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An Empirical Analysis of Income Risk and Social Insurance Policy in the United Kingdom

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"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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Abstract

This thesis examines the level of income risk in conjunction with private and social insurance mechanisms in the United Kingdom. In particular, I focus on the evolution of income risk and insurance mechanisms during the last decade. This thesis emphasises the importance of measuring the heterogeneity of risk and the nature of two insurance mechanisms (i) marriage and (ii) social insurance generated through welfare policies. I complement these findings with a discussion on how adverse income shocks affect welfare.

The first chapter sets the scene by offering a theoretical review of the background of income risk and its developments in the United Kingdom over the past four decades. At the same time it also offers information on the data set and the methodological approach of the thesis. The chapter presents the data set used in this work, from *Understanding Society: the United Kingdom Household Longitudinal Study* (UKHLS) with information of individuals and households in the United Kingdom from 2009 to 2018. This chapter also introduces the model of income dynamics, which comprises a transitory and a permanent component following Friedman's Permanent Income Hypothesis (PIH).

The second chapter of the thesis measures the distribution of individual gross and net income risk in the United Kingdom. Whenever realised income differs from expected future income, individuals encounter an income risk. These risks are not uniformly distributed across individuals, which might result in losses of welfare. The current literature lacks an in-depth analysis of the potential heterogeneity of income risks. Therefore, this chapter examines the heterogeneity of individual income risk, based on social and demographic factors in the United Kingdom. Women face more than double the permanent income shock variance than for men. Further, individuals from Non-White ethnic backgrounds face slightly higher levels of permanent income shocks than White individuals. Government policies such as taxes and benefits do not mitigate the income risk distribution. Consequently, the chapter exposes evidence of income risk heterogeneity in the United Kingdom.

The third chapter quantifies the insurance opportunities arising from marriage in the United Kingdom. Marriage can reduce individual net income risk through income risk pooling with a partner. However, if one partner faces higher income volatility related to certain socioeconomic characteristics, marriage can lead to an increase in net income risk for one of the partners. Firstly, I find that marriage generates a form of income risk insurance as single individuals face considerably higher levels of net income risk

than those who are married. Secondly, the results indicate that the degree of marriage insurance depends on marital choice. Sharing the same socioeconomic background with a spouse is found to reduce levels of net income risk, compared to couples from different socioeconomic backgrounds. In addition, assortative couples face a lower probability of encountering permanent income shock. To test the robustness of these findings, a counterfactual exercise was created in the form of a synthetic dataset in which I randomise the couples based on their original marital choice. This controls for any endogeneity, for example, responses of labour supply. The test further supports my main finding.

The fourth chapter compares the impact of British welfare policies on net income risk for welfare receiving households. A major role of the welfare policy is to mitigate the impact of adverse income shocks through financial support such as benefits. This is particularly relevant as the British welfare system is currently undergoing a major reform. The new system, Universal Credit, provides considerably lower benefits to programme recipients for their daily expenses than the former Legacy System . I use a natural policy experiment to quantify the effects of a change in the welfare system on net income risk for programme receiving households., The main finding is that net income risk increases for households under Universal Credit compared to households under the Legacy System, as there is reduced social insurance for households under the new policy scheme. The lower cost to taxpayers associated with Universal Credit has reduced the effectiveness of the social insurance provided. The policy suggestions indicate the need for welfare policy design that focus on support that takes account of income risk.

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Abbreviations

AM	Assortative Marital Choice
BAME	Black Asian Minority Ethnicity
BHPS	British Household Panel Survey
BR	Benefit Recipients
CGM	Cross Group Marital Choice
DWP	Department for Work and Pension
EMBS	Ethnic Minority Boost Sample
FES	Family Expenditure Survey
FRS	Family Resource Survey
Geo. Location	Geographic Location
GPC	General Population Comparison
IEMBS	Immigrant and Ethnic Minority Boost Sample
IFS	Institute for Fiscal Studies
LS	Legacy System
M	Men
MI	Married Individuals
NAO	National Audit Office
NW	Non-White
ONS	Office for National Statistics
Orig	Original Sample
PIH	Permanent Income Hypothesis
UC	Universal Credit
UK	United Kingdom
UKHLS	Understanding Society: the UK Household Longitudinal Study
USA	United States of America
SI	Single Individuals
Syn	Synthetic Sample
TUC	Tracked Universal Credit Households
W	Women

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Dedication

I dedicate the thesis to my parents, Peter and Simone and my partner, Spyros.

Thesis Introduction

What is the nature of income risk? People face income changes during their working lifetime. They encounter economic hardship through job loss or illness, and they encounter unexpected relative prosperity, perhaps from a pay rise through a promotion. In other words, income risk captures the extent to which people experience sizable *unanticipated* income changes [1].

I measure income risk as the variance of income shocks to the idiosyncratic component of income. It reflects unanticipated income changes from an ex-ante perspective. The standard method of income risk analysis in the literature is based on the Permanent Income Hypothesis (PIH) by Friedman (1957). This theory asserts that income processes are characterised by permanent and transitory components (see e.g. Meghir and Pistaferri, 2011). According to the PIH, an individual's or household's consumption and savings choices respond differently to permanent income shocks compared to transitory ones. Permanent income shocks directly translate into changes in consumption choices, while transitory income changes or shocks may be smoothed across time (see e.g. Hall, 1978; Deaton and Paxson, 1994 and Blundell and Preston, 1998). The realised income variation generates challenges for individuals and households with low income to cover daily expenditures associated with the standards of living. Consequently, individual's or household's can face difficulties in smoothing consumption against adverse income shocks over time (Dickens, 2000; Blundell *et al.*, 2008; Jenkins, 2011; Gottschalk and Moffitt, 2009, 2012; Heathcote *et al.*, 2010; Hardy and Ziliak, 2014; Hannagan and Morduch, 2015; Hill *et al.*, 2017). This thesis contributes to the income risk debate by examining the income risk in the United Kingdom (UK).

It is important to understand the level and nature of income risk as it affects economic choice on an individual or household level. The response to adverse income shocks affects economic choices. Savings constitute a precautionary measure and allow partial insurance against idiosyncratic shocks. Another measure against adverse income shocks lies in an individual's (or household's) ex-post response, for example, by decreasing consumption

[1] I use the terms 'risk' and 'uncertainty' interchangeably. However, there is a technical difference. Knight (1921) argues that the difference between risk and uncertainty lies in what is known. A risky event has an unknown outcome, but the underlying outcome distribution is known. In other words, it is a 'known unknown'. In contrast, an uncertain event is based on an unknown outcome combined with an unknown distribution. He refers to an 'unknown unknown' event.

(Krussel and Smith, 1998; 2003; Jenkins, 2011). Consequently, they can use i) prudent measures such as savings or ii) react to adverse income shocks by undertaking corrective economic activities (Dickens, 2000; Jenkins, 2011; Gottschalk and Moffitt, 2009, 2012; Heathcote *et al.*, 2010; Hardy and Ziliak, 2014; Hannagan and Morduch, 2015; Hill *et al.*, 2017).

Moreover, income risk also entails other implications. Current empirical evidence shows that adverse income shocks affect not only an individual's or household's economic choices regarding personal resources, but also directly- and indirectly affects (among others): i) an individual's potential development because of poor health conditions (Halliday, 2007); ii) food insecurity (Leete and Bania, 2010; Dahl *et al.*, 2014; Wolf and Morrissey, 2017); iii) mortgage default (Diaz-Serrano, 2005); iv) fluctuating public benefits (Lambert and Henley, 2013; Mills *et al.*, 2014; Ben-Ishai, 2015); v) reduced educational achievement of children (Hardy, 2017); vi) reduced child health outcomes (Dahl and Lochner, 2012).

Ultimately, the individuals' or households' economic choices in response to adverse income shocks can lead to changes in aggregate consumption, saving, and labour supply (see e.g. Krussel and Smith, 1998, 2003; or Krueger *et al.*, 2016). Thus, the economic choices in response to risk and realisations of adverse income risk have macroeconomic effects and can lead to economic fluctuations.[2]

The presence of income risk in conjunction with incomplete labour markets implies that individuals or households cannot insure themselves against adverse income shocks. The incompleteness of markets for insurance against income risks is a result of adverse selection and moral hazard issues. Therefore other types of insurance against adverse income shocks play a key role in insuring individuals and households. Currently, there are two forms identified by the literature (i) social insurance and (ii) private insurance. This thesis contributes to the ongoing discussion by measuring the effects of each insurance mechanism on the level of income risk.

Social insurance usually mitigates the size of adverse income shocks. Policies generated by the government can supplement or partly replace the need for self-insurance through taxes and benefits, which are accessible to all individuals (or households). Current empirical findings provide a consensus on income risk mitigation through policy support. Meghir and Pistaferri (2004) and Blundell *et al.* (2008) find that government policies are a key factor that blunts the transmission of adverse income shocks into consumption

[2] This aligns with the discussion by Krussell and Smith (1998) and the subsequent literature, e.g. Krueger *et al.* (2016).

choices. As a consequence, partial self-insurance or social insurance can mitigate the impact of adverse permanent income shocks (Blundell *et al.*, 2008; Blundell and Etheridge, 2010; Heathcote *et al.*, 2010; Dolls *et al.*, 2012; Blundell *et al.*, 2013; Blundell *et al.*, 2016; Belfield *et al.*, 2017; Hill *et al.*, 2017; Bush *et al.*, 2020). In particular, during economic recessions, the government provides social insurance for individuals or households (Guvenen *et al.*, 2014; Belfield *et al.*, 2017).

Understanding the role of income risk is important to creating effective stabilisation, stimulus policies and government insurance programmes. Welfare policies conditional on an individual's (or household's) income can further supplement the need for self-insurance through a progressive welfare system. These mitigate the impact of adverse shocks to income through financial support for individuals or households with low income. Therefore, changes to the welfare framework have a direct impact on the well-being of programme recipients. However, the literature lacks a detailed analysis of the link between welfare reform and the level of income risk. This thesis exploits a natural experiment by examining the impact of a reform of the UK's welfare scheme on the level of income risk that the households face.

Another way of mitigating adverse income shocks occurs through partial private insurance. This relies on access to private resources such as saving for a rainy day, portfolio diversification, family ties and family planning, such as birth control and marriage. The focus in this thesis is on the role of marriage in mitigating income risk. The income risk insurance in marriage is based on pooling income between spouses (Becker, 1973; Attanasio *et al.*, 2005; Cherlin, 2010; Greenwood *et al.*, 2013; Frémeaux and Lefranc, 2017; Low *et al.*, 2018; Ejrnæs and Jørgensen, 2020). The marriage insurance is expressed through different channels, such as unemployment insurance, the added worker effect and the marriage premium (Becker, 1976; Hyslop, 2001; Ortigueira and Siassi, 2011; Christiansen, 2015; Choi and Valladares-Esteban; 2015; 2018). However, there is the possibility that some couples face higher income risk, for example by getting married to a person with a more volatile income stream (Eike *et al.*, 2019). More recent studies examine the role of homogamy and income inequality, including Schwartz (2019), Boertien and Permanyer (2019) and Milanovic (2019), but the literature does not analyse the role of marital choice with respect to income risk.

Moreover, the partial private insurance based on income pooling is affected by two key factors, referred to as i) extensive margin and ii) intensive margin. The former indicates whether a spouse is working, while the latter reflects the number of hours worked. I do not examine changes at the extensive margin of as I focus on working couples. Yet, the time worked, defined as the intensive margin, affects the response to an adverse income shock within a married couple (Blundell *et al.*, 2011b; Blundell *et al.*, 2013; Fisher *et al.*, 2013). I create a counterfactual exercise to examine the size of income risk mitigation and control for any endogeneity related to time worked by the partner. Within this exercise, I randomise the spouses of the couples by their marital choice, and thus, focus on the intensive margin of partial private insurance through marriage.

The empirical literature on income risk can be differentiated into several key groups. The initial literature focuses on the decomposition of income process, which includes work by Lillard and Willis (1978), MaCurdy (1982), Gottschalk and Moffitt (1994). The findings mainly focus on the distinction between permanent and transitory income shocks, the sources of income risk, its impact on consumption choices and the business cycle (see, for example, Lillie and Willis, 1978; MaCurdy, 1982; Blundell and Preston, 1998; Jarvis and Jenkins, 1998; Ramos, 2003; Blundell *et al.*, 2008; Heathcote *et al.*, 2010; Meghir and Pistaferri, 2011, 2004; Blundell *et al.*, 2013;).

The initial literature focuses on the effects of income shocks associated with their permanent or transitory nature. The majority of this work concentrates on examining the earnings process for male workers. Following the PIH theory, only permanent income shocks have a direct impact on lifetime incomes and so drive changes in income levels (Friedman, 1957; Hall and Mishkin, 1982). The first to study income risk based on the PIH were Lillard and Willis (1978), who used male annual earnings based on the PSID from the United States of America (USA). Their findings indicate that men seem to retain their position in the earnings distribution, which results in limited income mobility. Therefore, they find that most of the variation is related to permanent factors. More recently, Primiceri and van Rens (2009) found that permanent changes in income explain the increases in income risk in the 1980s and 1990s in the USA. Key drivers for the rise are related to low income and education levels (Heathcote, 2010; Hannagan and Morduch, 2015; Hill *et al.*, 2017). Similarly, Dickens (2000) and Ermish and Cheti (2005) show that income inequality increases with the persistence of permanent income shocks, thus demonstrating that such income shocks can contribute to income inequality.

Moreover, the literature shows that transitory income shocks are also important. MaCurdy (1982), Gottschalk and Moffitt (1994; 2012) and Baker (1997) decompose the income process for US data and they find increased transitory wages and earnings volatility, which contributes to a widening earnings distribution in the US labour market. The literature asserts possible factors of income instability such as a rise in wage or earnings instability, related to the decline in unionisation, the decline in regulation, and general increases in competition within industries (Gottschalk and Moffitt, 1994, 2012). Jenkins (2005) examines the role of income instability due to frequent job changes.

Another branch of work focuses on the impact of income risk on consumption choices. It combines the perspective of income risk with consumption inequality and includes studies such as Deaton and Paxson (1994), Cutler and Katz (1992), Carroll (2001) and Gourinchas and Parker (2002). They focus on examining the permanent income hypothesis through the empirical analysis of life-cycle profiles of consumption and income dispersion, using data drawn from several economies. In particular, the work in this area examines the transmission channels of income shocks into the individual's or household's consumption choice. A key factor in the transmission of income shocks is its durability. Blundell, Pistaferri and Preston (2008), Heathcote, Blundell, Low and Preston (2013) and Storesletten and Violante (2014) find that an individual's or household's consumption behaviour is sensitive to their income level. They find that individuals or households with low income are more sensitive to transitory income shocks than those with high incomes. As a result, income inequality across individuals or households influences the dispersion of income risk. While the literature highlights the role of partial self-insurance, to date there is no examination that jointly investigates the role of partial private and social insurance. My work offers a nuanced perspective on income risk which considers both insurance mechanisms.

Further, the literature offers evidence on how income risk evolves during the business cycle. Guvenen *et al.*, (2014) show that income risk is more likely to be negative during recessions. Using different methods, Storesletten *et al.* (2004), Angelopoulos *et al.* (2019), Bush and Ludwig (2020) and Bush *et al.* (2020) analyse the dynamics for the USA based on the PSID, and the BHPS for the UK. Their findings suggest that variation of income risk over the business cycle is asymmetrical. In particular, some key theorists, Mankiw (1986), Brav *et al.* (2002), Storesletten *et al.* (2004; 2007), Guvenen *et al.* (2014), and Sanchez and Wellschmied (2020), examine the link between the counter cyclical risk of asset prices and economic volatility. Even though this study includes a recession (2009), it does not provide explicit differentiation between contractions and expansions.

However, there are also alternative indicators for income changes and income developments. Another part of the literature studies earnings and income fluctuations using measures, such as the amount and regularity of income changes (Gosselin and Zimmerman, 2008; Dahl, DeLeire, and Schwabish, 2011; Hacker *et al.*, 2014; Western *et al.*, 2016), frequency in worked hours (Abowd and Card, 1989), the coefficient of variation (Leete and Bania, 2010; Gennetian *et al.*2015), and the percentage change in labour income

(Dynan, Elmendorf, and Sichel, 2012; Hardy and Ziliak, 2014; Wolf *et al.,* 2014). These measures examining income changes are not the focus of this thesis, which rather follows the approach by Heathcote *et al.*, (2010) and Blundell and Etheridge (2010,) based on the PIH. This provides a flexible tool that enables me to analyse unanticipated income changes and allows me to disentangle permanent and transitory income risk, which the alternative approach mentioned above cannot provide.

This thesis, in examining the potential heterogeneity of income risk and its partial private and social insurance mechanisms, focuses only on income risk . Yet, it is important to highlight that there are other types of risk, such as health risks or mortality risks. The relevance of these types of risk rises with increasing age (Blundell *et al.*, 2020). Another string of risk currently reflected in the literature is the wealth effect, which refers to how shocks to the value of assets influence consumption choices (Japelli and Pistaferri, 2017). In addition, the literature also discusses the dynamics between interest rate risk and labour market risk, focusing on how households use portfolio decisions efficiently to mitigate labour market risk (Davis and Willen, 2000).

Thesis Contribution

This thesis contributes to the literature with new findings on the size of income risk in the United Kingdom. It also addresses the level of income risk in conjunction with both private and social insurance mechanisms. Income risk is measured across British people, focusing on the evolution of income risk and insurance mechanisms over the last decade. The emphasis is on the importance of measuring the heterogeneity of risk across people and on the nature of two insurance mechanisms (i) marriage and (ii) social insurance generated through welfare policies. Findings are complemented by discussing how adverse income shocks affect individual and household welfare and the probability of individuals (or households) facing adverse income shocks.

The first chapter contributes to the thesis by setting the scene and offering a theoretical review of the background of income risk and its developments in the United Kingdom over the past four decades. At the same time, it also offers information on the data set and the methodological approach of the thesis. The second chapter contributes to the literature (see, e.g. Blundell and Etheridge (2010), Gottschalk and Moffitt (1994), Dickens (2000), Heathcote *et al.* (2010) and Jenkins (1995, 2005)) with novel findings on the size and heterogeneity of income risk in the United Kingdom. The present empirical evidence shows that the size and impact of income risk are not uniformly distributed. A vast body of work provides evidence of the impact of adverse income shocks. In particular, the income risk literature in the United Kingdom focuses on the development of transitory and permanent income risk to explain income and consumption inequality during the past decades. In addition, these studies predominantly focus on examining the income risk of individual males or households with male heads. However, the literature lacks a recent analysis of the distribution of income risk in the UK. Thus, chapter 2 offers a novel perspective by examining the size and heterogeneity of income risk.

The third chapter contributes to the literature on the insurance effect of marriage on income risk. In particular, the third chapter finds that marital choice plays a crucial role in the degree of insurance against adverse income shocks (post marriage). Sharing the same socioeconomic background with a spouse is found to reduce levels of net income risk compared to couples with spouses from different socioeconomic backgrounds. In addition, assortative couples face a lower permanent income risk. Employing a counterfactual exercise to control for potential endogeneity issues, I find that the results are robust.

The fourth chapter contributes to the literature by using a natural policy experiment based on the ongoing British welfare reform. It quantifies the effects of a change in the welfare system on net income risk for programme receiving households. To date, and to the best of my knowledge, nobody has examined the effect of this particular welfare reform on income risk. The main contribution is that net income risk increases for households under the new system, Universal Credit, compared to households under the former Legacy System. The findings indicate reduced social insurance for households under the new policy scheme. Furthermore, the effects are more prominent for benefit-receiving households with children. The lower cost to taxpayers associated with Universal Credit has reduced the effectiveness of the social insurance mitigating income risk.

Thesis Review

This thesis examines income risk across British individuals and households in conjunction with private and social insurance mechanisms against unanticipated income changes.

The first chapter sets the scene for the thesis. It offers an income risk literature review while also providing information on the data set and the methodological approach of the thesis. This chapter explains the distinct income risk types and their development in the United Kingdom over the past four decades. Further, the chapter presents the data set used in this work, namely, Understanding Society: the United Kingdom Household Longitudinal Study (UKHLS). This includes income, socioeconomic and welfare support information on British individuals (and households) from 2009 to 2018. This chapter also introduces the model of income dynamics which comprises a transitory and a permanent component based on the PIH by Friedman (1957).Thus, this chapter provides a foundation for the three following chapters.

In the second chapter the size and potential heterogeneity of individual gross and net income risks is investigated. The literature highlights the role of lack of education and low incomes as being key factors contributing to the uneven distribution of income risk (Gottschalk and Moffitt, 1994; Dickens, 2000; Jenkins, 2005; Heathcote *et al.*, 2010; Brewer and Wren-Lewis, 2012; Hill *et al.*, 2017). To this date, there is no widespread analysis of social factors that influence the heterogeneity of income risk. The majority of the literature focuses on earnings risk for men, with the recent exceptions of Angelopoulos *et al.* (2017) and Belfield *et al.* (2017). My work contributes to the understanding of the heterogeneity and degree of income risk based on a detailed group decomposition of net and gross income risk. This reveals that income risk is not uniformly distributed. Women encounter more than double the permanent income shock variance than men and are more likely to encounter adverse income shocks compared to men. Individuals from Non-White ethnic backgrounds face marginally higher levels of permanent income shocks compared to White individuals. In particular, Non-White individuals encounter considerably higher levels of transitory income shocks compared to White individuals. They also indicate a 1.1 percentage point higher likelihood of a 20 per cent adverse permanent income shock compared to White individuals. Moreover, policies such as taxes and benefits do not mitigate the income risk heterogeneity, so these income risk patterns translate into net income. As a consequence, this chapter provides evidence for income risk heterogeneity in the UK.

