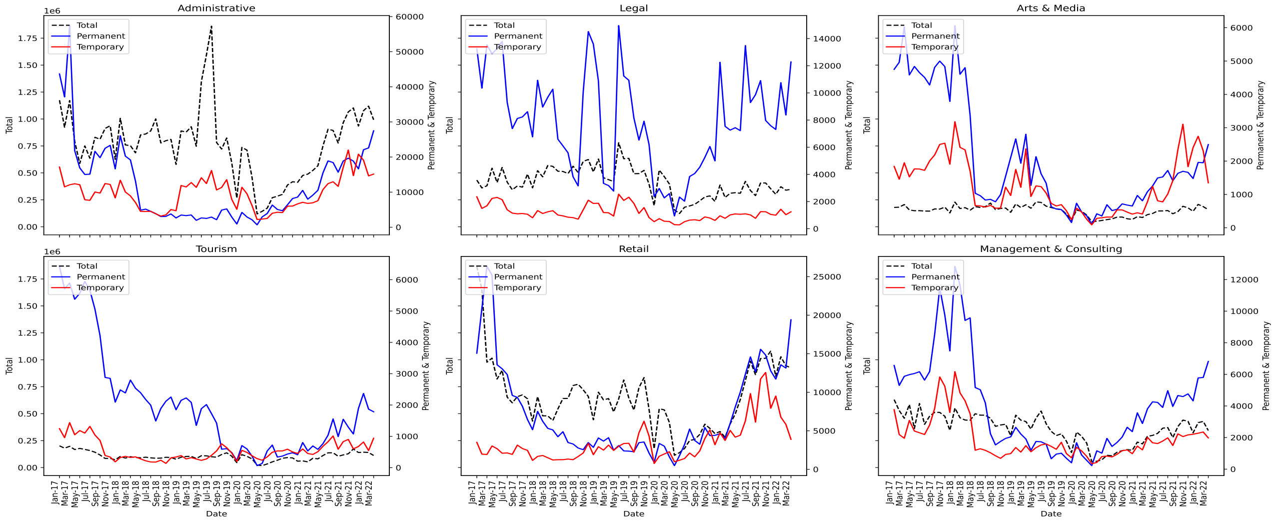

Figure 2.29: Monthly vacancies by industries in the UK, from January 2017 to March 2022, continued. *Source:* Adzuna (2022).

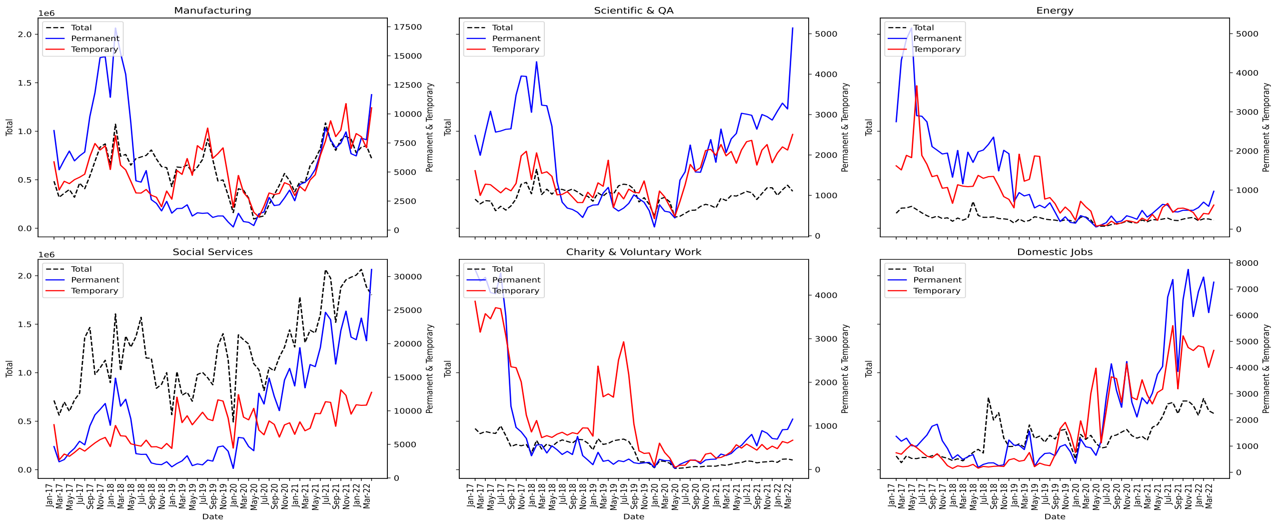

Figure 2.30: Monthly vacancies by industries in the UK, from January 2017 to March 2022, continued. *Source:* Adzuna (2022).

2.A.7 Industrial Differences in Temporary Employment

Although this chapter provides preliminary evidence that higher uncertainty is associated with a greater likelihood of temporary employment, it raises an important question: are industrial differences in temporary employment relevant for the effects of uncertainty? Table 2.9 presents the annual average share of temporary employment (to total employment) across different SIC industries. Certain industries, such as agriculture, forestry, and fishing (SIC 1), along with public administration, education, and health (SIC 8), consistently exhibit higher-than-average shares of temporary employment, while industries such as manufacturing (SIC 3) and transport and communications (SIC 6) typically maintain lower-than-average shares.

Year/SIC	1	2	3	4	5	6	7	8	9	Mean
1992	9.57	4.42	3.52	6.58	5.30	3.98	4.78	7.86	8.41	6.05
1993	7.72	3.85	3.48	7.00	4.89	4.24	5.27	7.91	9.51	5.98
1994	8.68	6.89	4.06	6.65	5.26	4.88	6.02	9.32	10.20	6.88
1995	8.12	8.20	4.47	7.07	5.12	5.37	7.01	9.54	10.13	7.23
1996	8.05	8.65	4.38	6.45	5.17	5.71	7.05	9.56	11.12	7.35
1997	8.10	9.33	4.56	6.80	5.10	5.94	7.36	9.68	10.82	7.63
1998	8.12	8.95	4.43	6.86	5.28	5.83	7.03	9.85	11.52	7.55
1999	7.69	9.24	4.55	7.21	5.37	5.90	7.06	9.95	11.14	7.68
2000	7.30	7.15	4.71	6.31	4.92	5.76	7.05	9.53	10.49	7.01
2001	7.26	7.20	4.61	5.73	4.81	5.46	7.13	9.27	10.60	6.85
2002	6.54	6.13	4.15	5.65	4.58	5.05	6.78	8.59	9.92	6.22
2003	7.41	5.48	4.25	5.07	4.49	4.87	6.62	8.31	9.53	5.93
2004	6.74	5.68	3.70	4.57	4.43	4.67	6.43	7.89	9.09	5.74
2005	6.61	5.13	3.54	4.33	4.02	4.61	6.01	7.41	8.37	5.41
2006	6.62	4.90	3.46	4.20	3.88	4.55	5.82	6.91	8.24	5.23
2007	6.61	3.86	3.36	3.35	4.01	3.80	4.75	6.97	8.40	4.75
2008	7.20	3.04	3.06	2.83	4.22	3.00	4.21	6.70	8.63	4.76
2009	6.71	4.38	3.28	2.78	4.10	4.04	4.75	6.59	8.09	4.97
2010	4.41	3.35	3.78	3.61	4.63	4.49	5.01	7.00	8.97	5.03
2011	5.90	4.50	4.32	4.55	4.44	4.18	4.93	6.82	8.92	5.40
2012	7.18	4.71	4.20	4.19	4.50	4.84	5.27	7.04	9.17	5.68
2013	5.92	4.49	4.54	3.32	4.78	4.44	5.13	6.89	8.35	5.32
2014	7.19	3.40	4.81	3.84	4.98	4.55	4.82	7.17	9.79	5.62
2015	5.04	3.43	4.21	4.32	5.23	4.22	4.66	6.89	8.94	5.22
2016	6.14	3.89	4.22	4.21	5.35	4.13	4.44	6.72	8.55	5.29
2017	5.36	3.15	3.62	3.53	4.67	4.03	4.74	6.47	8.17	4.86
2018	4.18	3.41	3.29	3.43	4.48	4.14	4.41	6.13	7.87	4.59
2019	6.59	2.77	3.51	3.10	4.43	3.83	3.81	5.84	7.50	4.60
2020	6.47	2.82	2.91	2.45	4.52	3.58	3.74	5.89	7.91	4.48
2021	5.20	2.18	3.17	2.84	4.68	4.03	4.00	6.24	6.64	4.09
2022	5.51	3.18	2.54	2.64	4.77	3.59	3.88	6.25	6.11	4.05

Table 2.9: Share of temporary employment to total employment across industries from 1992 to 2022. *Notes:* For the Standard Industrial Classification (SIC) values, 1 = agriculture, forestry, and fishing industry; 2 = energy and water; 3 = manufacturing; 4 = construction; 5 = distribution, hotels, and restaurants; 6 = transport and communication; 7 = banking and finance; 8 = public admin, education, and health; 9 = other services. The values in red (blue) denotes that the share of temporary employment is higher (lower) than the annual average across all industries. The values displayed are in percent. Source: Office of National Statistics (2024f).

The question then arises: are these industrial differences in temporary employment associated with the effects of uncertainty in the UK? It is common that countries with lower employee protection legislation (EPL) often exhibit a smaller share of temporary employment compared to those with stronger protection. According to Dibiasi and Sarferaz (2023), countries with less stringent EPL experience larger declines in output and employment following uncertainty shocks. By extension, while EPL in the UK is uniform across industries, the variation in the share of temporary employment across industries could suggest that uncertainty shocks may have varying impacts depending on the industry. Industries with a lower share of temporary employment, such as manufacturing, may be more adversely affected by uncertainty; temporary employment incurs lower adjustment costs compared to permanent employment, offering firms flexibility in adjusting labor inputs in the face of uncertainty. Consequently, in industries with fewer temporary labour, firms may face greater rigidity in response to uncertainty, exacerbating the negative effects. Given that the UK has experienced stagnant investment in recent years (Alayande & Coyle, 2023; Riley, Rincon-Aznar, & Samek, 2018), and if investment is predominantly concentrated in industries such as manufacturing—rather than industries such as public administration, education, and health—an uncertainty shock could result in a disproportionately larger decline in investment at the aggregate level. Indeed, Coyle and Mei (2023) argue that the UK's post-2008 productivity slowdown is largely attributable to the manufacturing and information and communication (ICT) industries, both of which exhibit lower-than-average shares of temporary employment. Further research is needed to explore the role of industrial differences in temporary employment in shaping the aggregate effects of uncertainty.

Chapter 3 The Impact of Uncertainty on Temporary Employment

3.1 Introduction

Temporary employment—characterized by contracts with a predetermined termination date—has become an integral feature of modern labour markets. Over the past four decades, temporary employment has spiked in OECD countries, accounting for more than 10 percent of the workforce and accompanied by a diversification of temporary employment arrangements including seasonal jobs, fixed-term contracts, agency work, apprenticeship agreements, and even self-employment schemes (Boeri & Garibaldi, 2024). In some developing countries, nearly three-quarters of wage and salaried employees are in temporary employment (International Labour Organization, 2019). The growth of digital platforms such as TaskRabbit and Upwork facilitates on-demand, short-term work arrangements across a wide range of industries (McKinsey & Company, 2022), further fueling the rise of temporary employment.

A key determinant of the prevalence of temporary employment is the strictness of employment protection legislation. High dismissal costs associated with permanent employees incentivise firms to favour temporary employees, which typically involve lower firing costs and greater operational flexibility. Therefore, firms may use temporary employment to reduce overall labour costs (Boeri & Garibaldi, 2024; Golden & Appelbaum, 1992) and increase labor input flexibility for demand fluctuations (Benito & Hernando, 2008; Devicienti, Naticchioni, & Ricci, 2018; Ono & Sullivan, 2013). These motives may become particularly relevant during periods of heightened uncertainty: when firms face volatile demand and challenges in accurately forecasting demand, the high firing costs of permanent employees can make it risky to commit to employees on permanent contracts, as workforce adjustments become costly if market conditions deteriorate. Instead, temporary employment may become a more attractive alternative as it enables firms to adjust labour inputs more frequently and at a lower cost.

While the adverse impacts of uncertainty on aggregate employment and investment are well documented (see, for example, Arellano, Bai, & Kehoe, 2019; Berger, Dew-Becker, & Giglio, 2020; Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018), the role of uncertainty in shaping *labour composition*—in particular, the prevalence of temporary employment—remains underexplored. Existing studies focusing on total employment may mask interesting and potentially distinct dynamics of permanent and temporary employment in response to uncertainty. Temporary employment may exhibit greater elasticity to fluctuations in uncertainty, while permanent employment adjustments are more constrained by stricter labour regulations and higher dismissal costs. Consequently, during an uncertainty shock, even if total employment falls, the decline in temporary employment is likely to exceed that of permanent employment. As uncertainty recedes, firms may remain cautious in their hiring decisions, favouring temporary contracts over permanent ones as the higher adjustment costs of permanent employment make hiring or firing mistakes more costly. Exploring these dynamics provides insights into how firms adapt workforce composition under uncertainty. This chapter provides answers to a basic question: does uncertainty affect the prevalence of temporary employment? By exploring this question, this chapter highlights a new channel of how uncertainty affects the economy, specifically through the labour market.

This chapter provides novel empirical evidence of the relationship between uncertainty and the size of temporary employment by estimating a Bayesian Vector Autoregressive (VAR) model for the UK. The UK is an interesting context to explore because, like any other countries, it is affected by global events such as the Great Financial Crisis and COVID-19, but it also uniquely suffers exceptionally high uncertainty during the Brexit negotiations (Bank of England, 2019). In the meantime, the UK's reliance on temporary employment has also been consistent.[1] In the VAR model, I treat uncertainty as an exogenous source of business cycle fluctuations, in line with, for example, Carriero, Marcellino, and Tornese (2023) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019). I use the macroeconomic uncertainty measures developed by Dibiasi and Sarferaz (2023): these measures are derived by first decomposing GDP growth revisions into two parts—a noise component, which captures the portion of the forecast error orthogonal to the true value, and a news component, which reflects the portion of the forecast error that provides information about the true value. Dibiasi and Sarferaz (2023) estimate changes in the variance of the news component in GDP growth revisions using the econometric framework introduced by Jurado, Ludvigson, and Ng (2015) to construct the macroeconomic uncertainty measures. Impulse response functions of the VAR show that a one-standard-deviation increase in macroeconomic uncertainty results in a peak increase of approximately 0.5% in temporary employment—defined as the number of employees with temporary contracts—slightly after 8 quarters following the shock. Although the value appears small, uncertainty 4 standard deviations above its mean—a scenario observed in practice during crises in the UK such as the Great Recession and the COVID-19 pandemic—corresponds to an approximately 2% rise in temporary employment. This result highlights how major economic crises may trigger sizable increase in temporary employment. The VAR analysis also shows that following a macroeconomic uncertainty shock, the share of temporary employees who take up temporary employment in the first place because they fail to find permanent employment increases, while the share of temporary employees who do *not* want permanent employment decreases, potentially suggesting that firms respond to heightened uncertainty by reducing their demand for permanent employees, rather than households becoming more willing to accept temporary employment.

A battery of robustness checks confirm the baseline results. In particular, robustness checks demonstrate that, although confidence and uncertainty are closely linked in certain theoretical models (Baker, Bloom, & Davis, 2016; Ilut & Schneider, 2014), the observed increase in temporary employment may not driven by economic agents' perceptions of adverse economic conditions (since uncertainty rises in recessions and falls in booms). In other words, the association between macroeconomic uncertainty and temporary employment appears distinct from variations linked to changes in consumer confidence.

[1] Temporary employment in the UK is elaborated further in the previous chapter.

The baseline results also remain consistent across alternative VAR specifications, different measures of uncertainty, and the inclusion of additional controls. Meanwhile, the baseline results also raise important questions, particularly regarding productivity. For example, is the rise in temporary employment following a uncertainty shock associated with productivity implications? Additionally, does overall uncertainty in the economy correspond to heightened uncertainty in labour productivity, thereby amplifying its association with temporary employment? Incorporating labour productivity into the VAR analysis reveals that the uncertainty-driven increase in temporary employment does not exacerbate the decline in labour productivity, suggesting the negative association between temporary workers and productivity reported in the literature (see, among others, Autor, Kerr, & Kugler, 2007; Cappellari, Dell'Aringa, & Leonardi, 2012) may not be attributable to the lower productivity of temporary workers themselves, but rather to the confounding effects of uncertainty, which simultaneously drives both the decline in productivity and the increase in temporary employment. Furthermore, when accounting for specifically uncertainty in labour productivity, the increase in temporary employment remains statistically significant for a longer duration following a macroeconomic uncertainty shock; this finding indicates that uncertainty in labour productivity may serve as an additional channel through which macroeconomic uncertainty drives increases in temporary employment.

To account for the empirical results, I proceed with a partial equilibrium model which singles out the role of uncertainty in shaping labour composition. Specifically, I augment the firm's problem as in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), with two types of labour—permanent and temporary. In the UK, the classification of permanent and temporary labour is based on contract duration, with temporary labour generally employed on contracts lasting less than a year. However, in the model, contract duration is not explicitly incorporated; instead, the distinction is conceptualized through a trade-off between adjustment costs and destruction rates: permanent labour is characterized by higher adjustment costs but lower destruction rates (analogous to longer contract duration), while temporary labour features lower adjustment costs but higher destruction rates (similar to shorter contract duration). Although this abstraction is not ideal as it omits contract duration, it offers a simplified representation of real-world dynamics for the purposes of the analysis. Wages and productivity are assumed to be identical for both labour types, ensuring the focus remains on the trade-off between adjustment costs and destruction rates. Firms face exogenous processes for aggregate and idiosyncratic productivity, with innovations that vary over time. To manage the high dimensionality of the state space, the model abstracts from capital. Most of the parameter values are taken directly from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The lack of UK-specific estimates for adjustment costs, wages and productivity of both permanent and temporary labour necessitates the calibration of these parameters. I also adopt a simulated method of moments (SMM) estimation procedure to obtain the values for parameters governing the uncertainty process, which has not been previously estimated for the UK in the literature.

By examining the distribution of firms by their productivity-to-permanent labour and productivity-to-temporary labour ratios after the idiosyncratic and aggregate productivity shocks have been drawn but before firms have adjusted, the analysis finds that heightened uncertainty induces a leftward shift in the firing threshold and a rightward shift in the hiring threshold; this dual shift expands the range of inaction, irrespective of the type of labour. The mechanism driving this result stems from the presence of labour adjustment costs, which renders any errors in hiring or firing decisions prohibitively expensive. Consequently, firms exercise greater prudence in their labour-related choices. Simulations of the model further show that uncertainty shocks lead to a decline in the aggregate share of temporary labour (temporary labour as a proportion of total labour) by approximately 2% on impact. While both permanent and temporary labour decrease, the reduction in temporary labour is more pronounced. This is attributed to temporary labour's higher attrition rate as well as lower adjustment costs, making it less costly and less "irreversible" for firms to dismiss temporary labour compared to permanent ones. Following the initial decline, the share of temporary labour experiences a rebound and overshoot during the recovery phase. As firms gradually recover from the uncertainty shock, they resume hiring but disproportionately increase their reliance on temporary labour. Although the rebound and overshoot is a feature of the partial equilibrium framework where the lack of price adjustments leads to exaggerated dynamics, more realistic simulations that combine uncertainty shocks with negative first-moment shocks (as Chapter 1 shows recessions are often characterized by both types of shocks) mitigate but do not eliminate the overshoot in the share of temporary labour during the recovery. This suggests that firms become more cautious in the aftermath of heightened uncertainty and react by favouring temporary labour over permanent labour, as the higher adjustment costs incurred by permanent labour makes hiring or firing mistakes of permanent labour costlier than that of temporary labour. These findings highlight the strategic value of labour flexibility during uncertain times.

Sensitivity analysis confirms that the results are robust to variations in labour destruction rates and alternative parameterizations of the uncertainty process. The analysis further highlights the distinct roles of adjustment costs: while fixed adjustment costs primarily drive the initial impact of uncertainty shocks, linear adjustment costs are critical in shaping firms' responses during the recovery phase, particularly in the dynamics of the share of temporary labour. Introducing a wage penalty and productivity difference between permanent and temporary labour—arguably a more realistic representation of labour market conditions—preserves the baseline dynamics of the share of temporary labour. Policy experiments reveal that wage subsidies targeted exclusively at permanent labour are more effective than blanket subsidies for both types of labour in reducing the share of temporary labour during uncertainty shocks, as such targeted policies increase the relative attractiveness of permanent labour, the less "irreversible" input.

This chapter contributes to the literature on investment under uncertainty—or to be precise, hiring under uncertainty. The *real option* channel posits that uncertainty expands the inaction range between hiring and firing, as firms face (partially) irreversible and non-convex adjustment costs, leading to a reduction in hiring (see Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Guglielminetti, 2016; Kandoussi & Langot, 2022; Lin, 2018; Pries, 2016; Riegler, 2014). This chapter extends this literature by examining how uncertainty differentially affects permanent versus temporary employment, recognizing that the two types of labour involve distinct adjustment costs. Studies specifically addressing the effects of uncertainty on the prevalence of temporary employment remain relatively scarce, with notable exceptions being Lotti and Viviano (2012) and Cao, Shao, and Silos (2021). This chapter distinguishes itself from these studies in terms of granularity, country of focus, and empirical methodology. In particular, it provides novel VAR evidence on the relationship between uncertainty and temporary employment. This chapter also explores the dynamics of the share of temporary employment over the business cycle by using a simple model capturing the trade-off between labour adjustment costs and separation rates as the primary mechanism through which uncertainty impacts labour composition, bypassing reliance on match quality and job promotions which are the common consideration in the literature.

The structure of this chapter is as follows. Section 3.2 provides a review of the literature on uncertainty and its relationship with temporary employment. Section 3.3 introduces the Bayesian VAR analysis used to examine the relationship between uncertainty and temporary employment. Section 3.4 outlines the partial equilibrium model, detailing the calibration and estimation of parameters governing the uncertainty process. Section 3.5 studies the effects of uncertainty shocks on the aggregate share of temporary labour. Section 3.6 presents robustness checks to validate the findings from Section 3.5. Section 3.7 examines the effectiveness of wage subsidies in reducing the share of temporary labour during periods of heightened uncertainty. Section 3.8 discusses the limitations of the analysis. Finally, Section 3.9 concludes.

3.2 Literature Review

In this section, I review the literature on the impacts of uncertainty on the labour market.

3.2.1 Uncertainty and Labour Market Fluctuations

This chapter relates most obviously to the extant literature on investment under uncertainty[2]—or to be precise, hiring under uncertainty. The *real option* channel posits that uncertainty expands the inaction range between hiring and firing, as firms face (partially) irreversible and non-convex adjustment costs, leading to a reduction in hiring (see Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018; Guglielminetti, 2016; Kandoussi & Langot, 2022; Lin, 2018; Pries, 2016; Riegler, 2014). The *aggregate demand* channel suggests that heightened uncertainty prompts households to reduce consumption

[2] Earlier work dating at least to Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1994), and Abel, Dixit, Eberly, and Pindyck (1996) collectively emphasize the idea that uncertainty incentivizes firms to postpone investment when such decisions are costly to reverse. Recent work on investment under uncertainty includes Bloom, Van Reenen, and Bond (2007), Bloom (2009), Gilchrist, Sim, and Zakrajšek (2014), Bachmann and Bayer (2013), and Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011).

and increase precautionary savings, which in turn depresses demand (Basu & Bundick, 2017), leading to higher job separation rates and lower job finding rates (see Ravn & Sterk, 2017). The *reallocation* channel proposes that increased uncertainty intensifies the reallocation process due to the higher likelihood of extreme returns, resulting in a net increase in unemployment as firings and quits outpace hirings (see Schaal, 2017). The *financial constraints* channel posits that during high uncertainty, firms increase liquidity buffers by downscaling operations, which lowers job creation and raises job destruction (see Mecikovsky & Meier, 2019). Jo and Lee (2019), using a comprehensive set of worker flow and stock indicators within a stochastic volatility-in-mean framework that allows simultaneous estimation of historical uncertainty and its impacts, validate the significance of the real option channel while also highlighting the influence of other channels in shaping the labour market's response to uncertainty shocks.

Research on the effects of uncertainty on the labour market frequently employs various adaptations of search-and-matching models, with continuous advancements. For example, Leduc and Liu (2016) highlight the interactions between the real option channel—via search frictions—and the aggregate demand channel—made possible by nominal rigidities—for the transmission of uncertainty shocks in raising unemployment, while Den Haan, Freund, and Rendahl (2021) reinforce this real option channel by eliminating the free-entry condition and introducing heterogeneity in firm productivity in the standard search-and matching model. While these developments are both significant and promising, the literature is now witnessing the emergence of innovative methodologies that address previously overlooked aspects of uncertainty research. For instance, Bamieh, Coviello, Ichino, and Persico (2023) exploit quasi-experimental variation in uncertainty generated by litigation, which is rare in the uncertainty literature, to demonstrate the negative causal impact of uncertainty on hiring. Additionally, Dibiasi and Sarferaz (2023) provide novel measures for Switzerland's labour adjustment costs—a critical component of the real option channel—addressing a notable gap in the literature, as these costs have been largely unexplored outside the U.S. context. Furthermore, Song, Zor, Chen, Yan, and Li (2024) construct firm-level economic policy uncertainty measures through text analysis, following the methodology of Baker, Bloom, and Davis (2016), and find that uncertainty significantly reduces executive compensation while leaving ordinary employees' wages unaffected, thereby reducing within-firm wage inequality.

There is also a growing body of literature focusing on the heterogeneous impacts of uncertainty on the labour market. Martínez Matute and Urtasun (2018) combine variability from country, sector and size at the firm level to disaggregate microeconomic uncertainty and find significant labour market responses in firms facing credit constraints and in countries with stricter employment protection laws. Choi, Furceri, and Yoo (2024) also find that the adverse employment effects of uncertainty are amplified in countries with rigid employment protection or industries characterized by higher natural layoff rates. Shoag and Veuger (2016) leverage preexisting state institutions that heighten uncertainty to provide causal evidence that local uncertainty increases unemployment. More recently, Belianska (2023) demonstrate that unskilled workers experience a steeper decline in employment during periods of heightened uncertainty. These studies underscore the heterogeneous impacts of uncertainty on the labour market; this chapter contributes to this literature by examining how uncertainty differentially affects permanent versus temporary employment.

3.2.2 Uncertainty and Labour Contracts

Uncertainty affects various aspects of labour contracts. The literature on this subject begins with the foundational work of Gray (1978), who develops a theoretical framework showing that economic uncertainty increases the likelihood of unforeseen contingencies, thereby shortening contract length. Contrasting this view, Danziger (1988) propose that heightened aggregate real uncertainty enhances the value of the protection offered to workers within a contract, leading to longer contract duration. More recent empirical studies provide mixed evidence on these theoretical propositions: Murphy (2000), using a generalized-probit, simultaneous equation model, supports Danziger (1988)'s hypothesis, showing that real uncertainty can indeed be associated with longer contracts. However, Rich and Tracy (2004), through a structural VAR analysis, find that both nominal and real uncertainty tend to shorten desired contract duration.[3] In a different context, Guthrie (1998) provides evidence from China that organizations facing uncertainty are more

[3]The distinction between nominal uncertainty (uncertainty regarding the nominal values in the economy) and real uncertainty (uncertainty about real economic factors, such as productivity) appears important. Danziger and Neuman (2005) find that nominal uncertainty increases the delay in renewal of labour contracts, while real uncertainty decreases the delay.

inclined to institutionalize labour contracts, moving away from the traditional lifetime employment model that was a hallmark of the socialist system.

A related and emerging subset of literature examines the impact of uncertainty on contract types, specifically differentiating between contracts with a specific end date (temporary employment) and those without (permanent employment). Holmlund and Storrie (2002) suggests that adverse macroeconomic conditions in Sweden lead firms to favor temporary contracts, with employees increasingly willing to accept them, although the study does not explicitly address the role of uncertainty. Theophilopoulou (2022), in her exploration of the relationship between uncertainty and inequality, briefly raises the possibility that heightened uncertainty may drive firms to prefer temporary over permanent contracts. More recently, Bloom, Davis, Foster, Ohlmacher, and Saporta-Eksten (2022) provide empirical evidence from a US survey of subjective uncertainty, showing that businesses under high uncertainty tend to shift from less flexible to more flexible factor inputs, including labour. This chapter aligns with this specific literature on the impact of uncertainty on labour contract type.