The third chapter quantifies the insurance opportunities arising from marriage in the United Kingdom. Marriage can reduce individual income risk through income risk pooling with a partner. However, if one partner faces higher income volatility related to certain socioeconomic characteristics, marriage can lead to an increase in income risk for their partner. A comprehensive body of work has identified different insurance channels of marriage such as income pooling, unemployment insurance, the added worker effect, and the benefits of a marriage premium (Antonovices and Town, 2004; Ortigueira and Siassi, 2011; Choi and Valladares-Esteban, 2015, 2018; Christiansen *et al.*, 2015). A smaller body of work has examined the adverse impact on an individual's welfare due to a marriage. Dynan *et al.* (2012) find evidence for income inequalities generated by marriage (Becker, 1973, 1974; Goodman and Greave, 2010; Lise and Seitz, 2011; Eike *et al.*, 2018). The chapter adds to the literature by quantifying the degree of insurance induced by marriage against adverse income shocks. The first finding indicates that married couples show an insurance against adverse income shocks compared to single individuals. The second finding indicates that private insurance through marriage depends on marital choice. Assortative married couples encounter lower levels of income risk and face a 1.4 percentage point lower likelihood of facing 20 per cent adverse income shock compared to couples who differ in these characteristics. To test the robustness of my findings, a counterfactual was created based on a synthetic data set, which randomises the married couples associated with the marital choice. This controls for any endogeneity issues, for example, responses of labour supply. I also complement the findings with a marital choice based on education. A similar pattern in income risk across married couples can be found. As a result, the findings indicate that marital choice plays a role in the insurance against adverse income shocks.

The fourth chapter compares the impact of British welfare policies on income risk for welfare receiving households. Welfare policies provide social insurance for households in financial distress, mitigating the impact of adverse income shocks through financial support such as benefits. This is particularly relevant as the British welfare system is currently undergoing a major reform. The new system, Universal Credit, provides considerably lower benefits to welfare receiving households for daily expenses than the former Legacy System. Thus, my work contributes to understanding how the design of welfare systems affects the welfare of households who face unexpected income changes. The current literature highlights the role of welfare systems in smoothing income. Several key channels have been identified, such as the redistributive character of the welfare system, its progressiveness and the degree of benefit payments. This work complements findings including Kniesner and Ziliak (2002), Blundell and Etheridge (2010), Jenkins (2011), Avram *et al.*(2019) and DeNardi (2019). This analysis uses a natural policy experiment—resulting from the British welfare policy reform—to quantify the effects of the change in the welfare system on household income risk. Specifically, it is found that households under Universal Credit face higher income risk than under the Legacy System. Universal Credit recipients are almost twice as likely to face an adverse permanent income shock of 10 per cent compared to households under the Legacy System. This indicates a reduced social policy insurance for households under the new policy scheme, particularly for welfare receiving households with children. The lower costs to taxpayers associated with Universal Credit have decreased the effectiveness of the social insurance provided by the new welfare policy. The implication is that income risk should be considered within the welfare policy design.

CHAPTER

1

OVERVIEW: INCOME RISK IN THE UNITED KINGDOM

1.1 Introduction

This chapter offers a review of income risk in the United Kingdom during the past decade. It begins with an explanation of the nature of income risk and an overview that combines economic analysis and the theoretical background of income risk. Further, it outlines the underlying data set and methods on which the three following chapters are based. The thesis contributes to an extensive literature on trends in income risk and inequality in recent decades (other work on the UK includes Cowell and Jenkins, 1994; Jenkins, 1995; Atkinson, 1997, 1999; Brewer and Wren-Lewis, 2016).

The UK has experienced an increase in income inequality over the past 40 years, particularly during the 1980s. Empirical evidence shows the increase in income inequality is at least partly associated with earnings differentials, which are in turn attributed to technological change, globalisation, and labour market deregulation (see, for example, Blundell and Etheridge, 2010; Belfield *et al.*, 2017; and Blundell *et al.*, 2018). In the 1990s income inequality stabilised at a higher level. Greater investment in welfare support, for example through child care and pension income along with higher redistribution during the 1990s and 2000s, stabilised the trend around its current levels (Blundell *et al.*, 2016; Belfield *et al.*, 2017; Angelopoulos *et al.*, 2018; Avram *et al.*,2019).

Yet, there is a large part of the increase in inequality which cannot be attributed to the above factors. In particular, the rise in earnings and income inequality is apparent even after controlling for observable characteristics such as education, location and demographics (see for example, Blundell and Etheridge, 2010). Increasing residual earnings and income inequality suggest that there are other contributory factors which may have to do with uncertainty at the individual or household level. Dickens (2000) examines the dynamic structure of male wages using the New Earnings Survey Panel and finds that permanent earnings risk plays a crucial role in determining income distribution from 1975 to 1995 in the UK. He finds evidence of a permanent component of earnings that increases over the life cycle and is highly persistent. In the same vein, Ermish and Cheti (2005) show that income inequality increases through the persistence of income shocks through time, and they find that permanent income shocks contribute to the rise in income inequality in the UK during the 1980s.

Changes in inequality since the mid-1990s have been on a smaller scale than the sharp increases seen in the 1980s. Ramos (2003) and Daly and Valetta (2008) find that the transitory variance of male earnings increased while earnings persistence falls during this period based on the BHPS dataset. Jenkins and Cappellari (2014) estimate the earnings volatility of men and women between 1991 and 2008. They find that despite earnings volatility, there is a constant trend during this period. Further, they find that labour market volatility, which accounts for individuals with zero earnings, has fallen. They argue that a critical driver is associated with stronger employment attachment. Similarly, Blundell and Etheridge (2010) document the link between income inequality and income fluctuations. Their findings indicate that the transitory earnings variance is flat while disposable income is u-shaped, falling in the early 1990s and rising subsequently. More recently, Jenkins (2011), Bartels and Bönke (2013) and Pruit and Turner (2020) find that the transitory income shock variance of male earnings increased significantly between the 1990s and 2005, but that of household net income remained flat.

The majority of the initial empirical income risk literature focused on its evolution in the USA, partly due to the readily available data. The findings suggest a rise in income risk from the 1970s until the 1980s associated with the rise in income inequality and the rise in female labour market participation, which is followed by a decline in earnings volatility from the 1980s through 2005. The body of work includes Lillard and Willard (1976), MaCurdy (1982), Hall and Mishkin (1982), Topel and Ward (1992), Deaton and Paxson (1994), Gottschalk and Moffit (1994), Altonji *et al.* (2003), Storesletten *et al.* (2004), Guvenen (2006), Krueger and Perri (2006), Heathcote *et al.* (2007), Blundell *et al.* (2008), Sabelhaus and Song (2009; 2010) and Heathcote *et al.* (2010).

Recently, the ongoing debate surrounding income risk analysis has expanded to other economies. It focuses on different underlying factors that contribute to changes in the level of income risk. Bach *et al.* (2007), Krebs and Yao (2018) and Fuchs-Schündeln *et al.* (2010) map income risk geographically. They provide evidence for the different development of permanent and transitory income shocks in former East and West Germany. Bonhomme and Robin (2009) examine the change in the magnitude of earnings mobility in France during the 1990s based on income levels and education. Similarly, Baker and Solon (2003) and Brzozowski *et al.* (2010) examine the development of wage and income risk in Canada in relation to income inequality. The general findings are that permanent income shocks have contributed to the rise in income inequality during the past 30 years (see also Krueger *et al.* (2010)). De Nardi *et al.* (2019) in a comparative study of the USA and the Netherlands discuss the role of social insurance through welfare policies and family networks. My work contributes to the literature by providing a detailed examination of income risk heterogeneity within the United Kingdom from 2009 until 2018.

The chapter is structure as follows. Section 1.2 provides the theoretical background on income risk combined with empirical evidence. Section 1.3 provides an outlines of the dataset used throughout the thesis. Section 1.4 introduces the estimation approach of income risk. Section 1.5 sets out the income risk results for the UK sample and discusses several tools to quantify adverse permanent income shocks. Section 1.6 concludes.

1.2 Literature

1.2.1 Theoretical Review: Income Risk

This thesis uses the Permanent Income Hypothesis (PIH) characteristics to analyse the differences between income risks in conjunction with private and social insurance mechanisms. In particular, this section examines the theoretical literature associated with income risks. The PIH combines consumption smoothing with an income process decomposition, which enables the analysis of specific income risks. Prior work identifies separate sources related to income shocks and establishes a close relationship between income shocks and consumption decisions.

The PIH provides a simple framework to explain the notion of the two components. The uncertainty of future income can be separated into two stochastic components: a shock to permanent income and a shock to transitory income (Friedman, 1957; Hall and Mishkin, 1982; Meghir, 2004). During work-life, individuals face a different degree of income shocks. The nature of the income shocks can be either permanent, for example through job displacement, or a change in returns to education; or transitory, such as bonus payments (Meghir and Pistaferri, 2011). The PIH describes how individuals smooth consumption over their lifetime and suggests that an individual's or household's consumption and savings choices are determined not only by their current income but also by their expected income in future years, referred to as the permanent income. To maximise consumption utility over the life cycle, they consume less from a transitory change of income than from a permanent change to income (Friedman, 1957). For example, consumers with sizeable positive transitory income shocks save most of it. Thus, the PIH entails two key features: consumption smoothing and income decomposition. This chapter uses the distinction between the permanent and transitory income components (see eq. (1.2) and eq. (1.3)) to analyse the heterogeneity of income risks between individuals in the United Kingdom.

The hypothesis states that changes in permanent income, rather than changes in temporary income, are what drive the changes in a consumer choices. The key point is that transitory income shocks are mainly absorbed through self-insurance. They do not translate into consumption choice. In contrast, permanent income shocks are not smoothed through saving, but rather translate into a consumption response (Atkinson and Bourguignon, 2015; Blundell *et al.*, 2008; Meghir, 2004). The difference between the two shocks can generate a welfare loss for individuals or households (Drazen, 2000; Friedman, 1957; Jenkins, 2011). A permanent income shock has a substantial impact on an individual's income, resulting in a potential welfare loss through its effect on consumption. In addition, if an individual is liquidity constrained, a transitory income shock as well as a permanent income shock, might have a direct impact on consumption choices. The liquidity constraints imply a limit on the amount an individual can borrow, resulting in a reduced ability to smooth consumption from one period to the next combined with a limited amount of resources within one period. Consequently, a permanent income shock might affect an individual's consumption choice.

Another factor that influences an individuals or households ability to smooth consumption is associated with house ownership. British households and individuals who own a house are wealthy but are likely to be illiquid associated with their housing investment (Cloyne and Surico, 2019; Cloyne *et al.*, 2020). This situation implies that house owners are more exposed to adverse income shocks. In particular, Cloyne *et al.* (2020) find evidence for different consumption choices between house owners and tenants using survey data from the UK and the US. This is an interesting strand of the literature but requires consumption and house ownership information. However, the UKHLS dataset provides limited information about the former and thus it is not part of this analysis.

The PIH also connects permanent and transitory income risk with income inequality. For a given set of individuals, the variance in incomes in a specific period depends on the shocks to the permanent component that individuals have experienced in the past combined with transitory shocks within the respective period. The former implies that for this set of individuals the cross-section variance (income inequality) of income increases over time, while the latter affects only the ordering of the individuals within the income distribution in the specific period (income mobility) (Blundell and Preston, 1998; Jenkins, 2005). Blundell and Preston (1998) and Jenkins (2005) find evidence that a permanent income shock increases income and consumption inequality. The empirical evidence underpins the PIH and follows the theory regarding which permanent income shocks have an impact on income inequality.

An increase in income shock variance is driven by a change in either a permanent, a transitory or by both income shocks. The underlying factors driving such changes differ.

The increase in the permanent income variance is considered the key driver for the rise in income inequality between 1975 and 2000s in the UK according to Hill (1992), Dickens (2000) and Blundell and Etheridge (2010). Similarly, Dickens (2000) finds that the permanent component of earnings increases over the life cycle and there is a highly persistent serially correlated transitory component. The estimated variances of both these components have risen over this period, each partially explaining the increase in inequality from 1975 to 1995 in the UK (Dickens, 2000). Factors that contribute to the rise in the transitory variance include labour market competitiveness, a decrease in the minimum wage, and a decline in unionisation or increases in short-term contracted employment (Moffitt and Gottschalk, 1994, 2011). Caroll (2001), Ramos (2003) and Etheridge (2015) emphasise the role of income mobility as an explanation for an increase in transitory income variance in the UK. More recent evidence by Kalwij and Alessie (2007) shows that the upward trend of wage inequality in the UK has been driven by the transitory component. Consequently, the permanent and transitory income shocks stem from different sources.

The current literature offers evidence on the distinct transmission channels of the income shocks into individuals' (or households') consumption behaviour. Blundell *et al.* (2008) and Blundell *et al.* (2013) find that an individual's consumption behaviour is sensitive to the income level. They find individuals with low-income are more susceptible to transitory income shocks than those with a high-income. They also argue that the permanent income shock can be partially insured and find comprehensive insurance against transitory income shocks, mainly based on self-insurance in the form of accumulated savings. This indicates that income risk is not uniformly distributed across people. Blundell, Pistaferri and Preston (2008) find a difference in the ability to insure against income shocks , in particular when analysing individuals based on educational background and age (and thus proximity to retirement). Furthermore, Blundell, Low and Preston (2013) argue that taxes, transfers, and family labour supply play an essential role in the insurance against permanent income shocks in the UK. As a result, the nature of the income shock plays a significant role in the impact on consumption decisions.

Some literature finds evidence in line with the PIH, such as Lillard and Willis (1978). They were the first to study income processes based on the PIH decomposition using male annual earnings based on a panel dataset from the USA. Their findings indicate that the majority of cross-sectional earnings variation is related to permanent factors, which leads to limited income mobility - individuals tend to retain their position in the earnings distribution. Dickens (2000) finds that permanent income shocks play a significant role in determining income distribution in the UK. Blundell and Preston (1998) and Jenkins

(2005) find evidence that permanent income shocks increase income and consumption inequality.

MaCurdy (1982) uses a similar estimation approach based on the PSID dataset. However, he shows that male earnings are considerably influenced by the transitory component and finds evidence of earnings instability and income mobility. Similarly, Gottschalk and Moffitt (1994; 2011), Baker (1997) and Low, Meghir and Pistaferri (2010) investigate income mobility by decomposing the income process in the USA. They also find increased income variation, which contributes to widening earnings distribution in the US labour market. They identify possible reasons for the increases in wage instability, related to the decline in unionisation, the decline in regulation, and general increases in competition within industries. They also find that some income variation is related to frequently changing jobs. Jarvis and Jenkins (1998) find that income mobility appears to be greater for persons in the tails of the income distribution relative to those in the middle, and elderly adults compared to young adults.

Since the work of Bewley (1983), Huggett (1993) and Aiyagari (1994), there is a burgeoning literature on the heterogeneous agents incomplete markets models, and income risk lies at the core of these models. The literature has shown the importance of income risk on the agents' consumption and savings choices. The precautionary savings motive incetivise agents into engaging in asset holding, which works as a "buffer" stock, and is heavily driven by the uncertainty of their future income (Huggett, 1993; Aiyagari, 1994; Hubbard, Skinner and Zeldes, 1994; Carroll, 1997; Storesletten *et al.*, 2008; Krueger and Perri, 2011; Bayer *et al.* 2019). Predicting the effects of an income change on asset holdings requires knowledge of the degree of income risk and their level of liquid assets. Agents with higher income risk, all else being equal, should save more out of their current income to be able to smooth consumption over time, should an adverse shock happens. Agents with no liquid assets are forced to adjust their consumption in the occasion of an adverse income shock.

Additional extensions of the income risk analysis focus on incomplete markets and the business cycle. The economic agents not only face income risk but also this risk varies over the business cycle. Storesletten, Telmer and Yaron (2004).find that the variance of persistent shocks to disposable household income almost doubles in recessions for US. Similar evidence on the dynamics between income risk and the business cycle, is found by Angelopoulos *et al.* (2019) for the United Kingdom. In addition, Bayer *et al.* (2019) analyse income variations in a model with incomplete markets with a focus on liquid and illiquid assets. They find that increased uncertainty depresses aggregate demand as households respond by hoarding liquid assets for precautionary motives, thereby reducing both illiquid physical investment and consumption demand. However, the theoretical and numerical analyses using models of heterogeneous agents incomplete market models are outside the scope of this thesis.

This section discusses the theoretical background of income risk based on the PIH. It highlights the different dynamics of the shocks to the distribution of the permanent and transitory component and how these affect consumption choice. Moreover, it provides an extension on other models that account for the business cycle, additional uncertainty, buffer stock savings as well as the role of wealth.

1.3 Dataset

The United Kingdom Household Longitudinal Survey (UKHLS) is an extensive panel dataset that maintains income, welfare and socioeconomic information across a sample of Britain's population from 2009 to 2018. The UKHLS initially started with a sample of around 40,000 households and individuals. It collects data from each member within households such as demographics, labour market income, health conditions and information on welfare policies. The survey was launched in 2009, and the first nine waves within the framework of this thesis. Each wave reflects two calendar years in this period (see Table 1.1).

The aim of the survey is to reflect the life changes and stability of the British population in a representative sample. It is the follow-up study to the British Household Panel Survey (BHPS) with a broader based sample size and designed to be representative of the UK population. The primary survey sample consists of the General Population Sample (GPS), as well as four other components: the Ethnic Minority Boost Sample (EMBS), the General Population Comparison (GPC) sample, the previous BHPS sample, and the Immigrant and Ethnic Minority Boost Sample (IEMBS). The IEMBS is disregarded as it only starts in wave 2, meaning it is not comparable to the other samples. Thus the GPS combined with the GPC and EMBS is used.

One essential characteristic of this data set is its panel structure. This implies that each individual is reported in every period, and it enables the observation of the same individuals over the survey time horizon. It is a crucial feature to consistently analyse changes in income dynamics for the different individuals over the time periods. Another key feature of this survey is the information included. The UKHLS reports information on distinct sources of income, and on demographic and socioeconomic characteristics of the respondents, such as gender, education, geographical areas, marital status, social (professional) class, health status, and ethnicity. The EMBS makes the UKHLS a unique data set, unlike other panel data sets -such as BHPS-, which includes insufficient information on health and ethnicity characteristics.

The UKHLS has a particular structure in the time dimension, which is constructed in waves. Each wave reflects two calendar years, e.g. wave one contains 2009-2010, and wave two contains 2010-2011. This structure continues throughout the data set and implies an overlapping nature of the time periods in calendar years. Nevertheless, the data collection for a single wave is scheduled across 24 months, and so, corresponding to the construction of the sample design, no repeated observations of individuals are present. Table 1.1 translates the waves to the respective calendar years:

Table 1.1: Data Structure UKHLS

Wave	Years
1	2009-2010
2	2010-2011
3	2011-2012
4	2012-2013
5	2013-2014
6	2014-2015
7	2015-2016
8	2016-2017
9	2017-2018

Source: UKHLS

Notes: The data structure by translated from waves to years.

Furthermore, the sample weights are associated with the wave framework and include a person design weight for individuals and a household grid for households. This design weight corrects unequal probability of selection at several levels, such as unequal selection probability based on the boost in Northern Ireland, and unequal selection probability related to the selection of the EMBS. In particular, the weights for ethnic minorities are adjusted for their dual probability of being part of the GPS and the EMBS. An analysis in a calendar year decomposition would disregard the original sample design and disrupt the associated weights. Therefore, the original sample design is kept, working with the time horizon in waves.

The panel structure of the UKHLS allows observation of individuals and households over time. In particular, the wide span of labour income, socioeconomic and demographic information provides the key ingredients to quantify the income risk for individuals and households in the UK. Also the income risk estimation relies on the access to panel data. The UKHLS panel framework provides such a structure, which facilitating income risk estimation throughout this work.

Further, Table 1.2 reports the income information on individual and household level used throughout this thesis:

Table 1.2: Definition of Income Types

Income Type	Definition
Gross Individual Income	Weekly income of the individual before taxes and benefits
Gross Household Income	Weekly income of the household before taxes and benefits
Net Individual Income	Weekly income of the individual after taxes and benefits
Net Household Income	Weekly income of the household after taxes and benefits

Source: UKHLS

Notes: Income Type Definitions

1.4 Methodology

To measure idiosyncratic income risk a researcher needs to have a proxy of the idiosyncratic component of income. The typical approach in the literature to find a proxy for it is to assume that the log individual or household income is the sum of a time specific part, a deterministic part that typically is a function of age and education and a residual part. The latter is interpreted as the idiosyncratic component of income and is approximated as the residual of a first step Mincerian regression partialling out the time specific and deterministic parts (Mincer, 1974).