The two most closely related papers to this chapter are Lotti and Viviano (2012) and Cao, Shao, and Silos (2021). Lotti and Viviano (2012) utilize data from the Bank of Italy's annual survey on industrial and non-financial service firms, which collects firms' reported upper and lower bounds of expected demand. These bounds serve as a proxy for uncertainty in their panel regressions. Their analysis reveals a decline in overall labour demand alongside an increase in the share of temporary workers within the workforce when uncertainty increases. The authors also leverage an exogenous policy change in which the national government significantly reduced social contributions for firms hiring permanent workers aged 25 and older to establish causality between temporary employment and productivity. This chapter differs from Lotti and Viviano (2012) in terms of granularity, country of focus, and empirical methodology. Specifically, this chapter uses aggregate data within a simple Bayesian VAR model to provide macroeconomic evidence of the effects of uncertainty on temporary employment. The focus on the UK is particularly interesting given its relatively low employee protection legislation compared to Italy; despite lower levels of employment protection and a smaller share of temporary employment, the analysis still demonstrates that uncertainty increases temporary employment. In addition, this paper also jointly considers macroeconomic and microeconomic uncertainty rather than focusing on firm-specific uncertainty only.

On the other hand, Cao, Shao, and Silos (2021) develop a search and matching model à la Mortensen and Pissarides (1994) that incorporates match quality and allows for promotions, endogenous separations, and job-to-job transitions to explore how uncertainty affects the aggregate fraction of temporary and permanent employment in Canada. The core insight of their model is that uncertainty increases temporary employment when match quality drives contract choice: firms are inclined to offer permanent contracts to high-quality labour to avoid losing a valuable match, while offering temporary contracts to lower-quality labour. Under heightened uncertainty, where outcome dispersion is greater, low-quality matches benefit more from increased upside risk, whereas high-quality matches are more adversely impacted by increased downside risk. As a result, greater uncertainty enhances the attractiveness of temporary jobs while diminishing the appeal of permanent positions, leading to a higher proportion of temporary job offers. This chapter differs from Cao, Shao, and Silos (2021) in several key respects. Particularly, this chapter explores the labour market dynamics over the business cycle—an aspect not addressed by Cao, Shao, and Silos (2021). The partial equilibrium model used here, drawing heavily from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), is intentionally simpler; it emphasizes the trade-off between labour adjustment costs and separation rates as the primary mechanism through which uncertainty impacts labour composition, bypassing reliance on match quality and job promotions. Additionally, while Cao, Shao, and Silos (2021)'s analysis centers on the shift in aggregate uncertainty following the 2008 Financial Crisis, this chapter uses more recent data encompassing both the 2008 Financial Crisis and the COVID-19 pandemic. Another small difference is that while Cao, Shao, and Silos (2021) use variables aggregating the forces of both demand and supply in the labour market, this chapter attempts to isolate the effects of uncertainty on labour demand and labour supply. While imperfect, the empirical evidence presented in this chapter shows that the share of temporary employees who do *not* want permanent employment decreases after an uncertainty shock, potentially hinting at households' resistance towards temporary employment in heightened uncertainty.

3.3 Bayesian VAR analysis

In this section, I estimate a Bayesian Vector Autoregressive (VAR) model to explore the relationship between macroeconomic uncertainty and temporary employment.

3.3.1 Choice of Uncertainty Measure

In economics, uncertainty is typically characterized by the stochastic volatility of aggregate shocks, such as those arising from technological changes (Castelnuovo, 2023). Aggregate variables are assumed to follow a stochastic process, with random innovations drawn from a distribution with a mean of zero and a time-varying variance. An increase in this time-varying variance signals a rise in uncertainty.

In line with this definition, Dibiasi and Sarferaz (2023) compute quarterly macroeconomic uncertainty measures by defining macroeconomic uncertainty as the conditional volatility of an unpredictable forecast. Specifically, Dibiasi and Sarferaz (2023) consider the initial releases of real GDP from statistical agencies (the Office of National Statistics for the UK) as a forecast of the final release of real GDP. Similar to Jacobs and Van Norden (2011), Dibiasi and Sarferaz (2023) define the estimate published at period $t+j$ for period t's real GDP, y_t^{t+j}, or the updated version of y_t based on new information available at period $t+j$, as

$$y_t^{t+j} = \tilde{y}_t + \nu_t^{t+j} + \vartheta_t^{t+j}, \tag{3.1}$$

where $t = 1, ..., T$ and $j = 1, ..., L$. Dibiasi and Sarferaz (2023) set $L = 12$. Here, y_t^{t+j} is decomposed into the true value $\tilde{y}_t$, a news component ν_t^{t+j}, and a noise component ϑ_t^{t+j}. Drawing from the data revisions literature, the noise component is interpreted as the portion of the forecast error that is independent of the true value, while the news component represents the part of the forecast error that contains information about the true value. Dibiasi and Sarferaz (2023) obtain estimates of macroeconomic uncertainty by estimating changes in the variance of the news component in GDP growth revisions. In their econometrics framework, they introduce time-varying variance into the state-space model in Jacobs and Van Norden (2011):

$$Y_t = Z_{\alpha_t},$$

$$\alpha_t = \varphi_t + T_t\alpha_{t-1} + R_t\eta_t, \tag{3.2}$$

$$\text{with: } Y_t = \begin{bmatrix} y_t^{t+1} \\ y_t^{t+L} \end{bmatrix}, Z = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \end{bmatrix}, \alpha_t = \begin{bmatrix} \tilde{y}_t \\ \nu_t^{t+1} \\ \nu_t^{t+L} \\ \vartheta_t^{t+1} \\ \vartheta_t^{t+L} \end{bmatrix}, \varphi_t = \begin{bmatrix} c_t \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, T_t = \begin{bmatrix} \rho_t & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$R_t = \begin{bmatrix} \sigma_t^{\nu 1} & \sigma_t^{\nu L} & 0 & 0 \\ 0 & -\sigma_t^{\nu 1} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_t^{\vartheta 1} & 0 \\ 0 & 0 & 0 & \sigma_t^{\vartheta L} \end{bmatrix}, \text{and } \eta_t = \begin{bmatrix} \eta_t^{\nu 1} \\ \eta_t^{\nu L} \\ \eta_t^{\vartheta 1} \\ \eta_t^{\vartheta L} \end{bmatrix},$$

where c_t and ρ_t are time-varying coefficients[4] and σ_t^i time-varying standard deviation of η_t^i for $i = \nu 1, \nu L, \vartheta 1, \vartheta L$. Given the econometrics framework and following the definition in Jurado, Ludvigson, and Ng (2015), Dibiasi and Sarferaz (2023) define macroeconomic uncertainty at period t, given releases of GDP growth data $Y^T = \begin{bmatrix} Y_1' & Y_2' & \dots & Y_T' \end{bmatrix}'$ as:

$$U_t \equiv \sqrt{E\left[(\tilde{y}_t - E[\tilde{y}_t \mid Y^T])^2 \mid Y^T\right]} = \sqrt{(\sigma_t^{\nu 1})^2 + (\sigma_t^{\nu L})^2}, \tag{3.3}$$

which is the square root of the sum of variances of two rational forecast errors.[5] It is

[4]Dibiasi and Sarferaz (2023) include time-varying coefficients to capture structural change, although they mention that removal of these parameters changes the uncertainty measures only marginally.

[5]The forecastable component of $E[\tilde{y}_t \mid Y^T]$ must be removed to ensure that only unforecastable variations are categorized as uncertainty (Dibiasi & Sarferaz, 2023; Jurado, Ludvigson, & Ng, 2015).

important to note that this is not a real-time measure of uncertainty; it incorporates future information to estimate macroeconomic uncertainty present at period t. For further details on the priors and the Gibbs sampling procedure used to estimate the model's parameters, readers are referred to Dibiasi and Sarferaz (2023).

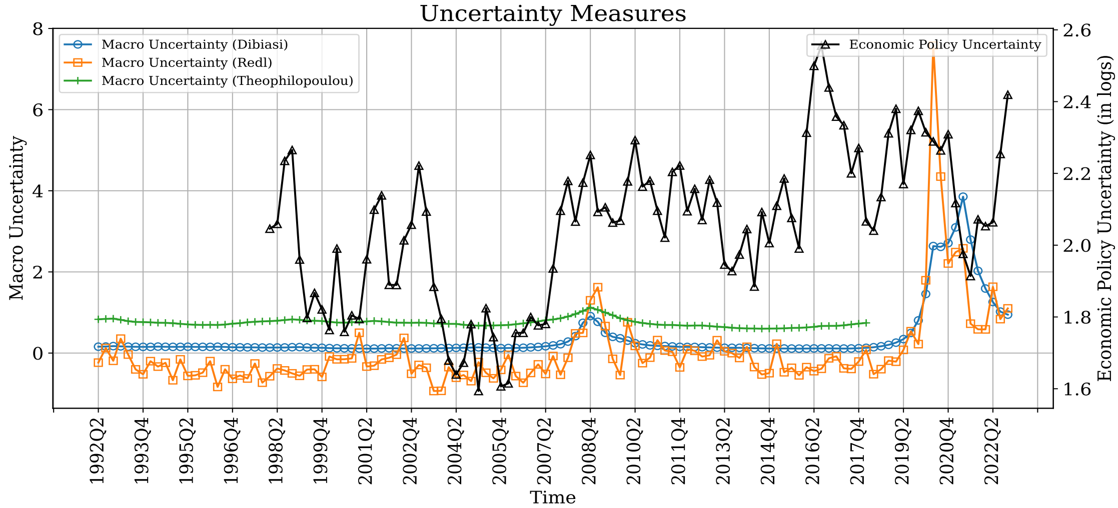

Figure 3.1: Uncertainty measures for the UK from 1992 to 2022. The left vertical axis displays three macroeconomic uncertainty measures: one by Dibiasi and Sarferaz (2023) (plotted with a hollow circle symbol), another by Redl (2020) (plotted with a hollow square symbol), and the third by Theophilopoulou (2022) (plotted with a plus symbol). The right vertical axis presents the Economic Policy Uncertainty (EPU) index, in logarithmic scale, as developed by Baker, Bloom, and Davis (2016) (plotted with a hollow triangle symbol). Note that the measure by Theophilopoulou (2022) is available only until 2018Q1 while the measure by Baker, Bloom, and Davis (2016) is available only since 1998. The uncertainty measures by Redl (2020) and Baker, Bloom, and Davis (2016) are originally monthly data, converted into quarterly averages. Figure 3.20 in the Appendix plots these uncertainty measures over the period from 1992 to pre-COVID-19 times.

Figure 3.1 compares the UK macroeconomic uncertainty measure developed by Dibiasi and Sarferaz (2023) with those constructed by Theophilopoulou (2022), Redl (2020), and the Economic Policy Uncertainty (EPU) index by Baker, Bloom, and Davis (2016). Notably, the measure by Dibiasi and Sarferaz (2023) closely resembles that of Theophilopoulou (2022), as both are based on the uncertainty framework proposed by Jurado, Ludvigson, and Ng (2015); the key distinction lies in the scope of data: while Dibiasi and Sarferaz (2023) focuses on real GDP, Theophilopoulou (2022) uses a comprehensive dataset of macroeconomic and financial variables.[6] Similar to other uncertainty measures, Dibiasi and Sarferaz (2023)'s measure shows an increase during the 2008 Financial Crisis, with an even more pronounced spike during the COVID-19 pandemic.

[6]Similar to Theophilopoulou (2022), the macroeconomic uncertainty measure for the UK developed by Redl (2020) also employs the uncertainty framework introduced by Jurado, Ludvigson, and Ng (2015). However, Redl (2020)'s approach differs in two aspects: the dataset used is slightly different, and the measure is constructed at a monthly frequency rather than quarterly.

While the macroeconomic uncertainty measure developed by Dibiasi and Sarferaz (2023), as seen in Figure 3.1, exhibits an anticipated increase during periods commonly associated with heightened uncertainty, readers at this point may question the measure's validity. The measure's validity hinges on the assumption articulated by Aruoba (2008): that the initial release of real GDP serves as an efficient forecast, reflecting all available information at the time, while subsequent revisions refine this forecast by incorporating new data. According to this assumption, revisions are correlated with the final value but are uncorrelated with the information available at the time of the initial release, making them unpredictable based on the initial information set. The description of the GDP publication process in the UK up to 2018 detailed by Scruton, O'Donnell, and Dey-Chowdhury (2018) supports the interpretation by Dibiasi and Sarferaz (2023) that the first GDP release can be viewed as a forecast by statistical agencies of the final true GDP.[7] They describe that the ONS publishes three GDP estimates per quarter: the first estimate is released 25 days after the end of the quarter and is based solely on output data, which represents approximately 45% of the final data content. This estimate relies on forecasts for the final month of the quarter, which often has less data available compared to the preceding months. Approximately two months after the quarter ends, the ONS releases the second estimate of GDP, which incorporates data on income and expenditure, raising the data content to about 65%. The final estimate is published roughly 85 days after the quarter's end and includes approximately 90% of the overall data content. Therefore, it appears that the GDP publication process by the ONS aligns with the assumption about the news component in the macroeconomic uncertainty measures by Dibiasi and Sarferaz (2023).

The macroeconomic uncertainty measure developed by Dibiasi and Sarferaz (2023) offers distinct advantages over other uncertainty methodologies. Indicators measuring implied volatility in stock market returns, such as the VXO index, might reflect shifts in market sentiment more than underlying economic fundamentals (Jurado, Ludvigson, & Ng, 2015; Nowzohour & Stracca, 2020). In contrast to the method of Jurado, Ludvigson, and Ng (2015) in deriving econometric estimates of uncertainty using a comprehensive array of macroeconomic variables and global indicators, Dibiasi and Sarferaz (2023) partially outsource the information acquisition to the statistical agency. Although the

[7]Since July 2018, the ONS publishes two rather than three releases of real GDP per quarter (Scruton, O'Donnell, & Dey-Chowdhury, 2018).

macroeconomic uncertainty measure by Dibiasi and Sarferaz (2023) centers primarily on real GDP growth, statistical agencies integrate a plethora of sensitive data— information accessible only to statistical agencies— to construct coherent macroeconomic variables (Dibiasi & Sarferaz, 2023). The macroeconomic uncertainty measure by Dibiasi and Sarferaz (2023) also serves as a complement to the uncertainty indicators derived from textual data (Ahir, Bloom, & Furceri, 2022; Baker, Bloom, & Davis, 2016); while the latter excels in providing timely assessments of uncertainty levels through text analysis, the former distinguishes itself by evaluating uncertainty based on prediction accuracy, offering a complementary perspective rooted in forecast precision. Therefore, I use the macroeconomic uncertainty measure for the UK developed by Dibiasi and Sarferaz (2023) for the Bayesian VAR analysis in the next section.

3.3.2 Baseline Bayesian VAR

To examine how temporary employment responds to macroeconomic uncertainty shocks, I use a VAR model. The baseline model is defined as:

$$X_t = c + \sum_{j=1}^{p} B_j X_{t-j} + \upsilon_t \tag{3.4}$$

where X_t represents a vector of endogenous variables at time t, c a vector of constants accounting for the deterministic component of the variables, B_j a coefficient matrix corresponding to the j-th lag, and υ_t a vector of error terms at time t, with $\upsilon_t \sim N(0, \Omega)$. The endogenous variables includes macroeconomic uncertainty, industrial production, total employment, and temporary employment in the UK.[8] The data used in the analysis are at a quarterly frequency, spanning the period 1992Q2-2022Q4. All variables except the macroeconomic uncertainty measure are expressed in logs. The baseline VAR model also contains a constant c. The lag length p is set to 4, which is standard in the literature.[9] All variables enter in levels, since differencing or filtering the data removes information about the long-run properties of the data (Lütkepohl, 2013).

[8]Total (Temporary) employment is measured as the number of (temporary) employees in the economy. The Appendix contains further description of all the variables used in the Bayesian VAR model.

[9]Research using quarterly data and VAR models in the uncertainty literature commonly set lag length to 4. Examples include Bloom (2009), Jurado, Ludvigson, and Ng (2015), and Theophilopoulou (2022).

	Observation	Mean	SD	Min	Max
Macroeconomic Uncertainty	123	0.376	0.667	0.109	3.855
Industrial Production (log)	123	2.007	0.040	1.909	2.079
Total Employment (log)	123	7.463	0.035	7.403	7.518
Temporary Employment (log)	123	6.195	0.031	6.104	6.253

Table 3.1: Summary statistics of the variables used in the baseline Bayesian VAR. The data are at a quarterly frequency and covers the period from 1992Q2 to 2022Q4. The macroeconomic uncertainty measures are developed by Dibiasi and Sarferaz (2023). Total (Temporary) employment is measured as the number of (temporary) employees in the economy. The Appendix contains further description of the variables.

I adopt a Bayesian approach to estimation because it is more robust in the presence of highly persistent variables (Sims, Stock, & Watson, 1990), computationally simple (Uhlig, 2005), and offers a convenient method to construct error bands for impulse responses (Sims & Zha, 1999).[10] The model assumes a Minnesota prior since it is straightforward to implement with a small number of hyper-parameters that control the degree of shrinkage.[11]

The covariance matrix of the residuals Ω can be expressed as $\Omega = A_0 A_0'$ where A_0 captures the contemporaneous effect of the structural shocks ε_t :

$$\upsilon_t = A_0 \varepsilon_t. \tag{3.5}$$

I use the Cholesky decomposition to calculate the A_0 matrix, or in other words, to identify uncertainty shocks. Macroeconomic uncertainty is ordered first, implying that macroeconomic uncertainty does not react contemporaneously to other variables in the VAR model. The Cholesky identification strategy here is similar to many research in the uncertainty literature, including Bloom (2009), Leduc and Liu (2016), and Basu and Bundick (2017).

Figure 3.2 plots the impulse responses of the baseline VAR model. For each variable, the black solid line denotes the median responses of the variable to an one-standard-deviation shock in macroeconomic uncertainty, while the darker and lighter shaded areas around the

[10]The Appendix presents frequentist estimates of the baseline model. The results remain robust.

[11]The Appendix contains further information on the Minnesota prior. As a robustness check, I also use a flat prior to get data driven results. The results remain unchanged.

solid line represent respectively the 68-percent and 90-percent bootstrapped confidence intervals for the estimated median impulse responses. The figure shows that the responses of industrial production and total employment to a one-standard-deviation uncertainty shock are statistically significant and small on impact (approximately 0.3% and 0.05% respectively). A macroeconomic uncertainty shock corresponds to an immediate decline in industrial production and total employment, with the decrease more persistent in total employment. Note that, despite employing a rather straightforward identification strategy,[12] the observed response in industrial production aligns qualitatively with findings from other studies employing more sophisticated VAR models. Specifically, decline in industrial production has been reported in a VAR with shocks identified with volatility breaks in Angelini, Bacchiocchi, Caggiano, and Fanelli (2019), in a VAR with shocks identified with penalty function in Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016), in a panel VAR with shocks identified with Cholesky decomposition in Baker, Bloom, and Davis (2016), in a VAR *ala* Jurado, Ludvigson, and Ng (2015) with 120 lags in Carriero, Marcellino, and Tornese (2023), in a VAR with shocks identified with event restrictions in Ludvigson, Ma, and Ng (2021), and in a large VAR with shocks identified through common component of time-varying volatilities in Carriero, Clark, and Marcellino (2018). The observed decline in total employment also aligns qualitatively with, for instance, the increase in unemployment in a Markov-switching VAR in Netšunajev and Glass (2017) and in a non-linear (Smooth-Transition) VAR in Caggiano, Castelnuovo, and Groshenny (2014), as well as the decline in vacancies and job finding rate in a VAR with shocks identified through long-run restrictions in Guglielminetti (2016).

Interestingly, heightened macroeconomic uncertainty also corresponds to an expansion in temporary employment, albeit not immediately. The increase in temporary employment is statistically significant after 3 quarters following a one-standard-deviation macroeconomic uncertainty shock, and the increase remains statistically significant for approximately 15 quarters at the 68-percent level. The peak increase of approximately 0.5% in temporary employment occurs slightly after 8 quarters following the shock, supporting the findings in the literature that the responses of macroeconomic variables to uncertainty

[12]This chapter takes an existing uncertainty measure and then uses it in a small-scaled VAR. Carriero, Clark, and Marcellino (2018) point out that this practice may be problematic because the uncertainty around the uncertainty estimates is ignored in the VAR, and small VAR models may lead to omitted variable bias when assessing the impacts of uncertainty.

shocks build up over time (Alessandri, Gazzani, & Vicondoa, 2023; Bonciani & Oh, 2019; Carriero, Marcellino, & Tornese, 2023; Leduc & Liu, 2016). Therefore, I take into account the impulse responses over time to evaluate the significance of the macroeconomic effects of uncertainty shocks.

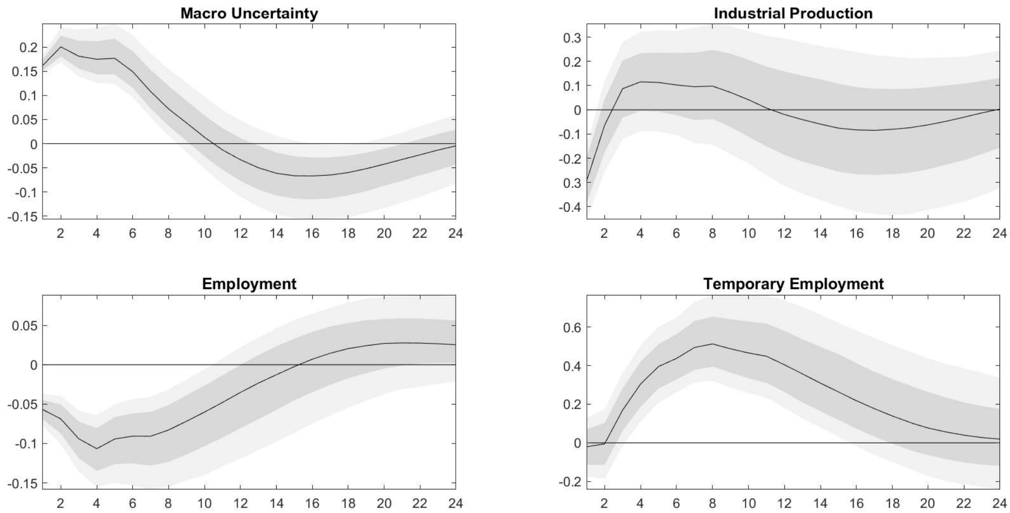

Figure 3.2: Impulse responses to a macroeconomic uncertainty shock. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

Temporary employment as a percentage of total employment in the UK typically fluctuates by small percentages, often less than 2%.[13] Therefore, a 0.5% peak increase in temporary employment could be considered moderate. On the modest responses of macroeconomic variables to an uncertainty shock, it is crucial to note that while macroeconomic uncertainty in the UK typically remains low, it surged nearly fourfold during the Great Recession and even more dramatically during the COVID-19 pandemic, as illustrated in Figure 3.1. The results suggest that uncertainty 4 standard deviations above its mean—a scenario observed in practice during crises—corresponds to a roughly 2% rise in temporary employment. This finding is noteworthy as it indicates that major economic crises such as the Great Recession and the COVID-19 pandemic may trigger

[13]Figure 3.23 in the Appendix presents the percentage change (quarter-on-quarter) in temporary employment as a percentage of total employment from 1993 to 2022.

sizable increase in temporary employment.

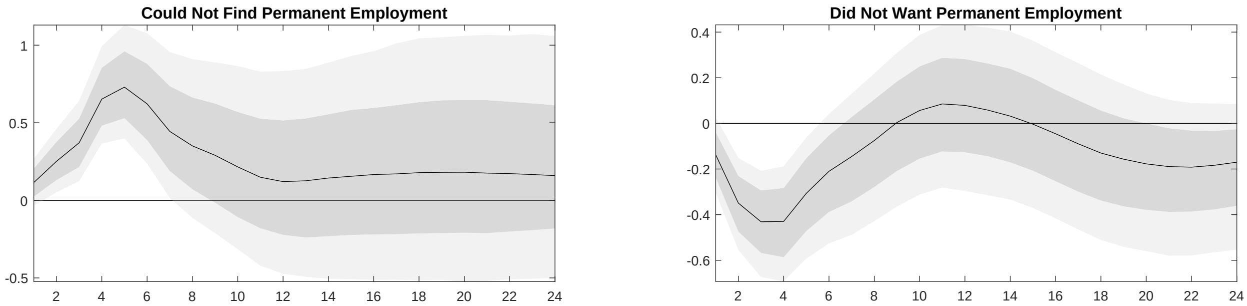

Figure 3.3: Impulse responses to a macroeconomic uncertainty shock. *Notes:* I re-estimate the baseline VAR model twice, substituting the temporary employment variable with, respectively, the share of temporary employees who accept temporary employment in the first place because they fail to find permanent employment, and the share of temporary employees who do *not* want permanent employment. For brevity, the responses of macroeconomic uncertainty, industrial employment, and total employment are not presented. In (a), temporary employment is measured by the share of temporary employees who cited 'failure to find permanent employment' as the reason for taking up temporary employment. In (b), temporary employment is measured by the share of temporary employees who did not want permanent employment. Further details on the variables are provided in the Appendix. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

Figure 3.2 also suggests that even after the macroeconomic uncertainty shock has died off, the decline in total employment, albeit small, is still statistically significant. This decline in total employment may reflect two possible dynamics: first, a decrease in consumption driven by a precautionary saving motive (Aaberge, Liu, & Zhu, 2017; Ben-David, Fermand, Kuhnen, & Li, 2018; Bertola, Guiso, & Pistaferri, 2005; Nam, Lee, & Jeon, 2021), which may further dampen firms' willingness to hire permanent employees;[14] and second, a decrease in households' resistance towards temporary employment, assuming it is perceived as a preferable alternative to unemployment.[15] Both factors could potentially contribute to an increase in temporary employment. To disentangle these effects, I re-estimate the baseline VAR model twice, substituting the temporary employment variable with, respectively, the share of temporary employees who accept temporary employment in the first place because they fail to find permanent employment, and the share of temporary employees who do *not* want permanent employment. Figure 3.3 (a) provides tentative support

[14]Kalcheva, McLemore, and Sias (2021) and Nam, Lee, and Jeon (2021) provide evidence that uncertainty has long-lasting effects on consumption choices, consistent with the theory of habit formation. It is possible that uncertainty may have lasting effects on firms' preferences in hiring temporary versus permanent employees. As shown in Figure 3.2, the increase in temporary employment persists for several quarters even after the initial uncertainty shock has subsided. However, further research is required to robustly establish habit formation in firms' labour decisions in an uncertainty shock, making it a promising and important avenue for future research.

[15]Jo and Lee (2019) find that uncertainty leads to drops in voluntary quits and increases in labour market entrants switching from non-participation.

to firms' reduced desire to commit to permanent employees: the share of temporary employees who take up temporary employment in the first place because they fail to find permanent employment increases following a macroeconomic uncertainty shock. However, Figure 3.3 (b) shows that the share of temporary employees who do *not* want permanent employment also decreases following a macroeconomic uncertainty shock, potentially hinting at households' enduring resistance towards temporary employment. Therefore, the IRFs in Figure 3.3 provide some suggestive evidence that the increase in temporary employment following an uncertainty shock may be related to firms' reduced demand for permanent employees rather than a decrease in households' resistance to temporary employment.

3.3.3 Robustness

In this section, I test the robustness of the baseline results to a variety of changes to the Bayesian VAR model, including controlling for consumer confidence, incorporating microeconomic uncertainty, employing alternative measures of macroeconomic uncertainty, varying the number of lags, using a flat prior, and adding additional control variables. In all the robustness checks, I find the baseline results to be confirmed: macroeconomic uncertainty shocks are associated with an increase in temporary employment.

Uncertain times or bad economic times?

It is a well established fact that uncertainty rises in recessions and falls in booms.[16] The responses of economic activity in the baseline VAR might be due to the economic agents' perceptions of bad economic times rather than uncertain times. As pointed out by Baker, Bloom, and Davis (2016), the connection between "confidence" and uncertainty is complex, with both concepts being closely linked in certain theoretical models.[17] Therefore, following Baker, Bloom, and Davis (2016) and Leduc and Liu (2016), I estimate a five-variable VAR model that includes a consumer confidence index from the GfK's Consumer Confidence Barometer as an additional control for the potential effects of perceptions of bad economic conditions.

[16]See Baker, Bloom, and Terry (2023) for examples of evidence of the countercyclicality of both macro- and micro-uncertainty.

[17]Ilut and Schneider (2014), using a New Keynesian business cycle model with Knightian uncertainty, find that TFP and confidence shocks can jointly account for approximately two-thirds of the fluctuations in major macroeconomic aggregates, with confidence shocks explaining around 70 percent of this variation.

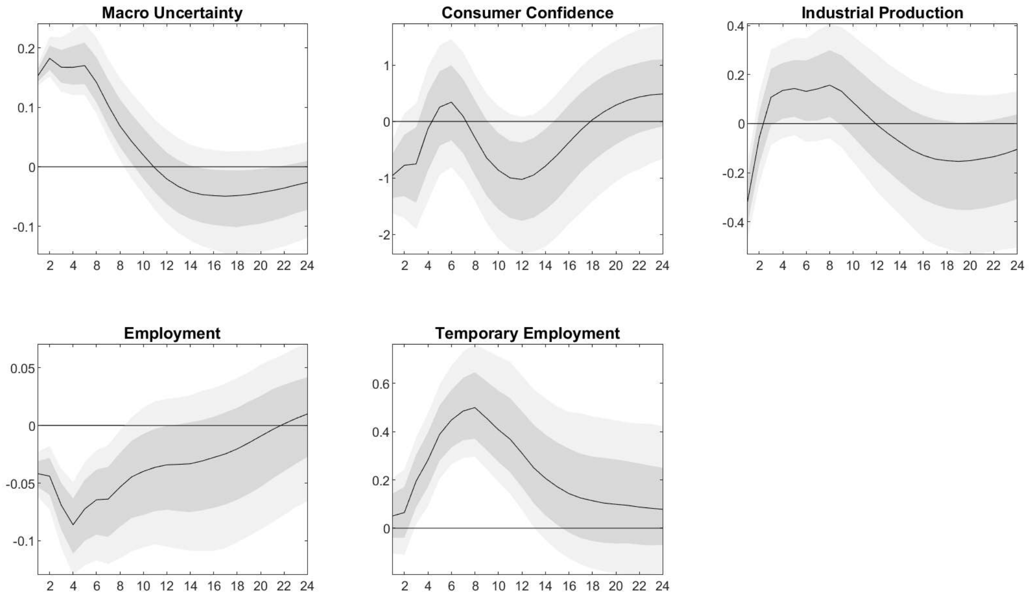

Figure 3.4: Impulse responses to a macroeconomic uncertainty shock, with consumer confidence as an additional control. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. The consumer confidence index, sourced from the GfK Consumer Confidence Barometer, measures consumer sentiment in the UK by surveying monthly a representative sample of approximately 2,000 individuals aged 16 and over; the survey captures respondents' perceptions of their personal financial situation and on the general economic condition over the past 12 months, their expectations for the next 12 months, and their intentions regarding major purchases and savings. Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty and the consumer confidence index, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

When I place consumer confidence after macroeconomic uncertainty in the causal ordering, the qualitative and quantitative patterns of the findings are very similar to the baseline VAR's, as shown in Figure 3.4. When I place consumer confidence first (before macroeconomic uncertainty) in the causal ordering, the peak increase in temporary employment, compared to the baseline VAR, only decreases slightly,[18] as shown in Figure 3.26 in the Appendix. These results suggest that the relationship between macroeconomic uncertainty and temporary employment is not reflecting the variations due to changes in consumer confidence.

[18]This result is consistent with Baker, Bloom, and Davis (2016), who document that including consumer sentiment first in the causal ordering as a control reduces the impact of uncertainty on industrial production and employment.

What about Productivity?

The baseline results raise questions on productivity. One may wonder whether the rise in temporary employment following an uncertainty shock has productivity implications, or whether overall uncertainty in the economy corresponds to heightened uncertainty in labour productivity, thereby amplifying its association with temporary employment. This subsection addresses these questions.

Does an Uncertainty-Driven Increase in Temporary Employment Correspond to Lower Productivity? The existing literature establishes that uncertainty affects productivity, particularly through channels such as heightened financial constraints (Choi, Furceri, Huang, & Loungani, 2018) and diminished innovation (Bloom & Van Reenen, 2002; Bloom, Van Reenen, & Bond, 2007; Bonciani & Oh, 2023).[19] Meanwhile, the literature documents a negative relationship between temporary work arrangements and productivity (Autor, Kerr, & Kugler, 2007; Cappellari, Dell'Aringa, & Leonardi, 2012).[20]

If temporary employees are indeed less productive, could the uncertainty-induced rise in temporary employment further exacerbate productivity decline? Lotti and Viviano (2012), by leveraging legislative changes in Italy as an exogenous source of variation in workforce composition, find that the negative relationship between temporary workers and total factor productivity (TFP) observed in the literature may not stem from the inherent productivity of temporary workers but rather from the effects of uncertainty itself; uncertainty both reduces TFP and incentivizes firms to hire more temporary workers for flexibility. The Bayesian VAR setup in this chapter is adapted to empirically test the findings of Lotti and Viviano (2012). Specifically, I run a 5-variable VAR by including

[19]The source of uncertainty is critical in understanding its effects on productivity. For example, the uncertainty arising from the COVID-19 pandemic results in disruptions and increased sanitization costs that reduce firm efficiency (Bloom, Bunn, Mizen, Smietanka, & Thwaites, 2023), while remote work arrangements enhance worker productivity (Barrero, Bloom, & Davis, 2021).

[20]Under the decreasing marginal returns to labour hypothesis, when firms are able to adjust their employment levels through the increased use of temporary employees, firms hire increasingly less productive workers (Boeri & Garibaldi, 2007). Under the "low-road" practice hypothesis, the combination of temporary employment and low level of training results in productivity slowdowns (Cappellari, Dell'Aringa, & Leonardi, 2012; Michie & Sheehan, 2003). Booth, Francesconi, and Frank (2002) find that temporary employees in the UK receive less training compared to permanent employees.

labour productivity.[21]

I vary the ordering of temporary employment and labour productivity within the VAR model to explore whether the observed dynamics between these variables differ depending on the assumed structure. In the first specification, labour productivity is ordered before temporary employment; in the second, temporary employment precedes labour productivity. By comparing the impulse responses of labour productivity to an uncertainty shock across both specifications, I examine whether the inclusion and ordering of temporary employment is associated with any notable differences in the behaviour of labour productivity.

Figure 3.27 and 3.28 in the Appendix show no difference in the decline of labour productivity due to uncertainty across both specifications; placing temporary employment before labour productivity in the VAR model does not worsen the labour productivity decline. This finding supports the argument by Lotti and Viviano (2012): the negative association between temporary workers and productivity reported in the literature may not be attributable to the lower productivity of temporary workers themselves, but rather to the confounding effects of uncertainty, which simultaneously drive both the decline in productivity and the increase in temporary employment.

Does Uncertainty in Labour Productivity Relate to Increases in Temporary Employment? The literature shows that when uncertainty in labour productivity rises—meaning when workers' abilities become less predictable—managers compress wage between perceived high- and low-ability workers (Gross, Guo, & Charness, 2015) and workers invest in firm-specific human capital to achieve employment security (Bai & Wang, 2003).[22] When uncertainty increases, firms also substitute workers with robots (Leduc & Liu, 2020). Building on this line of reasoning, it is plausible that increased uncertainty in labour productivity leads firms to favour temporary contracts. Temporary employment

[21] Labour productivity—measured as output per worker—is sourced from the ONS.

[22] More specifically, Bai and Wang (2003) note that the effect of uncertainty in labour productivity on firm-specific human capital investment depends on the initial level of uncertainty. When the initial level of uncertainty is low, an increase in uncertainty motivates workers to invest more in firm-specific human capital as they seek to enhance their job security. Conversely, when the initial uncertainty is already high, a further increase leads to a reduction in such investment, as the perceived benefits of investing become outweighed by the risks associated with uncertain returns.

allows firms to screen employees' skills and capabilities before committing to permanent employment, aligning with the hypothesis that temporary contracts serve as a screening device (see Houseman, Kalleberg, & Erickcek, 2003; Ichino, Mealli, & Nannicini, 2008; Jahn & Rosholm, 2014).

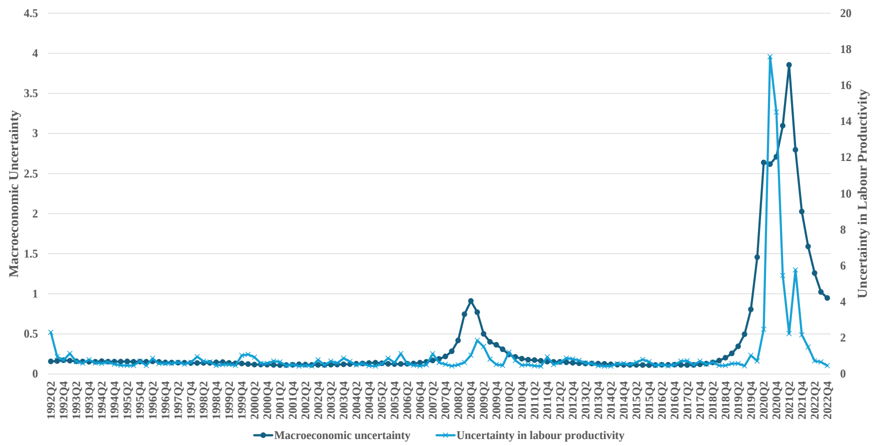

Figure 3.5: Time series of macroeconomic uncertainty constructed by Dibiasi and Sarferaz (2023) and the conditional heteroskedasticity of labour productivity (output per worker data sourced from the Office of National Statistics (2024g)) obtained from a GARCH(1,1) model, defined here as uncertainty in labour productivity. *Notes:* The horizontal axis displays time while the vertical axes uncertainty values.

To examine whether uncertainty in labour productivity corresponds to an increase in temporary employment, I first use a generalized autoregressive conditional heteroskedasticity GARCH(1,1) estimator on the time series of labour productivity to estimate its conditional heteroskedasticity, following the method in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). I define this conditional heteroskedasticity as uncertainty in labour productivity, plotted in Figure 3.5. I then estimate a simple 2-variable VAR, with uncertainty in labour productivity ordered before temporary employment. Figure 3.6 demonstrates that a one-standard-deviation shock to the uncertainty in labour productivity corresponds to a peak increase of approximately of 0.5% in temporary employment 6 quarters following the shock, with the effect remaining statistically significant for over 10 quarters. The magnitude of this increase is comparable to the results from the baseline four-variable VAR model with a macroeconomic uncertainty shock.

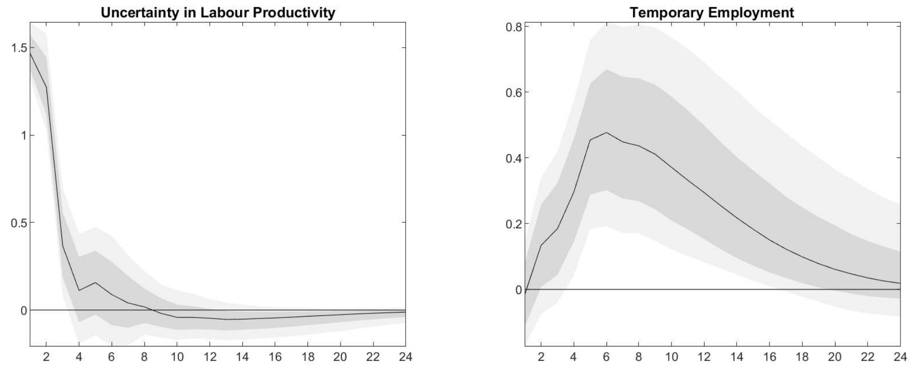

Figure 3.6: Impulse responses to an uncertainty in labour productivity shock in a 2-variable Bayesian VAR model. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Uncertainty in labour productivity is derived as the conditional heteroskedasticity of labour productivity obtained from a GARCH(1,1) model, following the method in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The time series of this uncertainty in labour productivity is presented in Figure 3.5. Further details on the variables are provided in the Appendix. Temporary employment enters in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

Motivated by the findings in the 2-variable VAR, I extend the baseline VAR model to include uncertainty in labour productivity, positioning this variable before temporary employment in the ordering. A potential concern with this specification is that macroeconomic uncertainty and labour productivity uncertainty may contain overlapping information, rendering the latter redundant. Figure 3.5 reveals that, while the two variables do indeed exhibit comovement, macroeconomic uncertainty tends to precede uncertainty in labour productivity. This suggests that macroeconomic uncertainty could potentially drive uncertainty in labour productivity. As seen in the baseline VAR model (Figure 3.2), macroeconomic uncertainty is associated with lowered employment levels. With an increase in the number of job seekers, and consequently a wider dispersion in their productivity, employers may find it more difficult to predict the productivity of potential hires, thereby heightening uncertainty in labour productivity. Hence, in this context macroeconomic uncertainty and uncertainty in labour productivity are distinct, and distinguishing between macroeconomic uncertainty and uncertainty specific to labour productivity is useful. Accounting for uncertainty in labour productivity, which might be induced by macroeconomic uncertainty, may amplify the association between macroeconomic uncertainty and temporary employment.

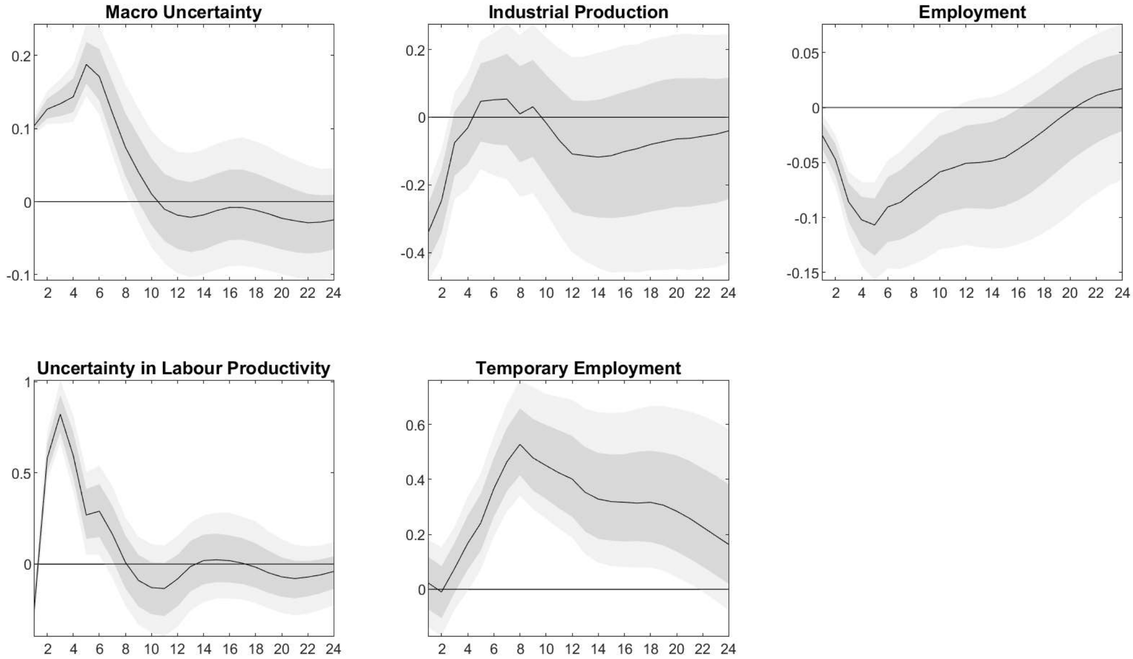

Figure 3.7: Impulse responses to a macroeconomic uncertainty shock, with uncertainty in labour productivity as an additional control. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Uncertainty in labour productivity is derived as the conditional heteroskedasticity of labour productivity obtained from a GARCH(1,1) model, following the method in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The time series of this uncertainty in labour productivity is presented in Figure 3.5. Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty and uncertainty in labour productivity, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

Figure 3.7 demonstrates that a macroeconomic uncertainty shock corresponds not only to a decline in output and employment, as anticipated, but also to an increase in uncertainty in labour productivity.[23] More importantly, consistent with the baseline VAR results, temporary employment also increases following the macroeconomic uncertainty shock. However, a noticeable difference emerges: when accounting for uncertainty in labour productivity, the increase in temporary employment remains statistically significant for a longer duration. These findings do not necessarily imply that the baseline results are entirely driven by uncertainty around labour productivity, but they do suggest

[23]Crowder and Smallwood (2019) find that unemployment is associated with uncertainty in labour productivity. As a robustness check, I order uncertainty in labour productivity before, rather than after, employment in the 5-variable Bayesian VAR in Figure 3.29. The results remain unchanged.

that uncertainty in labour productivity may play a role in shaping the responses to a macroeconomic uncertainty shock. In addition to the channels explored by Jo and Lee (2019) on how uncertainty affects the labour market, uncertainty in labour productivity may act as an additional channel associated with observed increases in temporary employment during periods of heightened macroeconomic uncertainty.

Microeconomic uncertainty

The analysis in this chapter has thus far focused on shocks to macroeconomic uncertainty. A natural question arises: does microeconomic uncertainty also have macroeconomic implications, particularly on temporary employment in the economy? In this subsection, I test the robustness of the baseline VAR model by replacing macroeconomic uncertainty with microeconomic uncertainty. Particularly, I use the microeconomic uncertainty measure derived in Chapter 1, which is defined as the dispersion of firms' productivity shocks. Given that this measure is annual rather than quarterly, I aggregate the quarterly data for industrial production, employment, and temporary employment into annual averages by calculating the arithmetic mean of the quarterly observations within each calendar year. I set the lag length to 1, which is standard in the literature for VAR models using annual data. Consistent with the baseline approach, I also estimate the model using Bayesian methods.

Figure 3.8 shows that the responses to microeconomic uncertainty shocks closely mirror those observed in response to macroeconomic uncertainty. A shock to microeconomic uncertainty corresponds to a decline in industrial production and total employment—outcomes consistent with existing literature—while also resulting in a rise in temporary employment that is statistically significant at the 68-percent level. The magnitude and duration of this increase in temporary employment are remarkably similar to those observed following a macroeconomic uncertainty shock, as illustrated in Figure 3.2. These findings suggest that uncertainty, whether macroeconomic or microeconomic in nature, corresponds to greater level of temporary employment. As a further robustness check, I estimate a mixed-frequency VAR, with microeconomic uncertainty ordered after macroeconomic uncertainty. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) find that both types of uncertainty tend to comove; ordering microeconomic uncertainty after macroeconomic uncertainty assumes that uncertainty at an aggregate level can feed into uncertainty at the industry and firm levels. This ordering is consistent with Baker, Bloom, and Davis (2016), Kumar, Gorodnichenko, and Coibion (2023), and Alfaro, Bloom, and Lin (2024), who emphasize the importance of capturing uncertainty about broader economic conditions and policies when assessing microeconomic uncertainty.[24] Given that the microeconomic uncertainty measure is annual frequency, while the other variables are available at a quarterly frequency, a mixed-frequency VAR is used to accommodate the data. Detailed specifications for the mixed-frequency VAR model are provided in the Appendix.

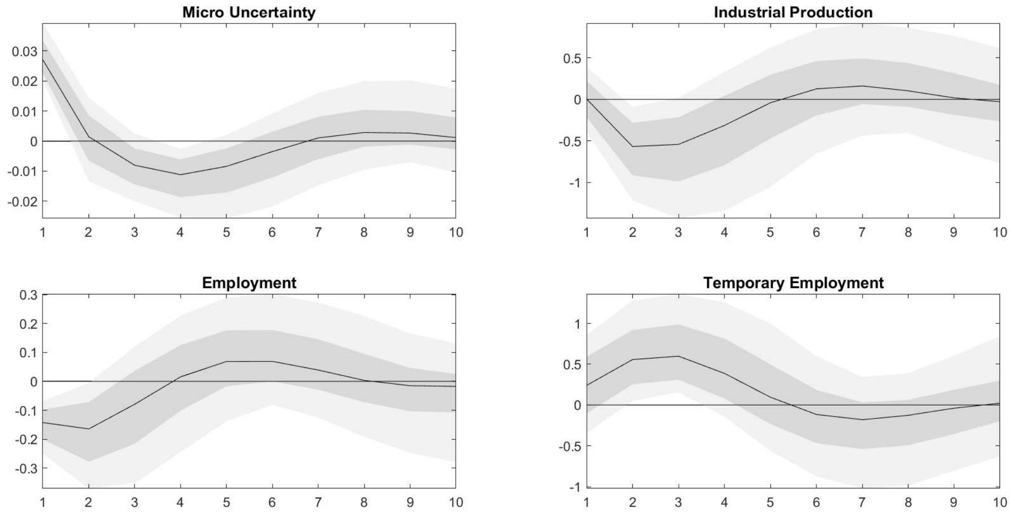

Figure 3.8: Impulse responses to a microeconomic uncertainty shock. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates years following the shock for each plot. The microeconomic uncertainty measure, derived in Chapter 1 using firm-level balance sheet data from the Financial Analysis Made Easy (FAME) database spanning from 2003 to 2022, is defined as the dispersion of firms' productivity shocks. The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. As the microeconomic uncertainty measure is available at an annual frequency, I aggregate the quarterly data for industrial production, employment, and temporary employment into annual averages by calculating the arithmetic mean of the quarterly observations within each calendar year. Unlike the baseline model using quarterly data, here I set the lag length to 1, which is standard in the literature. Further details on the variables are provided in the Appendix. Except for microeconomic uncertainty, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

Figure 3.9 illustrates that a macroeconomic uncertainty shock is associated with an

[24] As noted by Alfaro, Bloom, and Lin (2024), this interpretation helps explain why Brexit can have widespread contractionary effects on firms not directly involved in EU trade (Bloom, Bunn, Chen, Mizen, Smietanka, & Thwaites, 2019).

increase in microeconomic uncertainty, aligning with the stylized fact that the two are highly correlated (Bloom, 2014). As expected, both industrial production and total employment decline following the shock. However, a notable distinction from the baseline model emerges when microeconomic uncertainty is included as an additional control: the decline in employment is more pronounced and persists for a longer duration. This outcome is intuitive, as the combined effects of macroeconomic and microeconomic uncertainty are likely to exert greater pressure on the labour market. The variable of interest, temporary employment, behaves similarly to the results in the baseline model following an uncertainty shock (except that the increase remains statistically significant for a longer period at the 68-percent level). Overall, the association between uncertainty and temporary employment appears robust.

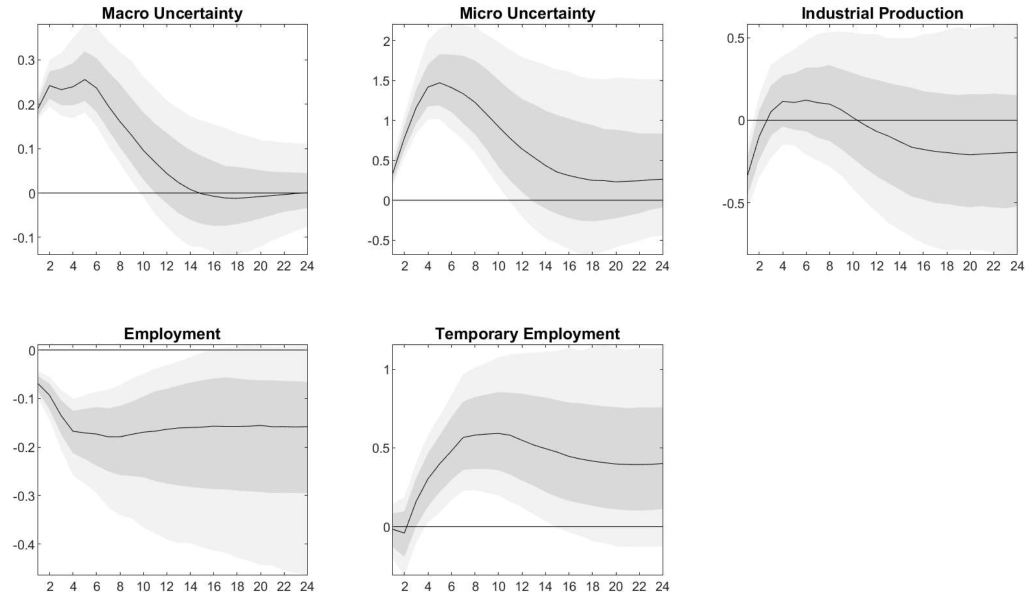

Figure 3.9: Impulse responses to a macroeconomic uncertainty shock, with microeconomic uncertainty as an additional control. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The microeconomic uncertainty measure, derived in Chapter 1 using firm-level balance sheet data from the Financial Analysis Made Easy (FAME) database spanning from 2003 to 2022, is defined as the dispersion of firms' productivity shocks. The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Given that the microeconomic uncertainty measure is annual frequency, while the other variables are available at a quarterly frequency, a mixed-frequency VAR is used to accommodate the data. Further details on the variables and the specifications for the mixed-frequency VAR model are provided in the Appendix. Except for macroeconomic and microeconomic uncertainty, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

Alternative BVAR specifications

I repeat the baseline VAR model using alternative uncertainty indicators: the macroeconomic uncertainty measure computed by Redl (2020) and the Economic Policy Uncertainty (EPU) index computed by Baker, Bloom, and Davis (2016).[25] Unlike the macroeconomic uncertainty measure constructed by Dibiasi and Sarferaz (2023), the measure developed by Redl (2020) follows the approach of Jurado, Ludvigson, and Ng (2015), defining uncertainty as the conditional variance of the unpredictable component common to a broad set of macroeconomic or financial variables. In contrast, the EPU index by Baker, Bloom, and Davis (2016) is derived from text analysis, quantifying the frequency of newspaper coverage related to policy-induced economic uncertainty.

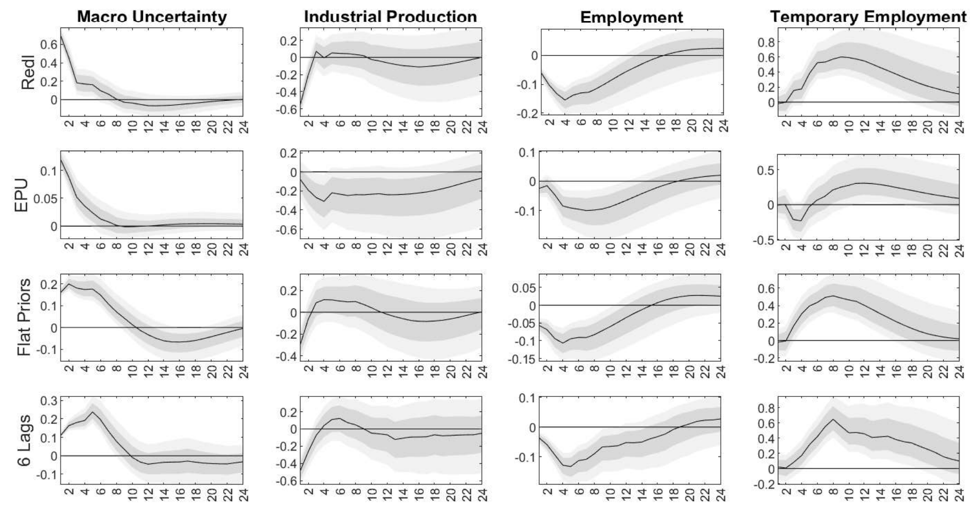

Figure 3.10: Impulse responses to a macroeconomic uncertainty shock under alternative Bayesian VAR specifications. *Notes:* The first row displays the impulse responses using the macroeconomic uncertainty measure from Redl (2020) as the uncertainty proxy. The second row shows the impulse responses when the Economic Policy Uncertainty (EPU) index from Baker, Bloom, and Davis (2016) is used as the proxy. The third row presents the impulse responses obtained using a flat prior instead of a Minnesota prior. The fourth row illustrates the impulse responses when the lag length is set to 6 rather than the baseline of 4. The macroeconomic uncertainty measure in the third and fourth rows is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Further details on the variables and uncertainty measures are provided in the Appendix. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. Except for macroeconomic uncertainty, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

[25]The macroeconomic uncertainty measure computed by Redl (2020) is available at monthly frequency, while the EPU index computed by Baker, Bloom, and Davis (2016) is available at monthly and daily frequency. I use the quarterly average of the two measures respectively in the VAR.

The first row in Figure 3.10 shows that the results remain robust when using the macroeconomic uncertainty measure computed by Redl (2020). The second row in Figure 3.10 indicates that a statistically significant increase in temporary employment following an uncertainty shock is also observed when the EPU is used as a proxy for uncertainty. Although the effect appears later than in the baseline results, the VAR captures an initial dip in temporary employment before its subsequent rise in response to the uncertainty shock. Rather than contradicting the baseline results, this pattern can be viewed as complementary. An intuitive explanation is that, immediately after a surge in uncertainty, firms may respond by laying off temporary employees due to the lower costs of dismissal.[26][27] As firms cope with the aftermath of uncertainty, they might prefer to offer temporary contracts instead of permanent ones as a precautionary measure since the higher adjustment costs—fixed disruption costs and hiring or firing expenses—associated with permanent labour makes any hiring or firing mistakes of permanent labour costlier than that of temporary labour, leading to an overall increase in temporary employment.