In turn, the idiosyncratic component of income is modelled as a sum of two subcomponents, a purely transitory and a permanent one (see e.g. Deaton and Paxson, 1994;

Blundell and Preston, 1998; Heathcote *et al.*, 2010; Meghir and Pistaferri, 2011; and Japelli and Pistaferri, 2017). Using panel data, this methodology exploits the variance-covariance structure of the idiosyncratic income component to identify the properties of the distribution of transitory and permanent income shocks. The advantage of this approach is that it provides a simple and flexible framework to distinguish between transitory and permanent income shocks (Japelli and Pistaferri, 2017).

Yet, there are drawbacks which are associated with the underlying assumptions. To test the empirical implications of the response to income risk one has to consider the available information set. Income risk is highly subjective and lies in the 'eye of the beholder' (Japelli and Pistaferri, 2017; Meghir and Pistaferri, 2011). The underlying assumption is that the response to income shocks reflects the size of information available to individuals or households. Thus, it as has to be assumed that they have no better information than the econometrician.

1.4.1 Empirical Model

This section describes the model used in this analysis. It follows the approach by Blundell and Etheridge (2010) and Heathcote *et al.* (2010), who analyse trends in income dynamics in the UK and the USA respectively. This thesis focuses on the UK and uses the panel data from the UKHLS over the time horizon from 2009 to 2018. In line with the literature, I analyse the 'residual' dispersion (Brzozowski *et al.*, 2010; Fuchs-Schündeln *et al.*, 2010; Heathcote *et al.*, 2010). Note that all chapters consider a version of the model presented below. Within each chapter, I consider different definitions of incomes and households instead of individuals in some cases.

I consider individual log net income, $y^g_{i,c,t}$, for a household i, belonging to a cohort c and population subgroup g, and observed in year t. I assume the following model

$$\ln y^g_{i,c,t} = \beta^g X_{i,c,t} + u^g_{i,c,t} \tag{1.1}$$

which means that the log net income consists of a determinist (or explained by observables) linear part $\beta^g X_{i,c,t}$ and a residual (unexplained or idiosyncratic) part $u^g_{i,c,t}$. $X_{i,c,t}$ includes a constant term, a quadratic in experience approximated by age, dummies for region of residence, dummy for gender, dummy for marital status and time fixed effects. Following Blundell and Etheridge (2010) I also include as a regressor the logarithm of the household size. The superscript g denotes the eight subgroups defined by the combination of three variables: sex (men and women), ethnicity (White and Non-White), education (degree holders or not).[1] Moreover, I consider three cohorts. Controlling for the observables captures the idea that expected changes to income do not represent risk (see Japelli and Pistaferri, 2017).

I further assume that the residual term, $u^g_{i,c,t}$, consists of two components, a permanent component, $p^g_{i,c,t}$, and a transitory component, $\varepsilon^g_{i,c,t}$; the permanent component is a random walk while the transitory component is a purely $i.i.d$ shock. In addition, the two components are additive (in logs). Formally, the model is written as

$$u^g_{i,c,t} = p^g_{i,c,t} + \varepsilon^g_{i,c,t} \Rightarrow \tag{1.2}$$

$$u^g_{i,c,t} = p^g_{i,c,t-1} + \zeta^g_{i,c,t} + \varepsilon^g_{i,c,t} \tag{1.3}$$

where $\zeta^g_{i,t} \sim N(0, \sigma_{\zeta^g_t})$ and $\varepsilon_{i,t} \sim N(0, \sigma_{\varepsilon^g_t})$ are innovations that are uncorrelated over time, $i.i.d.$ across individuals, and orthogonal to each other. The variances are potentially time varying and different across population subgroups, but do not depend on the cohort.[2] Note that the assumption of the random walk means that the cross section variance of a cohort is increasing in time due to the accumulation of shocks by the individuals.

[1] Analytically, the eight subgroups are: i) male, degree, White; ii) male, degree, Non-White; iii) male, no degree, White; iv) male, no degree, Non-White; v) female, degree, White; vi) female, degree, Non-White; vii) female, no degree, White; viii) female, no degree, Non-White.

[2] The assumption of normality of shocks is very typical in this literature, see for example Brzozowski *et al.* (2010), Fuchs-Schündeln *et al.* (2010) and Heathcote *et al.* (2010).

Identification Scheme in Levels

Two alternative approaches to identifying income shocks are used in the current literature. The identification schemes are based on i) levels and ii) first-differences estimation. The first, more common in macroeconomic applications (e.g., Storesletten *et al.*, 2004b; Guvenen, 2007; Heathcote *et al.*, 2008), uses moments in log income levels. The second, common in labour economics (e.g., Abowd and Card, 1989; Meghir and Pistaferri, 2004; Blundell *et al.*, 2008), uses moments based on income growth rates–or first-differences in log income. Both identification schemes can be used to estimate the permanent-transitory model. Yet, they differ regarding the set of moments, which identify the structural parameters (Heathcote *et al.*, 2010). The level identification scheme enables me to exploit more data observations compared to the first-differences approach. The presence of the identification scheme puzzle provides evidence for the robustness of the results, as the ranking in the groups are the same (for more details see Appendix B).

Consider the within-cohort cross sectional variance and covariance of $u^g_{i,c,t} = p^g_{i,c,t-1} + \zeta^g_{i,c,t} + \varepsilon^g_{i,c,t}$ (see detailed derivation in Method Appendix E):

$$\begin{aligned} var_c(u_{i,c,t}) &= var_c(p^g_{i,c,t-1}) + var_c(\zeta^g_{i,c,t}) + var_c(\varepsilon^g_{i,c,t}) \\ &= var_c(p^g_{i,c,t-1}) + \sigma_{\zeta^g_t} + \sigma_{\varepsilon^g_t} \\ cov_c(u_{i,c,t+1}, u_{i,c,t}) &= var_c(p^g_{i,c,t-1}) + \sigma_{\zeta^g_t}. \end{aligned}$$

Then, the model is estimated based on the following within-cohort moment restrictions:

$$var_c(u_{i,c,t}) - cov_c(u_{i,c,t+1}, u_{i,c,t}) = \sigma_{\varepsilon^g_t} \quad (1.4)$$

$$var_c(u_{i,c,t}) - cov_c(u_{i,c,t}, u_{i,c,t-1}) = \sigma_{\zeta^g_t} + \sigma_{\varepsilon^g_t} \quad (1.5)$$

This model is exactly identified: that is, we have the same number of moments restrictions and unknowns. The first set of restrictions identifies $\sigma_{\varepsilon^g_t}$ in eq.(1.4) for $t = 1, .., 8$. Given the identification of $\sigma_{\varepsilon^g_t}$, the second set of restrictions identifies $\sigma_{\zeta^g_t}$ with in eq.(1.5) for $t = 2, .., 8$. Note that, as stated earlier, under the true model the above moments do not depend on cohort, c. Therefore, to estimate variances at date t, I average across all the three cohorts for a given year t i.e.

$$\sum_{c\in C}[var_c(u_{i,c,t}) - cov_c(u_{i,c,t+1}, u_{i,c,t})] = \sigma_{\varepsilon_t^g} \quad (1.6)$$
$$\sum_{c\in C}[var_c(u_{i,c,t}) - cov_c(u_{i,c,t}, u_{i,c,t-1})] = \sigma_{\zeta_t^g} + \sigma_{\varepsilon_t^g} \quad (1.7)$$

where the set C denotes the set of cohorts.

Identification Scheme in First-Differences

Consider the within-cohort cross sectional variance and covariance of $\Delta u^g_{i,c,t} = u^g_{i,c,t} - u^g_{i,c,t-1} = \zeta^g_{i,c,t} + \varepsilon^g_{i,c,t} - \varepsilon^g_{i,c,t-1}$ (see detailed derivation in Method Appendix E):

$$cov_c(\Delta u_{i,c,t+1}, \Delta u_{i,c,t}) = -\sigma_{\varepsilon_t^g} \quad (1.8)$$
$$var_c(\Delta u_{i,c,t}) = \sigma_{\zeta_t^g} + \sigma_{\varepsilon_t^g} + \sigma_{\varepsilon_{t-1}^g}. \quad (1.9)$$

Then, the model is estimated based on exactly these within-cohort moment restrictions. This model is exactly identified; that is, we have the same number of moments restrictions and unknowns. The first set of restrictions identifies $\sigma_{\varepsilon_t^g}$ in eq.(1.4) for $t = 2, .., 8$. Given the identification of $\sigma_{\varepsilon_t^g}$, the second set of restrictions identifies $\sigma_{\zeta_t^g}$ with in eq.(1.5) for $t = 2, .., 8$. Again, under the true model the above moments do not depend on cohort, c. Therefore, to estimate variances at date t, I average across all the three cohorts for a given year t i.e.

$$\sum_{c\in C}[cov_c(\Delta u_{i,c,t+1}, \Delta u_{i,c,t})] = -\sigma_{\varepsilon_t^g} \quad (1.10)$$
$$\sum_{c\in C}[var_c(\Delta u_{i,c,t})] = \sigma_{\zeta_t^g} + \sigma_{\varepsilon_t^g} + \sigma_{\varepsilon_{t-1}^g} \quad (1.11)$$

where the set C denotes the set of cohorts.

1.4.2 Standard Errors

To compute the standard errors, I follow MaCurdy (2007), and use the block bootstrap procedure for 1,000 replications. The resulting standard errors and confidence intervals account for serial correlation of arbitrary form, heteroskedasticity as well as for the fact that we use pre-estimated residuals. This estimation process is a standard procedure and is used in similar research, such as Hall and Horrowitz (1996), Etheridge (2015), Greenwood (2014), Meghir and Pistaferri (2004).

1.5 Results and Discussion

This section provides an overview of how income risk is distributed in the UK. It focuses on the results of the entire UKHLS sample maintaining all individuals.

I focus on the adverse impact of the income shocks between individuals or households by calculating the monetary loss of a one-standard deviation negative shock (as per cent from the mean) and by calculating the utility loss that a one-off loss would imply under log utility (see eq. (1.12)). The associated welfare losses in each section can be approximated by considering an individual's log utility in a regular period and comparing it to a period where a negative income shock is realised. According to the theory (see section 1.2) the permanent income shock should directly transfer into consumption behaviour. Therefore, a drop in income translates into a drop of consumption. Consequently, this section focuses on the utility and welfare impact of permanent shocks only. Assuming that income is fully consumed (i.e. individuals do not save or borrow), this allows for a welfare comparison:

$$\text{Utility Welfare Loss} = \frac{\ln(\mu) - \ln(\mu_{reduced})}{\ln(\mu)} \tag{1.12}$$

where, μ is the mean of the weekly wage, $\mu_{reduced}$ is the difference between the mean and one standard deviation change of a negative income shock in monetary terms. Therefore, the utility welfare loss illustrates the impact of the permanent income shock. It expresses the differences in the income risks between individuals or households and identifies the utility welfare loss associated with the income risk. Consequently, the following section outlines several measures for adverse permanent income shocks.

Another way to quantify the impact of permanent income shocks focuses on the associated probabilities of encountering an income gain or income loss. I assume a normal distribution and compute the distribution for the shocks to the permanent component of labour income as $\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{U.K}}\right)$. In Table 1.5 I document the probability that an individual receives an idiosyncratic shock to a permanent component of their income that increases (decreases) their permanent income by a specific percentage, compared to what it would have been had it received the mean $\zeta_{i,t}$ shock. Severe gains (losses) in income refer to a 50 or 20 per cent probability. Such a gain (loss) in income translates into situations associated with an increase in pay, for example through a promotion, or a reduction in income due to a spell of unemployment . In particular, self-employed individuals are prone to considerable reductions in income. Another way to think about such events in a household setting would be if one member faces a change in job associated with a wage reduction or raise. These probabilities are adjusted in Chapter 4 based on the low-income nature of the households that receive support under either the Legacy System or Universal Credit.

Within this thesis, it is assumed that the income shocks to the permanent component are normally distributed. The "normality" assumption is chosen to keep the model in its simplest form to examine unanticipated income changes using the UKHLS data set. In the literature there are examples that account for the tail changes such as Guvenen *et al.* (2014), Angelopoulos et al (2019) and Bush et al (2020). The key approach is to use higher moments than the second such as skewness to examine the asymmetry and kurtosis of the income shock distribution. However, this analysis requires relatively large samples on the cross section. The reason is that the higher moments than variance, skewness and kurtosis, require large samples to be estimated accurately. The afforementioned studies typically use the whole sample to conduct such examination. In contrast to these studies, the subsequent chapters of this thesis focus on a group decomposition approach and the respective samples are relatively small (also note, as discussed earlier that the identification is per period t). Consequently, the analysis of the tails of the income shock distribution is not a viable approach for this thesis as a whole. Nevertheless, I leave this type of analysis for future research.

1.5.1 Income Risk in the United Kingdom

The first set of results focuses on income risk dispersion across the U.K. In particular, it focuses on age differences between British individuals considering the levels of income risk. Table 1.3 also reports transitory and permanent income shocks of individuals for the entire sample. It reports a permanent income shock of $\sigma^2_{\zeta_t^{UK}} = 0.0160$ and a transitory income shock of $\sigma^2_{\varepsilon_t^{UK}} = 0.0854$. In addition, Table 1.3 supports the difference between the permanent and transitory income shock variance by showing the variance of each income shock variance from 2010 until 2018. I consider the impact of a one standard deviation change in the permanent income shock. The results in Table 1.4 indicate that British individuals encounter a utility welfare loss of 2.41 per cent. Further, Table 1.5 shows the probability of facing a positive or a negative income shock with different degrees of income losses and gains. The results indicate that British individuals are 3.88 per cent likely to face an income loss of 20 per cent due to an adverse income shock. In contrast, they encounter almost double the probability of 7.44 per cent of encountering a 20 per cent income gain.

Table 1.3: Income Risk Estimation, UK

Group	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
Entire Sample	0.0854***	0.0160***
s.e.	(0.0032)	(0.0035)
Sample Size	150,572	

Notes: Table 1.3 indicates the income risk based on transitory and permanent income shock variances; Individual Net Income; The estimation is based on the level estimation method; The bootstrap standard errors are based on 1000 replications and presented in parentheses;*significant at p<0.1;**significant at p<0.05;***significant at p<0.01.

Table 1.4: Utility Welfare Loss, UK

Subgroup	Loss in per cent	Utility Welfare Loss in per cent
Entire Sample	12.65%	2.41%

Notes: Table 1.4 shows the utility welfare loss for individuals in the UK; Net Individual Income; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 1.5: Probabilities of Permanent Income Shocks, UK

Probability of income gain/loss		Permanent income shock in per cent
		Entire Sample
		$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{UK}}\right)$
income gain>50%:	$Pr(\zeta_{i,t} > \ln(1.50))$	0.07%
income gain>20%:	$Pr(\zeta_{i,t} > \ln(1.20))$	7.44%
income loss>50% :	$Pr(\zeta_{i,t} < \ln(0.50))$	0.06%
income loss>20%:	$Pr(\zeta_{i,t} < \ln(0.80))$	3.88%

Notes: Table 1.5 indicates the likelihood of an individual to encounter a permanent income shock. The probabilities of gains/losses are with respect to the level of permanent income under the mean shock. Note that $\zeta_{i,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

Figure 1.1 provides an overview of the distribution of individual income risk in the United Kingdom. It shows the transitory and permanent income shock variances for individuals from 2009 until 2018. This is the most recent analysis of income risk in the United Kingdom. Blundell and Etheridge (2010) report the income risk based in the British Household Panel Survey (BHPS) from 1991 until 2005. The income risk is shown in Blundell and Etheridge (2010) and indicates the same magnitude as in the first difference identification found in Appendix B.

As a part of a project trying to uncover 'cross sectional facts for macroeconomists', Heathcote *et al.* (2010), Fuchs and Schündeln *et al.* (2010), Brzozowski *et al.* (2010), Jappelli and Pistaferri (2010), Domeij and Folden (2010) use panel data sets for US, Germany, Canada, Italy and Sweden respectively to estimate the size of income risk. In particular, Brzozowski *et al.* (2010) find that wage and income inequality have increased substantially from the end 1960s to 2005. Yet, the increase was partially mitigated by the canadian tax and transfer system. As a result, the increase in consumption inequality has been relatively mild in Canada. Similarly, Domeij and Folden (2010) find low levels of consumption inequality in Sweden from 1978 to 2004. Yet, they show a rise in Swedish earnings inequality in the early 1990s, and that much of this increase was associated with labour market movements. Heathcote *et al.* (2010) use the PSID and find that changes in the distribution of hours worked sharpen the rise in earnings inequality before 1982, but mitigate its increase thereafter. Taxes and transfers decrease the level of income inequality, especially at the bottom of the distribution, but have little effect on the aggregate trend. Further, Fuchs and Schündeln *et al.* (2010) find a geographical difference in income risk in Germany. By compaing former East and West Germany they show that the institutional framework plays a role in the degree of income risk. Households in former East Germany encountered considerably less income risk compared to households in West Germany. The studies highlight the importance of the tax and welfare system.

During last decade and within the framework of the afromentioned project no studies examine income risk year by year in the UK, US or any other major european country from 2010 to 2018. The studies cover the period form the end 1960s until the early 2000s. This highlights the novelty of the estimates depicted in Figure 1.1.

Figure 1.1: Individual Income Risk in the United Kingdom

Notes: Figure 1.1 reports individual income risk based on level estimation in the United Kingdom.

1.6 Conclusion

This chapter provides a foundation for the thesis and reviews income risk and its developments in the UK. It explains the background of income risk and key factors that influence it, and the evolution of income inequality. It also introduces the empirical approach based on the PIH by Friedman (1957). In doing so, it provides information on two identification schemes used in the literature and the estimation approach of this thesis. It enables the analysis of income risk based on the variance of permanent and transitory income shocks. The primary data set used throughout the thesis is the UKHLS with income, welfare policy, demographic and socioeconomic information from 2009 to 2018. The economic agents the economic agents differ based on the focus of the chapter, whether on individuals, households or both.

The thesis contributes to the literature with a unique perspective on the level of income risk, focusing on the evolution of income risk and insurance mechanisms during the last decade. It emphasises the importance of measuring the heterogeneity of risk among population groups and on the nature of two insurance mechanisms (i) marriage and (ii) social insurance generated through welfare policies. I complement these findings with a discussion on how income shocks potentially affect well-being. To date, this thesis is the only one to address the level of income risk considering both private and social insurance mechanisms in the UK.

CHAPTER

2

INCOME RISK HETEROGENEITY IN THE UNITED KINGDOM

2.1 Introduction

An individual's well-being depends not only on their average income or expenditure but also on their income variation. Once actual income varies from expected future income, a form of income risk occurs. The subsequent income variation, in turn, might decrease an individual's well-being. To understand the effects of income risk on an individual's well-being, it is necessary to examine the size of adverse income shocks and the dispersion of associated risk. Is income risk uniformly distributed? Not necessarily; it depends on several factors. For example, adverse labour income shocks affect individuals with limited private (income) resources, other than labour, to a greater extent. Another example, if a group of the population has persistently lower income than another group, then the welfare policy (benefits and taxes) has different effects on their income risk. In turn, the heterogeneity of income risk also adds another dimension to income inequality. Although the literature discusses the sources of income risk, it lacks a detailed perspective on income risk heterogeneity.

This chapter contributes to the literature of income risk by measuring the size and heterogeneity of individual gross and net income risk in the UK between 2009 and 2018 providing evidence for considerable income risk heterogeneity. The finding of this chapter suggests an uneven distribution of income risk across British individuals, in terms of gender and ethnicity. The group decomposition reveals that women and Non-White individuals face higher levels of income risk compared to men and White individuals. The resulting adverse income shocks are associated with a considerable decrease in well-being. Women are five times as likely to face an adverse income shock of 20 per cent as compared to men. Non-White individuals show a 1.1 per cent point higher likelihood of a 20 per cent adverse income shock compared to White individuals. This uneven distribution reveals an income risk heterogeneity in the UK, thus providing a nuanced perspective on the nature of income risk.

The second main contribution is the provision of evidence on unconditional insurance mechanisms by examining the effects tax and benefits system on mitigating income risk. Welfare policies usually target to support the lower parts of the income distribution. Therefore, it is expected that the welfare policies are likely to reduce income risk for the low income individuals. Indeed, there is evidence that benefits decrease the magnitude of adverse income shocks in the general population (see, e.g. Kniesner and Ziliak, 2002; Blundell and Etheridge, 2010; Angelopoulos *et al.*, 2019). Nevertheless, it might not be enough to alleviate income risk that they face, especially permanent income shocks.

In other words, they might still be exposed to large and permanent in nature income fluctuation even if they are now smaller than the pre policy income shock. Given that in my sample I find considerable differences in mean incomes between sociodemographic groups (see Appendix B.2), it is important to examine the effects of policy on mitigating income risk, especially for sociodemographic groups with relatively lower income.

This chapter provides a unique perspective on levels of gross and net income risk, by examining detailed group-specific characteristics. In investigating the widespread presence of income risk across British individuals, the size and heterogeneity of gross and net income risk is analysed, based on socioeconomic and demographic factors such as gender, ethnicity, marital status, parenthood, geographical location and employment status. The majority of the earnings risk literature focuses on education and income levels, but this paper contributes to the debate by offering in-depth analysis across a wider variety factors in seeking to understand the heterogeneity of income risk.

Following Chapter 1 the analysis applies the Permanent Income Hypothesis (Friedman, 1957). It decomposes the income process to consider long-term features, such as job displacement or changes in returns to education, and transitory characteristics such as bonus payments (Meghir and Pistaferri, 2011). In theory, an individual's consumption and savings behaviour responds differently to permanent or transitory income shocks. Permanent income shocks directly translate into consumption choices, while transitory income shocks can be smoothed, unless, for example, an individual is liquidity constrained. In that case adverse transitory income shocks can contribute to welfare losses (see detailed literature review in the first Chapter).

The group-specific decomposition is a unique approach to examining the heterogeneity of individual gross and net income risk. It is a tool that reveals whether individuals who share specific characteristics also share a similar degree of income risk, and consequently indicates a heterogeneous distribution of income risk between individuals. To direct welfare policy appropriately, it is necessary to identify this heterogeneity of individual gross and net income risk between groups in the UK (see Section 1.4 for a detailed review).

The literature focuses on the sources of income risk, with empirical evidence identifying low levels of education and income as key drivers. Within this discussion the literature also considers the distinction between permanent and transitory income shocks and their subsequent impact on consumption choices (see for example Lillie and Willis, 1978; MaCurdy, 1982; Deaton and Paxson, 1994; Blundell and Preston, 1998; Meghir and Pistaferri, 2004, 2011; Ramos, 2003; Blundell *et al.*, 2008; Heathcote *et al.*, 2010; Blundell *et al.*, 2013). By decomposing changes in the distribution of income in the UK, the findings of this chapter complement existing work, including Jenkins (1995, 2005), Dickens (2000), Blundell and Etheridge (2010), Heathcote *et al.* (2010), Brewer and Wren-Lewis (2012) and Belfield *et al.* (2017). To date, the literature offers sparse analysis on the heterogeneity of income risk based on a wider range of socioeconomic and demographic characteristics. The only studies that currently feature income risk for female workers in the UK are Belfield *et al.* (2017) and Angelopoulos *et al.* (2017). The key contribution of this chapter is a detailed analysis of the heterogeneity based on gender for income risk in the UK.

Further, the literature provides evidence for inequality in earnings and income risk (see e.g. Meghir and Pistaferri, 2004, and Chang and Kim, 2006, both for the USA, and Angelopoulos *et al.* ,2017, 2020, for the UK) and inequality in mean earnings and income between different groups in the population (earnings premia) (see, e.g. Heathcote *et al.*, 2010, for the USA and Blundell and Etheridge, 2010, for the UK). Usually, these comparisons focus on education and sometimes gender. This inequality in risk and mean income can increase wealth accumulation and wealth inequality via direct and indirect effects (see Angelopoulos *et al.*, 2020 and Kim, 2019).

The UKHLS maintains income information from 2009 to 2018. The estimation method uses the dynamics of weekly income in the UK. The income risk approach is based on work by Heathcote *et al.*, (2010). Following the literature, I focus on 'residual' dispersion. The income process is specified to allow for temporary and permanent income shocks. Further, the income process uses two distinct identification schemes: levels and first differences. These schemes are estimated by exploiting the variance and covariance structure of the residual term in the respective identification scheme. The differences in income dynamics are examined for individuals with different group characteristics such as: gender, marital status, parenthood, ethnicity, urban-rural classification and employment status.

The chapter is organised into six sections. Section 2.2 reviews the theoretical and empirical evidence. Section 2.3 describes the data. Section 2.4 introduces the empirical model and presents the underlying methodology. Section 2.5 reports the estimates of the variances for each wave and provides the time series evidence. It also discusses the implications of the results. Section 2.6 concludes the chapter.

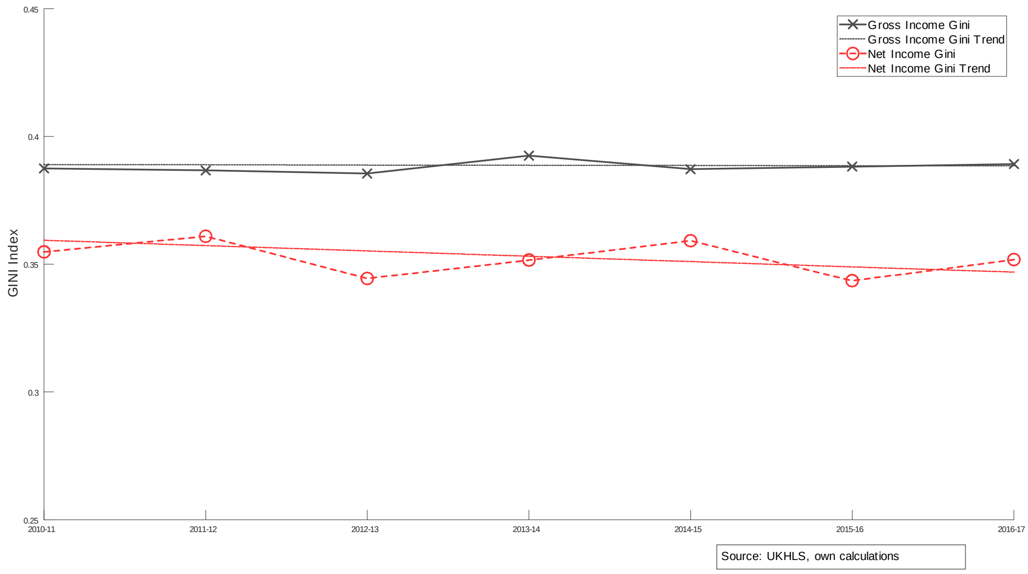
2.2 Related Literature

2.2.1 Income Inequality

Recent evidence from the Office of National Statistics (ONS) Report (2019) indicates a gradual decline in income inequality over the past decade in the UK. Similarly, the Family Resource Survey (2019) also indicates a continually improving trend, based on a decrease in wage differences, for example the gender pay gap. The median disposable income in the UK for the financial year 2017/18 is estimated to have been £28,400, which is higher than at the time of the great financial crisis. An increase in disposable income has primarily been driven by a rise in household income from employment, related to both average earnings growth in real terms in 2017/18, and continued growth in employment rates (ONS, 2019). However, to assess the development of income inequality, a deeper analysis is required, including indicators such as the Gini coefficient.

Figure 2.1 shows the Gini coefficient, based on the Understanding Society data set (UKHLS), indicating the level of income inequality in the UK. The Gini coefficient is a tool that measures the distribution of income within an economy, where 0 indicates complete income equality and 1 indicates complete income inequality (Atkinson and Bourguignon, 2015). In this case, the income Gini coefficient fluctuates between 0.39 and 0.36 between 2009 and 2018. The estimates of the income Gini coefficient indicate that income inequality is still relatively high in the UK. The estimates are comparable to those by Blundell and Etheridge (2010), who determine the Gini coefficient for the UK using the Family Expenditure Survey (FES) and British Household Panel Survey (BHPS) data sets, covering the period 1978 to 2005.

Figure 2.1: Gross and Net Income GINI UK



Notes: Figure 2.1 shows the gross and net income GINI index for the United Kingdom with trend lines from 2010 until 2017.

The income Gini coefficient (Figure 2.1) and average income developments provide an overview of UK income distribution. However, to analyse the dispersion of income risk across individuals, income variation has to be considered. Therefore this chapter focuses on the income shock variance of individuals who share certain group characteristics such as gender, ethnicity, employment status, marital status, parenthood and urban-rural classification. These groups may vary in their exposure to adverse income shocks. By considering several income measures, this analysis provides a new perspective on the nature of income risk. Here, I provide information on each of the groups' income developments based on the primary characteristics.

The development of wage rates across workers provides evidence for the gender pay gap. Considering the weekly wage premium between men and women indicates a marginally increasing trend (see Table 2.1). Over the last two decades, inequality in male earnings for the UK has increased. This is partly due to an increase in the male hourly wage inequality, driven by a fall in the number of hours worked by men on low incomes (Shin and Solon, 2010; Jenkins, 2018; Coutler, 2018). Female earnings inequality has decreased across the vast majority of the distribution as inequality in the number of hours worked has fallen (Belfield *et al.*, 2017). The gender pay gap among full-time employees stands at 8.9 per cent which indicates a decline of only 0.6 percentage points since 2012 (Smith, 2019), although it is the lowest since 1997, when the gender pay gap was 17.4 per cent (Smith, 2019). There is also evidence of an age effect related to the gender pay gap. A woman's wage does not tend to rise with age and work experience. Instead, hourly wages for women reach their peak in the early thirties age group and decrease for each subsequent age group. Only women with high levels of educational qualifications combined with a career in the public sector indicate a strong 'career progression' in wages (Heathcote *et al.*, 2014; Gardiner, 2018).

Marital status and family planning of individuals influence their employment choice. This in turn, affects the labour market mobility between married and single individuals. Married individuals tend to opt for an occupation with a more stable income compared to single individuals (Choi and Valladares-Esteban, 2015; Ejrnæs and Jørgensen, 2020). Family planning is a key factor that contributes to the need for more stable employment among married workers. Further, post-childbirth women lose labour market experience as they temporarily drop out of the labour market. In addition, when these women return to the labour market, they tend to work in part-time positions. Part-time work offers mothers more flexibility. However, it also tends to reinforce the gender pay gap due to the lack of wage growth. This lack of wage growth is associated with less training, less skill accumulation over time and lower informal networking opportunities and promotions (Joyce, 2018). From a researcher's standpoint, it is unclear whether the part-time occupation is based on choice or the lack of alternative options. As a result, the income inequality by gender is characterised by distinct payment and progression rates associated with employment status patterns. Therefore, this chapter uses a detailed group decomposition approach to examine the dispersion of income risk based on gender.

The British labour market is also shaped by income inequalities related to a worker's ethnic background. The disadvantage for individuals across Black Asian and minority ethnicity (BAME) is reflected in lower income and occupation immobility compared to White individuals. The literature refers to this type of inequality as the ethnic minority ratio (Catney and Sabater, 2015; ONS, 2020). Hill *et al.*, (2018) observes that individuals of 'African' ethnicity are the most likely to have a weekly income of less than £400 compared to White individuals (Finch, 2017). These income differences are mainly related to the occupational distribution. Individuals of BAME backgrounds are under-represented in high- and mid-skilled jobs (ONS, 2020). They are more likely to be employed in part-time, low-income employment and self-employment (see Appendix *B*). The UKHLS data indicates a clear trend of the wage premium between Non-White/BAME and White individuals (see Table 2.1). The ethnic inequalities in the labour market play a major part in the high poverty rates among some ethnic minority groups (Catney and Sabater, 2015). The differing experiences between ethnic groups in labour market participation lead to questions on their exposure to income risk. Consequently, this chapter focuses on income risk dispersion based on ethnicity.

In recent years, the UK labour market has undergone changes with respect to types of employment. The British labour market has experienced an increase in self-employment and part-time work. Since the Great Financial Crisis, the rise in the share of self-employed workers has increased to 14 per cent in the British labour market (Giupponi and Xu, 2020). This has contributed to the growth in non-traditional employment forms, and also to the growth in overall employment. However, the average gross income of solo or single self-employed individuals [1] in 2018 was 30 per cent lower compared to employees (Giupponi and Xu, 2020). Moreover, since 2013, the share of part-time workers and workers with a zero-hours contract has increased by around a quarter of the UK workforce (Clegg, 2019). As a consequence, in the aftermath of the Great Financial Crisis, employment has shifted towards part-time employment and self-employment.

The geographical location contributes to income inequality in the UK. In 2018, median workplace-based earnings in predominantly urban areas (excluding London) were £22,900, while in predominantly rural areas they were slightly lower at £21,400 (Finch, 2018; ONS, 2018). Urban residents earn more on average than people living in rural areas. As a result, a clear income difference based on the urban-rural classification can be observed. In contrast, the income inequality trends related to local authorities in the United Kingdom are inconclusive. Hill *et al.*, (2010) and the ONS Report (2018) do not find a clear pattern between regional allocations. The UKHLS data indicates an increasing trend in the wage premium between urban and rural individuals revealing that geographical classification contributes to the income divide (see Table 2.1). London is a key city which shows higher income inequality compared to other cities in the UK. Notably, earnings inequality has increased faster in London over the last decade than anywhere else in the UK (Hill *et al.*, 2010).

The development of the UK economy needs be taken into account when discussing the heterogeneity of income risk, as the thesis focuses on the period from 2009 to 2018.

[1] This term refers to sole traders or company owner-managers without employees (Giupponi and Xu, 2020).

The UK's 'Great Recession', beginning in 2007/2008, was characterised by sharp falls in real wages and productivity, alongside evidence of growing labour market polarisation. Unemployment in the UK rose from 5.1 per cent in early 2008 to a recessionary high of eight per cent in early 2010 (ONS, 2017). It was also accompanied by a sharp and prolonged drop in gross domestic product (GDP), by six per cent from 2008 to 2009. On the other hand, there was a growth in part-time jobs and in self-employment (Coutler, 2018; Clegg, 2019; Giupponi and Xu, 2020). Further, the literature highlights the role of income risk during the business cycle. The current evidence indicates that during recessions adverse income risk rises in magnitude (Guvenen *et al.*, 2014).

Despite the seeming improvements in terms of the reduction in income inequality in the UK shown by the ONS Report (2019) and Family Resources Survey Report (2019), current evidence indicates that income inequality affects individuals unevenly, although reflecting characteristics such as gender, ethnicity, marital status and geographical location (see Table 2.1). This chapter compares the patterns of income risk across individuals. It does not consider patterns within groups.

Table 2.1: Wage Premium, Group Characteristics

Wave	Gender $\frac{Women}{Men}$	Ethnicity $\frac{Non-White}{White}$	Marital Status $\frac{Single}{Married}$	Geo. Location $\frac{Rural}{Urban}$
1	0.6698	0.9554	0.8713	0.9666
2	0.6648	0.9205	0.8599	0.9582
3	0.6687	0.8809	0.8495	0.9717
4	0.6662	0.9299	0.8554	0.9714
5	0.6676	0.9271	0.8409	0.9559
6	0.6598	0.9620	0.8345	0.9820
7	0.6773	0.9401	0.8248	0.9930
8	0.6725	0.9488	0.8299	0.9653
9	0.6753	0.8990	0.8308	0.9765

Based on net income of UKHLS, own calculations.

2.2.2 Income Risk Heterogeneity

This section reviews the empirical work related to income risk heterogeneity. The PIH offers a framework to analyse the heterogeneity of gross and net income risk based on social and demographic factors. Its key characteristics are based on the notion of consumption smoothing and the decomposition of the income process into permanent and transitory components (see eq. (1.2) and (1.3) in chapter 1).

A key concern of the UK government is the development of income inequality. Recent evidence in the ONS Report (ONS, 2018) indicates a gradual decline in income inequality over the past decade and the Family Resources Survey indicates an improvement in gender income inequality, for example, in the gender pay gap since 2010 (FRS , 2017; Jenkins, 2011; ONS, 2017). However, it is not only the average income inequality that might affect an individual's welfare, but also their exposure to income variation. If individuals have a low income, this does not imply that their exposure to income risk is also low. Their low income might make these individuals more exposed to adverse income shocks (Gorbachev, 2011; Gottschalk and Moffitt, 1994; Jenkins *et al.*, 2011). Having a precise measure of income variation is essential to assess the degree of the loss in wellbeing associated with income risks (Gottschalk and Moffitt, 1994; Jenkins *et al.*, 2011).

The group-specific analysis offers a tool to examine the heterogeneity of income risk across British individuals. The majority of the literature discusses dispersion in earnings risk amongst men in the USA[2]. Empirical evidence in the literature relating to the UK, such as Blundell and Etheridge (2010), Belfield (2017) and Dickens (2009), focuses on analysis of general trends in earnings risks to explain income inequality. To date, it is not well understood how income risk is distributed across British individuals in relation to social and demographic factors. This chapter contributes to the literature with a detailed analysis of these factors on the heterogeneity of gross and net income risk in the UK.

The PIH combines income risks with income inequality. Income inequality reflects the variance in the distribution of incomes in a specific period. The income risk is measured as the variance in permanent and transitory income shocks. For a given set of individuals, the variance in incomes in a specific period depends on the shocks to the permanent component that individuals have experienced in the past combined with transitory shocks

[2] This body of work includes Lillard and Willard (1976), MaCurdy (1982), Hall and Mishkin (1982), Topel and Ward (1992), Deaton and Paxson (1994), Gottschalk and Moffit (1994), Altonji *et al.* (2003), Storesletten *et al.* (2004), Guvenen (2006), Krueger and Perri (2006), Heathcote *et al.* (2007), Blundell *et al.* (2008), Sabelhaus and Song (2009; 2010) and Heathcote *et al.* (2010)

within the respective period. The former implies that for this set of individuals the cross-section variance (income inequality) of income increases over time, while the latter affects only the ordering of the individuals within the income distribution in the specific period (income mobility) (Blundell and Preston, 1998; Jenkins, 2005). Permanent income shocks are associated with structural changes in the labour market such as the decline in unionisation, the decline in regulation, general increases in competition within industries, the decline in blue-collar manufacturing jobs and the increased reliance on part-time and contingent work arrangements (Gottschalk and Moffitt, 1994, 2009; Haider, 2001; Keys, 2008; Heathcote *et al.*, 2010; Ziliak, Hardy, and Bollinger, 2011; Dynan, Elmendorf, and Sichel, 2012; Western, Bloome, Sosnaud, and Tach, 2016). The increase in the permanent income variance is considered to be a contributory factor in the rise in income inequality between 1975 and the end of the 1980s in the UK (see Chapter 1 for more details).

The literature has established that the level of education and income are key factors influencing income risk. The higher the education level, the higher the returns to education. As a result of the higher income associated with the education level, individuals can smooth adverse income shocks across time. In contrast, individuals with low incomes face financial constraints. A large body of work focuses on the link between income variation and education combined with income levels. Moffitt and Gottschalk (1994, 2011) studied the trends in male earnings from the 1970s and 1980s in the USA. They analysed occupational differences based on the sector worked in and union membership. In particular, increases in between-job instability have been large for less educated, Non-White, and private sector workers (Jaeger and Stevens, 1999). Meghir and Pistaferri (2004). find a difference in the variance of income shocks based on educational background, underpinning evidence of stratification related to income shock exposure. Similarly, Angelopoulos *et al.* (2017) show that private and public insurance mechanisms against an increase in idiosyncratic risk are less effective for households with no university degree. Yet, the literature lacks a detailed group decomposition across social factors. This chapter provides an in-depth decomposition to analyse income heterogeneity.

The key contribution refers to the dynamics of income risk and the general tax and benefit system. In contrast to welfare policies designed against low wage realisations such as Universal Credit, workers automatically contribute through taxes and benefit payments to the system. In particular, benefits enable individuals to smooth adverse income shocks across time. Kniesner and Ziliak (2002) refer to an explicit insurance mechanism. In contrast, taxes reduce income volatility, thereby constituting an indirect measure against adverse income shocks. The effects of the tax-benefit social insurance system in mitigating adverse income shocks has been demonstrated in work by Blundell and Etheridge (2010) for the UK and in Domeij and Flodén (2010) for Sweden. The British tax-benefit system indicates that benefits mitigate adverse income shocks more extensively than taxes (Blundell and Etheridge, 2010; Belfield *et al.*, 2017; Avram *et al.*,2019; Angelopoulos *et al.*, 2020). To understand the income risk-mitigating impact of the British tax and benefit system, I distinguish separate types of income, such as gross income, income with benefits, income minus taxes and net income. My findings are in line with the empirical evidence of the literature.

A large body of work discusses income risk based on male earnings. The widespread availability of data has led to the main focus on income risk of men[3]. This perspective has widened with the examination of income inequality. Studies document average income levels and changes in the level of income based on several income indicators across men and women, such as Heathcote *et al.* (2010) for the USA and Domeij Flodén (2010) for Sweden and USA, and Angelopoulos *et al.* (2019) for the UK. Also within the analysis of family insurance, income risk for women plays a key role (Mandel and Stier, 2009; DeNardi *et al.*, 2019). The findings suggest that female income risk differs amongst women depending on the presence of children and motherhood. Evidence is sparse on income risk heterogeneity by gender in the UK. To date, the only study that features female income risk for the UK is Angelopoulos *et al* .(2017), and Belfield *et al.* (2017) emphasise the role of female labour market participation in the reduction of household income risk. This thesis contributes to the discussion by offering new evidence on individual gross and net income risk that focuses on gender differences.

A small body of work discusses the link between income risk and ethnicity. One of the first papers on gross income risk, Lillard and Willis (1978), focuses on ethnic backgrounds in the USA, finding that the permanent income shock for African-American individuals is about 44 per cent larger than for White individuals. More recently, the literature examines the growing gaps in household income risk. The evidence suggests that ethnic minorities encounter higher levels of income change, which creates more income variation (Banerjee, 2009). In particular, the evidence suggests that Black and Hispanic households have insufficient savings or assets to buffer against income changes (Jaeger and Stevens, 1999; Hamilton and Darity, 2017; Darity *et al.*, 2018; Gibson-Davis and Percheski, 2018). Thus, the limited empirical evidence indicates an uneven dispersion of gross income risk

[3]Research that focuses on male income risk in earnings: Lilliard and Willis (1976), McCurdy (1984), Deaton and Paxson (1994), Gottschalk and Moffitt (1994), Blundell and Preston (1998), Dickens (2000), Meghir and Pistaferri (2004), Ramos (2003,2006), Blundell et al. (2008), Blundell, Low and Preston (2013), Bush and Ludwig (2020), Pruit and Turner (2020).

based on ethnicity. Further, to date, there is no evidence on income risk dispersion in the UK. This chapter adds to the literature by examining the income risk heterogeneity based on ethnicity.