As a further robustness check, I re-estimate the baseline VAR with a flat prior so the results are data-driven. The third row in Figure 3.10 illustrates that the relationship between macroeconomic uncertainty and temporary employment remains consistent with the baseline VAR when a flat prior is used. Similarly, the fourth row in Figure 3.10 confirms the robustness of the results when the baseline VAR is re-estimated with 6 lags instead of 4, indicating that the results are not sensitive to the choice of lag length.

Additional controls

In the uncertainty literature, it is standard practice to include a broad set of variables in VAR models to estimate the impacts of uncertainty shocks.[28] The baseline VAR model is limited to four variables to mitigate the risk of overfitting, given the relatively short time series, and to simplify the interpretation of the dynamics among the variables. As

[26]The OECD Employment Database (2019) shows that the employment protection legislation for regular contracts is four times stricter than for temporary contracts in the UK.

[27]In Section 3.4, simulations confirm that firms dismiss temporary employees at a higher rate than permanent employees in the immediate response to an uncertainty shock.

[28]Bloom (2009) includes the S&P 500 index before the uncertainty measure in the variable order to ensure the impact of stock-market levels is already controlled for since both variables are naturally expected to be dynamically related. Most papers also include a measure of the stance of monetary policy as a control. For instance, Bloom (2009) and Jurado, Ludvigson, and Ng (2015) use the federal funds rate in their VAR model. Papers which prove uncertainty operates through an aggregate demand channel that decreases both economic activity and prices, such as Leduc and Liu (2016) and Basu and Bundick (2017), include inflation rate, unemployment rate and/or hours worked in their VAR models.

a robustness check, I run an 8-variable VAR model featuring the FTSE All-Share (FTAS) index, the bank rate, business investment, and consumption as additional controls.[29] All variables except macroeconomic uncertainty and the bank rate enter in log levels. As per the baseline model, this 8-variable VAR is estimated with Bayesian methods and the lag length is set to 4. Figure 3.11 confirms the robustness of the baseline VAR results: after controlling for the stock-market levels, bank rate, business investment, and consumption, the increase in temporary employment is significant at the 90-percent level approximately 3 quarters after a macroeconomic uncertainty shock, although the effect persists for a shorter duration compared to the baseline VAR results.

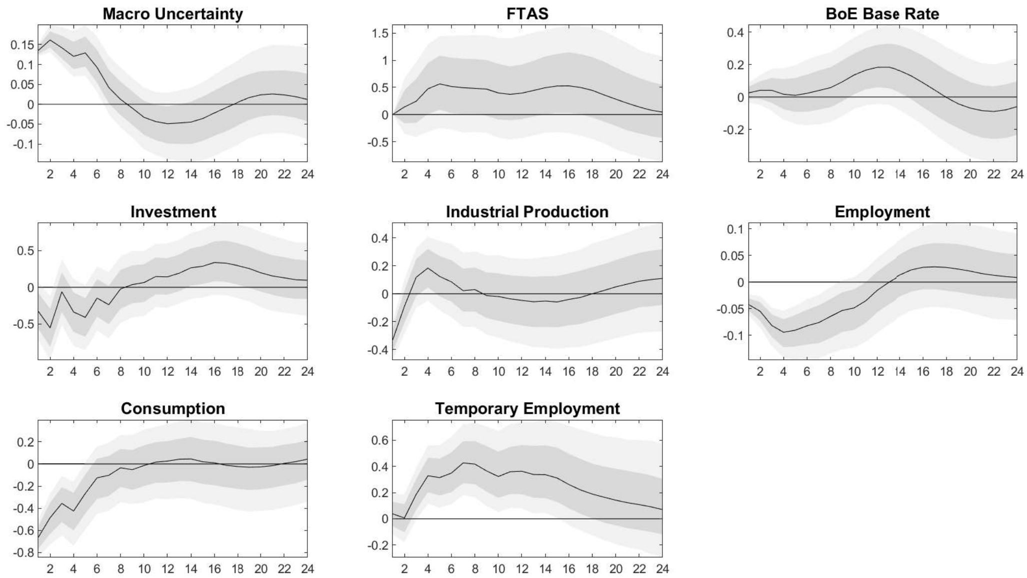

Figure 3.11: Impulse responses to a macroeconomic uncertainty shock in an 8-variable Bayesian VAR model. *Notes:* The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The FTSE All-Share (FTAS) index is obtained from Yahoo Finance. The bank base rate is derived as the quarterly average of the monthly bank rate, sourced from the Bank of England (BoE). Investment is defined as the chained value measure of business investment, and consumption the chained value measure of household final consumption expenditure, both sourced from the Office for National Statistics (ONS). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty and bank rate, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

[29] I base the ordering of variables in the 8-variable VAR on the VARs in Christiano, Eichenbaum, and Evans (2005) and in Bloom (2009). Following Bloom (2009), putting a stock market variable before uncertainty ensures the impact of stock market levels is already accounted for when analyzing the impact of uncertainty shocks, and positioning the bank rate after uncertainty reflects the assumption that shocks first impact the stock market and then prices. Investment follows the bank rate, as it is influenced by interest rate changes and tends to be more forward-looking than other real economy variables, such as industrial production. Consistent with Christiano, Eichenbaum, and Evans (2005), consumption is ordered after industrial production and employment. A description of the variables is provided in the Appendix.

3.4 Partial Equilibrium Model

To account for the empirical results, I proceed with a partial equilibrium model which singles out the role of uncertainty in shaping labour composition. Specifically, I augment the firm's problem as in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), with two types of labour—permanent and temporary, where heterogeneous firms incur adjustment costs for adjusting their employment levels. Capital is deliberately absent for simplicity. As is standard in the RBC literature, firms are subject to an exogenous process for aggregate and idiosyncratic productivity. Also following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I allow the second moment of the innovations to productivity to vary over time. In other words, during periods of heightened uncertainty, productivity shocks can be larger than in normal times. The adjustment costs and destruction rates are also exogenous and varied to approximate the concept of contract duration, thereby introducing two distinct types of labour—permanent and temporary. The calibration of these parameters related to adjustment costs and destruction rates is not grounded in rigorous empirical estimation but rather relies on stylized assumptions; this constitutes the primary limitation of the analysis presented in this chapter. Addressing this limitation, such as through formal estimation of these parameters, remains an important direction for future research, contingent on the availability of more granular and comprehensive datasets.

The model features a trade-off between adjustment costs and destruction rates: permanent labour is characterized by higher adjustment costs but lower destruction rates (similar to longer contract duration), while temporary labour features lower adjustment costs but higher destruction rates (similar to shorter contract duration). During periods of heightened uncertainty, the high firing costs of permanent labour make it risky to commit to labour on permanent contracts, as labour adjustments become costly if market conditions worsen.

3.4.1 Technology

A firm j produces output according to

$$y_{j,t} = A_t z_{j,t} (n_{j,t})^{\nu}, \qquad \nu < 1. \tag{3.6}$$

In Equation 3.6, $n_{j,t}$ denotes labour hours employed by firm j at time t. In this framework, labour is the only variable input. The labour input is composed of both permanent and temporary labour:

$$n_{j,t} = m^{per} n_{j,t}^{per} + m^{tem} n_{j,t}^{tem}, \tag{3.7}$$

where m^l denotes the labour productivity, which is assumed to be fixed and varies by labour type $l \in \{per, tem\}$, with per indicating permanent labour and tem temporary labour. Equation 3.7 treats permanent and temporary labour as perfect substitutes.[30] The assumption that permanent and temporary labour are additively separable introduces several limitations. First, separability disregards potential complementarities between the two types of labour, thereby overlooking the productivity gains that may arise when they are used together. Second, it fails to account for the inherent differences in flexibility between the two types of labour: temporary labour is often employed for short-term tasks, whereas permanent labour typically forms the core of the workforce for ongoing operations. By ignoring these distinctions, the model cannot fully capture how firms strategically allocate and optimise labour inputs based on task requirements and their need for flexibility. While this chapter adopts a simple framework for analytical tractability, addressing these limitations lies beyond its scope and is left for future research.

Aggregate productivity, A_t, and idiosyncratic productivity, $z_{j,t}$, are two separate processes determining firm j 's productivity. These components of productivity follow autoregressive (AR) processes:

[30]Equation 3.7 also implies that permanent and temporary labour contribute to total labour input in an identical manner, disregarding any systematic differences in their relative importance across industries. In practice, some industries may rely more heavily on temporary labour due to the nature of their demand, while others may prioritise permanent labour. A more flexible specification could address this limitation by modifying the equation to $n_{j,t} = \alpha m^{per} n_{j,t}^{per} + (1-\alpha) m^{tem} n_{j,t}^{tem}$, where α represents a share parameter that determines the relative weight of permanent labour in the overall labour input. Future research could calibrate α to reflect industry-specific characteristics to analyze how permanent and temporary labour contribute to total labour input across different industries.

$$\log(A_t) = \rho^A \log(A_{t-1}) + \sigma^A_{t-1}\varepsilon_t, \text{ and} \tag{3.8}$$

$$\log(z_{j,t}) = \rho^Z \log(z_{j,t-1}) + \sigma^Z_{t-1}\varepsilon_{j,t}, \tag{3.9}$$

where ρ^A and ρ^Z represent autocorrelation coefficients measuring the degree of persistence in the respective AR processes. The variance of innovation to the productivity processes, σ^A_t and σ^Z_t, varies over time according to a two-state Markov chain (low and high uncertainty): $\sigma^A_t \in \{\sigma^A_L, \sigma^A_H\}$, with transition probability $\Pr(\sigma^A_{t+1} = \sigma^A_j \mid \sigma^A_t = \sigma^A_k) = \pi^{\sigma^A}_{k,j}$; $\sigma^Z_t \in \{\sigma^Z_L, \sigma^Z_H\}$, with transition probability $\Pr(\sigma^Z_{t+1} = \sigma^Z_j \mid \sigma^Z_t = \sigma^Z_k) = \pi^{\sigma^Z}_{k,j}$. The volatility in $z_{j,t}$ results in time-varying productivity dispersion across firms. Meanwhile, volatility in A_t affects all firms, as it represents aggregate uncertainty that induces more volatile shocks across the entire economy. As emphasized by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), the timing assumption in Equation 3.8 and 3.9 means firms are informed beforehand that the distribution of shocks in the next period is changing. This assumption portrays firms' uncertainty about future economic environments.

3.4.2 Labour Adjustment Costs

It is important to first clarify that the distinction between permanent and temporary labour in the model differs from how these categories are defined in real-world contexts. In the UK, the classification of permanent and temporary labour is typically based on contract duration, with temporary labour generally employed on contracts lasting less than a year. However, in the model, contract duration is not explicitly incorporated; instead, the distinction is conceptualized through a trade-off between adjustment costs and destruction rates: permanent labour is characterized by higher adjustment costs but lower destruction rates (analogous to longer contract duration), while temporary labour features lower adjustment costs but higher destruction rates (similar to shorter contract duration). In other words, whereas real-world labour is essentially of a *single* type employed under different contract terms, the model assumes two distinct types of labour, classified based on their adjustment costs and destruction rates. Although this abstraction is not ideal as it omits contract duration, it offers a simplified representation of real-world dynamics for the purposes of the analysis.

From a labour perspective, assuming wages are identical for permanent and temporary employment, permanent employment is inherently more desirable than temporary employment. This preference arises because labour prioritizes destruction rates—the termination of employment leads to unemployment and the need to search for new work—over labour adjustment costs, which are typically a greater concern for firms. This assumption aligns with the existing literature; for instance, Booth, Francesconi, and Frank (2002) provide evidence from the UK that temporary employment are generally perceived as less desirable than permanent employment, as temporary labour report significantly lower levels of job satisfaction compared to their permanent counterparts.

In the model, the law of motion for hours worked by labour type $l \in \{per, tem\}$ is given by

$$n^l_{j,t} = (1 - \delta^l)n^l_{j,t-1} + s^l_{j,t}, \tag{3.10}$$

where δ denotes the job destruction rate of hours worked, and $s_{j,t}$ the net flow into hours worked. Similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), the destruction rate is assumed to be fixed and exogenous, that is, due to factors such as voluntary quits and mutually agreed contract terminations. Endogenous separations are not considered because, as highlighted by Oikonomou (2021), the impact of the real options channel on employment becomes theoretically ambiguous when separations are endogenous.[31] Specifically, higher uncertainty can lead firms to be more cautious in both hiring and firing decisions—reducing the job-finding rate while also lowering the separation rate. The overall effect on employment thus depends on the relative strength of these opposing forces. To maintain focus on the effects of uncertainty on temporary employment, this analysis abstracts from endogenous separations and defers

[31] While endogenous separations can be easily incorporated into search-and-matching models, the real options channel is not active in such models when a representative firm is assumed and a free-entry condition is imposed; the free-entry condition nullifies the value of the real option to wait in each period, preventing the real options channel from influencing firm behavior (Den Haan, Freund, & Rendahl, 2021).

their exploration to future research.

The labour adjustment costs, AC, which are dependent on labour type $l \in \{per, tem\}$, are governed by

$$AC^l = \mathbb{I}(|s^l| > 0) y(z, A, n) F^l + |s^l| H^l w^l, \tag{3.11}$$

where F denotes the fixed disruption cost and Hw the linear hiring/firing cost expressed as a fraction of wage.[32] For a firm that hires both permanent and temporary labour, the total labour adjustment costs are the sum of the adjustment costs for permanent labour (AC^{per}) and the adjustment costs for temporary labour (AC^{tem}). The presence of adjustment costs mean that $n^{per}_{j,t-1}$ and $n^{tem}_{j,t-1}$ are state variables.

3.4.3 Value Function

The seven state variables of the model are (i) aggregate productivity, A, (ii) a firm's idiosyncratic productivity, z, (iii), the firm's hours stock supplied by permanent labour from the previous period, n^{per}_{-1}, (iv) the firm's hours stock supplied by temporary labour from the previous period, n^{tem}_{-1}, (v) the current value of macroeconomic uncertainty, σ^A, (vi) the current value of microeconomic uncertainty, σ^Z, and (vii) the joint distribution of idiosyncratic productivity and firm-level hours worked in the last period, μ.

Let $V = V(n^{per}_{-1}, n^{tem}_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ be the value function of a firm. Also, let AC^{per} be the shorthand notation for $AC^{per}(n^{tem}, n^{per}_{-1}, z, n^{per}; A, \sigma^A, \sigma^Z, \mu)$, AC^{tem} for $AC^{tem}(n^{per}, n^{tem}_{-1},$
$z, n^{tem}; A, \sigma^A, \sigma^Z, \mu)$, and primes the value of next period variables. The firm optimally chooses hours worked by permanent and/or temporary labour to maximize

[32] Wages of permanent and temporary labour are assumed constant in the partial equilibrium model.

$$V = \max_{n^{per}, n^{tem}} \left\{ p(y - w^{per}n^{per} - w^{tem}n^{tem} - AC^{per} - AC^{tem}) + \beta \mathbb{E}V' \right\} \quad (3.12)$$

subject to the laws of motion for aggregate and idiosyncratic productivity (Equation 3.8 and 3.9) , macroeconomic and microeconomic uncertainty (detailed in Section 3.4.1), hours worked (Equation 3.10), and the joint distribution of idiosyncratic productivity and hours, $\mu' = \Gamma(A, \sigma^A, \sigma^Z, \mu)$.

In Equation 3.12, p represents the price of goods, w^{per} the wage of permanent labour, and w^{tem} the wage of temporary labour. All three parameters are treated as given in a partial equilibrium model. β is the discount rate reflecting the firm's time preference for future profits versus current profits. $\mathbb{E}V'$ is the expected continuation value, representing the expected value of the firm in the next period, given the optimal choice of labour inputs today and the evolution of economic conditions.

3.4.4 Parameter Values

Table 3.2 reports the parameter values in the baseline partial equilibrium model. Most of the parameter values are taken directly from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). I adopt a simulated method of moments (SMM) estimation procedure to obtain the values for parameters governing the uncertainty process, which has not been previously estimated for the UK in the literature.

The model is calibrated to a quarterly frequency. The discount factor, β, is chosen to correspond to an annual interest rate of 5%, a standard benchmark in the literature. I set the exponent on labour in the firm's production function to be $\nu = 0.5$, implying a CRS labour share of approximately two-thirds. Similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), the persistence parameters for aggregate and idiosyncratic productivity, ρ^A and ρ^Z, are set to 0.95.

The values of the labour destruction rates of permanent and temporary labour, taken from Kent (2008), are calibrated at 0.034 and 0.135 respectively; the labour destruction rate of temporary labour is higher than that of permanent labour's. Labour adjustment costs for the UK, however, have not been estimated in the literature. According to the OECD Employment Database (2019), the employment protection legislation for regular contracts is four times stricter than for temporary contracts in the UK.[33] Therefore, I use the labour adjustment costs in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) but assume temporary labour incurs only 25% of the hiring, firing, and fixed disruption costs incurred by permanent labour. For simplicity, I assume permanent and temporary labour are equally productive and consequently receive the same wages. In sum, the trade-off faced by firms is that permanent labour are more expensive to hire and fire, but they offer a lower labour destruction rate. I explore the robustness of the analysis to alternative parameter values in Section 3.6.

Parameters governing the uncertainty process are less familiar than the other parameters related to technology, preferences, and adjustment costs, necessitating a more detailed explanation of their calibration and estimation. First, similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I assume a unified process controls both microeconomic and macroeconomic uncertainty, as outlined in Section 3.4.1: when microeconomic uncertainty is low (or high), so is macroeconomic uncertainty.[34] This assumption is crucial to reduce the number of parameters governing the uncertainty process to only six: $\sigma_L^A, \sigma_H^A, \sigma_L^Z, \sigma_H^Z, \pi_{L,H}^{\sigma}$, and $\pi_{H,H}^{\sigma}$. Ideally, these would be estimated using a simulated method of moments (SMM). However, estimating parameter values of macroeconomic uncertainty for the UK requires reliable aggregate productivity data. Timely estimates of Solow residual for the UK are not yet available in the literature,[35] and current multi-factor productivity (MFP) measures by the ONS do not fully account for capital utilisation (Martin & Jones, 2022).[36] In the absence of updated UK aggregate productivity data, I use the same values in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) for the

[33]The OECD indicators evaluate the regulations on the hiring and dismissal of workers on regular contracts and on temporary contracts. The indicators are compiled using the Secretariat's own reading of statutory laws, collective bargaining agreements, and contributions from OECD member country officials and experts (OECD Employment Database, 2019).

[34]Chapter 1 provides evidence of the comovement of macroeconomic and microeconomic uncertainty through the business cycle.

[35]Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) use the aggregate U.S. Solow residual data from John Fernald's website in their SMM in estimating uncertainty parameters.

[36]Huo, Levchenko, and Pandalai-Nayar (2023) provide a utilization-adjusted TFP dataset for 29 countries, including the UK, but only up to 2007. Similarly, the KLEMS database lacks TFP data for the UK post-2019, a period covered by the analysis in this chapter.

Table 3.2: Model parameters.

Technology		
β	$0.95^{\frac{1}{4}}$	Annual discount factor of 95%
ν	0.5	CRS labour share
ρ^A	0.95	Quarterly persistence of aggregate productivity
ρ^Z	0.95	Quarterly persistence of idiosyncratic productivity
Labour		
δ^{per}	0.034	Labour destruction rate of permanent labour
δ^{tem}	0.135	Labour destruction rate of temporary labour
F^{per}	0.021	Fixed cost of changing hours by permanent labour in % of annual sales
F^{tem}	0.005	Fixed cost of changing hours by temporary labour in % of annual sales
H^{per}	0.018	Hiring/firing cost of permanent labour in % of annual wage bill
H^{tem}	0.005	Hiring/firing cost of temporary labour in % of annual wage bill
m^{per}	1	Productivity of permanent labour
m^{tem}	1	Productivity of temporary labour
Uncertainty		
σ^A_L	0.67	Quarterly standard deviation of macroproductivity shocks (%)
$\frac{\sigma^A_H}{\sigma^A_L}$	1.6	Macrovolatility increase in high uncertainty state
σ^Z_L	5.3	Quarterly standard deviation of microproductivity shocks (%)
$\frac{\sigma^Z_H}{\sigma^Z_L}$	3.1	Microvolatility increase in high uncertainty state
$\pi^{\sigma}_{L,H}$	6.5	Quarterly transition probability from low to high uncertainty (%)
$\pi^{\sigma}_{H,H}$	91.4	Quarterly probability of remaining in high uncertainty (%)

Notes: The values for δ^{per} and δ^{tem} are taken from Kent (2008). σ^Z_L, $\frac{\sigma^Z_H}{\sigma^Z_L}$, $\pi^{\sigma}_{L,H}$, and $\pi^{\sigma}_{H,H}$ values are estimated using a simulated method of moments (SMM). All remaining parameters, except where stated otherwise, are taken from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The values for m^{per} and m^{tem} are derived based on the author's assumptions, with alternative values for these parameters discussed in Section 3.6.3. The values for F^{per} and H^{per} are sourced from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), which assumes a single type of labour; in this model, these values are applied to permanent labour. The values for F^{tem} and H^{tem} are derived under the assumption that temporary labour incurs only 25% of the hiring, firing, and fixed disruption costs associated with permanent labour. Additional details on the parameters are provided in the main text.

quarterly standard deviation of macroproductivity shocks, σ^A_L, and the macrovolatility increase in high uncertainty state, $\frac{\sigma^A_H}{\sigma^A_L}$. These values imply that aggregate volatility is 0.67% with low uncertainty and increases by 60% during uncertainty shocks.

I proceed with SMM to estimate the remaining uncertainty parameters. I target the mean, standard deviation, skewness, kurtosis, and serial correlation of the time series of the cross-sectional interquartile range of firm TFP shocks computed from the annual Financial Analysis Made Easy (FAME) sample covering 2003–2022.[37] The SMM estimator

[37] The time series of the cross-sectional interquartile range of firm TFP shocks is derived and plotted in Chapter 1.

minimizes the sum of squared percentage deviations of the model and data moments. Appendix 3.A.7 contains further details of the SMM estimation procedure.

Table 3.3 lists the corresponding targeted moments. The estimated model appears to capture the overall time series properties of microeconomic uncertainty in the data. The final four rows of Table 3.2 present the point estimates of the uncertainty parameters. The estimation procedure reveals that periods of high uncertainty occur with a quarterly probability of 6.5%. These periods are persistent, with a 91.4% probability of remaining in a heightened uncertainty state each quarter. Idiosyncratic volatility is estimated at 5.3%, increasing by approximately 210% during high uncertainty. In Section 3.6, I explore the sensitivity of the results to changes in these uncertainty parameters.

Micro-moments	Data	Model
Mean	27.00	27.96
Standard deviation	3.71	3.27
Skewness	0.35	0.44
Kurtosis	1.70	1.60
Serial correlation	0.76	0.78

Table 3.3: Moments of the uncertainty process. The SMM procedure follows Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). Data moments are derived from the cross-sectional interquartile range of estimated shocks to firm-level productivity, expressed as percentages. Model moments are computed similarly, adjusted for measurement error in firm-level regressions and aggregated to an annual frequency. The model are based on a simulation of 1,000 firms over 5,000 quarters, with the first 500 periods discarded to mitigate initialization effects.

At this point, it is natural to ask how these estimated uncertainty process parameters compare to those for the US, as presented in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), and why idiosyncratic volatility increases so sharply during periods of high uncertainty. I will first address the comparison with the US. Relative to the US estimates in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), the transition probability from low to high uncertainty is higher for the UK (6.5% for the UK versus 2.6% for the US), while the probability of remaining in a high uncertainty state is slightly lower (91.4% for the UK versus 94.3% for the US). The standard deviation of microproductivity shocks is almost identical between the two countries (5.3% for the UK and 5.1% for the US), but the increase in microvolatility during high uncertainty is lower in the UK (3.1) than in the US (4.1). It is important to note that these parameter values are not directly comparable, as the US and UK economies differ in structural aspects. Most importantly, the analysis in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) covers a longer period (1972–2010), whereas the analysis in this chapter spans a shorter, more recent timeframe (2004–2022), which includes the Covid-19 pandemic—a period of pronounced uncertainty, as shown in Chapter 1. This difference likely contributes to the higher estimated transition probability from low to high uncertainty in the UK analysis. Additionally, disparities in sectoral composition, labour market flexibility, or even fiscal and monetary policy responses between the two countries may explain why the increase in microvolatility during high uncertainty is greater in the US than in the UK.

Next, the large estimated increase in microeconomic uncertainty when an uncertainty shock hits is crucial for matching the behavior of the observed productivity shock dispersion in the data, which is illustrated in Chapter 1. Similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), it is important to note that the two series—the underlying volatility of micro productivity shocks in the model and the proxy for microeconomic uncertainty used for model estimation—are distinct. Specifically, the latter is measured at an annual frequency, whereas the former is measured quarterly. It is also worth noting that the estimated increase in microeconomic uncertainty following a shock is even larger in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018).[38] Thus, the magnitude of the estimated increase in microeconomic uncertainty in an uncertainty shock in this analysis is not unreasonable.

Two final points need to be made regarding the SMM estimation. First, recall that the underlying uncertainty process parameters, including the estimated transition probability from low to high uncertainty, $\pi^{\sigma}_{L,H}$, as well as the probability of remaining in a high uncertainty state, $\pi^{\sigma}_{H,H}$, are derived by targeting five moments of the time series for the microeconomic uncertainty proxy, as previously discussed. This approach differs from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), where the authors estimate these parameters by targeting not only the moments of microeconomic uncertainty but also

[38]Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) explain that the large estimated jumps in underlying uncertainty feed into a more muted variability of their uncertainty proxy due to measurement error in the micro data. Unlike Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), the microeconomic uncertainty proxy used in this chapter is derived from firm-level TFP measures calculated using the method proposed by Ackerberg, Caves, and Frazer (2015), which provides more robust and consistent estimates.

those of macroeconomic uncertainty in the data. As a result, their SMM estimation uses more information than mine in estimating the underlying uncertainty process parameters. Second, there is measurement error in the model moments. The microeconomic moments are derived from the cross-sectional dispersion of innovations in regressions of firm-level TFP on lagged values, as detailed in Chapter 1. To generate comparable moments in the model, it is required to simulate a panel of individual firms.[39] Several challenges arise from this simulation. The firm data, which are simulated at a quarterly frequency, must be aggregated to an annual frequency to align with the timing structure of the FAME data sample. Additionally, the simulated TFP measure is effectively a *mismeasured* Solow residual, as the partial equilibrium model used excludes capital. Consequently, the resulting Solow residual does not account for capital inputs, which is a significant limitation of the analysis. However, abstracting from capital is necessary due to the large number of state variables incorporated in the partial equilibrium model. In future research, I intend to address this limitation by targeting macroeconomic moments in the SMM estimation, which would allow the model to better capture real-world uncertainty dynamics, and by incorporating capital into the model, which would enable a more accurate representation of the Solow residual.

3.5 Effects of an Uncertainty Shock

This section analyzes the quantitative implications of the model and presents the effects of an uncertainty shock.

3.5.1 Uncertainty and Inaction

The wait-and-see effect is a well-known fact in the uncertainty literature: in the presence of nonconvex adjustment costs—costs that are not proportional and often include fixed or lump-sum components—firms delay hiring or investing until their productivity or profitability reaches a sufficiently high threshold where the benefits outweigh these adjustment costs. Similarly, firms delay firing or disinvesting until productivity drops below a threshold where the benefits of reducing labour or capital exceed the associated costs. Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I demonstrate graphically how firms value the flexibility of waiting rather than immediately reacting to changes in productivity. Figure 3.12(a) depicts the hiring and firing freeze for

[39]The Appendix contains further details on the simulation.

permanent labour by plotting the distribution of firms by their productivity/permanent labour ratios, $\frac{Az}{n_{-1}^{per}}$, after the idiosyncratic and aggregate productivity shocks have been drawn but before firms have adjusted. The vertical solid line on the left represents the firing threshold, while the one on the right the hiring threshold, when uncertainty is low. Firms to the left of the firing threshold reduce permanent labour, while firms to the right of the hiring threshold expand their permanent labour. Firms between these thresholds remain inactive in their permanent labour decisions. As such, the region delineated between these two lines is commonly referred to as the "inaction zone", where firms wait for more significant shifts in productivity before making labour adjustments.