The geographic location of individuals also influences income risk. The nature of the work, such as seasonal work in rural areas, may lead to income fluctuation and, in turn, a higher level of income volatility. Moreover, institutional changes are also reflected in geographical dimensions. Fuchs and Schündeln *et al.* (2010) find a considerable difference associated with the geographical location. They observe that income shocks in East and West Germany developed in different ways. Since the reunification of Germany, the earnings risk findings show a modest rise (Bach *et al.*, 2007; Fuchs-Schündeln *et al.*, 2010). Consequently, the geographical location associated with the type of employment offered or the institutional framework might influence the level of income risk. To date, an in depth income risk analysis based on the geographical location does not exist in the UK.

The majority of the empirical literature focuses on how income risk contributes to the development of income inequality. The evidence identifies key drivers such as low levels of education and income as contributors to the level of income risk. Within this debate the literature discusses sources of income risk, the distinction between the permanent and transitory income shocks and their subsequent impact on consumption choices (see, for example Lillie and Willis, 1978; MaCurdy, 1982; Deaton and Paxson, 1994; Blundell and Preston, 1998; Ramos, 2003; Meghir and Pistaferri, 2004; Blundell *et al.*, 2008; Blundell *et al.*, 2013; Heathcote *et al.*, 2010; Meghir and Pistaferri, 2011). The findings of this chapter complement existing work, including Blundell and Etheridge (2010), Dickens (2000), Heathcote *et al.* (2010), Jenkins (1995, 2005), Brewer and Wren-Lewis (2012) and Belfield *et al.* (2017), by decomposing changes in the distribution of income in the UK. To date, the literature offers sparse analysis on the heterogeneity of income risk based on a wide range of socioeconomic and demographic characteristics. The key contribution of this chapter is a detailed analysis of the heterogeneity of income risk.

2.3 Data

2.3.1 Sample Selection

The analysis is based on the UKHLS dataset. The original sample of the dataset needs modifications to match the requirements of the analysis. I keep only individuals with full interviews, and remove incomplete interviews. As a consequence, the sample maintains consistent information of individuals across each wave. I concentrate on individuals in the labour market with a positive income. Consequently, in any wave, individuals aged between 25 to 60 years are included, in line with current research that defines the working age to be between 25 to 60 years, as, after the age of 25, most individuals have completed their education (e.g. postgraduate), and the usual retirement age for individuals is around the age of 60. Although one can find a variety of income changes after the retirement age, these income changes rarely stem from labour income uncertainty. Thus, I follow the related literature and create an age band from 25 to 60 (Blundell and Etheridge, 2010; Guvenen *et al.*, 2010; Heathcote *et al.*, 2010; Busch *et al.*, 2018).

To analyse the individual group heterogeneity, I split each of the samples based on the six subgroups: gender, ethnicity, marital status, parenthood, urban-rural classification and employment status. The decomposition of the samples enables me to examine the heterogeneity of income risk in distinct income types. Moreover, I construct cohort bands to account for fixed effects in the level identification scheme, and I also separate the sample into three age cohorts according to when the individuals turn 25 and enter the labour market, namely: below or equal to 1990 (Cohort 1), 1991 to 2000 (Cohort 2), and above or equal to 2001 (Cohort 3). The number of cohorts is dictated by the size of the sample.

I drop all imputed income variables. The measure of gross and net income is usual weekly wages, and the weekly wage is defined as the multiplication of typical monthly wages by 12, and then divided by 52 weeks. This approach is used for each of the four income types. It is a precise measure of income applied in related literature (Heathcote *et al.*, 2010). The panel structure of the survey and its additional information are the foundation for the examination focusing on heterogeneity in income risk across British individuals.

Four income types are considered in analysing income risk. These are differentiated by separating the distinct components from gross income to net income based on taxes and benefits. The analysis follows the structure of the dataset in incorporating the tax and benefit components such as income tax and child benefits. The differentiation by income type enables the examination of income risk mitigation through the tax and benefit system (see Appendix *B* for more details on the income variables). Unfortunately, the UKHLS does not provide enough information to allow for analytical decomposition of the various sub-components of taxes and benefits.

The income variables are deflated using the retail price index (RPI), and I trim the top and bottom of the observations of wages in any wave by 0.25 per cent, to deal with possible outliers in recorded wages and ensure robust results. These changes to the original sample construct a homogeneous sample of individuals, who are observed across all waves, and are of interest for the analysis.

2.3.2 Variables

This section describes the key variables of this income risk analysis. I create several dummy variables such as education and region, based on the original sample. The UKHLS reports the education bands as follows: 'University degree', 'A-levels O-levels or apprenticeship', and 'No degree'.

I also construct a regional variable based on the regions of the UK: North-East, North-West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South-East, South-West, Wales, Scotland, and Northern Ireland. The geographical areas 'urban' and 'rural' are separate variables, also provided by the dataset. Whether an individual is married or single is reflected in the marital status variable. The marital status group is designated by a binary dummy variable 'married' and 'single'. The group of single individuals includes those who are divorced, widowed or single, while the married group includes i) married couples, ii)civil partnerships, and iii) couples living together. The marital status variable is pooled into a binary dummy variable as otherwise the sample size would have been too small to examine (see Table B2.3).

The parent variable reflects whether an individual has children. These include biological and adopted children. Individuals who have a child and those who do are considered. The sample size for individuals with more than three children is small. Therefore, I construct a binary variable 'Parent' and 'Non-Parent'. Also, full-time working individuals and part-time working individuals are based on an already constructed variable from the original dataset. Full-time working individuals are classified as those working equal to or above 30 hours (or 25 or more for the teaching professions). Part-time working individuals are those with an hourly workload of below 30 hours per week. In addition, the variables 'employed' and 'self-employed' are formed based on the existing classification of the UKHLS. Thus, the 'employed' variable refers to an individual who works for an employer. Self-employed individuals can either be single self-employed, which means that they are the sole trader of the company without employees or the head of a company with employees. The education group reflects the level of qualification achieved. It is based on a binary dummy variable that refers to i) university degree holders and ii) non-university degree holders. These former is an indication for high levels of education qualifications, while the latter one indicates low level of education qualifications. Non-university degree includes the following educatioun qualifications. A-level, GCSE and other qualifications. These are based on the existing information on education in the UKHLS sample.

The ethnicity variable is constructed based on ethnic background, provided by the survey and supported by the EMBS. The UKHLS provides data on the following ethnic groups: Indian, Pakistan, Bangladesh, Caribbean, and African within the sampled areas. Within the UKHLS framework the ethnicity refers to individuals reporting a related person (e.g. their parents or grandparents) coming from the same ethnic group. On this basis, a dummy variable is constructed: 'White', to include individuals from a British, and Northern Irish ethnicity; 'Non-White' to include Asian, African, Arabic, and Caribbean individuals, as otherwise, the sample size is too small to infer meaningful results.

2.4 Methodology

2.4.1 Empirical Model

This section describes the model used in this analysis. It follows the approach by Blundell and Etheridge (2010) and Heathcote *et al.*, (2010), who analyse trends in income dynamics in the UK and the USA respectively. I focus on the UK, using panel data from the UKHLS over the time horizon from 2009 to 2018. In line with the literature, I analyse the 'residual' dispersion (Brzozowski *et al.*, (2010), Fuchs-Schündeln *et al.*, (2010), Heathcote *et al.*, (2010)). In this chapter I focus on individuals.

I consider individual log gross and net income, $y^g_{i,c,t}$, for an individual i, belonging to a cohort c and population subgroup g, and observed in year t. I assume the following model

$$\ln y^g_{i,c,t} = \beta^g X_{i,c,t} + u^g_{i,c,t} \tag{2.1}$$

which means that the log gross and net income consist of a determinist (or explained by observables) linear part $\beta^g X_{i,c,t}$ and a residual (unexplained or idiosyncratic) part $u^g_{i,c,t}$. $X_{i,c,t}$ includes a constant term, a quadratic in experience approximated by age, dummies for region of residence, dummy for gender, dummy for marital status and time fixed effects. The superscript g denotes the 8 subgroups defined by the combination of three variables: sex (men and women), ethnicity (White and Non-White), education (degree holders or not).[4] Moreover, I consider three cohorts. Controlling for the observables captures the idea that expected changes to income do not represent risk (see Japelli and Pistaferri, 2017). The idea is to examine the heterogeneity of income shocks based on certain characteristics. In doing so, I also examine different income types such as gross income, net income, income with benefits and income minus taxes. The differentiation by income type enables me to examine possible insurance mechanisms through the tax and benefit system.

The key interest concerns the patterns in the group-specific decomposition namely, gender and ethnicity. The results for the entire sample reflect the ranking of the gender

[4] Analytically, the 8 subgroups are: i) male, degree, White; ii) male, degree, Non-White; iii) male, no degree, White; iv) male, no degree, Non-White; v) female, degree, White; vi) female, degree, Non-White; vii) female, no degree, White; viii) female, no degree, Non-White.

and ethnicity decomposition, supporting the robustness of the results (see Appendix $B2$). The income shock exposure holds across both identification schemes (see Appendix $B2$).

Additionally, I also implement a robustness test based on employment status. The robustness test exercise, uses the same approach with a different Mincerian regression also controlling for employment status ($ftpt_{i,c,t}$) as a full-time or part-time working individual (Mincer, 1974). This implies that working full-time or part-time is a choice. It contrasts the Mincerian regression in eq. (2.1), which represents the employment status as an income shock. The results indicate the same findings in the dispersion of income risk. Consequently, the income risk heterogeneity estimates across British individuals are robust.

I further assume that the residual term, $u^{g}_{i,c,t}$, consists of two components, a permanent component, $p^{g}_{i,c,t}$, and a transitory component, $\varepsilon^{g}_{i,c,t}$; the permanent component is a random walk while the transitory component is purely a $i.i.d$ shock. In addition, the two components are additive (in logs). The formal expression of $u^{g}_{i,c,t}$, can be found in Chapter 1, Section 1.4.

2.5 Results and Discussion

The key contribution of this chapter focuses the heterogeneity of individual gross and net income risk in the UK. The findings provide evidence of income risk heterogeneity across individuals based on specific socioeconomic and demographic factors. The estimates indicate an uneven distribution of income risk across UK individuals. The group decomposition reveals that particularly women face higher levels of individual gross and net income risk compared to men. Women are five times as likely to face an adverse income shock of 20 per cent compared to men. The resulting adverse income shocks are associated with a decrease in wellbeing. Similarly, Non-White individuals indicate a 1.1. percentage point higher likelihood of a 20 per cent adverse income shock compared to White individuals. Yet, the difference in permanent income risk based on ethnicity is not as significant as that based on gender. The approach to examining the impact of income risks reflects the utility welfare loss and likelihood of adverse permanent income shocks (see Section 1.5 for more details). This analysis reveals new patterns of income risk heterogeneity in the UK.

The following section reports the results and discusses the key findings and their economic implications. Of particular interest are the results of the group-specific decomposition of the permanent and transitory income shock estimates. I use the residuals of the regressions and specify the income process that allows for temporary and permanent income shocks. I focus on the group heterogeneity estimated in the level identification scheme as this contains more data. The results of the first difference identification are used as a robustness check, as they report the same income risk patterns. I exploit the variance and covariance structure to disentangle the transitory and permanent income shock as seen in Chapter 1. Individual income risk estimates are obtained by firstly using a standard Mincerian regression for each fixed subgroup based on gender, education and ethnicity (see Section 2.4.1) (Mincer, 1974). In each regression, I control for all observable factors and an additional time dummy as seen in eq. (2.1). The results for the entire UK sample and the identification scheme in first differences indicate the same findings in the distribution of income risk, which provides evidence that the results are robust (see Section 2.5.3 and Appendix *B* for robustness checks).

Moreover, I calculate the risk ratio based on the levels of income risk on gender and ethnicity. The risk ratio is defined as the ratio of the permanent income shocks based on gender (women and men) and ethnicity (Non-White and White individuals). It expresses the differences and the degree of income variation between the respective groups. A high level of risk ratio indicates a high degree of permanent income shocks resulting in higher income variation. In contrast, a low risk ratio indicates few permanent income shocks indicating income stability. It therefore serves as an indicator of income variation related to permanent income shocks and endorses the economic relevance of this chapter.

2.5.1 Results: Income Risk based on Gender

This section focuses on income risk patterns based on gender [5]. In doing so, it provides a thorough review of individual income risk based on group characteristics. It also explores the income risk pattern across distinct income types. The income risk estimates in Table 2.2 show that women encounter higher levels permanent income shock variance compared to men. However, men are more exposed to higher levels of transitory income shocks relative to women (see Table 2.2). Thus, a distinct pattern in the level of income risk across gender can be observed.

Further, the group decomposition based on income types in Table 2.2 indicates different levels of income risk across men and women. In particular, it provides evidence for distinct income risk mitigation effects based on taxes and benefits. The estimates show that income with benefits decreases the level of income risk more than income minus taxes. The size of the income risk mitigation depends on gender as comparing income across the income types shows. The respective differences from gross income to net income are, $\sigma^2_{\varepsilon_t^{Women}} = 0.0300$ and $\sigma^2_{\zeta_t^{Women}} = 0.0205$ and for $\sigma^2_{\varepsilon_t^{Men}} = 0.0100$ and $\sigma^2_{\zeta_t^{Men}} = 0.0080$. The risk ratio decreases from 2.4 to 2.3 comparing gross and net income (see Table 2.2). In addition, the permanent risk estimates between women and men are significantly different at the 90 per cent confidence interval. Thus, the key finding is a gender difference in income risk that translates from gross income into net income, as women face higher income risk compared to men.

Further, the results in Table 2.2 indicate a reduction in income risk from gross to net income, however the heterogeneity of income risk is observed in net income risk. Therefore, the second finding is that benefit and taxes insure individuals differently against adverse income shocks. Benefits have a stronger insurance mechanism as they show a lower risk ratio of the permanent income shock variance. The results in Table 2.2 show that through benefits and taxes income risk is decreases by, $\sigma^2_{\varepsilon_t^{Women}} = 0.03$ and $\sigma^2_{\zeta_t^{Women}} = 0.03$ for women and by, $\sigma^2_{\varepsilon_t^{Men}} = 0.01$ and $\sigma^2_{\zeta_t^{Men}} = 0.008$ for men. The insurance dynamics of taxes and benefits are in line with Kniesner and Ziliak (2002) and Avram *et al.* (2019).

Overall, the results in Table 2.2 and Figure 2.2 indicate an insurance induced by taxes and benefits, which depends on gender. In particular, when considering the difference in the levels of permanent income shocks, $(\sigma^2_{\zeta,t})$ highlights the difference based on gender. Women encounter less income risk reduction through the tax and benefit system than

[5] Appendix F gives the results for the entire UK sample, which indicates the same group- specific ranking as the ethnicity decomposition. It shows that the results are robust.

men. As a result, Table 2.2 reveals an income risk heterogeneity based on gender that translates from gross to net income risk.

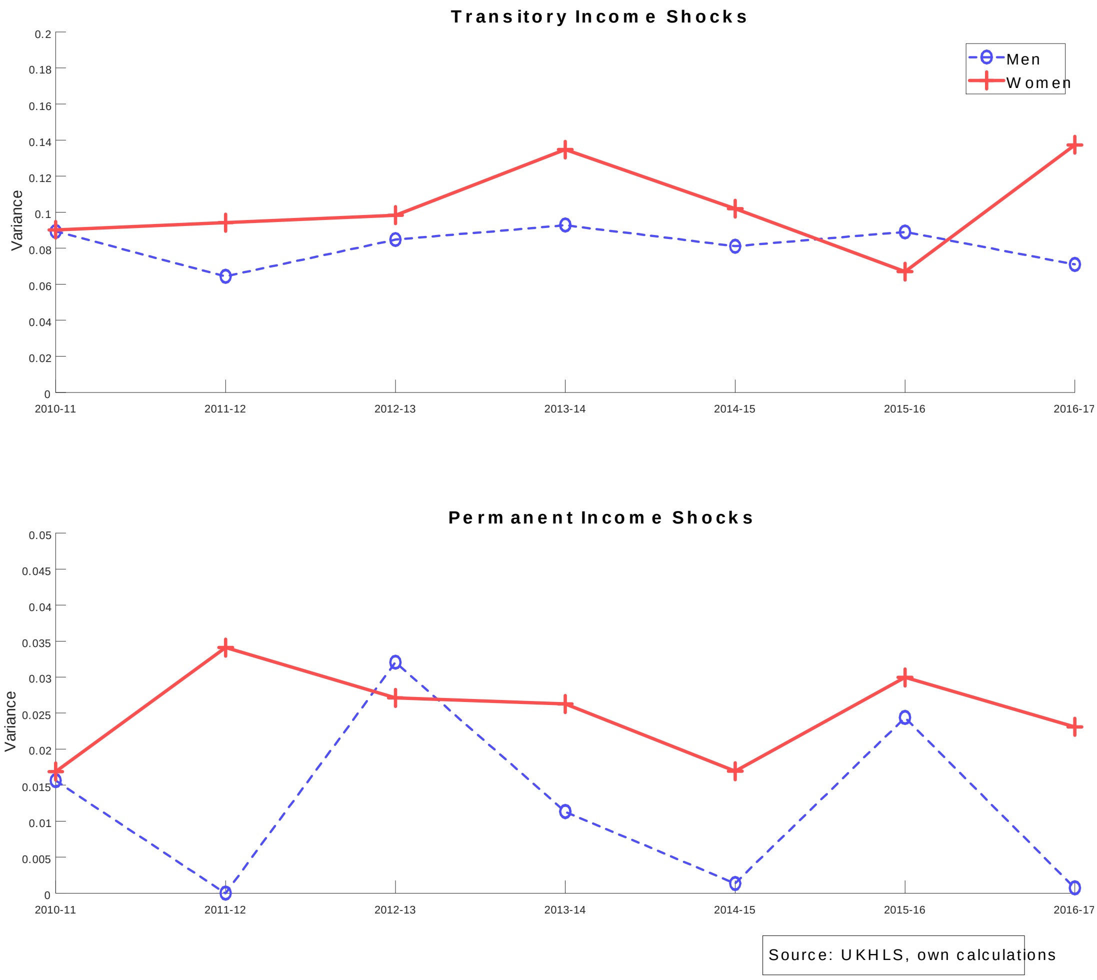
Table 2.2: Individual Income Risk, Gender

Groups	Women		Men		
	Transitory $\sigma^2_{\varepsilon_t^{Women}}$	Permanent $\sigma^2_{\zeta_t^{Women}}$	Transitory $\sigma^2_{\varepsilon_t^{Men}}$	Permanent $\sigma^2_{\zeta_t^{Men}}$	Risk Ratio $\frac{Women}{Men}$
Gross Income	0.1316***	0.0454***	0.0893***	0.0187***	2.4***
s.e.	(0.0027)	(0.0029)	(0.0032)	(0.0035)	
Income plus Benefits	0.1137***	0.0359***	0.0705***	0.0166***	2.2***
s.e.	(0.0036)	(0.0028)	(0.0023)	(0.0020)	
Income minus Taxes	0.1201***	0.0330***	0.0733***	0.0144***	2.3***
s.e.	(0.0029)	(0.0021)	(0.0013)	(0.0019)	
Net Income	0.1016***	0.0249***	0.0793***	0.0107***	2.3***
s.e.	(0.0027)	(0.0029)	(0.0032)	(0.0035)	
Sample Size	94,785		78,327		

Notes: Table 2.2 shows the gross and net income risk based on gender.
Individual Income Types; The estimation is based on the level estimation method; The bootstrap standard errors are based on 1000 replications and presented in parentheses; The risk ratio is based on $\sigma^2_{\zeta,t}$; $p < 0.1$;**significant at $p < 0.05$;***significant at $p < 0.01$.

The difference in permanent and transitory net income shock variances from 2010 to 2017 is shown in Figure 2.2. The estimates in Figure 2.2 support the average income shocks based on gender, highlighting that the levels of permanent income shock variance are higher for women than for men. The high permanent income shock for women can be related to their low-income profile and their employment status.

Figure 2.2: Net Individual Income Risk based on Gender



Notes: Figure 2.2.shows that Women face higher levels of transitory and permanent income shocks compared to men from 2010 until 2017.

Gender Decomposition

This section analyses the gender difference for net income risk based on a detailed group decomposition in Table 2.3 to.2.6 and Figure 2.2. Thus, I examine the level of income risk across men and women based on, ethnicity, marital status, parenthood, urban-rural classification, and employment status. Appendix B indicates the results for the entire UK sample and for the estimation in first differences. The results in Appendix B indicate the same group-specific ranking as the gender decomposition in first-differences, showing that the results are robust.

The estimates of the gender breakdown in Table 2.3 to 2.6 and Figure 2.2 show that men and women face different levels of income risks. Women encounter higher degrees of permanent income shocks in each subgroup. For some subgroups such as geographical location gender independent patterns are reported. The high permanent income shock of women may be related to their low employment status, income profile, the economic situation in the UK between 2009 and 2018, and low progression rates for women (for details, see discussion). As a consequence the findings indicate a net income risk heterogeneity based on gender. Further, the gross income risk estimates in Appendix Tables $B2.11 - B2.12$ provide evidence for the same income risk heterogeneity based on the subgroups.

The decomposition by ethnicity indicates marginal differences. The results in Table 2.3 show that men and women of Non-White ethnicity encounter marginally higher levels of income risks, compared to White individuals. The estimates indicate an income risk heterogeneity based on ethnicity for both men and women. The average estimates for men of Non-White ethnicity reveal higher income shock variances compared to men of White ethnicity, with the respective differences being, $\sigma^2_{\varepsilon_t^{Men}} = 0.0150$ and $\sigma^2_{\zeta_t^{Men}} = 0.0017$. The same pattern is observed for women, with the respective differences being, $\sigma^2_{\varepsilon_t^{Women}} = 0.0151$ and $\sigma^2_{\zeta_t^{Women}} = 0.0014$. This also reflects existing labour market challenges faced by individuals with Non-White ethnicity (Catney and Sabater, 2015; Hill *et al.*, 2010; ONS, 2018).

Table 2.3 provides evidence regarding net income risk difference based on marital status. Married individuals face considerably lower levels of net income risk compared to single individuals. The average estimates for men show lower permanent income shock variances, with the respective differences being, $\sigma^2_{\varepsilon_t^{Men}} = 0.0874$ and $\sigma^2_{\zeta_t^{Men}} = 0.0038$ between married and single men. Similarly, the results show that married women face higher levels of permanent income shock, compared to their single counterparts, with the respective differences being, $\sigma^2_{\varepsilon_t^{Women}} = 0.0191$ and $\sigma^2_{\zeta_t^{Women}} = 0.0034$. The risk ratio underpins the gender differences based on marital status. Married women face considerably higher permanent income shocks compared to married men, as the risk ratio indicates: $\frac{Women}{Men} = 1.6$. The estimates indicate net income risk heterogeneity related to the marital status of individuals. Single individuals may have higher labour market mobility compared to married couples (Becker, 1973; Guner, Kulikova and Valladares-Esteban, 2015; Gardiner, 2017). Moreover, the combined income of married couples might represent private insurance against income shocks.

Table 2.4 provides evidence regarding net income risk heterogeneity based on education across gender. Individuals with a university degree face increased income risks compared to individuals with no university degree. The findings complement evidence on the role of education and income risk in the literature such Angelopoulos *et al.* (2019). In addition, the results also indicate a difference based on gender. High educated women with a university degree encounter increased transitory and permanent income shock variances compared to high educated men, with the respective difference being, $\sigma^2_{\varepsilon_t^{University}} = 0.0298$ and $\sigma^2_{\zeta_t^{University}} = 0.0113$ (see Table 2.4). Also,non-university degree male individuals encounter lower transitory and permanent income shock variances compared to their female counterpart, with the respective difference being, $\sigma^2_{\varepsilon_t^{NonUniversity}} = 0.0186$ and $\sigma^2_{\zeta_t^{NonUniversity}} = 0.0156$ (see Table 2.4). The risk ratio reflects the income variation based on gender for a university degree with $\frac{Women}{Men} = 1.7$ and no university degree $\frac{Women}{Men} = 2.8$ (see Table 2.4).

The net income risk estimates indicate a difference based on parenthood. Parents face higher levels of income shocks compared to Non-Parents, as per the estimates in Table 2.5. The average income risk estimates for fathers indicate higher income shock variances compared to men without children, with the respective differences being, $\sigma^2_{\varepsilon_t^{Men}} = 0.0773$ and $\sigma^2_{\zeta_t^{Men}} = 0.0094$ (see Table 2.5). The same pattern can be observed for mothers, with the respective differences being, $\sigma^2_{\varepsilon_t^{Women}} = 0.0605$ and $\sigma^2_{\zeta_t^{Women}} = 0.0105$. The risk ratio is higher for Non-Parents with $\frac{Women}{Men} = 1.5$, emphasising higher income variation. The higher risk ratio for Non-Parents may be related to the income mobility individuals without children have, compared to parents. Parents tend to choose employment with higher income stability. Yet, the presence of children also contributes to income variation, which reflects in the relatively higher income risk for parents, irrespective of their gender (ONS, 2018)

Results based on where individuals are located reveal a regional income shock difference for both women and men (see Table 2.5). The average estimates for men living in a rural area indicate higher levels of income risk compared to men living in urban areas, with the respective differences being, $\sigma^2_{\varepsilon_t^{Men}} = 0.0072$ and $\sigma^2_{\zeta_t^{Men}} = 0.0052$. Women living in rural areas also face higher income shocks compared to women living in urban areas. The regional difference for women is, respectively, $\sigma^2_{\varepsilon_t^{Women}} = 0.0032$ and $\sigma^2_{\zeta_t^{Women}} = 0.0022$. Thus, rural living individuals face higher levels of net income risks compared to urban living individuals irrespective of their gender. The level of net income risk exposure based on gender might differ marginally, but the results indicate a regional net income risk heterogeneity. Rural-living men and women encounter higher net income risks, resulting in an net income risk heterogeneity, based on the urban-rural classification. Seasonal work dependence is a factor that contributes to the difference in net income risk for urban and rural- living individuals (Finch, 2017).

Part-time working individuals face higher income shocks than full-time working individuals, and this is the case for both men and women (see Table 2.6). The average variance estimates of employment status indicate a higher transitory income shock variance, compared the permanent income shock for both men and women (see Table 2.6). The average estimates for part-time working men report higher income shock variances compared to full-time working men, with the respective differences being, $\sigma^2_{\varepsilon_t^{Men}} = 0.0036$ and $\sigma^2_{\zeta_t^{Men}} = 0.0087$. Similar findings are identified for women, with results showing that part-time working women face higher income shock variances compared to full-time working women, with the respective differences being, $\sigma^2_{\varepsilon_t^{Women}} = 0.0349$; $\sigma^2_{\zeta_t^{Women}} = 0.0146$. The risk ratio based on employment status is higher for part-time workers $\frac{Women}{Men} = 1.3$ compared to full-time employed $\frac{Women}{Men} = 1.1$.

Employment status estimates indicate a clear pattern, in which part-time workers face a higher net income risk than full-time workers. In particular, the income risk based on employment status are higher for women. The heightened net income risk for part-time working individuals may indicate differences in wage flexibility, and higher levels of net income risk exposure related to lifestyle (Hill *et al.*, 2010).

Similar patterns can be observed for self-employed and employed individuals. Self-employed individuals encounter higher levels of income risk compared to employed individuals, and this is the case for both men and women. The average estimates for self-employed working men report that they face higher income shock variances compared to employed men, with the respective differences being, $\sigma^2_{\varepsilon_t^{Men}} = 0.1294$ and $\sigma^2_{\zeta_t^{Men}} = 0.0035$ (see Table 2.6). The results show that self-employed women face higher income shock variances compared to employed working women, with the respective differences being, $\sigma^2_{\varepsilon_t^{Women}} = 0.1012$ and $\sigma^2_{\zeta_t^{Women}} = 0.0119$. Employment status indicates a clear pattern in which self-employed workers face significantly higher levels of net income risk than employed workers, supported by a high risk ratio $\frac{Women}{Men} = 1.8$ compared to employed individuals with a considerably lower risk ratio $\frac{Women}{Men} = 1.3$.

The results indicate heterogeneity in net income risk related to employment status, as the differences indicate higher levels of income risk for women. This may reflect the fact that self-employed individuals bear the entire income risk. This is not the case for employed individuals, who encounter less income risk by the nature of their employment status (Gash, 2008).

Table 2.3: Individual Income Risk, Gender

Groups	Women		Men		
	Transitory $\sigma^2_{\varepsilon_t^{Women}}$	Permanent $\sigma^2_{\zeta_t^{Women}}$	Transitory $\sigma^2_{\varepsilon_t^{Men}}$	Permanent $\sigma^2_{\zeta_t^{Men}}$	Risk Ratio $\frac{Women}{Men}$
			Ethnicity		
White	0.0992***	0.0244***	0.0781***	0.0161***	1.5***
s.e.	(0.0016)	(0.0019)	(0.0035)	(0.0024)	
Sample Size	78,801		65,947		
Non-White	0.1143***	0.0258***	0.0931***	0.0178***	1.4***
s.e.	(0.0006)	(0.0005)	(0.0080)	(0.0028)	
Sample Size	15,331		11,680		
			Marital Status		
Married	0.1121***	0.0260***	0.0893***	0.0159***	1.6***
s.e.	(0.0016)	(0.0011)	(0.0035)	(0.0038)	
Sample Size	63,657		56,104		
Single	0.0930***	0.0226***	0.1767***	0.0197***	1.1***
s.e.	(0.0022)	(0.0012)	(0 .0034)	(0.0044)	
Sample Size	30,983		22,126		

Notes: Table 2.3 indicates the income risk heterogeneity based on gender.
Individual Net Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$.

Table 2.4: Individual Income Risk, Gender

Groups	Women		Men		
	Transitory $\sigma^2_{\varepsilon_t^{Women}}$	Permanent $\sigma^2_{\zeta_t^{Women}}$	Transitory $\sigma^2_{\varepsilon_t^{Men}}$	Permanent $\sigma^2_{\zeta_t^{Men}}$	Risk Ratio $\frac{Women}{Men}$
		Education			
University Degree	0.1163***	0.0264***	0.0865***	0.0151***	1.7***
s.e.	(0.0016)	(0.0011)	(0.0054)	(0.0091)	
Sample Size	26,113		21,314		
Non-University Degree	0.0943***	0.0241***	0.0757***	0.0085***	2.8***
s.e.	(0.0056)	(0.0049)	(0.0061)	(0.0012)	
Sample Size	56,096		47,049		

Notes: Table 2.4 indicates the income risk heterogeneity based on gender.
Individual Net Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$.

Table 2.5: Individual Income Risk, Gender

Groups	Women		Men		Risk Ratio
	Transitory $\sigma^2_{\varepsilon_t^{Women}}$	Permanent $\sigma^2_{\zeta_t^{Women}}$	Transitory $\sigma^2_{\varepsilon_t^{Men}}$	Permanent $\sigma^2_{\zeta_t^{Men}}$	$\frac{Women}{Men}$
			Parenthood		
Parent	0.1529***	0.0321***	0.1577***	0.0237***	1.4***
s.e.	(0.0036)	(0.0031)	(0.0086)	(0.0091)	
Sample Size	46,386		32,781		
Non-Parent	0.0924***	0.0216***	0.0804***	0.0143***	1.5***
s.e.	(0.0038)	(0.0028)	(0.0042)	(0.0045)	
Sample Size	48,399		45,546		
			Urban-Rural Classification		
Urban	0.1017***	0.0240***	0.1007***	0.0125***	1.9***
s.e.	(0.0046)	(0.0028)	(0.0035)	(0.0038)	
Sample Size	74,095		61,101		
Rural	0.0985***	0.0262***	0.1079***	0.0177***	1.5***
s.e.	(0.0038)	(0.0025)	(0.0072)	(0 .0082)	
Sample Size	20,690		17,226		

Notes: Table 2.5 indicates the income risk heterogeneity based on gender; Individual Net Income; The estimation is based on the level identification scheme;The risk ratio is based on $\sigma^2_{\zeta,t}$; The bootstrap standard errors are based on 1000 replications and presented in parentheses; *significant at $p < 0.1$;**significant at $p < 0.05$;***significant at $p < 0.01$.

Table 2.6: Individual Income Risk, Gender

Groups	Women		Men		Risk Ratio
	Transitory $\sigma^2_{\varepsilon_t^{Women}}$	Permanent $\sigma^2_{\zeta_t^{Women}}$	Transitory $\sigma^2_{\varepsilon_t^{Men}}$	Permanent $\sigma^2_{\zeta_t^{Men}}$	$\frac{Women}{Men}$
Full-time	0.0557***	0.0143***	0.0662***	0.0131***	1.1***
s.e.	(0.0045)	(0.0025)	(0.0029)	(0.0032)	
Sample Size	43,350		57,771		
Part-Time	0.0906***	0.0289***	0.0698***	0.0218***	1.3***
s.e.	(0.0057)	(0.0039)	(0.0028)	(0.0031)	
Sample Size	24,135		5,598		
Employed	0.0638***	0.0140***	0.0501***	0.0111***	1.3***
s.e.	(0.0036)	(0.0028)	(0.0051)	(0.0023)	
Sample Size	62,861		55,044		
Self-Employed	0.1650***	0.0259***	0.1795***	0.0146***	1.8***
s.e.	(0.0086)	(0.0029)	(0.0044)	(0.0038)	
Sample Size	5,080		8,674		

Notes: Table 2.6 indicates the income risk heterogeneity based on gender.
Individual Net Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$.

Discussion: Gender Decomposition

This section discusses the implications associated with the gender decomposition pertaining to income risk. I consider the impact of one standard deviation change in the permanent income shock (see Table 2.7), and its effect on the utility welfare loss. The estimates in Table 2.3-2.6 and Figure 2.2 show that women have on average a higher variance in permanent income shocks, compared to men. In addition, Table 2.7 indicates a lower welfare loss for men at a 1.88 per cent utility welfare loss, compared to women at 3.19 per cent. The results reveal a net income risk heterogeneity based on gender (see Table 2.7).

Another way to quantify permanent income shocks is by expressing them in terms of probabilities, as in Table 2.8. The probabilities of income gains and losses indicate the size of permanent income shocks based on gender in Table 2.8. It shows the likelihood of facing a 20 or 50 per cent positive or negative income shock. The results indicate that women are 7.9 per cent likely to face an income loss of 20 per cent due to an adverse income shock, whereas the corresponding figure for men is only 1.5 per cent. Thus the likelihood of women facing an adverse income shock of 20 per cent is almost five times that of men.

The heterogeneity of income risk based on group decomposition reveals an uneven dispersion of income risk. This also translates from net income into net income risk patterns. The results in Table 2.7 show that men face a higher reduction in individual income risk than women. Considering the different income risk types, it is evident that taxes and benefits mitigate adverse income shocks to differing degree. The findings support Kniesner and Ziliak's (2002) approach.

Factor that likely related to the education attainment is marital choice and family planning. Women with more education are the least likely to marry and are less likely to have children. The literature shows that the marriage gap has eroded as the returns to marriage have changed (Isen and Stevenson, 2010; Choi and Valladares-Esteban, 2015). Marriage and remarriage rates have risen for women with a college degree relative to women with fewer years of education. However, the patterns of, and reasons for, marriage have changed. College educated women marry later, have fewer children, are less likely to view marriage as 'financial security', are happier in their marriages and with their family life, and are not only the least likely to divorce, but have had the biggest decrease in divorce since the 1970s, compared to women without a college degree. In contrast, there have been fewer changes in marital patterns by education for men. The role of marital choice in mitigating income risk is examined in detail in Chapter 3.

Women face higher income variation based on career disruptions due to child-birth. Post-child-birth women lose labour market experience as they temporarily drop out of the labour market. Part-time work offers mothers more flexibility, yet the nature of the part-time position reinforces the exposure to income risk associated with the lower wage. The low rate of payment is also combined with a lack of wage growth in part-time work, associated with less training, less skill accumulation over time and lower informal networking opportunities and promotions (Mandel and Stier, 2009; Blundell *et al.* 2016; Joyce, 2018). The evidence of higher levels of income risk for mothers supports this as well. As a result, women are more vulnerable to income shocks compared to men. The higher variance in permanent income shocks also reduces their well-being.

The UK's 'great recession' was characterised by sharp falls in real wages and productivity, alongside evidence of growing labour market polarisation. Unemployment in the UK rose from 5.1 per cent in early 2008 to a recessionary high of eight per cent in early 2010 (Coutler, 2017; Clegg, 2019). As a measure for counteracting rising unemployment, part-time and short-time and temporary work increased during the crisis (Coutler, 2017; Clegg, 2019;). The low-income associated with part-time positions limits the ability to smooth adverse income shocks for women. The UKHLS data set also indicates that the majority of women are in part-time employment. The additional rise in part-time work associated with the recession contributes to the higher variance in permanent income shocks for women.

The results of this research indicate an income risk heterogeneity based on an individual's gender. Existing policies do not mitigate the difference in the heterogeneity of income risk across gender. Underlying reasons for the higher income risk for women may be related to employment status, parenthood, the great recession in the UK, and specific income variance patterns. The British government should consider the degree of income risk when developing welfare policies.

Table 2.7: Utility Welfare Loss, Gender

Subgroup	Loss in per cent	Utility Welfare Loss in per cent
Women	15.80%	3.19%
Men	10.34%	1.88%

Net Individual Income; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 2.8: Probabilities of Permanent Income Shocks, Gender

Probability of income gain/loss		Permanent income shock in per cent	
		Women	Men
		$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{Women}}\right)$	$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{Men}}\right)$
income gain>50%:	$Pr(\zeta_{i,t} > \ln(1.50))$	0.51%	0.01%
income gain>20%:	$Pr(\zeta_{i,t} > \ln(1.20))$	12.36%	3.88%
income loss>50% :	$Pr(\zeta_{i,t} < \ln(0.50))$	0.45%	0.13%
income loss>20%:	$Pr(\zeta_{i,t} < \ln(0.80))$	7.86%	1.55%

The probabilities of gains/losses are with respect to the level of permanent income under the mean shock. Note that $\zeta_{i,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

2.5.2 Results: Income Risk based on Ethnicity

This section reports the dispersion of income risk by focusing on ethnicity in the UK [6]. Tables 2.9 to 2.12 and Figure 2.3 report the group decomposition of the levels of income risk associated with an individual's ethnic background. The results of the ethnicity decomposition show that Non-White and White individuals face distinct levels of net income risk. Non-White individuals encounter slightly higher transitory and permanent income risks in each group compared to White individuals. The results indicate that the income risk is also observed in a net income risk heterogeneity. The results support findings in the literature, which emphasise the challenges existing in the labour market for individuals of Non-White ethnicity (Finch, 2017; Hill *et al.*, 2010; ONS, 2018). In addition, for robustness the dispersion of income risk across the subgroups reflect the patterns in gross income risk (see Appendix B). The ethnicity decomposition did not show any considerable age effects. Therefore, this decomposition is not part of the discussion in this section.

The decomposition based on income types in Table 2.9 reveals different levels of income risk based on ethnicity. Similarly,the decomposition also within the ethnicity framework regarding taxes and benefits indicates a different income risk mitigation effect. Benefits have a stronger insurance mechanism as they show a lower risk ratio of the permanent income shock variance. The results in Table 2.9 show that through benefits and taxes income risk is decreases by, $\sigma^2_{\varepsilon_t^{White}} = 0.0300$ and $\sigma^2_{\zeta_t^{White}} = 0.0054$ for White individuals and by, $\sigma^2_{\zeta_t^{Non-White}} = 0.0100$ and $\sigma^2_{\zeta_t^{Non-White}} = 0.0086$ for Non-White individuals. The estimates show that income with benefits decreases the level of income risk compared to income minus taxes. The findings are in line with Kniesner and Ziliak (2002) and Avram *et al.* (2019).

Moreover, the level of income risk mitigation depends on ethnicity as comparing gross and net income for White and Non-White individuals indicates, with the respective differences between gross and net income being, $\sigma^2_{\varepsilon_t^{White}} = 0.0300$ and $\sigma^2_{\zeta_t^{White}} = 0.0054$ and for $\sigma^2_{\varepsilon_t^{Non-White}} = 0.0100$ and $\sigma^2_{\zeta_t^{Non-White}} = 0.0086$. Thus, the results in Table 2.9 indicate a reduction in income risk from gross to net income. Yet, a difference can be observed based on ethnicity as Non-White individuals encounter less income risk reduction relative to White individuals. Further investigation based on the subgroups indicate an income risk heterogeneity based on ethnicity.

[6] Appendix F indicates the results for the entire UK sample, which indicates the same group-specific ranking as the ethnicity decomposition, showing that the results are robust.

As a consequence, the results in Table 2.9 indicate an insurance induced by taxes and benefits, which depends on ethnicity. In particular, when considering the difference in the permanent income shocks ($\sigma^2_{\zeta^g_t}$) supports the difference based on ethnicity. Non-White individuals face less income risk reduction through the tax and benefit system than White individuals. Thus, the estimates provide evidence of an income risk heterogeneity based on ethnicity that translates from gross income into net income. The risk ratio decreases marginally, indicating the same level of income variation across all income types. Further, the permanent risk estimates between White and Non-White individuals are significantly different at the 90 per cent confidence interval.