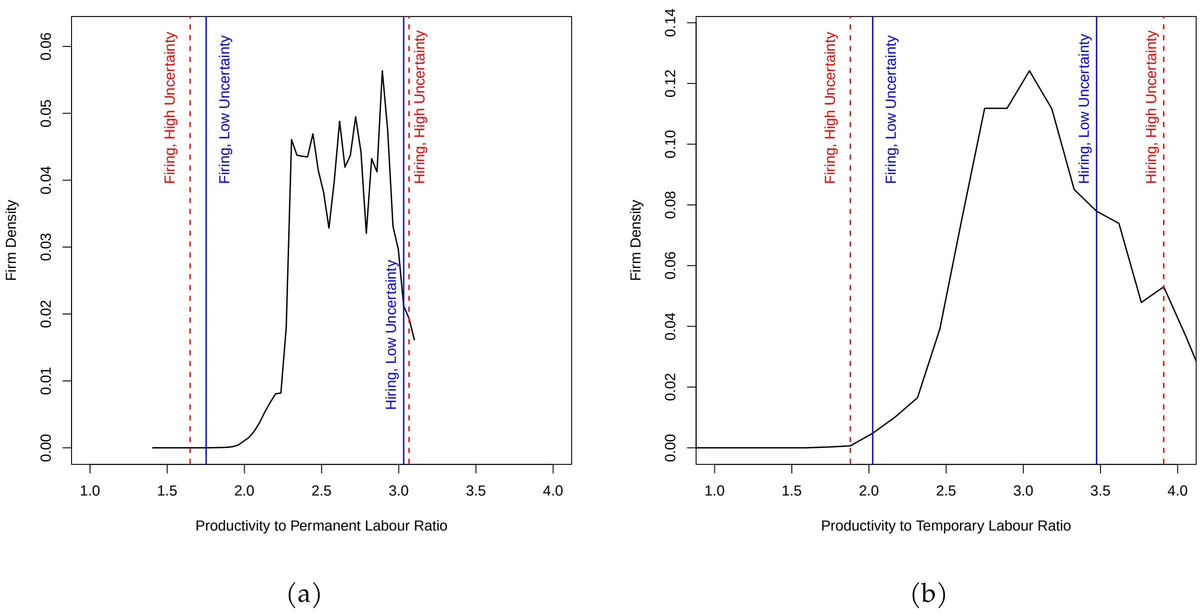

Figure 3.12: Heightened uncertainty raises the hiring and firing thresholds for both permanent and temporary labour. *Notes*: The left (right) panel plots the simulated cross-sectional marginal distribution of micro-level permanent (temporary) labour inputs following productivity shock realizations and prior to labour adjustments. It plots a representative period characterized by average aggregate productivity under low uncertainty. The hiring and firing thresholds are derived from firm policy functions based on average micro-level productivity realizations, conditional on the aggregate state of the economy under low uncertainty (solid lines) and a high uncertainty counterfactual (dotted lines).

Figure 3.12(a) also introduces a counterfactual scenario marked by vertical dotted lines, representing the case of high uncertainty. Uncertainty shifts the firing threshold to the left and the hiring threshold to the right, thereby expanding the range of inaction. This is because adjustment costs associated with permanent labour render any errors in hiring or firing decisions prohibitively expensive, prompting firms to exercise greater prudence in their permanent labour-related choices.

Meanwhile, Figure 3.12(b) plots the distribution of firms by their productivity/temporary labour ratios, $\frac{Az}{n_{-1}^{tem}}$, after idiosyncratic and aggregate productivity shocks but prior to any corresponding firm adjustments. The vertical solid lines represent the case of low uncertainty, while the vertical dotted lines the case of high uncertainty. Consistent with the findings for permanent labour, the impact of uncertainty is also evident in the case of temporary labour. Specifically, uncertainty also extends the range of inaction for temporary labour.

Figure 3.12 demonstrates that, irrespective of the type of labour, firms exhibit increased caution under heightened uncertainty due to the presence of labour adjustment costs. In the figure, the shift in firing and hiring thresholds are smaller for permanent labour and larger for temporary labour, consistent with the higher adjustment costs of permanent labour in the model—firms adjust temporary labour more aggressively during periods of high uncertainty because it is less costly and more reversible. However, the analysis in Figure 3.12 considers permanent and temporary labour separately; it is not clear what the final effect of uncertainty on permanent and temporary labour would be if firms consider both types of labour together in their decision-making process. To address this, the next section explores the impulse response functions of an uncertainty shock, providing a more comprehensive analysis of how firms adjust their labour decisions under uncertainty.

3.5.2 Baseline Results

I model a pure uncertainty shock following the approach in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). To evaluate the impact of uncertainty on the aggregate share of temporary labour, I simulate 2700 economies, each of 100-quarter length. For the first 45 quarters, the simulations run unconditionally. I introduce an uncertainty shock by imposing a high uncertainty state after 45 quarters. Each economy evolves normally after the shock period. To derive the impulse response function for any macroeconomic variable, I calculate the period-by-period average of the aggregate variable across all simulated economies; the impact of the uncertainty shock is measured as the percentage deviation of this average in period t from its pre-shock level.

Figure 3.13 illustrates the impact of an uncertainty shock. During an uncertainty shock, output declines by over 1%. This result is qualitatively aligned with key findings in the uncertainty literature, including Bloom (2009), Jurado, Ludvigson, and Ng (2015), and Basu and Bundick (2017). In this model, where labour is the sole input, the drop in output is entirely attributable to a reduction in total labour. The increase in uncertainty raises the real option value of inaction, prompting firms to temporarily halt hiring. As exogenous labour attrition continues, this hiring freeze results in a net decline in employment. The contraction in total labour—comprising both permanent and temporary labour—is slightly over 2%. Notably, as described in Bloom (2009), if quits were endogenized, the impact of uncertainty shocks on total labour would likely be dampened, as the labour depreciation rate is expected to decrease following the shock. Labour productivity, defined simply as output per unit of labour in this model, increases during the uncertainty shock, as the reduction in total labour exceeds the decline in output.

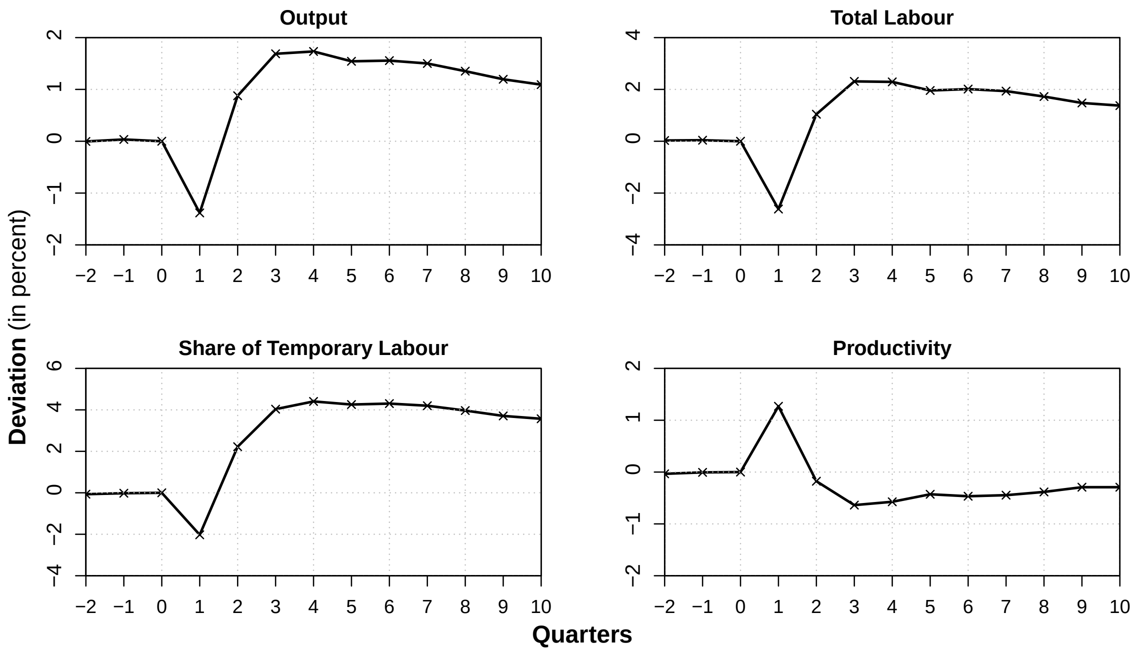

Figure 3.13: The impact of an uncertainty shock. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. An uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. The figure depicts the percentage deviation of cross-economy averages for output, total labour (the sum of permanent and temporary labour), the share of temporary labour (temporary labour as a proportion of total labour), and labour productivity (defined as output per unit of labour) relative to their pre-shock values in quarter 0.

The aggregate share of temporary labour also decreases by approximately 2% in response to the uncertainty shock. While both permanent and temporary labour decline, the reduction in temporary labour is more pronounced.[40] This decline is driven by two factors. First, although more firms freeze hiring across both types of labour, the

[40]Section 3.A.8 in the Appendix presents the IRFs for permanent and temporary labour separately.

higher attrition rate of temporary labour compared to permanent labour results in a disproportionately lower share of temporary labour. Second, although firms also freeze firing during uncertainty shocks, temporary labour involves lower adjustment costs than permanent labour. In other words, dismissing temporary labour is less costly, making their dismissal relatively less 'irreversible' in the context of uncertainty. Consequently, the aggregate share of temporary labour declines during the uncertainty shock.

As uncertainty subsides, the economy begins its recovery. Figure 3.13 shows that, following the initial decline, there is a rebound and subsequent overshoot in both output and total labour. The hiring freeze is short-lived, as firms resume hiring to address the pent-up demand for labour that accumulates during the uncertainty shock. Total labour, and consequently output, rise above their long-run trends after the initial decline; this overshoot is driven by the increased variance in productivity, which incentivizes hiring due to the convexity of labour choices in productivity—a phenomenon associated with the Oi (1961), Hartman (1972), and Abel (1983) effects. The magnitude of the overshoot reflects significant labour adjustments, which are feasible in this partial equilibrium framework as consumption is not explicitly modeled.[41] Labour productivity now falls below its long run trend as the increase in total labour outpaces the rise in output after the uncertainty shock.

The rebound and subsequent overshoot following the initial decline are also evident in the share of temporary labour. Recall that the model assumes a significant persistence of the uncertainty process. As firms gradually recover from the uncertainty shock, hiring resumes, and firms increase their reliance on temporary labour more than on permanent labour, given the lower adjustment costs and hence greater "reversibility" associated with temporary labour. The interpretation here diverges slightly from that in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), who attribute the overshoot in labour in a partial equilibrium framework primarily to the dominance of the Oi-Hartman-Abel effect. While Figure 3.13 confirms that the Oi-Hartman-Abel effect drives the overshoot in total labour and output, it also highlights the continued presence of

[41] As demonstrated in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), in a general equilibrium framework, the inclusion of consumption dynamics moderates the rebound, resulting in a smoother and more persistent output cycle.

the real-option effect, captured by the increased share of temporary labour which reflects firms' cautious response to lingering uncertainty, even as overall labour and output recover.

The current model exhibits at least two unattractive features. First, the overshoot of output and labour does not fully capture the true effects of uncertainty. This limitation arises as an inherent trade-off within the partial equilibrium framework, where the lack of price adjustments leads to exaggerated dynamics. Second, empirical evidence presented in Chapter 1 indicates that recessions are characterized by both first- and second-moment shock—manifested as a decline in the average growth rate of TFP and output, alongside an increase in their variance.

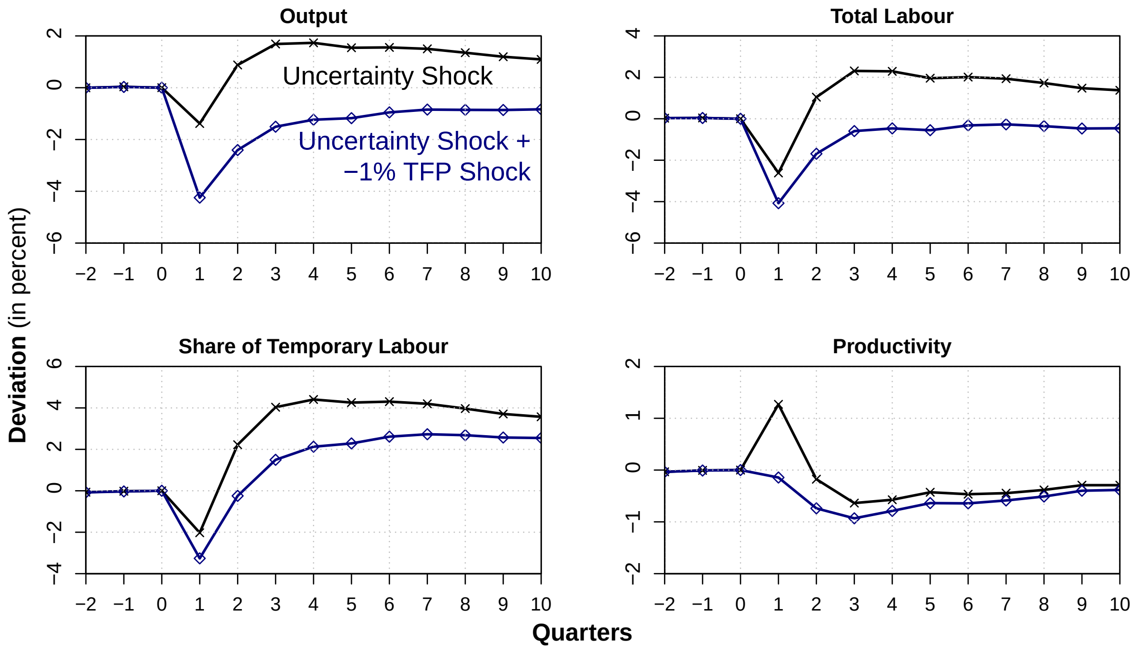

Figure 3.14: Adding a -1% first-moment shock. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline ($\times$ symbol) an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. For the uncertainty and TFP shock ($\diamond$ symbol) an aggregate productivity shock with average equal to -1% is also introduced in the quarter labeled 1, after which the economy evolves normally. The figure depicts the percentage deviation of cross-economy averages for output, total labour (the sum of permanent and temporary labour), the share of temporary labour (temporary labour as a proportion of total labour), and labour productivity (defined as output per unit of labour) relative to their pre-shock values in quarter 0.

A natural solution to the first issue would be to adopt a general equilibrium framework, which allows prices to adjust endogenously. Ideally, such a framework would also incorporate capital, providing a more comprehensive analysis of the effects of uncertainty. However, introducing endogenous wages and prices significantly increases computational complexity, while the inclusion of capital introduces an additional state variable, further complicating the problem. Given the preliminary nature of this chapter, I leave the general equilibrium analysis to future research. The second issue is more tractable. Addressing it requires simulating an uncertainty shock in conjunction with a negative TFP shock, as demonstrated in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). It turns out that solving this second problem can also mitigate the first, as the combination of these shocks reduces the overshooting of output and labour, offering a more realistic depiction of the effects of uncertainty.

To produce a more realistic simulation, I introduce an uncertainty shock alongside a -1% exogenous first-moment shock. The details of this numerical experiment are provided in Section 3.A.6 in the Appendix. Figure 3.14 illustrates that the inclusion of the first-moment shock eliminates the overshoot in output and labour, as well as the immediate rise in productivity observed with the uncertainty shock alone. Interestingly, while the addition of the first-moment shock mitigates the increase in the share of temporary labour during the recovery, it does not eliminate it. A negative TFP shock in isolation[42] leads to a continuous decline in the share of temporary labour, as firms reduce hiring. This reduction occurs because temporary labour, with its lower adjustment costs, is more easily dismissed during downturns. An uncertainty shock in isolation, on the other hand, prompts a different adjustment process: some firms draw significantly higher productivity shocks than before and respond by increasing hiring. Given the persistent nature of uncertainty, firms favour temporary over permanent labour, given the lower adjustment costs and hence higher 'reversibility' associated with temporary labour. Coupling this uncertainty shock with a negative TFP shock means that this readjustment would be moderated, but Figure 3.14 highlights that the increase in the share of temporary labour is still evident. These findings suggest that simultaneous first- and second-moment shocks in this partial equilibrium framework generate dynamics for the share of temporary labour that align closely with the VAR evidence presented in earlier sections.

[42] Section 3.A.8 presents IRFs for a negative TFP shock in isolation.

3.6 Sensitivity Analysis

This section evaluates the robustness of the results by analyzing alternative parameterizations of adjustment costs, labour destruction rates, productivity and wages, as well as the uncertainty process. Additionally, Section 3.A.9 in the Appendix extends the sensitivity analysis by using an alternative approach to compute the effects of uncertainty and examine results under denser grid specifications. Overall, the results are robust to these changes. These robustness tests also reveal additional insights: First, while fixed adjustment costs primarily drive the initial impact of an uncertainty shock—consistent with the existing literature—linear adjustment costs play a pivotal role in shaping firms' responses during the recovery phase. Second, the magnitude of the increase in the share of temporary labour during recovery from an uncertainty shock is sensitive to the labour destruction rates assumed in the model. Third, incorporating both a wage penalty and a productivity difference between permanent and temporary labour—arguably a more realistic representation of labour market conditions—preserves the baseline dynamics of the share of temporary labour following an uncertainty shock.

3.6.1 Alternative Adjustment Costs

The response of economic agents to shocks is often shaped by frictions. In the case of an uncertainty shock, the real-options channel, first identified by Bernanke (1983), emphasizes the critical role of adjustment costs in dampening investment and hiring. However, accurately measuring adjustment costs remains a significant challenge (Dibiasi & Sarferaz, 2023). As noted by Bloom (2009), "off-the-shelf" estimates of adjustment costs are rarely available for incorporation into macroeconomic models. Thus, obtaining *separate* estimates for adjustment costs of permanent and temporary labour is even more challenging (Aguirregabiria & Alonso-Borrego, 2014).

There are two possible approaches to address this issue. The first, and ideal, option would be to use a general equilibrium model that incorporates the household side of the economy to structurally estimate adjustment costs. While structural estimation could be conducted in a partial equilibrium framework, this approach is less suitable for an SMM routine because a partial equilibrium model—lacking capital and assuming fixed prices—may not be sufficiently rich to generate credible estimates for permanent and temporary labour adjustment costs. The second option is to calibrate these adjustment costs using values from other studies, even though the available literature on this topic is limited. Given that estimating the adjustment costs of permanent and temporary labour is beyond the scope of this paper, I adopt the second approach and leave structural estimation to future research. To ensure robustness, I test my results against alternative adjustment cost estimates provided in the existing literature.

Recall that I use the labour adjustment costs from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), with the additional assumption that temporary labour incurs only a quarter of the hiring, firing, and fixed disruption costs faced by permanent labour. This assumption is based on evidence from OECD Employment Database (2019), which shows that employment protection legislation for regular contracts in the UK is four times stricter than for temporary contracts. Before testing the robustness of the baseline results, I analyze two alternative cases: one in which the linear adjustment costs for both types of labour are removed, and another in which the fixed adjustment costs for both types of labour are removed. This analysis is motivated by findings in the literature that increased uncertainty can reduce hiring, investment, and consumption when agents face fixed or partial adjustment costs (the real-options channel). Therefore, fixed costs in this model are likely to play a more significant role than linear costs.

Figure 3.15 illustrates the role of fixed adjustment costs in driving the effects of uncertainty on the aggregate share of temporary labour. Due to space constraints, the effects on output, total labour, and labour productivity are not presented. Figure 3.15 shows that the model incorporating only fixed adjustment costs (without linear hiring and firing costs) produces results similar to the baseline case, while the model with only linear costs does not. This indicates that the dynamics of the share of temporary labour following an uncertainty shock are primarily driven by frictions associated with fixed adjustment costs rather than linear adjustment costs. This is because, in the model, the fixed adjustment costs for each type of labour, represented by $\mathbb{I}(|s^l|> 0)y(z, A, n)F^l$ for labour type $l \in \{per, tem\}$, depends on aggregate and idiosyncratic productivity, which is influenced by the overall state of the economy. In contrast, the linear adjustment costs for each type of labour are expressed as a fraction of the wage, which is assumed to remain fixed. Consequently, the impact of an uncertainty shock on the aggregate share of temporary labour is predominantly driven by fixed adjustment costs rather than linear adjustment costs. Intuitively, fixed adjustment costs are incurred irrespective of the scale of adjustment, creating a threshold effect that discourages firms from making small changes to their workforce, as the cost remains constant regardless of the magnitude of the adjustment. These fixed costs introduce a non-linear decision threshold: firms will only adjust their labour input when the expected benefits, or avoided losses, exceed the fixed costs. During an uncertainty shock, this "inaction zone" becomes particularly relevant, as firms "wait-and-see" to avoid committing to costly labour adjustments. In contrast, linear adjustment costs are proportional to the scale of the adjustment and do not impose a similar threshold. As firms are less likely to undertake large-scale labour adjustments during an uncertainty shock due to the option value of waiting, linear adjustment costs are comparatively less important in the immediate aftermath of the shock.

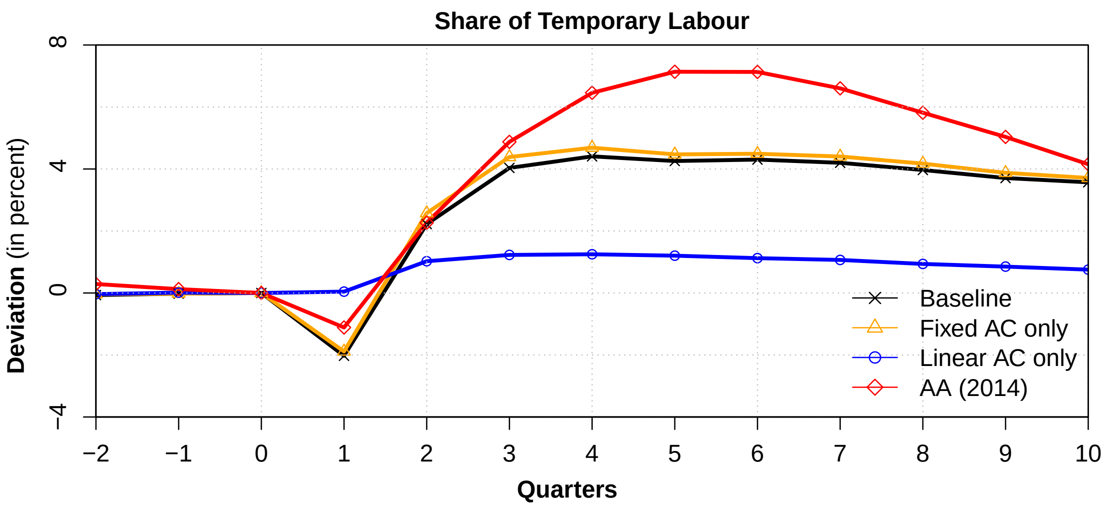

Figure 3.15: The impact of an uncertainty shock on the aggregate share of temporary labour (temporary labour as a proportion of total labour) is primarily driven by fixed adjustment costs. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline ($\times$ symbol) an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. In addition, I plot the responses assuming respectively (i) fixed adjustment costs only ($\triangle$ symbols), (ii) linear adjustment costs only ($\circ$ symbols), and (iii) adjustment costs calibrated to Aguirregabiria and Alonso-Borrego (2014), with hiring costs of 0.101 (0.089), firing costs of 0.528 (0.013), and fixed costs of 0.108 (0.107) for permanent (temporary) labour. The figure depicts the percentage deviation of cross-economy average for the share of temporary labour relative to its pre-shock value in quarter 0.

Does this imply that linear costs—firing and hiring costs—are unimportant? The argument that temporary labour is less expensive to dismiss rests largely on its lower firing costs compared to permanent labour, a point emphasized repeatedly in this chapter. Does this mean that these firing and hiring costs are trivial? It is important to note that the interpretation of the role of linear adjustment costs in this chapter differs from the existing literature, as the focus here is on two distinct types of labour whereas most studies on adjustment costs consider a single type of labour. While the results suggest that the impact of an uncertainty shock on the aggregate share of temporary labour is primarily driven by fixed adjustment costs rather than linear adjustment costs, this does not imply that hiring and firing costs, which differ between permanent and temporary labour, are negligible. This distinction is highlighted in a robustness check where I replace the baseline adjustment cost parameter values with those estimated in Aguirregabiria and Alonso-Borrego (2014) for Spain.[43] Specifically, the parameter values for permanent (temporary) labour are set as follows: hiring costs at 0.101 (0.089), firing costs at 0.528 (0.013), and fixed costs at 0.108 (0.107).

Figure 3.15 demonstrates that, using the adjustment cost values from Aguirregabiria and Alonso-Borrego (2014), the initial decline in the share of temporary labour following an uncertainty shock is smaller than in the baseline case. This indicates that when the difference in fixed costs between permanent and temporary labour is minimal (0.108 for permanent labour versus 0.107 for temporary labour), the immediate impact of an uncertainty shock on the share of temporary labour is reduced. However, the dynamics during the recovery phase are notably different: the subsequent rebound and overshoot are more pronounced when using the values from Aguirregabiria and Alonso-Borrego (2014) compared to the baseline scenario. This difference can be attributed to the significant disparity in firing costs between the two types of labour. As firms recover from the uncertainty shock gradually (due to the persistent nature of the uncertainty process), they remain cautious in addressing the pent-up demand for hiring. Given the significantly lower firing costs of temporary labour compared to permanent labour while the difference in hiring costs between the two is relatively small, firms exhibit a stronger preference than in the baseline case for temporary labour during the recovery.[44] These results suggest that while fixed adjustment costs primarily drive the initial impact of an uncertainty shock, linear adjustment costs play a critical role in shaping firms' responses during the recovery phase. The patterns in the share of temporary labour suggest that accounting for both

[43]Ideally, adjustment cost estimates specific to the UK for both permanent and temporary labour would be used, but such estimates are not currently available in the literature.

[44]The literature highlights that a significant gap in firing costs between permanent and temporary labour has broader implications beyond the demand for temporary labour. For instance, Dolado and Stucchi (2012) find that as this gap widens, both the effort levels of temporary workers and firms' temp-to-perm conversion rates decline.

fixed and linear adjustment costs could be important when modelling labour market responses to uncertainty shocks.

There is more to be done to enhance the robustness of these results. I have limited the scope of robustness checks related to adjustment costs due to the absence of studies that jointly estimate the adjustment costs of permanent and temporary labour for the UK. However, recent advancements in the literature offer promising developments. For instance, firm surveys are used to estimate labour adjustment costs, including differences across sectors (see Dibiasi, Mikosch, & Sarferaz, 2024). In the future, survey data from UK firms could be used to provide estimates of adjustment costs for both permanent and temporary labour and enable more rigorous testing of the robustness of the findings presented in this chapter.

3.6.2 Alternative Destruction Rates

In the baseline scenario, the destruction rate for permanent labour is set at 0.034, while for temporary labour it is 0.135, based on the estimates from Kent (2008). The difference between the two rates is large. To test the robustness of the results, I explore alternative values where the difference in destruction rates is smaller. Specifically, I set the destruction rate for temporary labour to 75% of the destruction rate for permanent labour. Additionally, I use estimates from Varejão and Portugal (2007) for Portugal, where the destruction rate is 0.031 for permanent labour and 0.132 for temporary labour.[45] I also consider the estimates from Cao and Leung (2010) for Canada, where the destruction rate is 0.086 for permanent labour and 0.064 for temporary labour. While neither of these alternatives is ideal due to the lack of UK-specific estimates, they provide useful points of comparison. Note that the destruction rates from Varejão and Portugal (2007) for Portugal are very similar to the baseline values, whereas the estimates from Cao and Leung (2010) for Canada feature a reversal, with the destruction rate for permanent labour exceeding that of temporary labour. These robustness checks help assess the sensitivity of the results to varying assumptions about labour destruction rates in the absence of UK-specific estimates.

[45]Varejão and Portugal (2007) estimate separation rates for permanent and temporary workers in expanding, stable, and declining establishments in Portugal. I derive the destruction rates for permanent and temporary labour by averaging these separation rates across the three establishment types.

Figure 3.16 plots the effects of varying destruction rates on the aggregate share of temporary labour. Due to space constraints, the corresponding effects on output, total labour, and labour productivity are not presented. The figure demonstrates that reducing the gap between the destruction rates of permanent and temporary labour does not significantly alter the initial drop in the share of temporary labour following an uncertainty shock. However, the recovery trajectory differs: the rebound and overshoot in the share of temporary labour are smaller when the gap between the destruction rates of the two types of labour is reduced. This finding suggests that firms' preference for temporary labour over permanent labour during the recovery phase weakens when there is a smaller difference in the destruction rates for the two types of labour. This occurs because a smaller difference in destruction rates reduces the relative advantage of temporary labour, diminishing the trade-off between the two types of labour.