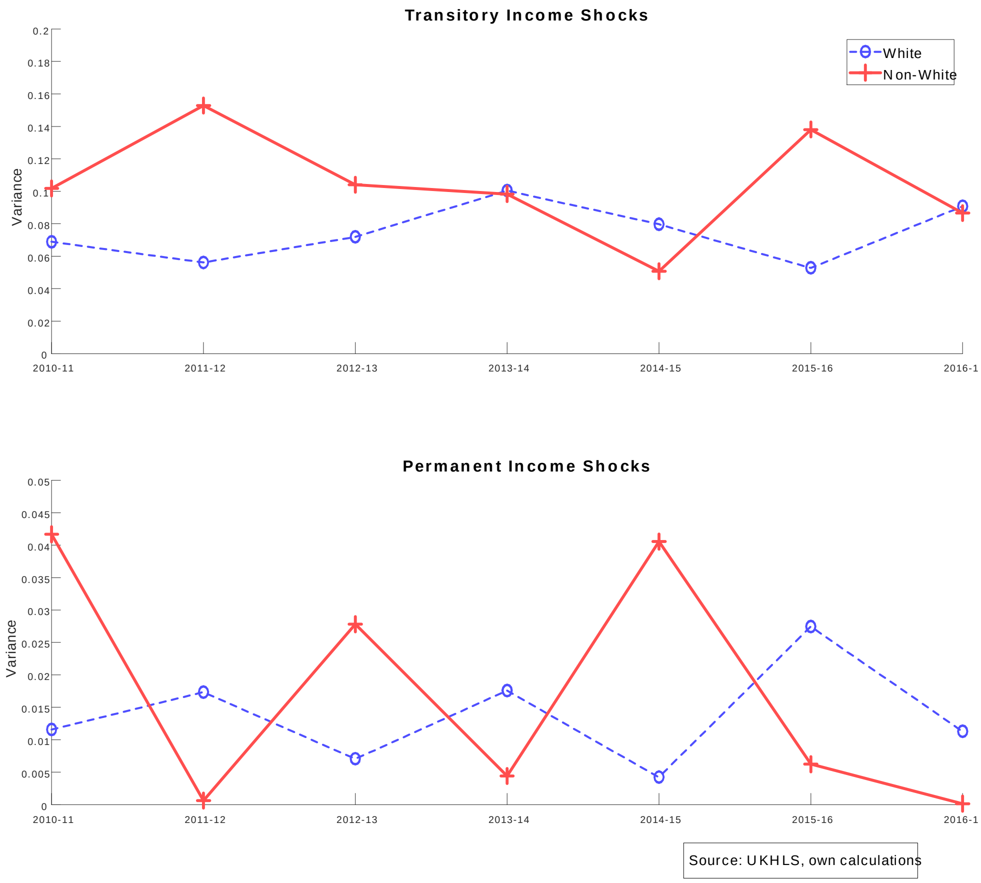
In addition, Figure 2.3 shows the estimates of individual net income risk decomposition based on ethnicity from 2009 to 2017. It shows that Non-White individuals face marginally higher levels of income risk during this period.

Table 2.9: Individual Income Risk, Ethnicity

Groups	White		Non-White		
	Transitory $\sigma^2_{\varepsilon^{White}_t}$	Permanent $\sigma^2_{\zeta^{White}_t}$	Transitory $\sigma^2_{\varepsilon^{Non-White}_t}$	Permanent $\sigma^2_{\zeta^{Non-White}_t}$	Risk Ratio $\frac{Non-White}{White}$
Gross Income	0.1031***	0.0192***	0.1081***	0.0248***	1.3***
s.e.	(0.0080)	(0.0024)	(0.0035)	(0.0038)	
Income plus Benefits	0.0932***	0.0176***	0.0101***	0.0216***	1.2***
s.e.	(0.0056)	(0.0019)	(0.0031)	(0.0031)	
Income minus Taxes	0.0886***	0.0169***	0.0998***	0.0197***	1.2***
s.e.	(0.0046)	(0.0029)	(0.0041)	(0.0035)	
Net Income	0.0731***	0.0138***	0.0981***	0.0162***	1.2***
s.e.	(0.0035)	(0.0038)	(0.0080)	(0.0024)	
Sample Size	144,748		27,011		

Notes: Table 2.9 shows the gross and net income risk based on ethnicity;
Individual Income Types; The estimation is based on the level estimation method;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$; *significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$.

Figure 2.3: Net Individual Income Risk based on Ethnicity



Notes: Figure 2.3 shows that Non-White individuals face higher levels of transitory and permanent income shocks compared with White individuals from 2010 until 2017.

This section analyses the ethnicity difference for net income risk based on a detailed group decomposition in Table 2.10 and Table 2.12 and Figure 2.3. Thus, I examine the level of income risk across White and Non-White based on, gender, marital status, parenthood, urban-rural classification, and employment status. Appendix *B* indicates the results for the entire UK sample and for the estimation in first differences. The results in Appendix *B* indicate the same group-specific ranking as the ethnicity decomposition, showing that the results are robust.

The results in Table 2.10 indicate that men and women based on Non-White ethnicity encounter marginally higher levels of net income risk compared to men and women of White ethnicity. Comparing the income risk of women of White and Non-White ethnicity, indicates a difference of $\sigma^2_{\varepsilon_t^{Women}} = 0.0151$ and $\sigma^2_{\zeta_t^{Women}} = 0.0014$. Similarly, the difference between White and Non-White men are relatively small with $\sigma^2_{\varepsilon_t^{Men}} = 0.0150$ and $\sigma^2_{\zeta_t^{Men}} = 0.0017$. Yet, the difference between the subgroup of white men and women reflects the findings we saw in the previous section. The estimates indicate a net income risk heterogeneity based on gender. The risk ratio based on gender indicates these differences with relatively small ratios $\frac{Non-White}{White} = 1.1$ for women and $\frac{Non-White}{White} = 1.1$ for men, indicating low income variation (Table 2.10). Thus, while considerable gender differences are observed, marginal differences based on ethnicity are evident.

Marital status indicates a difference amongst individuals based on ethnicity. Non-White married and single individuals face higher levels of income shocks than White individuals, with the respective difference being, $\sigma^2_{\varepsilon_t^{Married}} = 0.0164$ and $\sigma^2_{\zeta_t^{Married}} = 0.0036$ (see Table 2.10). Further, considering the differences for single individuals based on ethnicity the differences indicate, $\sigma^2_{\varepsilon_t^{\text{Si}ngle}} = 0.0325$ and $\sigma^2_{\zeta_t^{\text{Si}ngle}} = 0.0050$. The risk ratio reflects the income variation based on ethnicity for married $\frac{Non-White}{White} = 1.3$ and for singles $\frac{Non-White}{White} = 1.2$ (see Table 2.10). The finding of lower levels of income risk for married individuals, independent of ethnicity, provides evidence for a private insurance. This finding on marital status complements income risk patterns on gender (Gardiner, 2017; Guner, Kulikova and Valladares-Esteban, 2015). The role of private insurance through marriage is examined in detail in Chapter 3.

The results in Table 2.11 report the levels of income risk related to an individual's parenthood status and distinguish between the ethnicity of an individual's background. The decomposition based on the presence of children reveals differences in income risk. The income risk estimates for Non-White parents indicate higher levels, compared to White individuals with the respective differences being, $\sigma^2_{\varepsilon_t^{Parents}} = 0.0115$ and $\sigma^2_{\zeta_t^{Parents}} = 0.02078$. The level of income risk for individuals with no children is marginally different across ethnicity, $\sigma^2_{\varepsilon_t^{Non-Parent}} = 0.025$ and $\sigma^2_{\zeta_t^{non-Parent}} = 0.0011$. The results show that White parents face lower income shock variances, relative to Non-White parents. The parenthood risk ratio supports the net income risk difference based on ethnicity, with a higher risk ratio $\frac{Non-White}{White} = 1.4$ for parents and $\frac{Non-White}{White} = 1.1$ with no children. Thus, there is an income risk heterogeneity based on ethnicity for individuals with children.

Also regional differences in income risk can be observed. These refer to the urban or rural geographical location in which individuals live. Rural living Non-white individuals face higher levels of net income risk than White individuals living in the same area, $\sigma^2_{\underline{2}\varepsilon_t^{Rural}} = 0.0064$ and $\sigma^2_{\zeta_t^{Rural}} = 0.0100$. The difference in income risk across ethnicity for urban areas indicate that $\sigma^2_{\varepsilon_t^{Urban}} = 0.0188$ and $\sigma^2_{\zeta_t^{Urban}} = 0.0010$. Table 2.11 reports the results based on where they live, whether in rural or urban areas. The risk ratio highlights the significant difference between individuals located in distinct areas, with $\frac{Non-White}{White} = 1.1$ for urban areas. A considerably higher risk ratio based on geographical location can be observed for rural Non-White individuals: $\frac{Non-White}{White} = 1.5$ (see Table 2.11). It should be highlighted that the sample size for rural Non-White individuals is considerably smaller, which might contribute to the higher income risk variation. Other factors are associated with the seasonal work in which Non-White individuals are employed (ONS, 2018). As a result, an income risk heterogeneity across individuals from different ethnic backgrounds can be observed that is associated with their geographic location.

Individuals of Non-White ethnicity encounter a higher level of income risk based on their employment status (see Table 2.12). The differences based on ethnicity considering part-time working individuals is $\sigma^2_{\varepsilon_t^{Part-Time}} = 0.0438$ and $\sigma^2_{\zeta_t^{Part-Time}} = 0.0067$. The results show that part-time working Non-White individuals face higher levels of income shock risk across all the employment classifications, with a risk ratio of $\frac{Non-White}{White} = 1.3$ for part-time working individuals. Moreover, the employment status indicates a clear pattern in which self-employed workers face considerably higher levels of net income risk than employed workers. Here, also a difference in income risk based on ethnicity can be observed, $\sigma^2_{\varepsilon_t^{Self-employed}} = 0.0625$ and $\sigma^2_{\zeta_t^{self-employed}} = 0.0073$.This is related to the fact that a self-employed person bears most of the responsibility, unlike employed individuals. The risk ratio for the self-employed is $\frac{Non-White}{White} = 1.2$, indicating income variation between Non-White and White individuals (see Table 2.12). Further, part-time worker face higher levels of income risk compared to employed individuals. This is also associated with the nature of the employment status in lower incomes compared to full-time employed individuals. The results indicate an income risk heterogeneity related to the employment status of the individual.

Table 2.10: Individual Income Risk, Ethnicity

Groups	White		Non-White		
	Transitory $\sigma^2_{\varepsilon_t^{White}}$	Permanent $\sigma^2_{\zeta_t^{White}}$	Transitory $\sigma^2_{\varepsilon_t^{Non-White}}$	Permanent $\sigma^2_{\zeta_t^{Non-White}}$	Risk Ratio $\frac{Non-White}{White}$
			Gender		
Women	0.0992***	0.0244***	0.1143***	0.0258***	1.1***
s.e.	(0.0016)	(0.0019)	(0.0006)	(0.0005)	
Sample Size	78,801		15,331		
Men	0.0781***	0.0161***	0.0931***	0.0178***	1.1***
s.e.	(0.0035)	(0.0024)	(0.0080)	(0.0028)	
Sample Size	65,947		11,680		
			Marital Status		
Married	0.0759***	0.0143***	0.0923***	0.0179***	1.3***
s.e.	(0.0038)	(0.0041)	(0.0081)	(0.0017)	
Sample Size	101,807		17,411		
Single	0.0892***	0.0176***	0.1217***	0.0226***	1.2***
s.e.	(0.0037)	(0.0017)	(0.0084)	(0.0024)	
Sample Size	42,744		9,558		

Notes: Table 2.10 indicates the income risk heterogeneity based on ethnicity; Individual Net Income; The estimation is based on the level identification scheme; The bootstrap standard errors are based on 1000 replications and presented in parentheses; The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$; ***significant at $p < 0.01$

Table 2.11: Individual Income Risk, Ethnicity

Groups	White		Non-White		Risk Ratio
	Transitory $\sigma^2_{\varepsilon_t^{White}}$	Permanent $\sigma^2_{\zeta_t^{White}}$	Transitory $\sigma^2_{\varepsilon_t^{Non-White}}$	Permanent $\sigma^2_{\zeta_t^{Non-White}}$	$\frac{Non-White}{White}$
			Parenthood		
Parent	0.0841***	0.0189***	0.0956***	0.0267***	1.4***
s.e.	(0.0044)	(0.0047)	(0.0048)	(0.0038)	
Sample Size	62,890		15,719		
Non-Parent	0.0759***	0.0181***	0.1009***	0.0192***	1.1***
s.e.	(0.0101)	(0.0009)	(0.0014)	(0.0014)	
Sample Size	81,858		11,292		
			Urban-Rural Classification		
Urban	0.0746***	0.0134***	0.0934***	0.0144***	1.1***
s.e.	(0.0038)	(0.0041)	(0.0033)	(0.0035)	
Sample Size	107,871		26,427		
Rural	0.0865***	0.0208***	0.0929***	0.0308***	1.5***
s.e.	(0.0073)	(0.0083)	(0.0070)	(0.0024)	
Sample Size	36,877		5,844		

Notes: Table 2.12 indicates the income risk heterogeneity based on ethnicity.
Individual Net Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$

Table 2.12: Individual Income Risk, Ethnicity

Groups	White		Non-White		Risk Ratio
	Transitory $\sigma^2_{\varepsilon_t^{White}}$	Permanent $\sigma^2_{\zeta_t^{White}}$	Transitory $\sigma^2_{\varepsilon_t^{Non-White}}$	Permanent $\sigma^2_{\zeta_t^{Non-White}}$	$\frac{Non-White}{White}$
Full-time	0.0652***	0.0123***	0.0813***	0.0142***	1.2***
s.e.	(0.0031)	(0.0034)	(0.0047)	(0.0081)	
Sample Size	87,622		12,747		
Part-Time	0.2072***	0.0245***	0.1634***	0.0312***	1.3***
s.e.	(0.0038)	(0.0035)	(0.0023)	(0.0035)	
Sample Size	25,069		4,446		
Employed	0.0478***	0.0119***	0.0583***	0.0128***	1.0***
s.e.	(0.0038)	(0.0041)	(0.0081)	(0.0017)	
Sample Size	91,206		13,427		
Self-Employed	0.3234***	0.0335***	0.3859***	0.0408***	1.2***
s.e.	(0.0035)	(0.0034)	(0.0030)	(0.0018)	
Sample Size	8,710		19,354		

Notes: Table 2.13 indicates the income risk heterogeneity based on ethnicity.
Individual Net Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$

Discussion: Ethnicity Decomposition

This section discusses possible factors related to the income risk heterogeneity associated with the ethnicity decomposition. I provide several measures for adverse permanent income shocks differentiated by the ethnic background of the individuals. The decomposition by income types reveals a difference in reduction of income risk based on ethnicity. Table 2.9 indicates that the income risk from net to net income after taxes and benefits persists on a higher level for Non-White individuals compared to White individuals. The results demonstrate an income risk heterogeneity that translates from net to net income risk.

In Table 2.14 I consider the effect of one standard deviation change in the permanent income shock. The results show that individuals of Non-White ethnicity face marginally higher levels of income risk in each subgroup. Table 2.13 shows that Non-White individuals encounter a welfare loss of 2.43 per cent, compared to White individuals at 2.21 per cent. Although the small sample of Non-White individuals implies some limitations to formulating implications, the overall results suggest an income risk heterogeneity based on individuals' ethnic background.

Table 2.14 shows the probability of encountering a 20 per cent or 50 per cent income gain or loss based on ethnicity. It quantifies the impact of positive and negative income shocks. The results indicate that Non-White individuals are 3.97 per cent likely to face an income loss of 20 per cent due to an adverse income shock. In contrast, White individuals face a 2.87 per cent likelihood of encountering a 20 per cent income loss. Consequently, Non-White individuals are 1.1 percentage points more likely to encounter an adverse income shock of 20 per cent. The results support the evidence of income risk heterogeneity based on ethnicity.

Factors that drive this inequality may be related to employment status. The majority of Non-White individuals work in part-time jobs or occupations that require low educational skills. A recent study indicates that ethnic minority groups are commonly under-represented in mid-skilled and professional occupations, and tend to work in low-income jobs, compared to individuals of White ethnicity (Catney and Sabater, 2015). Occupational status is associated with low income, which makes it more challenging for these individuals to smooth adverse income shocks (Jenkins *et al.*, 2010). In addition, Giupponi and Xu (2020) provide evidence of how employment dynamics have changed since the Great Financial Crisis. In the past ten years, sole or single self-employment has increased considerably. The nature of self-employment is a factor that contributes to higher income risk, as they bear full responsibility for generating an income. The majority of self-employed individuals, approximately 60.12 per cent, are Non-White individuals. As a consequence, individuals of Non-White ethnicity face higher income risk. Therefore, an underlying factor in income risk is associated with employment status.

The results of this research indicate a higher income risk for individuals of Non-White ethnicity, compared to individuals of White ethnicity. Also the income decomposition reveals a stronger income risk reduction effect for White individuals. As a consequence, the findings confirm an income risk heterogeneity based on ethnicity. In addition, tax and transfer policies do not mitigate the difference in the heterogeneity of income risk across ethnicity. The difference in income risk stems primarily from employment status and educational attainment. To improve the situation, policymakers should focus on supporting educational attainment and employment for individuals of Non-White ethnicity in their policy design.

Table 2.13: Utility Welfare Loss, Ethnicity

Subgroup	Loss in per cent	Utility Welfare Loss in per cent
White	11.75%	2.21%
Non-White	12.73%	2.43%

Individual Net Income; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 2.14: Probabilities of Permanent Income Shocks, Ethnicity

Probability of income gain/loss		Permanent income shock in per cent	
		White	Non-White
		$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{White}}\right)$	$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{Non-White}}\right)$
income gain>50%:	$Pr(\zeta_{i,t} > \ln(1.50))$	0.03%	0.07%
income gain>20%:	$Pr(\zeta_{i,t} > \ln(1.20))$	6.00%	5.57%
income loss>50% :	$Pr(\zeta_{i,t} < \ln(0.50))$	0.10%	0.21%
income loss>20%:	$Pr(\zeta_{i,t} < \ln(0.80))$	2.87%	3.97%

The probabilities of gains/losses are with respect to the level of permanent income under the mean shock. Note that $\zeta_{i,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

2.5.3 Robustness Check

Tables 2.15 and 2.17 report the findings of the robustness test for the income risk heterogeneity. The robustness test exercise uses the same approach with a different Mincerian regression controlling also for employment status ($ftpt_{i,c,t}$) as a full-time or part-time working individual (Mincer, 1974). It implies that working full-time relative to working part-time is a choice, contrasting the Mincerian regression in eq. (2.1) in which employment status resembles an income shock. The key finding is the heterogeneity of income risk based on the group decomposition. The same patterns are found using the adjusted Mincerian regression for the entire UK sample. The exercise supports the ranking of the groups and provides robustness for the findings.

Another aspect is that some individuals might be less ambitious to get a higher salary if their spouses make more money. I tested this with a robustness exercise by adding a dummy variable for those women with a male spouses are above the 75th percentile of the spouses' income distribution. The changes are to the 4th decimal point.

Table 2.15: Robustness Individual Income Risk, UK

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
	Gender	
Women	0.1019***	0.0251***
s.e.	(0.0036)	(0.0029)
Sample Size	94,785	
Men	0.0799***	0.0163***
s.e.	(0.0043)	(0.0031)
Sample Size	78,327	
	Ethnicity	
White	0.0781***	0.0139***
s.e.	(0.0024)	(0.0018)
Sample Size	144,748	
Non-White	0.0931***	0.0162***
s.e.	(0.0041)	(0.0021)
Sample Size	27,011	

Notes: Table 2.16 indicates robust income risk results. UK Net income; The estimation is based on the level identification scheme:*significant at $p < 0.1$;.**significant at $p < 0.05$; ***significant at $p < 0.01$; The bootstrap standard errors are based on 1000 replications and presented in parentheses.

Table 2.16: Robustness Individual Income Risk, UK

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
	Marital Status	
Married	0.0588***	0.0199***
s.e.	(0.0027)	(0.0021)
Sample Size	119,761	
Single	0.0638***	0.0227***
s.e.	(0.0047)	(0.0046)
Sample Size	53,109	
	Parenthood	
Parent	0.0865***	0.0174***
s.e.	(0.0039)	(0.0014)
Sample Size	79,185	
Non-Parent	0.0778***	0.0191***
s.e.	(0.0036)	(0.0018)
Sample Size	93,945	
	Rural Urban Classification	
Urban	0.0775***	0.0145***
s.e.	(0.0042)	(0.0029)
Sample Size	135,196	
Rural	0.0865***	0.0209***
s.e.	(0.0041)	(0.0027)
Sample Size	37,916	

Notes: Table 2.17 indicates robust income risk results. UK Net income; The estimation is based on the level identification scheme:*significant at $p < 0.1$;.**significant at $p < 0.05$; ***significant at $p < 0.01$; The bootstrap standard errors are based on 1000 replications and presented in parentheses.

Table 2.17: Robustness Individual Income Risk, UK

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
Full-time	0.0669***	0.0141***
s.e.	(0.0039)	(0.0028)
Sample Size	101,121	
Part-Time	0.2029***	0.0301***
s.e.	(0.0074)	(0.0027)
Sample Size	29,733	
Employee	0.0493***	0.0121***
s.e.	(0.0023)	(0.0017)
Sample Size	117,905	
Self-Employed	0.3283***	0.0328***
s.e.	(0.0079)	(0.0034)
Sample Size	13,754	

Notes: Table 2.18 indicates robust income risk results. UK Net income; The estimation is based on the level identification scheme:*significant at $p < 0.1$;.**significant at $p < 0.05$; ***significant at $p < 0.01$; The bootstrap standard errors are based on 1000 replications and presented in parentheses.

2.6 Conclusion

This chapter measures the degree and the heterogeneity of gross and net income risks across UK individuals. The results reveal an income risk heterogeneity based on gender and also marginally for ethnicity in the UK. The analysis uses the income decomposition by Friedman (1957), which distinguishes transitory and permanent income components, as seen in the PIH (see Chapter 1 for more details). The income process is estimated in income levels and as a robustness test as well in first-differences. The group-specific patterns are robust for both identification schemes (see Appendix B). I use the UKHLS data set, which contains income and socioeconomic information from 2009 to 2018 for individuals in the UK.