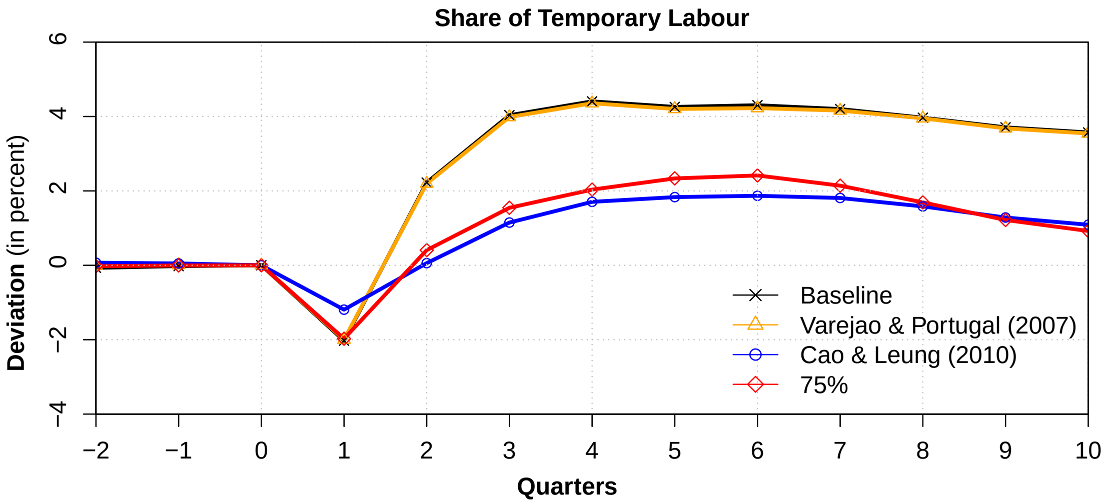

Figure 3.16: The impact of an uncertainty shock on the aggregate share of temporary labour (temporary labour as a proportion of total labour) under alternative labour destruction rates. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline ($\times$ symbol, destruction rates are set at 0.034 and 0.135 for permanent and temporary labour respectively, based on the estimates from Kent (2008)), an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. The figure also includes responses under three alternative scenarios: (i) temporary labour's destruction rate is set to 75% of permanent labour's destruction rate ($\diamond$ symbol), (ii) labour destruction rates calibrated to Varejão and Portugal (2007) ($\triangle$ symbol), and (iii) labour destruction rates calibrated to Cao and Leung (2010) ($\circ$ symbol). The figure depicts the percentage deviation of cross-economy average for the share of temporary labour relative to its pre-shock value in quarter 0.

When the destruction rate estimates from Varejão and Portugal (2007) are used, the dynamics of the share of temporary labour closely resemble those in the baseline case. This is expected, as the destruction rates for both types of labour in Varejão and Portugal (2007) (for Portugal) are very similar to the baseline values. Using the estimates from Cao and Leung (2010) (for Canada) results in a smaller initial decline in the share of temporary labour following an uncertainty shock, as well as a significantly smaller rebound and overshoot during recovery—approximately half the magnitude observed in the baseline case. This outcome is particularly interesting because, despite the destruction rate for permanent labour being higher than that for temporary labour in the Cao and Leung (2010) estimates, the dynamics of the share of temporary labour in Figure 3.13 are still preserved. Overall, these findings indicate that the results are robust to alternative labour destruction rates. However, the magnitude of the increase in the share of temporary labour during recovery from an uncertainty shock is sensitive to the destruction rates used.

3.6.3 Alternative Wage and Productivity Parameters

The baseline model assumes that permanent and temporary labour are equally productive and, consequently, receive similar wages. This assumption is adopted because the model heavily builds upon the framework of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), which provides an exhaustive way to model adjustment costs—a key focus in emphasizing the real-options channel in the uncertainty literature. To maintain this focus and avoid introducing excessive complexity, the model assumes identical productivity and wages for both types of labour. In this section, I relax this assumption and incorporate alternative productivity and wage values that better reflect labour market differences.

The literature consistently documents that temporary labour earns lower wages and receives less training compared to their permanent counterparts (Booth, Francesconi, & Frank, 2002; Westhoff, 2022). Therefore, I consider two scenarios. First, I introduce a 10% wage penalty for temporary labour. This value is based on findings by Gebel (2010), who, using propensity score matching on data from the British Household Panel Survey (1991–2007), shows that labour market entrants with temporary contracts experience a 10% wage gap.[46] In this scenario, I assume equal productivity between permanent and temporary labour for simplicity. Second, I impose both a 9% wage penalty and a 9.5% productivity difference for temporary labour. This implies that temporary labour earns 9% less and is 9.5% less productive than permanent labour. These figures are derived from Booth, Francesconi, and Frank (2002), who, using pooled probit regression on British Household Panel Survey data, report that male workers on fixed-term contracts have a

[46] Other estimates exist as well. For instance, Tito (2011) reports a 6.5% wage premium for permanent contracts in the UK. I use the 10% wage penalty for temporary labour as a starting point.

12% lower probability of receiving work-related training compared to their permanent counterparts, while for female workers, the probability is 7% lower. Additionally, they estimate a wage gap of 11% for women and 7% for men on fixed-term contracts. I arrive at the calibrated values by averaging the reported wage gaps and training probabilities across genders.

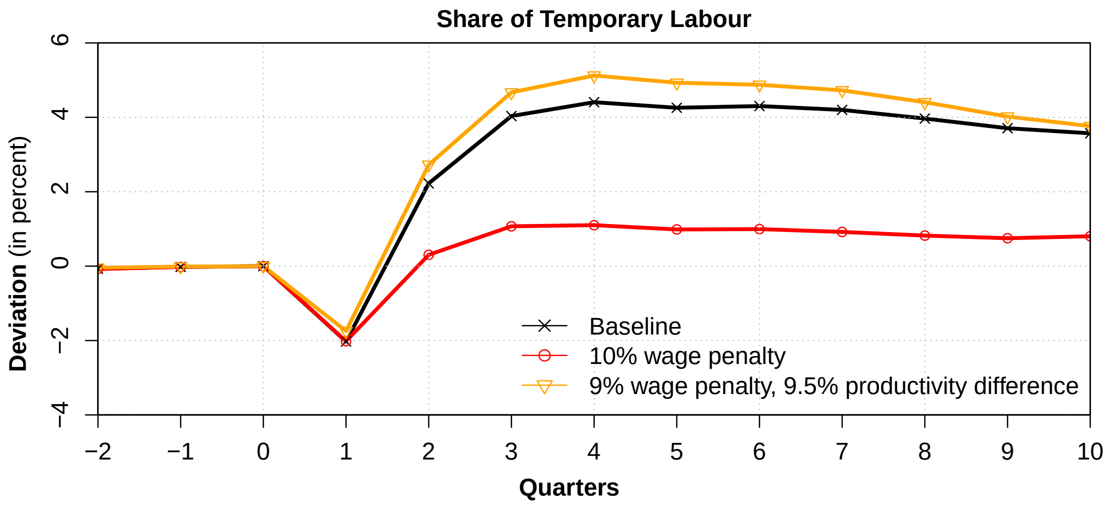

Figure 3.17: The impact of an uncertainty shock on the aggregate share of temporary labour (temporary labour as a proportion of total labour) under alternative wage and productivity parameters. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline (× symbol) an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. In addition, I plot the responses assuming a 10% wage penalty for temporary labour (○ symbol), and a combination of a 9% wage and a 9.5% productivity penalty for temporary labour (▽ symbols). The figure depicts the percentage deviation of cross-economy average for the share of temporary labour relative to its pre-shock value in quarter 0.

Figure 3.17 illustrates the effects of an uncertainty shock on the aggregate share of temporary labour under alternative calibrated values for productivity and wages. Due to space constraints, the corresponding effects on output, total labour, and labour productivity are not shown. The figure reveals that introducing a 10% wage penalty for temporary labour, while keeping productivity identical between temporary and permanent labour, results in a relatively muted rebound and overshoot during the recovery phase compared to the baseline scenario. However, when both wage penalty and productivity difference are introduced, the dynamics of the share of temporary labour more closely resemble the baseline, with the overshoot slightly more pronounced than in the baseline case.

Why is the rebound and overshoot muted when temporary labour is cheaper but equally productive compared to permanent labour? Intuitively, one might expect the recovery to be more pronounced, as temporary labour becomes more cost-effective. However, the muted response can be explained by firms' cost structure during the uncertainty shock. While the initial decline in the share of temporary labour is similar to the baseline, the overall losses incurred by firms are lower because temporary labour, being cheaper, imposes lower hiring and firing costs (which are modeled as a fixed fraction of the wage bill). Consequently, during the recovery phase, while firms continue to prefer temporary labour due to its lower adjustment costs, they are also better positioned to afford permanent labour (which is more stable due to its lower destruction rate) because the overall financial strain during the uncertainty shock is reduced. As a result, the rebound and overshoot in the share of temporary labour is subdued. When both a wage penalty and a productivity difference are introduced, on the other hand, the dynamics are different. The fixed adjustment costs, which are tied to productivity, and the linear adjustment costs, which depend on wages, are both affected. This makes temporary labour relatively more attractive than permanent labour, as the combined wage penalty and lower productivity further amplifies the cost advantages of temporary labour during the recovery. Consequently, the rebound and overshoot in the share of temporary labour become slightly more pronounced compared to the baseline scenario.

It is reassuring that in the robustness check incorporating both a wage penalty and a productivity difference—arguably a more realistic representation of labour market conditions for permanent and temporary labour—the baseline dynamics of the share of temporary labour following an uncertainty shock are preserved.

3.6.4 Alternative Uncertainty Parameters

In this subsection, I test the robustness of the results under alternative parameterizations of the uncertainty process. Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I reduce the value of each uncertainty parameter by 25% because the calibrated and estimated values in Section 3.4.4 indicate significant jumps in both micro- and macro-uncertainty, high persistence of the uncertainty process, and a moderately frequent occurrence of high uncertainty states. Specifically, I consider a 25% reduction in the following parameters: (i) the macrovolatility jump, from 1.6 to 1.2; (ii) the microvolatility jump, from 3.1 to 2.3; (iii) the transition likelihood from low to high uncertainty, from 0.065 to 0.049; (iv) uncertainty persistence, from 0.91 to 0.68; (v) the baseline value of microvolatility, from 0.053 to 0.04; and (vi) the baseline value of macrovolatility, from 0.0067 to 0.005. Additionally, I conduct an experiment calibrating all uncertainty parameters to the values estimated in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018).

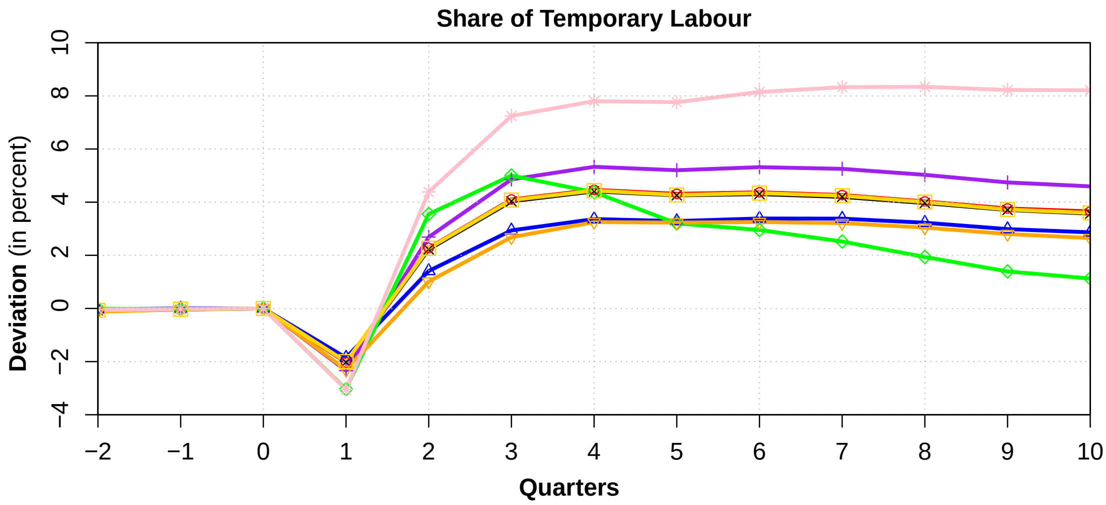

Figure 3.18: The impact of an uncertainty shock on the aggregate share of temporary labour (temporary labour as a proportion of total labour) is robust to alternative calibrations of uncertainty parameters. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline ($\times$ symbol) an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. In addition, I plot the responses assuming a 25% reduction in the high-uncertainty increase in macro volatility ($\circ$ symbols), the high-uncertainty increase in micro volatility ($\triangle$ symbols), the frequency of an uncertainty shock (+ symbols), the persistence of an uncertainty shock ($\diamond$ symbols), the low-uncertainty micro volatility (∇ symbols), and the low-uncertainty macro volatility ($\square$ symbols). Additionally, I also plot the responses using parameter values calibrated to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) (* symbols). The figure depicts the percentage deviation of cross-economy average for the share of temporary labour relative to its pre-shock value in quarter 0.

Figure 3.18 illustrates the effects of these variations on the aggregate share of temporary labour. Due to space constraints, the effects on output, total labour, and labour productivity are not presented. The figure demonstrates that, overall, the results remain robust to these parameter changes, maintaining the dynamics reported in Figure 3.13. The only notable exception arises when the persistence of the uncertainty shock is reduced by 25%. At this lower persistence level, the impact becomes short-lived: within 10 quarters of the uncertainty shock, the share of temporary labour nearly returns to its pre-shock level. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) observe that the estimated persistence of uncertainty shocks (0.94 in their paper and 0.91 in this chapter) may appear high, but these values capture the endogenous amplification of uncertainty due to sluggish economic growth. This interaction between uncertainty and weak growth is particularly relevant for the UK, where economic growth has been adversely affected by the 2008

Financial Crisis (Blundell, Crawford, & Jin, 2014; Pessoa & Van Reenen, 2014) and further exacerbated by the prolonged turbulence surrounding Brexit (Born, Müller, Schularick, & Sedláček, 2019; Redl, 2017). Therefore, the increase in the share of temporary labour under high uncertainty persistence (0.91) observed in the baseline scenario aligns with the economic conditions described.

3.7 Wage Subsidy in the Presence of Uncertainty

This section presents a thought experiment on the effectiveness of wage subsidies in addressing the impact of uncertainty shocks. In practice, such a subsidy would function similarly to a tax cut. Consider an economy aiming to reduce its reliance on temporary labour while increasing the share of permanent labour. As shown in the previous section, the share of temporary labour declines on impact during an uncertainty shock; this section explores how effective wage subsidies could be in further reducing the share of temporary labour during periods of heightened uncertainty compared to normal times. These policy experiments are merely illustrative; they are intended to document and quantify the potential impact of such measures under conditions of elevated uncertainty rather than drawing definitive conclusions about the efficacy of wage policies.

The policy experiments I consider aim to temporarily stimulate hiring of specific types of labour by reducing the effective wage paid by firms. Specifically, in the first policy experiment, the policy involves an unanticipated 1% wage bill subsidy applied to both permanent and temporary labour for one quarter.[47] The second policy experiment introduces an unanticipated 1% wage bill subsidy exclusively for permanent labour, also lasting for one quarter. The third policy experiment implements an unanticipated 1% wage bill subsidy exclusively for temporary labour for the same duration. Finally, the fourth policy experiment combines an unanticipated 1% wage bill subsidy for permanent labour with a 0.5% wage bill subsidy for temporary labour, both applied for one quarter. In all policy experiments, I simulate the policy impulse under two scenarios: during an uncertainty shock and in normal times where no such shock occurs. By comparing the marginal effects in these two scenarios, I attempt to identify the effectiveness of wage

[47] In a general equilibrium framework, this subsidy would typically be financed through mechanisms such as a lump-sum tax on households.

subsidies during heightened uncertainty.

Figure 3.19 illustrates the net impact of each policy experiment on the share of temporary labour. To calculate the net effect of the policy in the absence of an uncertainty shock, I first solve for the policy's impact on the share of temporary labour when no uncertainty shock occurs. From this, I subtract the baseline behaviour of the share of temporary labour in a scenario with no uncertainty shock and no subsidy. This provides the net effect of the policy in normal times. Similarly, to determine the net impact of the policy during an uncertainty shock, I calculate the policy's effect on the share of temporary labour under conditions of heightened uncertainty. From this, I subtract the baseline behaviour of the share of temporary labour in the presence of an uncertainty shock but without any subsidy.

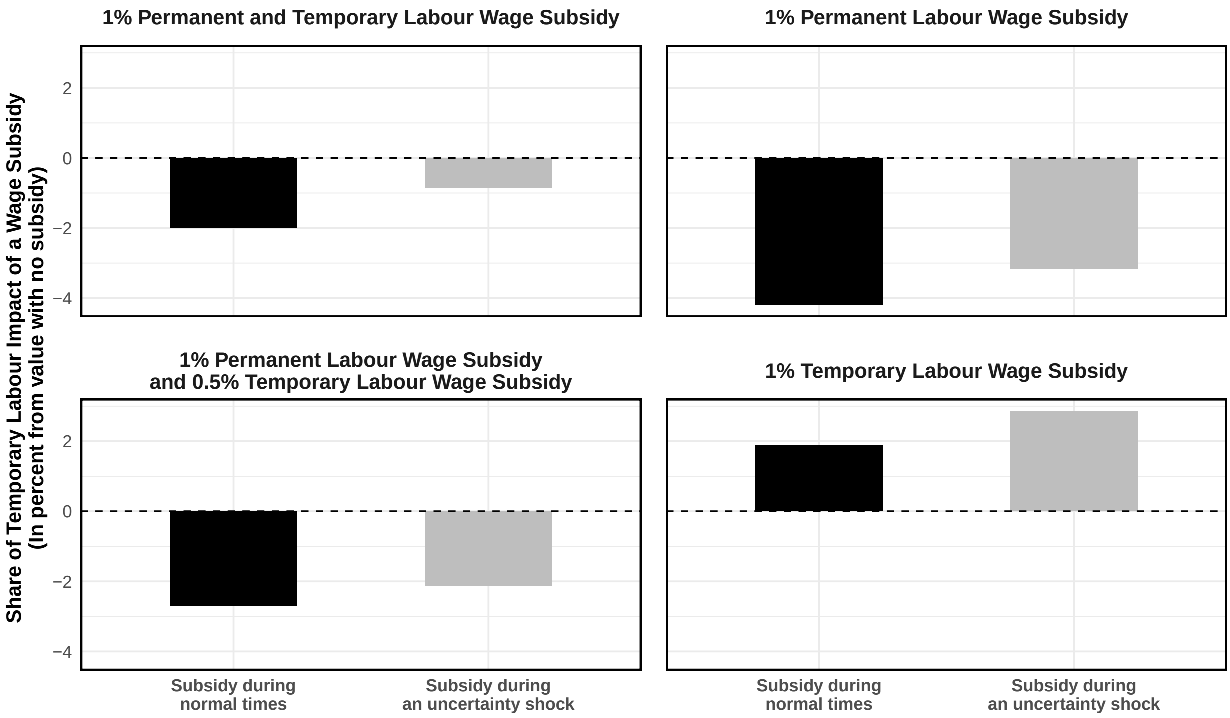

Figure 3.19: The impact of wage subsidies on temporary labour as a proportion of total labour. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the normal times scenario (black bars), an unanticipated 1% wage bill subsidy is introduced for all firms in quarter 1, with the economy evolving normally thereafter. The percentage difference is calculated as the deviation between the cross-economy average of the subsidy and no-subsidy share of temporary labour paths in quarter 1. For the uncertainty shock scenario (grey bars), the same wage subsidy is applied in quarter 1, but an uncertainty shock is also imposed simultaneously. Each subplot corresponds to a different policy experiment: (i) a 1% wage subsidy for both permanent and temporary labour, (ii) a 1% wage subsidy for permanent labour only, (iii) a combined 1% wage subsidy for permanent labour and 0.5% wage subsidy for temporary labour, and (iv) a 1% wage subsidy for temporary labour only. The bars illustrate the percentage difference in the share of temporary labour between the subsidy and no-subsidy cases under each scenario.

Figure 3.19 reveals that the presence of uncertainty dampens the impact of a 1% wage subsidy for both permanent and temporary labour by more than half. This finding aligns with the conclusions of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), which demonstrate that uncertainty reduces firms' responsiveness to policy stimuli. However, this particular policy experiment does not differentiate the effectiveness of subsidies targeting permanent versus temporary labour. Figure 3.19 further shows that, in normal times, a 1% wage subsidy exclusively for permanent labour is the most effective for reducing the share of temporary labour. Intuitively, a 1% wage subsidy exclusively for temporary labour increases the share of temporary labour during normal times. During an uncertainty shock, the effectiveness of a 1% wage subsidy for permanent labour decreases but remains the most effective policy for reducing the share of temporary labour. Interestingly, a 1% wage subsidy for temporary labour during an uncertainty shock leads to an even greater increase in the share of temporary labour compared to normal times. These results underscore the role of the real-options channel: During heightened uncertainty, firms exhibit a stronger preference for more "reversible" inputs during uncertain times; subsidies targeting these "reversible" inputs—temporary labour in this context—amplify this preference in shaping firms' labour decisions. Finally, the experiment combining a 1% wage subsidy for permanent labour with a 0.5% wage subsidy for temporary labour achieves a greater reduction in the share of temporary labour compared to a policy offering a 1% subsidy for both types of labour. This outcome is expected, as the relative cost advantage of the more "reversible" input is now reduced.

In conclusion, the findings suggest that targeted policies, such as wage subsidies exclusively for permanent labour, appear to be more effective in reducing the share of temporary labour. These subsidies enhance the relative attractiveness of the more "irreversible" input—in this case, permanent labour. Conversely, during an uncertainty shock, one might anticipate that the share of temporary labour would decline even with the presence of wage subsidy exclusive for temporary labour, as more firms dismiss temporary employees due to their lower adjustment costs. However, the findings reveal the opposite: a wage subsidy exclusively for temporary labour actually leads to a greater increase in the share of temporary labour during uncertainty, as the subsidy further increases the attractiveness of the more 'reversible' input. It is however important to emphasize that these policy experiments are intended to be illustrative; they do not account for the direct impact of policy on uncertainty. In the UK, permanent employment is not strictly "permanent," as firms retain the ability to dismiss permanent labour; while the model assumes exogenous destruction rates, in reality there is a risk that firms may resort to dismissals once the subsidy period ends. The feasibility of implementing such wage subsidies also remains questionable, as their effectiveness hinges on the government's ability to access and utilise timely and accurate measures of uncertainty. Furthermore, it should be noted that this analysis is conducted within a partial equilibrium framework with fixed prices and without capital, which inherently limits the model's ability to fully capture the real-world implications of these policies.

On increasing the share of permanent labour, policy options beyond wage subsidies also exist. For example, Italy implemented a reduction in social contributions paid by firms for newly hired permanent workers aged at least 25 years who had not been employed under an open-ended contract in the 24 months prior to their hiring, to incentivise firms to hire labour on permanent contracts (Lotti & Viviano, 2012).[48] However, in systems where workers are adequately protected during periods of job loss and society actively supports workers in improving their job prospects—such as under the flexicurity model in Denmark (Kreiner & Svarer, 2022)—direct government intervention in the labour market may not be necessary. Future research could yield valuable insights into which policy options are most effective in reducing the share of temporary labour during periods of heightened uncertainty compared to normal times.

3.8 Limitations

This section discusses the limitations of the VAR analysis and the partial equilibrium model.

Although the VAR results in Section 3.3 survive multiple robustness tests, it is important to acknowledge a key limitation: the analysis relies on Cholesky decomposition for shock identification; this method imposes a recursive structure, assuming causal relationships by ordering variables in a specific sequence and thereby restricting certain shocks to have no contemporaneous effect on specific endogenous variables. However, there is no

[48]The Italian government introduced this tax credit in 2000 but reduced the benefit in 2003 and discontinued it entirely in 2007, although some Italian regions introduced similar incentives after 2007. (Lotti & Viviano, 2012).

compelling theoretical justification for restricting the timing of the relationship between uncertainty and real activity (Carriero, Clark, & Marcellino, 2018; Ludvigson, Ma, & Ng, 2021). There are alternative VAR identification strategies (see Section 1.1.2 in Chapter 1) that can address the shortcomings of recursive structures. I plan to explore these advanced identification strategies in the future to refine the analysis.

The VAR analysis incorporates the number of individuals in temporary employment as a measure of temporary employment. While useful, this measure is a stock variable and may not fully capture the dynamic effects of uncertainty. A more insightful alternative could be vacancy data for temporary positions, a flow variable that better isolates labour demand.[49] Specifically, tracking vacancies for temporary versus permanent positions during periods of economic uncertainty can reveal firms' preferences in labour contracts when uncertainty rises. This approach is particularly compelling because vacancy data is available at very high frequencies (e.g., daily); when combined with high-frequency uncertainty measures (such as the daily Economic Policy Uncertainty (EPU) data by Baker, Bloom, and Davis (2016)), this method could add robustness to the analysis since the use of high-frequency data to explore the impact of uncertainty remains scarce in the literature.

In addition, the VAR analysis focuses exclusively on the UK, but it can be readily extended to include additional countries for enhancing the robustness of the findings on the effects of uncertainty on temporary employment. For instance, the EU Labour Force Surveys (EU-LFS) conducted by Eurostat across EU member states provide data on temporary employment, including reasons for temporary employment, which are the core variables required for the baseline VAR analysis. This analysis could be expanded into a panel VAR framework to examine the effects of uncertainty on temporary employment. However, it is important to note that definitions of temporary employment vary across countries.

The partial equilibrium model is also not without limitations. These limitations are briefly mentioned throughout the chapter, but they warrant a brief formal discussion

[49] The UK's vacancy data from Adzuna are available at no cost to researchers, but cover a limited time period, starting only from 2017.

in this section. First, the distinction between permanent and temporary labour in the model deviates from real-world definitions. In the UK, the classification of employment as permanent or temporary is based on contract duration. In contrast, the model does not explicitly incorporate contract duration. Instead, it conceptualizes the distinction through a trade-off between adjustment costs and destruction rates. While this abstraction is a simplification aimed at facilitating tractable analysis, it does not fully align with real-world dynamics. Incorporating contract duration to align the model's definition of permanent and temporary labour with UK's classifications represents a promising direction for future research to quantify the impact of uncertainty on temporary employment.

Second, the model has two notable limitations: it excludes capital for simplicity and operates as a partial rather than a general equilibrium model. By omitting capital, the model assumes that output is solely a function of labour, oversimplifying the production process and neglecting the relationship between capital and labour. This omission prevents the model from capturing firms' investment decisions, which are particularly sensitive to uncertainty shocks (Bloom, Davis, Foster, Ohlmacher, & Saporta-Eksten, 2022; Bloom, Van Reenen, & Bond, 2007). Furthermore, a general equilibrium model offers advantages over a partial equilibrium model by accounting for interactions across multiple agents of the economy. For example, in a general equilibrium framework, an uncertainty shock could simultaneously decrease labour demand, wages, and household consumption, creating a feedback loop that dampens aggregate demand and affects firms' hiring decisions regarding permanent versus temporary labour—dynamics that are absent in a partial equilibrium model. Additionally, partial equilibrium models assume fixed prices and wages, which may not reflect actual economic behavior and could lead to inconsistencies if these assumptions are unrealistic. Despite these limitations, the choice to exclude capital and rely on a partial equilibrium framework is driven by practical considerations: the need for simplicity and computational feasibility. With seven state variables already incorporated, introducing capital and transitioning to a general equilibrium model would introduce significant computational complexity. I leave the incorporation of capital and the extension to a general equilibrium framework to future research.

Finally, the parameters governing adjustment costs, wages, and productivity for the UK are calibrated rather than estimated, primarily due to the lack of UK-specific estimates for these parameters. Estimating adjustment costs for permanent and temporary labour, for instance, would require detailed firm-level balance sheet data that explicitly differentiate between these two types of labour contracts. However, most available datasets aggregate labour without distinguishing contract types, making it difficult to estimate separate adjustment costs. The absence of a formal estimation process means that the chosen parameter values lack a statistical basis, preventing the assessment of their proximity to the "true" values or the uncertainty surrounding them. Addressing this limitation by formally estimating these parameters remains a priority for future research, contingent on the availability of more granular and comprehensive datasets.

3.9 Conclusion

This chapter explores the relationship between uncertainty and temporary employment. The first part of the chapter provides novel empirical evidence of the positive association between uncertainty and the size of temporary employment by estimating a Bayesian Vector Autoregressive (VAR) model for the UK. A one-standard-deviation increase in macroeconomic uncertainty results in a peak increase of approximately 0.5% in temporary employment slightly after 8 quarters following the shock. The results suggest that uncertainty 4 standard deviations above its mean—a scenario observed in practice during crises in the UK such as the Great Recession and the COVID-19 pandemic—corresponds to a roughly 2% rise in temporary employment. This result highlights how major economic crises may trigger sizable increase in temporary employment. The VAR analysis also provides suggestive evidence that the share of temporary employees who take up temporary employment in the first place because they fail to find permanent employment increases following an uncertainty shock, while the share of temporary employees who do not want permanent employment declines, hinting at firms' reduced demand for permanent employees rather than a decrease in households' resistance to temporary employment during heightened uncertainty.

The second part of the chapter features a partial equilibrium model which singles out the role of uncertainty in shaping labour composition. Specifically, I augment the firm's problem as in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), with two types of labour—permanent and temporary; the distinction between the two is conceptualized through a trade-off between adjustment costs and destruction rates. Firms face exogenous processes for aggregate and idiosyncratic productivity, with innovations that vary over time. The analysis reveals that uncertainty shocks lead to a decline in the aggregate share of temporary labour by approximately 2% on impact. Following the initial decline, the share of temporary labour experiences a rebound and overshoot during the recovery phase. As firms gradually recover from the uncertainty shock, they resume hiring but disproportionately increase their reliance on temporary labour. Although the rebound and overshoot is a feature of the partial equilibrium framework where the lack of price adjustments leads to exaggerated dynamics, more realistic simulations that combine uncertainty shocks with negative first-moment shocks (as Chapter 1 shows recessions are often characterized by both types of shocks) mitigate but do not eliminate the overshoot in the share of temporary labour during the recovery. This suggests that firms become more cautious in the aftermath of heightened uncertainty and react by favouring temporary labour over permanent labour, as the higher adjustment costs incurred by permanent labour makes hiring or firing mistakes of permanent labour costlier than that of temporary labour. These findings highlight the strategic advantage firms place on flexibility during uncertain periods. I also find that wage subsidies targeted exclusively at permanent labour appear to be more effective than blanket subsidies for both types of labour in reducing the share of temporary labour during uncertainty shocks, as such targeted policies increase the relative attractiveness of permanent labour, the more "irreversible" input. Overall, both empirical and simulation results indicate that uncertainty leads to an increase in the aggregate share of temporary employment.

There are several promising avenues for future research. Employing more advanced VAR identification strategies and incorporating high-frequency data—as discussed in Chapter 1 and 2—can strengthen the robustness of the findings. However, the most promising direction lies in the development of richer models with more accurately estimated parameters to provide deeper insights into the mechanisms driving firms' labour composition decisions under uncertainty.

3.A Appendix

3.A.1 Uncertainty Measures

Figure 3.20 presents four uncertainty measures for the UK from 1992 to 2018.

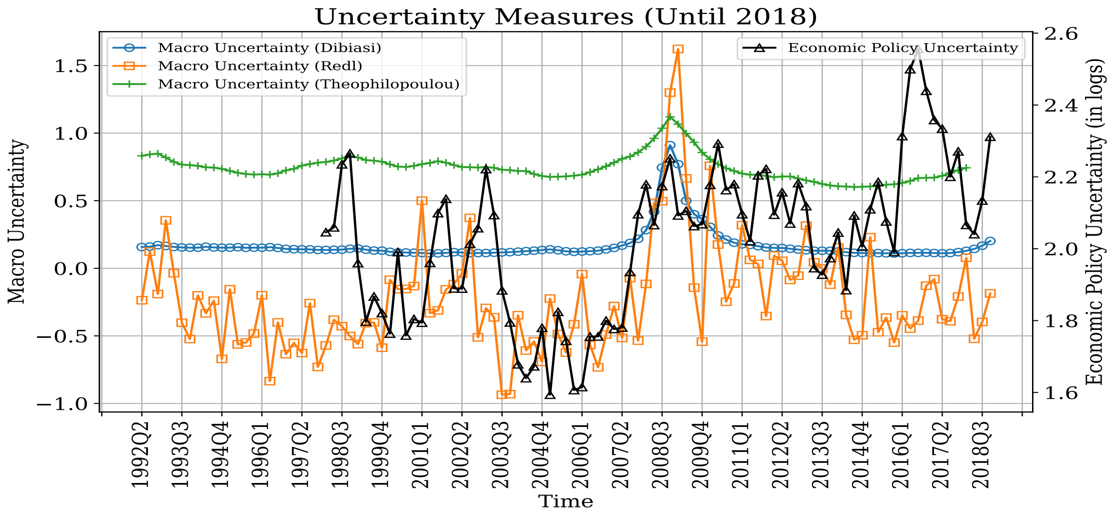

Figure 3.20: Uncertainty measures for the UK from 1992 to 2018. The left vertical axis displays three macroeconomic uncertainty measures: one by Dibiasi and Sarferaz (2023) (plotted with a hollow circle symbol), another by Redl (2020) (plotted with a hollow square symbol), and a third by Theophilopoulou (2022) (plotted with a plus symbol). The right vertical axis presents the Economic Policy Uncertainty (EPU) index, in logarithmic scale, as developed by Baker, Bloom, and Davis (2016) (plotted with a hollow triangle symbol). Note that the measure by Theophilopoulou (2022) is available only until 2018Q1 while the measure by Baker, Bloom, and Davis (2016) is available only since 1998. The uncertainty measures by Redl (2020) and Baker, Bloom, and Davis (2016) are originally monthly data, converted into quarterly averages.

3.A.2 BVAR Specification: Minnesota Prior

The BVAR model in this chapter assumes a Minnesota prior for estimation and identifies uncertainty shocks using Cholesky decomposition. The Bayesian framework, which integrates prior beliefs with observed data to yield a posterior distribution of parameters, and the Cholesky decomposition, which imposes a recursive structure whereby certain shocks have no contemporaneous impact on specific endogenous variables, are introduced in Chapter 1. Here, I explain the Minnesota prior.

The Minnesota prior, a widely-used prior distribution in Bayesian VARs, serves primarily to "shrink" the coefficients of the VAR model, thereby reducing the risk of overfitting. In Litterman (1986)'s original formulation, this prior assumes a normally distributed set of VAR parameters with a fixed covariance of the innovations. This chapter employs the BVAR toolbox developed by Ferroni and Canova (2021), which adopts the version of the Minnesota prior advanced by Sims and Zha (1998). In this approach, the covariance matrix of the innovations is treated as random, and multiple layers of shrinkage are applied through the use of dummy observations. Detailed in Ferroni and Canova (2021), the degree of shrinkage is governed by the following hyperparameters:

- τ, which regulates the prior tightness for the autoregressive coefficients of order one, with a larger τ indicating tighter priors;
- δ, which controls the prior tightness for the autoregressive coefficients of higher lags, where a larger δ implies faster lag decay;
- λ, which adjusts the weight on own-persistence (this prior captures the belief that a variable that has remained stable at its initial level is likely to continue at that level, independent of other variables);
- μ, which governs the weight on the co-persistence of the data (this prior captures the belief that when the data remains stable at its initial levels, it will generally persist in that state);
- ω, which regulates the weight assigned to the priors of the covariance matrix of innovations.

Following the approach outlined by Ferroni and Canova (2021), I begin by setting initial values (I use the default values in the BVAR toolbox, which follow Sims and Zha (1998)) for all hyperparameters and then maximize the log marginal likelihood to optimally estimate the hyperparameter τ. Using the mode value obtained from this initial maximization, I proceed to jointly maximize over τ, δ, and λ. In the final maximization stage, the remaining hyperparameters, μ and ω, are incorporated to obtain the optimal values for the entire set of hyperparameters. Once the maximum is identified, the posterior distribution is computed based on these optimal hyperparameter values.

3.A.3 Mixed-Frequency VARs: Recovering "Missing" Observations

I estimate a mixed-frequency VAR in Section 3.3.3 using the MATLAB toolbox developed by Ferroni and Canova (2021), which is based on the method outlined in Schorfheide and Song (2015). Here, I provide a brief explanation of the econometrics behind mixed-frequency VARs.

Let $Y_t^{(A)}$ represents a low-frequency (annual) variable at time t, and $X_t^{(Q)}$ a high-frequency (quarter) variable at time t. To handle unobserved variables (the quarterly counterparts of annual data), I vary the dimension of the vector of observables as a function of time t as in Durbin and Koopman (2012) and Schorfheide and Song (2015). Assuming $Y_t^{(A)}$ can be computed as the average of four quarterly observations, it is represented as:

$$Y_t^{(A)} = \frac{1}{4}(X_t^{(Q)} + X_{t-1}^{(Q)} + X_{t-2}^{(Q)} + X_{t-3}^{(Q)}) \tag{3.13}$$

The state-space representation in mixed-frequency VARs consists of a measurement equation and a state transition equation. The measurement equation defines how the low-frequency variable is constructed from the high-frequency data:

$$Y_t = Hs_t + \varepsilon_t, \tag{3.14}$$

where Y_t is the vector of observed variables, which includes data from different frequencies; s_t is the state vector at time t, which includes all high-frequency states; H is the measurement matrix that determines how the states relate to the observations; ε_t is the measurement errors. Equation 3.14 can be rewritten as:

$$\begin{pmatrix} X_t^{(Q)} \\ Y_t^{(A)} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix} \begin{pmatrix} X_t^{(Q)} \\ X_{t-1}^{(Q)} \\ X_{t-2}^{(Q)} \\ X_{t-3}^{(Q)} \end{pmatrix} + \varepsilon_t. \tag{3.15}$$

The state transition equation describes how the underlying states evolve over time:

$$s_t = Fs_{t-1} + u_t, \tag{3.16}$$

where F is the state transition matrix that captures the autoregressive dynamics, and u_t a vector of innovations assumed to be normally distributed: $u_t \sim N(0, \Sigma)$, where Σ is the covariance matrix.

Bayesian inference for mixed-frequency VARs requires a joint distribution of observables, latent states, and parameters conditional on the pre-sample used to initialize lags. Following Ferroni and Canova (2021), I use a Gibbs sampler to generate draws from the posterior distribution of the reduced form VAR parameters (autoregressive coefficients and the covariance matrix), conditional on observables and states; using these draws and the Kalman smoother, I estimate the unobserved states and implicitly recover the values of the variables whose higher-frequency observations are missing. Figure 3.21 presents the quarterly estimates of the annual microeconomic uncertainty used in Section 3.3.3.

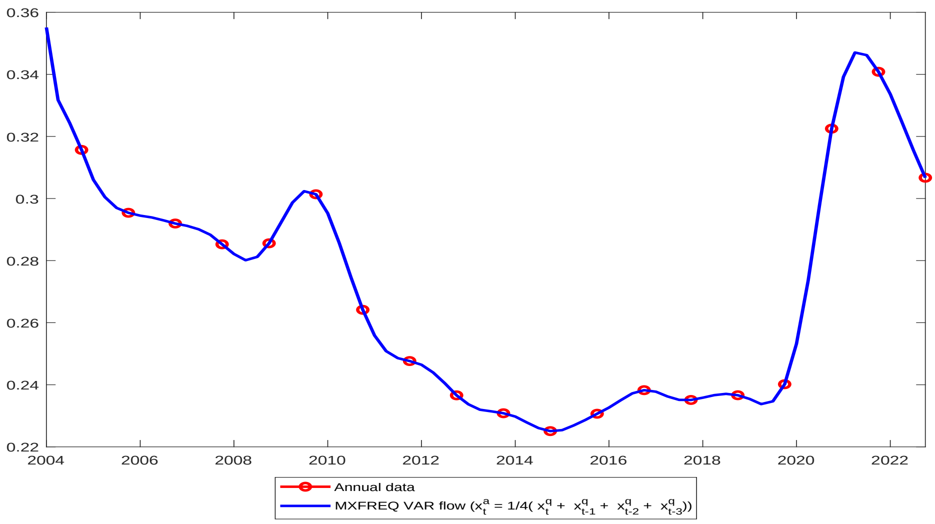

Figure 3.21: The microeconomic uncertainty measure derived in Chapter 1 is available at an annual frequency. I use a mixed-frequency VAR with Bayesian methods to estimate quarterly microeconomic uncertainty. The horizontal axis displays time in years, while the vertical axis displays microeconomic uncertainty values. The hollow red circles plot the annual microeconomic uncertainty data. The blue line plots the estimated quarterly microeconomic uncertainty based on the VAR with the other four quarterly variables (macroeconomic uncertainty, industrial production, total employment, and temporary employment).

3.A.4 Data

In this section, I provide a brief description of the variables in the Bayesian VAR model, accompanied by a table of summary statistics and figures of the time series for each variable.

	Observation	Mean	SD	Min	Max
Macroeconomic Uncertainty	123	0.376	0.667	0.109	3.855
Industrial Production (log)	123	2.007	0.040	1.909	2.079
Total Employment (log)	123	7.463	0.035	7.403	7.518
Temporary Employment (log)	123	6.195	0.031	6.104	6.253
FTAS (log)	123	3.438	0.138	3.049	3.629
Investment (log)	123	4.626	0.093	4.427	4.780
Consumption (log)	123	5.429	0.082	5.257	5.538
Consumer Confidence	123	-10.653	11.839	-44.667	8.667
Bank Rate	123	3.237	2.663	0.100	10.047
Labour Productivity (log)	123	1.954	0.042	1.854	2.009
CTEMP	123	0.321	0.062	0.217	0.434
DTEMP	123	0.272	0.032	0.191	0.331

Table 3.4: Summary statistics of the variables used in the Bayesian VAR. *Notes:* The macroeconomic uncertainty measures are developed by Dibiasi and Sarferaz (2023). FTAS refers to the UK FTSE All Share, CTEMP the proportion of individuals in temporary employment who could not find permanent employment, and DTEMP the proportion of individuals in temporary employment who did not want permanent employment.

Industrial Production

Industrial production (IP) is the output of industrial establishments and covers sectors such as mining and quarrying, manufacturing, electricity, gas and water supply. This paper uses the IP index for the UK from International Monetary Fund (2024), a seasonally-adjusted index (reference year = 2010) that expresses change in the volume of production output. The IMF data originate from the OECD Database.

Total Employment

Employment is a different, but similar, concept to jobs—it is a measure of people so a person with more than one job would therefore be counted once in the employment estimates. The number of employed individuals for the entire UK economy is collected in the Labour Force Surveys (LFS) by Office of National Statistics (2024b). They cover salaried employees aged 16 and over who did one hour or more of paid work per week and those who had a job that they were temporarily away from in all industries and services; the self-employed, military personnel and domestic servants are excluded. The data are seasonally adjusted and may be further sub-divided into permanent and temporary employees.

Temporary Employment

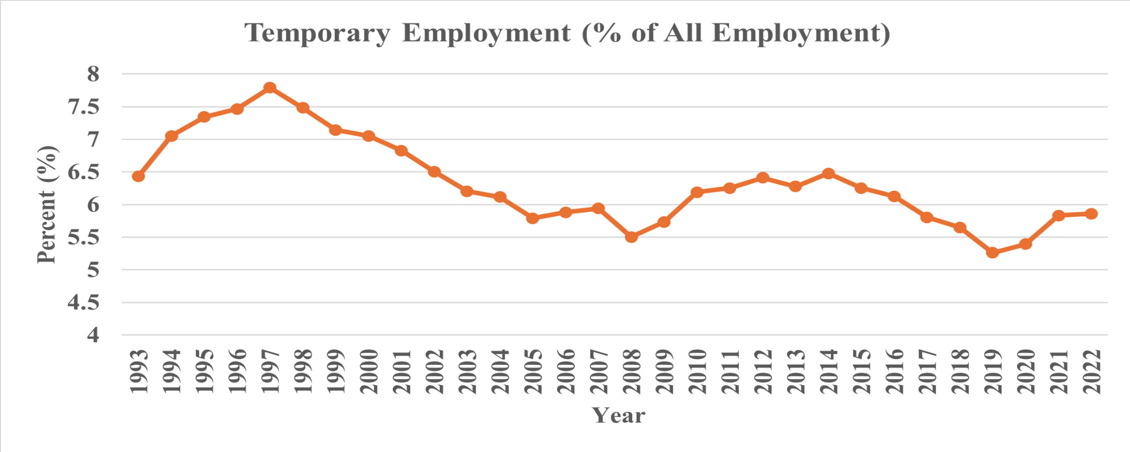

Figure 3.22: Average temporary employment as a percentage of total employment, 1993–2022. Yearly averages are calculated by summing the values for each quarter and dividing by 4. *Source:* Office of National Statistics (2024c).

Temporary employees, in its simplest definition, are employees who perform a job for only a short amount of time. Data on temporary employees in the entire UK economy are sourced from the Office of National Statistics (2024c). The sample includes employees who are agency workers, casual laborers, seasonal workers or with fixed-term contracts. The data are seasonally adjusted.

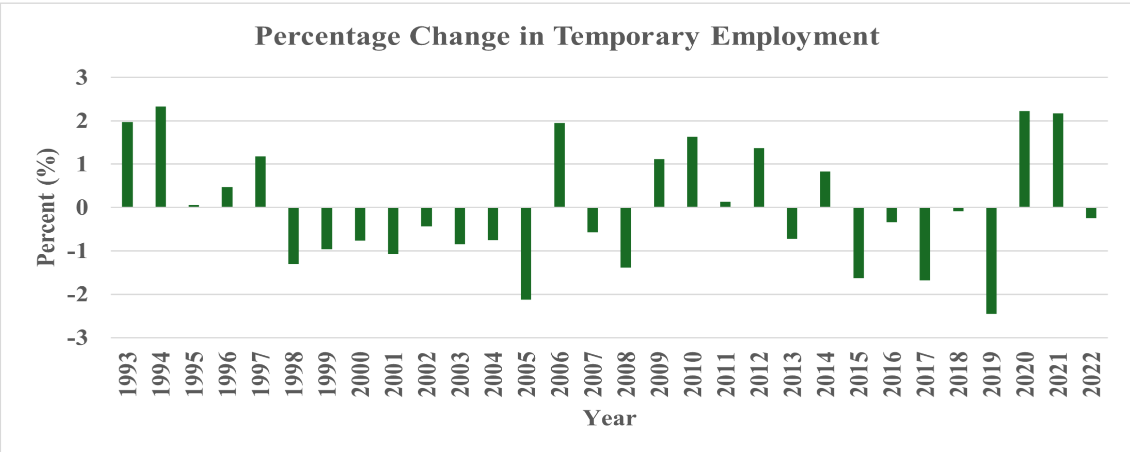

Figure 3.23: Percentage change (quarter-on-quarter) in temporary employment as a percentage of total employment, 1993–2022. Annual averages are calculated by summing the quarterly values for each year and dividing by 4. *Source:* Office of National Statistics (2024c).

The data contain a breakdown of reasons for temporary employment: i) Unable to find a permanent job; ii) Did not want a permanent job; iii) Had a contract with a period of training; and iv) Others (unspecified reasons). In addition, the data also identify part time temporary employees and reasons for part time temporary employment.

FTSE All-Share (FTAS)

The FTAS measures the performance of all eligible companies listed on the London Stock Exchange's main market that passed size and liquidity screenings. This chapter uses the adjusted price of the FTAS sourced from Yahoo Finance (2023).

Bank Rate

I derive the quarterly measurement from the monthly bank rate sourced from the Bank of England (2024). The bank rate is also sometimes called the 'BoE base rate'.

Consumption

I obtain the chained value measure of household final consumption expenditure (£m) from the Office of National Statistics (2024e). The data are seasonally adjusted.

Investment

I obtain the chained value measure of business investment (£m) from the Office of National Statistics (2024a). The data are seasonally adjusted.

Consumer Confidence

The GfK Consumer Confidence Barometer measures consumer sentiment in the UK by surveying monthly a representative sample of approximately 2,000 individuals aged 16 and over. The survey captures respondents' perceptions of their personal financial situation and on the general economic condition over the past 12 months as well as their expectations for the next 12 months. It also gauges their intentions regarding major purchases and savings. I source the GfK Consumer Confidence index from Datastream.

Labour Productivity

I obtain the output per worker data, calculated by dividing gross value added (in chained volume measures) by the number of workers, from the Office of National Statistics (2024g).

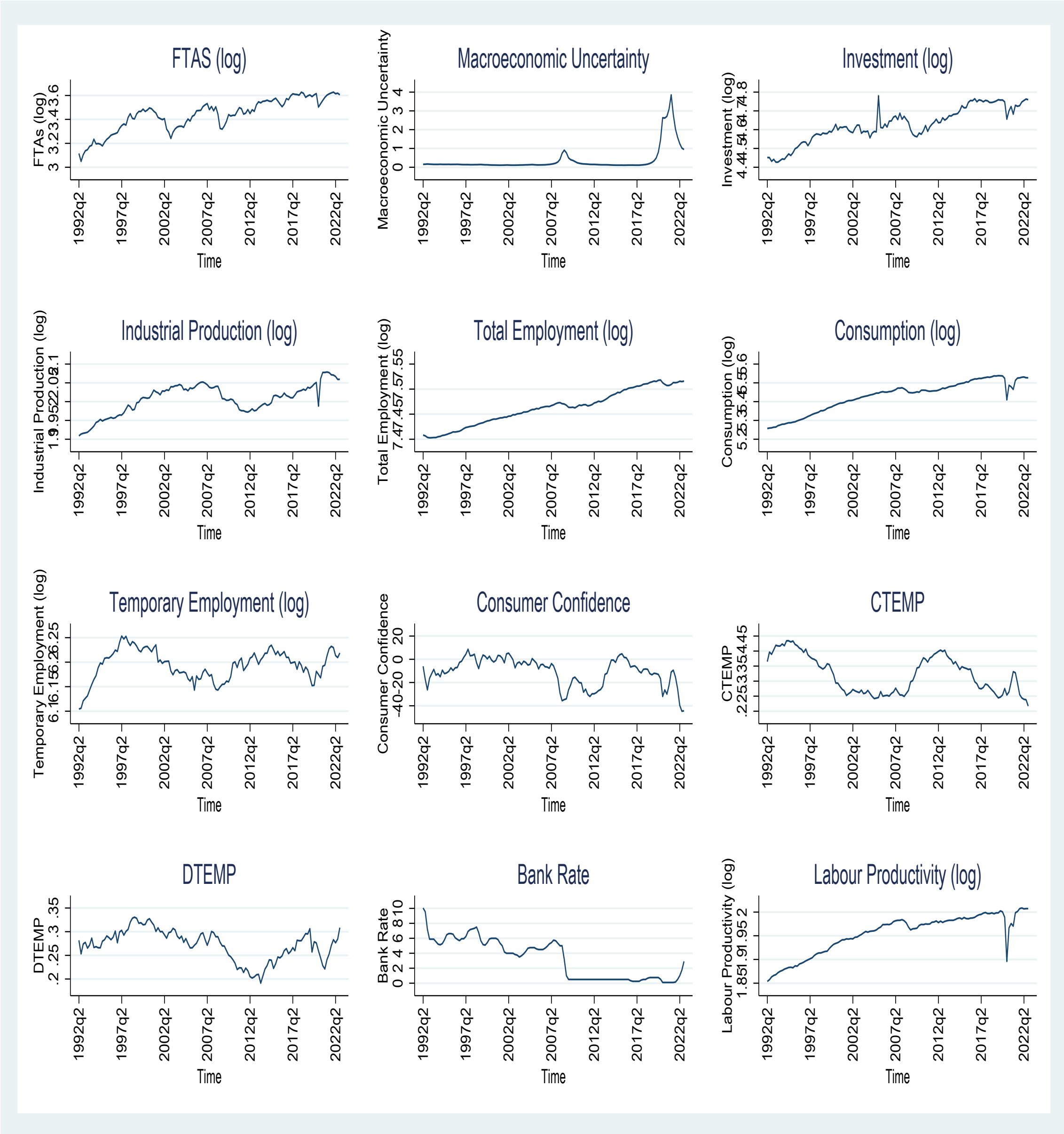

Figure 3.24: Time series plots of variables from 1992Q2 to 2022Q4. *Notes:* FTAS refers to the UK FTSE All Share, CTEMP the proportion of individuals in temporary employment who could not find permanent employment, and DTEMP the proportion of individuals in temporary employment who did not want permanent employment.

3.A.5 Robustness of the VAR Results

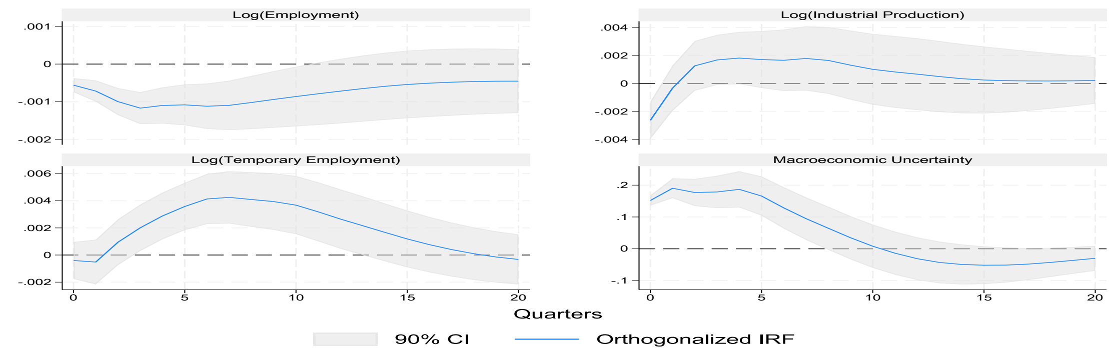

Figure 3.25: Impulse responses to a macroeconomic uncertainty shock, using frequentist approach. The ordering of the variables as well as the lag length follow the baseline model's. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty, the variables enter in log levels. The blue solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the shaded areas represent the 90-percent error bands.

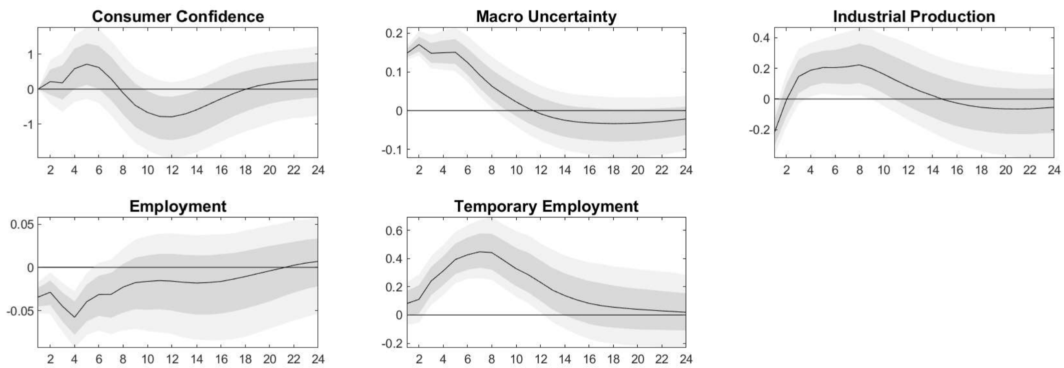

Figure 3.26: Impulse responses to a macroeconomic uncertainty shock, with consumer confidence as an additional control and ordered before macroeconomic uncertainty. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. The consumer confidence index, sourced from the GfK Consumer Confidence Barometer, measures consumer sentiment in the UK by surveying monthly a representative sample of approximately 2,000 individuals aged 16 and over; the survey captures respondents' perceptions of their personal financial situation and on the general economic condition over the past 12 months, their expectations for the next 12 months, and their intentions regarding major purchases and savings. Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty and the consumer confidence index, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

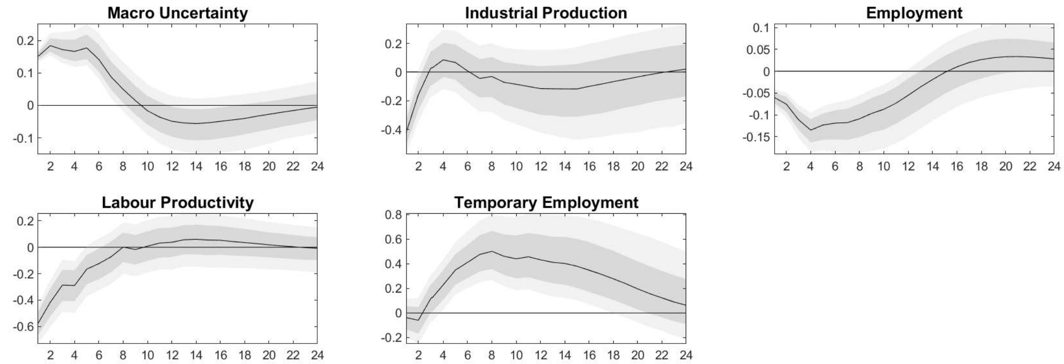

Figure 3.27: Impulse responses to a macroeconomic uncertainty shock, with labour productivity ordered before temporary employment. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Labour productivity, simply measured as output per worker, is sourced from the Office of National Statistics (ONS). Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

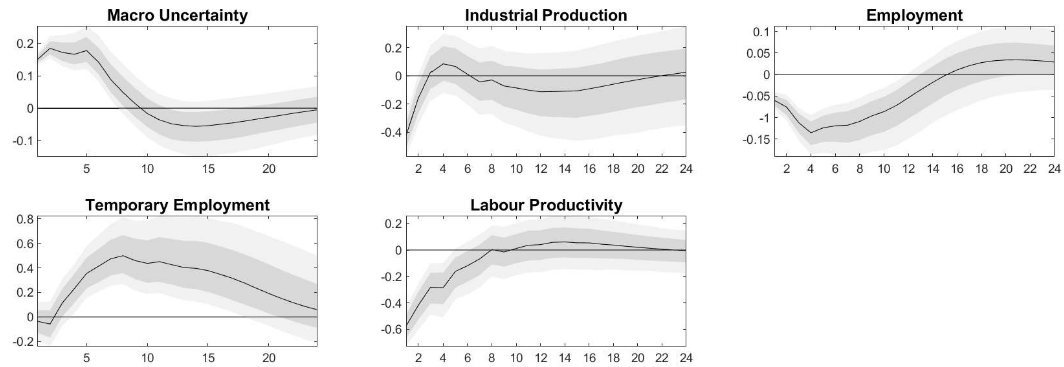

Figure 3.28: Impulse responses to a macroeconomic uncertainty shock, with labour productivity ordered after temporary employment. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Labour productivity, simply measured as output per worker, is sourced from the Office of National Statistics (ONS). Further details on the variables are provided in the Appendix. Except for macroeconomic uncertainty, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

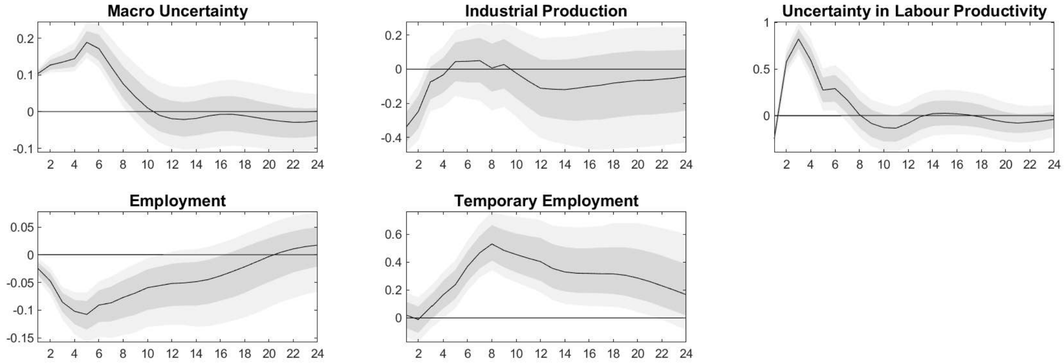

Figure 3.29: Impulse responses to a macroeconomic uncertainty shock, with uncertainty in labour productivity ordered before total employment. The vertical axis measures the magnitude of the responses while the horizontal axis indicates quarters following the shock for each plot. The macroeconomic uncertainty measure is sourced from Dibiasi and Sarferaz (2023). The industrial production index captures changes in the volume of output in sectors such as mining and quarrying, manufacturing, electricity, gas, and water supply. Employment is defined as the total number of individuals aged 16 and over who performed at least one hour of paid work per week. Temporary employment, a subset of total employment, represents the number of employees with contracts of a predetermined termination date, such as agency workers, casual labourers, seasonal workers, or employees on fixed-term contracts. Uncertainty in labour productivity is derived as the conditional heteroskedasticity of labour productivity obtained from a GARCH(1,1) model, following the method in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The time series of this uncertainty in labour productivity is presented in Figure 3.5. Further details on the variables are provided in the Appendix.Except for macroeconomic uncertainty and uncertainty in labour productivity, the variables enter in log levels. The black solid line denotes the median responses to an one-standard-deviation macroeconomic uncertainty shock, while the light and dark shaded areas represent the 90-percent and 68-percent bootstrapped error bands.

3.A.6 Model Solution and Simulation

This section outlines the solution algorithm for the model, drawing extensively from the methodology presented in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). It also details the practical numerical choices employed in implementing the solution method and discusses the computation of approximate impulse responses to assess the effects of an uncertainty shock.

Firm Problem Solution

I discretize the state space of the idiosyncratic firm problem. I choose log-linear grid of size n = 50 for the variable n^{per}, and n = 40 for the variable n^{tem}. While these grid sizes may appear relatively small, similar grid sizes have been successfully employed in the literature; for example, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) use a grid size of n = 91 for capital and n = 37 for labour. Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I discretize the exogenous productivity processes z and A following a straightforward generalization of Tauchen (1986) to the case of time-varying volatility, setting 5 discrete productivity points for both z and A. The value function iteration process is as follows:

1. Set an initial guess for the value function $V^0(A, z, \sigma^A, \sigma^Z, n_{-1}^{per}, n_{-1}^{tem})$ for each point in the state space grid. A common initial guess is zero.

2. Initialize the policy functions for permanent and temporary labour, which represent the firm's initial guesses for the optimal choices of labour.

3. Apply Howard policy acceleration: (i) for each iteration k, for each state $(A, z, \sigma^A, \sigma^Z, n_{-1}^{per}, n_{-1}^{tem})$ in the grid, use the current policy functions $n^{per,k}$ and $n^{tem,k}$ to compute the value function update:

$$\begin{aligned} V^{k+1}(A, z, \sigma^A, \sigma^Z, n_{-1}^{\text{per}}, n_{-1}^{\text{tem}}) = & \, p\left(y - w^{\text{per}} n^{\text{per},k} - w^{\text{tem}} n^{\text{tem},k} - AC^{\text{per}} - AC^{\text{tem}}\right) \\ & + \beta \mathbb{E}\left[V^k(A', z', \sigma^{A'}, \sigma^{Z'}, n^{\text{per}}, n^{\text{tem}})\right]. \end{aligned}$$

Repeat this step multiple times (200 times following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)) for each state to converge to the value function under the current policy functions. (ii) After converging to the value function under the current policies, update the policy functions by solving the maximization problem for each state, in other words, finding the optimal labour choices that maximize the value function, given the updated value function:

$$\begin{aligned} n^{\text{per},k+1}, n^{\text{tem},k+1} = \arg \max_{n^{\text{per}}, n^{\text{tem}}} \Bigg\{ & p\left(y - w^{\text{per}} n^{\text{per}} - w^{\text{tem}} n^{\text{tem}} - AC^{\text{per}} - AC^{\text{tem}}\right) \\ & + \beta \mathbb{E}\left[V^{k+1}(A', z', \sigma^{A'}, \sigma^{Z'}, n^{\text{per}}, n^{\text{tem}})\right] \Bigg\}. \end{aligned}$$

(iii) Check if convergence is achieved, that is,

$$\|n^{\text{per},k+1} - n^{\text{per},k}\| < \epsilon, \quad \|n^{\text{tem},k+1} - n^{\text{tem},k}\| < \epsilon,$$

where ϵ represents a pre-determined tolerance level. If the policy functions have not converged, set $k = k + 1$ and repeat steps (i) and (ii).

4. Once convergence is achieved, the resulting policy functions for permanent and

temporary labour are the optimal policy functions for the firm.

Unconditional Simulation

I simulate the model using $T = 5000$ periods of exogenous aggregate productivity and uncertainty realizations (A_t, S_t), $t = 1, ..., T$. Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I follow a histogram-based approach to track the cross-sectional distribution μ_t. Specifically, I track a histogram $\hat{\mu}_t$ of weights on individual points $(n_{-1}^{per}, n_{-1}^{tem}, z)$ in the firm-level discretized state space. μ_{t+1} is given by $\mu_{t+1}((n^{per}, n^{tem}, z')_j) = \Sigma_{(n^{per}, n^{tem}, z)_i} \mu_t($ $(n^{per}, n^{tem}, z')_i) \Pi^Z(z^i, z_j^{'}; S_t) \mathbb{I}(n_j^{per} = n_t^{per}((n^{per}, n^{tem}, z)_i), n_j^{tem} = n_t^{tem}((n^{per}, n^{tem}, z)_i)), i = 1, ..., n_{n^{per}} n_{n^{tem}} n_z$, with $n_t^{per}(k, n_{-1}^{per}, z)$ as the policy function for permanent labour and $n_t^{tem}(k, n_{-1}^{tem}, z)$ as policy function for temporary labour at period t, and $\Pi^Z(z, z'; S_t)$ the transition matrix over idiosyncratic productivity in period t. I discard the first 500 periods in the simulation to eliminate the influence of initial conditions.

Conditional Responses

I simulate $N = 2700$ independent economies of length $T_{IRF} = 100$. I select $T_{SHOCK} = 45$ as the shock period. In T_{SHOCK}, I impose high uncertainty for economy i. Thereafter, each economy i evolves normally for periods $t = T_{SHOCK} + 1, ..., T_{IRF}$. Let

$$\hat{X}_t = 100 \log\left(\frac{\bar{X}_t}{\bar{X}_{T_{SHOCK}} - 1}\right),$$

where $\hat{X}_t$ represents the percentage deviation of series X at period t from its pre-shock level and $\bar{X}_t = \frac{1}{N}\Sigma_i X_{it}$. Similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), the initial conditions used to initiate each simulation are a low uncertainty state, the median aggregate productivity state, and the cross-sectional distribution from a representative period in the unconditional simulation of the model.

Uncertainty Shock and First-Moment Shock

This section details the implementation of both an uncertainty shock and a -1% TFP (first-moment) shock as described in Section 3.5.2. For the uncertainty shock, I impose a high uncertainty state at the shock period, $T_{SHOCK} = 45$. To also incorporate a negative aggregate productivity shock averaging -1%, following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) I introduce a threshold probability $\bar{\xi}$ and draw independent uniform random variables $\xi_i \sim U(0,1)$ for each economy i. If $\xi_i < \bar{\xi}$, the aggregate productivity state is set to the lowest grid point value; otherwise, the aggregate productivity process evolves normally for economy i in period T_{SHOCK}. After the shock period, all economies evolve normally in subsequent periods. To ensure an average -1% TFP shock, I iteratively adjust $\bar{\xi}$ until the following condition is satisfied: $\hat{A}_{T_{SHOCK}} = 100\log\left(\frac{\bar{A}_{T_{SHOCK}}}{\bar{A}_{T_{SHOCK-1}}}\right) = -1$, where $\hat{A}_{T_{SHOCK}}$ represents the aggregate productivity change at the shock period. In this analysis, I find that $\bar{\xi} = 0.493$ achieves this target. For all individual aggregate series of interest, X, the plotted responses $\hat{X}_t$ are defined consistently with the baseline case, normalizing the shock period to $T_{SHOCK} = 1$ for plotting purposes.

3.A.7 Simulated Method of Moments (SMM)

The dataset X contains the microeconomic proxies of uncertainty, which are the cross-sectional interquartile range of TFP shocks constructed from the UK firm-level data spanning 2003-2022 in Financial Analysis Made Easy (FAME), derived and plotted in Chapter 1. The estimator is based on the $r \times 1 = 5 \times 1$ moment vector including the mean, standard deviation, skewness, kurtosis, and serial correlation of the components of X. The parameter vector θ is the $q \times 1 = 4 \times 1$ vector $(\sigma^Z_L, \frac{\sigma^Z_H}{\sigma^Z_L}, \pi^\sigma_{L,H}, \pi^\sigma_{H,H})'$. Since $r > q$, this is an overidentified SMM.

The SMM objective function is given by:

$$Q(\theta) = (m(\theta) - m(X))'W(m(\theta) - m(X)), \tag{3.17}$$

where $m(\theta)$ represents the vector of simulated moments as a function of the model parameters, $m(X)$ the vector of moments from the observed data, and $W = diag(1/m(X))^2$, a $r \times r$ symmetric matrix. θ is estimated by solving

$$\hat{\theta} = \arg\min_{\theta} Q(\theta), \tag{3.18}$$

in other words, I minimize the sum of squared percentage deviations of the model and data moments. The standard SMM assumptions apply: given that the model is correctly specified, the moments chosen are informative about the parameters, and sufficiently large sample sizes, the estimator $\hat{\theta}$ is asymptotically normal,[50] and converges in probability to the true population parameter θ.[51] Following standard SMM formulas, the estimated asymptotic covariance matrix for $\hat{\theta}$ is given by:

$$\hat{\Omega} = (1 + \frac{1}{S})(\hat{A}'W\hat{A})^{-1}\hat{A}'W\hat{\Sigma}W\hat{A}(\hat{A}'W\hat{A})^{-1'}, \tag{3.19}$$

where Σ represents the $r \times r$ asymptotic covariance matrix of $m(X)$, A the $r \times q$ Jacobian matrix of the moments with respect to θ, and S the simulation multiple parameter. If the parameter is coupled with a hat (ˆ), it means that the corresponding parameter is an estimate.

To find $\hat{\Omega}$, S, $\hat{\Sigma}$, and $\hat{A}$ are required. I compute model moments based on a simulation of 5000 quarters, discarding the initial 500 quarters. Given the conversion to annual frequency and the length of the sample, $S = \frac{1125}{19} \approx 59.21$. Therefore, the inflation factor is $1 + \frac{1}{S} \approx 1.017$, meaning that the standard errors increase by about 1.7% due to the randomness introduced by the simulation process. To obtain $\hat{\Sigma}$, I follow Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) in using block bootstrap procedures with random block length by computing 50000 bootstrap replications and choosing a mean block length of $4 \propto T^{\frac{1}{3}}$ years. To compute $\hat{\theta}$, I minimize the SMM objective function via particle swarm optimization introduced by Kennedy and Eberhart (1995). Similar to Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), I differentiate $m(\theta)$ at the estimated parameters $\hat{\theta}$ to obtain $\hat{A}$. With S, $\hat{\Sigma}$, and $\hat{A}$, it is now possible to find $\hat{\Omega}$.

[50] The asymptotic normality can be expressed as: $\sqrt{T}\left(\hat{\theta} - \theta\right) \xrightarrow{d} N(0, \Omega)$. This means that the scaled difference between the estimated parameter vector $\hat{\theta}$ and the true parameter vector θ converges in distribution to a normal distribution with a mean of 0 and a $q \times q$ asymptotic covariance matrix Ω.

[51] In other words, the SMM estimator is consistent: $\hat{\theta} \xrightarrow{p} \theta$. With a large enough sample size, the SMM estimator will give estimates close to the true parameters of the model, subject to regularity conditions.

3.A.8 Additional IRFs

The Effects of Uncertainty on Permanent and Temporary Labour

Figure 3.30 is similar to Figure 3.13, except that the IRFs for permanent and temporary labour are also presented here.

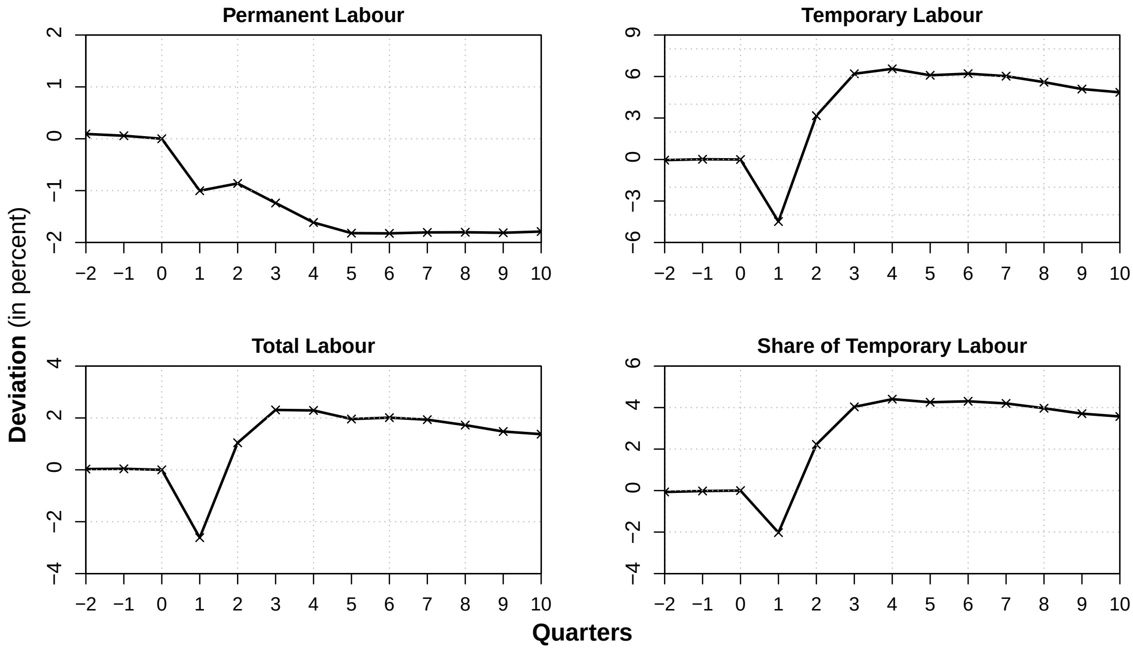

Figure 3.30: The impact of an uncertainty shock. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. An uncertainty shock is introduced in quarter 1, after which the economy evolves normally. The figure depicts the percentage deviation of cross-economy average for permanent labour, temporary labour, total (permanent + temporary) labour, and the corresponding share of temporary labour (temporary labour as a proportion of total labour) relative to their pre-shock values in quarter 0.

Uncertainty Shocks Versus TFP shocks

In the main text, it is shown that combining an uncertainty shock with a -1% TFP shock eliminates the overshoot in output and total labour observed under a pure uncertainty shock. This naturally raises the question of how the effects of a pure uncertainty shock compare to those of a pure -1% TFP shock. Figure 3.31 reveals that the initial drop in total labour is remarkably similar for both shocks, suggesting that a pure uncertainty shock can be as disruptive to labour as a pure TFP shock. Under a pure uncertainty shock, the share of temporary labour rebounds sharply and overshoots its pre-shock level, driven by firms' strategic substitution toward temporary labour due to its lower adjustment costs. In contrast, under a pure -1% TFP shock, the share of temporary labour declines gradually (before returning to its steady state). This gradual decline reflects a direct response to lower labour demand due to the persistence of the model's aggregate productivity process. These contrasting dynamics underscore the differing mechanisms at play. Uncertainty shocks amplify real-options effects, where firms delay hiring and firing decisions. These effects result in the initial declines and sharper rebounds in labour-related metrics. TFP shocks, on the other hand, are straightforward declines in productivity, leading to more predictable, smoother adjustments in labour.

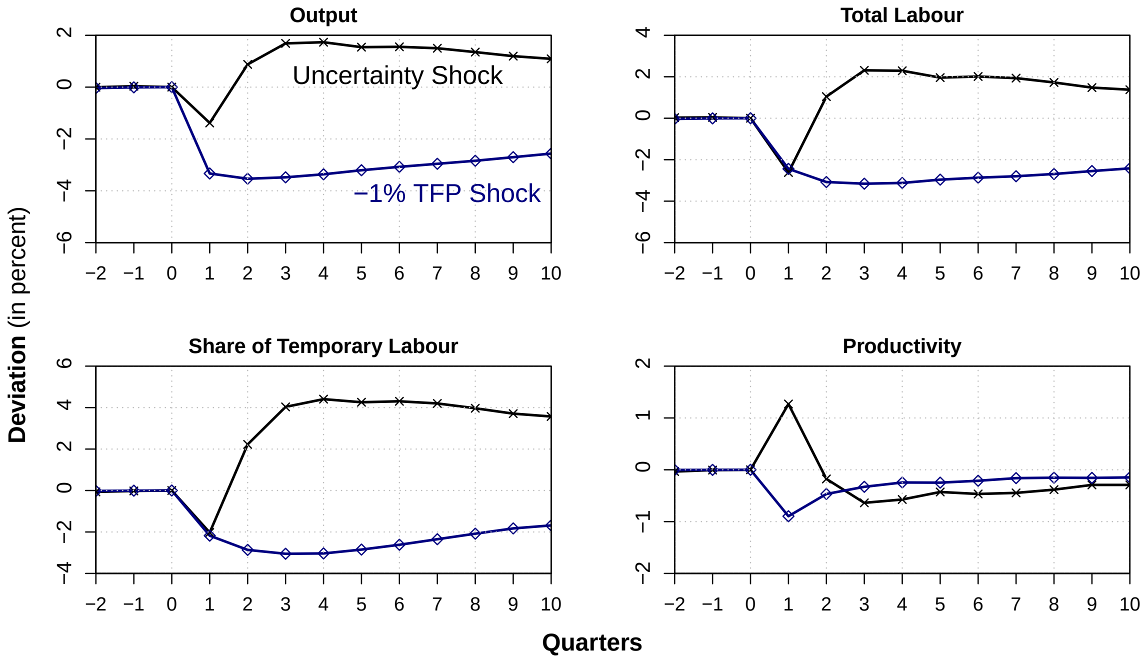

Figure 3.31: The impact of an uncertainty shock versus a pure TFP shock. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. An uncertainty shock (× symbol) or a TFP shock (⋄ symbol) are introduced in quarter 1, after which the economy evolves normally. The figure depicts the percentage deviation of cross-economy averages for output, total labour (the sum of permanent and temporary labour), the share of temporary labour (temporary labour as a proportion of total labour), and labour productivity (defined as output per unit of labour) relative to their pre-shock values in quarter 0.

3.A.9 Additional Sensitivity Analysis

This section compares the effects of uncertainty on the share of temporary labour derived from the baseline partial equilibrium model with results obtained using simulation differencing and finer grids.

Simulation Differencing

There is no consensus on a standard definition for conditional or impulse responses in nonlinear models. To complement the baseline method for computing the impulse responses, I also evaluate an alternative approach designed for nonlinear models as introduced by Koop, Pesaran, and Potter (1996). This method involves simulating two scenarios: in one, all macroeconomic aggregates evolve normally except during the period of the uncertainty shock, when high uncertainty is imposed; in the other, all macroeconomic aggregates are simulated unconditionally without any restrictions. The impact of the uncertainty shock is calculated as the cross-economy average percentage difference between these two scenarios. This approach is described in detail in the Online Appendix of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), to which I refer readers for a full explanation. Figure 3.32 demonstrates that the qualitative conclusions remain consistent across the two approaches to computing impulse responses.

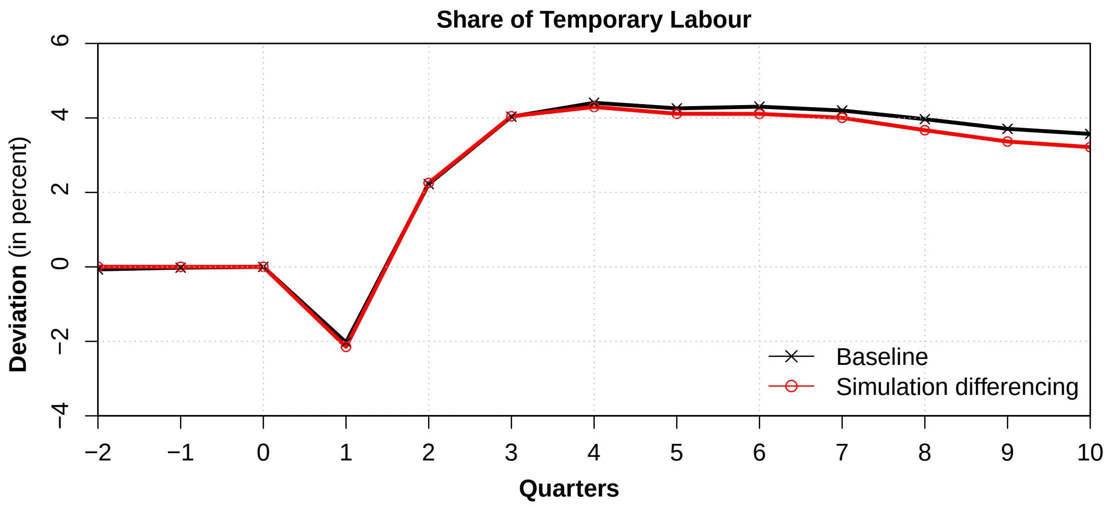

Figure 3.32: Results obtained from simulation differencing mirrors the baseline dynamics. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline ($\times$ symbol) an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. In addition, I plot the responses obtained from simulation differencing ($\circ$ symbols) based on the method in Koop, Pesaran, and Potter (1996). The parameters are identical across the two impulse responses. The figure depicts the percentage deviation of cross-economy average for the share of temporary labour (temporary labour as a proportion of total labour) relative to its pre-shock value in quarter 0.

Denser Grids

In the baseline solution, I use 5 discrete productivity points for both micro productivity z and macro productivity A. A coarser grid might smooth over nonlinear effects, leading to understated magnitudes in the IRFs. Therefore, I also solve the model using a denser grid with 10 grid points for each productivity process. This adjustment increases the size of the numerical grid by a factor of $100/25 = 4$. Additionally, I experiment with denser labour grids, increasing n^{per} from 50 to 100 and n^{tem} from 40 to 50. In both cases, the qualitative conclusions are robust to these changes. Although using an even denser grid is possible, such an approach would impose substantial computational costs.

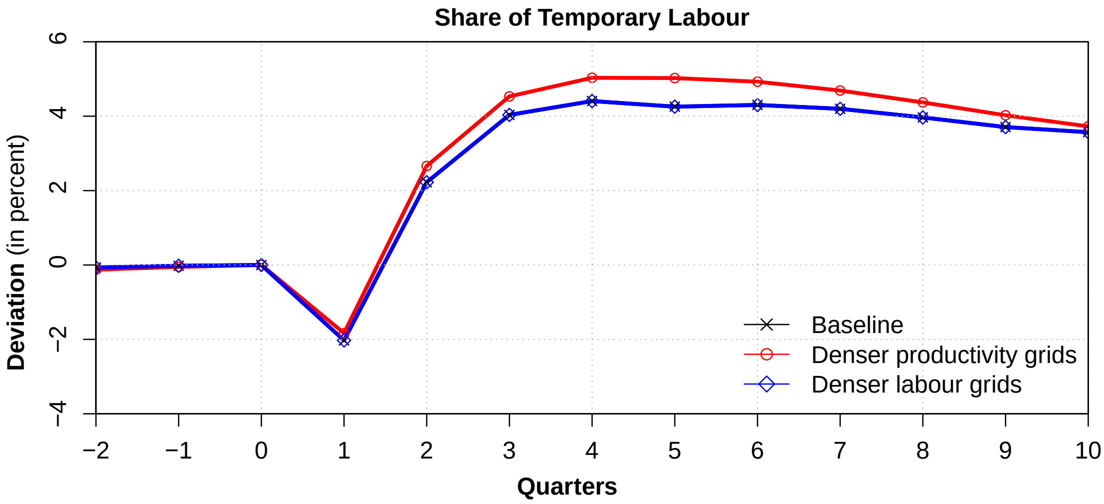

Figure 3.33: Baseline results remain robust when using denser grids. *Notes*: Results are derived from independent simulations of 2700 economies, each spanning 100 quarters. For the baseline ($\times$ symbol) an uncertainty shock is introduced in the quarter labeled 1, after which the economy evolves normally. In addition, I plot the responses obtained from using (i) denser productivity grids with 10 instead of 5 discrete productivity points for both z and A ($\circ$ symbol), and (ii) denser labour grids of size n = 100 for the variable n^{per} and n = 50 for the variable n^{tem} compared to the baseline grids of size n = 50 for n^{per} and n = 40 for n^{tem} ($\diamond$ symbol). The figure depicts the percentage deviation of cross-economy average for the share of temporary labour (temporary labour as a proportion of total labour) relative to its pre-shock value in quarter 0.

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