This chapter provides a unique perspective on the level of income risk, by examining detailed group-specific socioeconomic and demographic characteristics. In investigating the presence of income risk across British individuals, the size and heterogeneity of gross and net income risk is analysed, based on socioeconomic and demographic factors such as gender, ethnicity, marital status, parenthood, geographical location and employment status. The majority of the income risk literature focuses mainly on education and income levels, but this paper contributes to the debate by offering in-depth analysis across a wider variety factors in seeking to understand the heterogeneity of gross and net income risk. Consequently, the chapter offers a nuanced perspective on the nature of income risk.

The first key finding of this chapter is the income risk heterogeneity across several factors. I find that women are five times as likely to face an adverse income shock of 20 per cent compared to men. Similarly, Non-White individuals encounter a 1.1 per cent point higher likelihood of a 20 per cent adverse income shock compared to White individuals. Thus, the uneven distribution reveals a gross and net income risk heterogeneity based on gender and ethnicity. The underlying factors that contribute to the heterogeneity in income risks are related to employment status, parenthood, access to educational attainment and the economic situation of the UK from 2009 to 2018.

The second main contribution of this work concerns the dynamics of income risk and the general tax and benefit system. The decomposition based on gross income, with benefits, taxes and net income reveals that the reduction based on taxes and benefits varies. Both contribute to the reduction in income variation. However, the results show that benefits reduce adverse income shocks by a higher degree than income minus taxes. The results of income minus taxes shows marginal differences in income risk. Further, the results indicate that men and White individuals encounter a greater reduction in adverse income shocks than women and Non-White individuals. Thus, the results support the findings regarding income risk heterogeneity across individuals in the UK. In particular, for gender the results indicate that the gross income risk heterogeneity translates into an uneven distribution of net income risk across men and women. Consequently, policies such as taxes and benefits do not mitigate income risk heterogeneity.

The chapter provides evidence of an uneven distribution of income risk in the UK. Consequently, the UK government should take the degree of income risk into account when developing policies. Insights gained on net income risk heterogeneity should inform policy makers regarding those individuals who face higher levels of income risk, and thereby guide improvements in welfare policy design.

One limitation of this research is based on the time dimension of the UKHLS. Currently, information is available from 2009-2018. This short time period does not permit long-run analysis. Further, the UKHLS dataset does not include an annual income variable, which might have given additional insight into the policy implications of income risk heterogeneity.

Future research should focus on the different impacts of different income shock types. Income risks reflect only one type of income shock, yet there are others such as employment shocks, health shocks and wage shocks. The UKHLS provides information on each of these variables, which enables the examination of the distribution of income risk types in the UK. To date, the literature does not offer an analysis in this regard. Focusing on these distinct risk types would be a development of this work.

Another area of interest concerns the transmission of income risk into consumer behaviour. Such an examination would enable a more profound discussion of the impact of income shocks on consumption choices and might have implications for the insurance mechanism of welfare schemes in the UK (Gorman, 1953, 1961; Jorgenson *et al.*, 1980, 1982; Muellbauer, 1975; Blundell and Stoke, 2005; Chiappori and Ekeland, 2011). Both research avenues would develop ideas from the first chapter further and contribute to the existing empirical literature.

CHAPTER

3

MARRIAGE AND INCOME RISK IN THE UNITED KINGDOM

3.1 Introduction

Unexpected changes in income cause financial strain on many individuals. Marriage has often been seen as a way to increase financial stability. When a married couple combine their individual incomes, the volatility of their household income decreases. Consequently, married couples can offset adverse income shocks by pooling their income. Thus, marriage generates an insurance against adverse income shocks. This is a advantage relative to singles households. However, marriage also induces additional income risk when education and employment characteristics differ within a married couple. Consequently, marital choice influences the degree of insurance against adverse income shocks. The amount of risk faced by single individuals and married couples is an important question for understanding economic behaviour and for developing policy design. This chapter contributes to the income dynamics literature and investigates the relationship between marriage and net income risk. The contribution of this analysis is twofold; (i) it compares the insurance advantage of married households with single individuals and (ii) it finds that income risk mitigation based on marriage depends on marital choice. In particular, it measures the degree of private insurance between married couples, based on their marital choice in the UK from 2009 to 2018.

The key finding of this chapter concerns the role of marital choice in determining the magnitude of net income risk. I find lower levels of income risk amongst assortative married couples, namely those who share the same socioeconomic characteristics, compared to couples that do not share them. Assortative couples also face a 1.4 percentage point lower likelihood of facing 20 per cent adverse income shock compared to couples who differ in these characteristics. Another contribution is my innovative statistical decomposition quantifying the effect of marital choice on net income risk. This decomposition examines the magnitude of insurance between married couples. A key factor relates to the net income risk associated with the socioeconomic and educational background of married couples. Consequently, the chapter contributes to the income risk literature by providing evidence on the magnitude of marriage insurance against adverse income shocks based on marital choice. This chapter provides a unique perspective on the dynamics between marriage and net income risk.

The contribution of this research is to show empirically to what extent marriage reduces net income risk, drawing attention to cases where marriage increases income. A comprehensive body of work has identified different insurance channels of marriage such as income pooling, unemployment insurance, the added worker effect, and the benefits of a marriage premium (Antonovices and Town, 2004; Ortigueira and Siassi, 2011; Choi and Valladares-Esteban, 2015, 2018; Christiansen *et al.*, 2015; Chiappori *et al.*, 2020). A smaller body of work has examined the adverse impact of marriage on an individual's welfare, as Dynan *et al.* (2012) find evidence for income risks generated by marriage. Empirical evidence also supports the rise in income inequality related to assortative marital choice (Becker, 1973,1974; Goodman and Greave, 2010; Lise and Seitz, 2011; Eike *et al.*, 2018; Eeckhaut and Stanfors, 2019). To date, the literature does not provide an empirical analysis of the impact of marriage and marital choice on net income risk. Thus, this analysis complements current findings by quantifying the relative importance of changes in the composition of net income risk.

Married couples are differentiated by their marital choice so as to analyse the effects of such choice. The marital choice of a partner can be characterised as either an assortative or a cross-group choice. Becker (1973) introduced the assortative mating strategy, which argues that individuals tend to marry individuals from a similar background. If two individuals from the same group choose to marry, the net income risk for this couple should be similar; both members of the couple have more earnings stability than if they remained single. In contrast, if the married couple differs in their individual characteristics such as socioeconomic status, their income risk increases as one partner faces higher income fluctuations related to educational or employment factors. This chapter, follows the of PIH as it is the standard tool to measure the properties of the shocks to the two income components, which measure the income risk (see Chapter 1 for more details).

The longitudinal structure of the UKHLS facilitates analysis of the impact of marriage on net income risk. Further, allows estimation of the magnitude of insurance between married couples based on their marital choice. A synthetic data set randomises the partners of each marriage based on the marital choice. It ensures the removal of any endogeneity and serves as a robustness test. The estimation method uses the income dynamics in the UK, based on the approach by Heathcote *et al.* (2010). Following the literature, the chapter focuses on residual dispersion. The income process is specified for both temporary and permanent income shocks and is identified by using the level identification scheme, which is estimated by exploiting the variance and covariance structure of the residual term.

I find that assortative couples face a lower net income risk compared to couples from different socioeconomic backgrounds. Specifically, marriage is found to reduce levels of permanent income risk when married couples share the same socioeconomic characteristics. Couples married across socioeconomic groups indicate a loss in well-being reflected in a higher level of net income risk and are more likely to face adverse income shocks. In particular, the permanent net income risk for cross-group couples is considerably higher compared to assortative couples. Thus, the lower levels of income risk and consequently lower probability of adverse income shocks generate an income risk insurance for assortative married couples. I also test whether the levels of net income risk are influenced by education, examining the net income risk exposure associated with marital choice based on education. Based on the marital choice by education, the results are similar; assortative married couples are found to face lower net income risk compared to cross-group couples. Furthermore, the main finding indicates that marital choice influences income risk that couples face. A secondary observation is that the assortative couples are more likely to be composed of high-income spouses. This observation has no bearing on the finding of heterogenous income risk across marital choice groups. The reason is that I employ a model in natural logarithms and thus the "starting" point of an income change does not matter. Put it differently, the income shocks in this model are in fact percentage changes.

A counterfactual exercise is created based on the information in the data set. I create a synthetic data set, which randomises the partners of each marriage based on the marital choice. It ensures the removal of any endogeneity and serves as a robustness test. It provides evidence that the estimates still hold if the married couples are separated by their marital choice. The synthetic sample supports marital choice findings. Even though the magnitude of net income risk exposure is lower in the synthetic sample, the same ranking between marital choice can be identified. The lower degree of income risk in the synthetic sample is related to the removal of endogeneity and indicates that other factors contribute to the insurance mechanism. Thus, from this analysis, a new finding emerges: the degree of marital insurance depends on marital choice.

The chapter sets out to provide a review on the current literature in Section 3.2. It describes the data in Section 3.3 and explains the methodological approach in Section 3.4. Section 3.5 reports the results and discusses the welfare implications. Section 3.6 concludes.

3.2 Related Literature

3.2.1 Income Risk: Individuals and Married Couples

This section focuses on the empirical literature on marriage and its impact on income risk. It discusses several insurance channels identified in the literature, and also highlights risks that are associated with income risk.

Income risk is expressed in the variance of income shocks based on the PIH by Friedman (1957) (see chapter 1 for more details). The impact of the income shocks differs based on their nature (see eq. (1.2) and eq. (1.3)). This approach decomposes the income process into permanent components, such as job displacement and change in returns to education, and transitory characteristics, such as bonus payments (Meghir and Pistaferri, 2011). The theory asserts that an individual's consumption and savings choices respond differently to permanent income shocks than to transitory ones. Permanent income shocks directly translate into consumption choices, while transitory income shocks can be smoothed throughout time periods. Transitory income shocks are associated with mobility, namely transient changes within the income distribution (Blundell and Preston, 1998; Jenkins, 2005). However, if an individual cannot smooth income shocks, due to being constrained by liquidity, welfare losses can also arise from transitory income shocks (for more detail see Section 1.2). This risk and the subsequent ex post income instability make it difficult for people to cover their expenditures and can influence their well-being.

The impact of adverse income shocks reduces an individual's well-being and economic resources. It motivates the need for insurance against adverse income shocks. Such insurance potentially enables people to smooth consumption across time. Yet, there are risks associated with adverse selection and moral hazard issues. The failure of the labour market to generate an insurance against negative income shocks drives the need for social or private insurance. Private insurance consists of two key measures in which individuals and households can partially insure themselves against the impact of adverse income shocks by (i) using precautionary measures such as savings or a stock of asset and (ii) reacting with corrective economic activities.

This chapter focuses on private insurance opportunities through marriage. A couple can insure themselves against adverse income shocks by pooling their income, which enables them to offset a fall in their spouse's income partially. The partial insurance based on income pooling is affected by two key factors i) extensive margin and ii) intensive margin. The former indicates whether a spouse is working, while the latter reflects the number of hours worked. The sample includes working individuals only. Thus, changes at the extensive margin of working couples are not examined. Yet, the time worked, defined as the intensive margin, reflects the response to a adverse income shock within a married couple (Blundell *et al.*, 2011b; Blundell *et al.*, 2013; Fisher *et al.*, 2013; Boertien and Permanyer, 2019). In particular, if a spouse's exogenous income shocks are not perfectly correlated with the other spouse's shocks, income pooling reduces net income risk for both. I create a counterfactual exercise to examine the size of income risk mitigation and control for any endogeneity related to time worked by the partner. Within this exercise, I randomise the spouses of the couples by their marital choice. This enables me to investigate the robustness of my results and control for any endogeneity.

The literature shows that individual and household net income risk differ. It shows that the choice of how to use their economic resources depends on their capacity. The literature indicates that economic resources depend on levels of education and income (Dickens, 2000; Blundell *et al.*, 2018). Thus, individuals depend on their own resources. In contrast, households can use income pooling as self insurance. This partially offsets the impact on economic resources of negative income shocks. Therefore, households encounter less dispersion in their earnings growth than single individuals, which creates an advantage for households. In a comparative study, Pruit and Turner (2020) find that household dispersion risk is lower than single male dispersion risk. Also, Avram *et al.* (2019) highlight that household net income risk is lower compared to individual net income risk in the UK. The degree of income risk faced by single and married couples is important both for understanding economic behaviour and for the welfare consequences. This chapter contributes to the literature by analysing individual and household net income risk.

This chapter also complements the net income risk analysis with a counterfactual exercise. I create a synthetic sample in which I randomise married spouses based on their marital choice. A similar approach has been used by Eike *et al.* (2018). The choice reflects whether the spouses share the same socioeconomic background or differ in it. The UKHLS provides data on the married couples, which enables me to create groups based on assortative and cross socioeconomic marital choice. I use this distribution to then match the spouses with new partners based on their socioeconomic status. This method enables me to observe the net income risk of married couples with new spouses conditioned on their initial marital choice. This counterfactual method allows me to understand the dynamics between marital choice and insurance against negative income shocks, as it controls for the endogeneity associated with the partner.

3.2.2 Income Risk: Marriage and Marital Choice

Studies of marital choice and assortative mating are found across multiple research disciplines. In psychology, research focuses on partner selection based on personality attributes. The sociology literature concentrates on marital preferences by social factors and demographics. In economics marital choice tends to focus on spouses' economic resemblance and its underlying role in contributing to income inequality. This chapter contributes to the economics literature by examining the insurance opportunities that arise through marriage. In particular, I investigate the role of marital choice across married couples, asking how net income risk differs between married couples -and exploring whether marital choice increases or decreases the level of income risk.

The literature offers several marriage patterns across couples. The literature provide evidence for the role of education and age as key factors that influence marital choice. Highly-educated men and women marry at older ages compared to lower-educated individuals. Further, men and women who did not complete high school are less likely to marry than individuals with higher education (Waite, 2001; Aughinbaugh *et al.*, 2013; Musick and Michelmore, 2015; Grossbard *et al.*, 2019). Stevenson and Wolfers (2007) and Hamilton and Darity (2017) find differences in marriage patterns between ethnic groups in which Non-White individuals married later relative to White individuals. Moreover, European countries differ substantially in marriage ages. Individuals in northern European countries tend to marry at a later stage compared to eastern European countries (Kiernan, 2000). A key issue in the higher age at marriage is the commitment of women's careers in the labour market (Waite, 2001; Choo and Siow, 2006; Marti, 2006; Autor *et al.*, 2008; Autor, 2014; Greenwood *et al.*, 2014; Pestel, 2017). This chapter contributes to the literature by focusing on the underlying factors of socioeconomic and occupational backgrounds in marital choice.

The income risk literature lacks an analysis of the relationship between private insurance, marital choice and net income risk, with only vague evidence of the links involved. This chapter contributes to the present literature by exploring the impact of marriage on net income risk, taking into account marital choice. The marital choice decomposition is an innovative approach to examining the size of insurance between married couples. It allows the examination of different types of married couples in light of their socioeconomic and occupational backgrounds. The key contribution of this chapter is that marriage can be an insurance against negative income shocks, but the degree of insurance ultimately depends on marital choice.

The current literature outlines several channels of private insurance against negative income shocks. Income pooling between partners provides the underlying insurance. It enables married couples to partially offset income shocks. In particular, if a spouse's exogenous income shocks are not perfectly correlated with the other spouse's shocks, income pooling reduces negative income shocks for both. Thus, by adjusting relative labour supply and diversifying net income risk, married couples can smooth the impact of income shocks. This mechanism is an advantage compared to single individuals. Shore and Jensen (2015) find that the income volatility of households is significantly lower than that of individuals. Also a public poll indicates that people are aware that marriage provides a form of insurance against negative income shocks. According to the poll, 76 per cent of respondents list financial stability as an important reason for marriage in the USA. [1]. Marriage insurance is expressed through different channels, such as unemployment insurance, the added worker effect and the marriage premium (Becker, 1973, 1974; Christiansen, 2015; Choi and Valladares-Esteban, 2015; 2018; Hyslop, 2001; Ortigueira and Siassi, 2011).

Assortative marital choice reflects a form of homogamy. Becker (1973, 1974) originally introduced the concept, which refers to marriage between individuals from similar backgrounds. In contrast, non-assortative married couples or cross-group couples refer to married couples, who do not share the same socioeconomic status. Educational and socioeconomic homogamy are closely linked. The level of education influences the size of income an individual or married couple receives. The income and occupational level reflect the socioeconomic status. In particular, the UKHLS data set associates socioeconomic status with occupational background, which indicates the close affinity across educational and socioeconomic marital choice. Thus, this analysis complements the literature on assortative marital choice by focusing on socioeconomic homogamy.

The degree of household net income risk depends on the size of income risk associated with each spouse. Married couples with an assortative strategy do not face additional income risks because they share the same socioeconomic background (Frémeaux, 2014; Frémeaux and Lefranc, 2017). Their, low level of income risk in conjunction with income pooling provide them with an advantage to mitigate adverse income shocks. Yet, working in the same firm might decrease the insurance against income shock for assortative married couples, as adverse income shocks such as insolvency increase the income risk. However, the UKHLS does not provide the data to examine the risk of being employed in the same

[1] For details see "A Survey of LGBT Americans: Attitudes, Experiences and Values in Changing Times," Pew Research Center, June 13, 2013.

industry or firm for assortative couples. Therefore, such a robustness test cannot be done within this chapter.

A key channel of marriage insurance is expressed in unemployment insurance. Unemployment insurance is based on the income sharing between spouses. The income loss through unemployment is offset by the working spouse. Choi and Valladares-Esteban (2015, 2016) find evidence for marriage offering unemployment insurance. They show that married couples have lower unemployment rates than single individuals. Hyslop (2001) and Christiansen *et al.* (2015) also provide evidence for a sharing of labour market risk by married couples. They highlight the importance of partners in generating protection against negative income shocks in the USA, thus giving empirical evidence of the presence of unemployment insurance through a spouse.

The degree of net income risk sharing depends on the income level. Ortigueira and Siassi (2011) find that household risk sharing has its most substantial impact on low-income married couples. While high-income married couples mainly use savings to smooth consumption across periods of unemployment, low-income married couples rely on spousal labour supply. The average hours worked by wives of unemployed husbands are 8 per cent higher in low-income households than in households with working wives and employed husbands (Ortigueira and Siassi, 2011). For low-income married couples, unemployment insurance is an essential factor in smoothing adverse income shocks. As a consequence, the importance of unemployment insurance depends on the income level of married couples.

Another channel of insurance through marriage relates to the added worker effect. It investigates the role of marriage as a risk-sharing device focusing mostly on the propensity of wives to become employed. Findings indicate that an additional worker in the household provides a robust insurance mechanism. It allows wage shocks to be negatively (or positively) correlated between spouses. Christiansen *et al.* (2015) investigate the impact of marriage on risk sharing and find that the spouse is a key contributor to the smoothing of income shocks. In particular, Blundell *et al.* (2016) find that female labour supply is a key consumption insurance device against wage shocks faced by the husband. Thus, the added worker effect expresses another type of insurance through marriage.

An additional benefit of marriage is reflected in the marriage premium, which refers to the increase in the productivity and earnings of husbands caused by entering marriage. Evidence shows that married men make, on average, almost 30 per cent more than single men in hourly wages (Jackson *et al.*, 2017). According to Antonovices and Town (2004), marriage also secures long-term financial stability. On average, entering marriage improves an individual's wages by 27 per cent (Antonovices and Town, 2004). Nevertheless, current evidence indicates the presence of a marriage premium mainly for White men (Jackson *et al.*, 2017). Moreover, it is also argued that working longer and more regularly incentivises a spouse to increase productivity and to further reap income benefits (Antonovices and Town, 2004; Becker, 1973; Brown, 2000; Cohen, 2002; Jackson *et al.*, 2017). Thus, married couples have access to a marriage premium.

An extensive literature provides evidence for the marriage insurance mechanism. This mechanism operates through income pooling in the form of the added worker effect and unemployment insurance. Additional marital benefits accrue through the marriage premium. The income risk literature lacks analysis regarding the degree of insurance offered by marriage, as it focuses mainly on the income pooling and risk sharing of a couple. This analysis provides new insight based on the influence of marital choice.

In contrast, the marriage gap provides evidence of how income risk rises due to marriage. The marriage gap refers to the difference in income between spouses. This difference is particularly high if married couples do not share the same socioeconomic background, in other words, where the spouses are from different socioeconomic groups. Thus, a spouse who would have encountered low-net income risk as a single person faces higher income volatility and subsequently a higher net income risk post marriage. In this case, marital choice generates additional net income risk for at least one spouse within the marriage. Benson and McKay (2015) find evidence for a marriage gap by investigating married couples based on income levels and age. Their findings indicate different outcomes of marriage stability based on income level (Benson and McKay, 2015). As a result, marital choice can generate additional net income risk by introducing income volatility associated with the spouse. Thus, this chapter examines the role of marital choice in the degree of private insurance against adverse income shocks.

Marriage does not necessarily translate into an insurance. Marriage can generate a negative impact on married couples by inducing income volatility through the income risk associated with the spouse's socioeconomic background. Higher income risk of a spouse results in a welfare loss, expressed in higher income volatility for at least one spouse. Recent findings support this perspective by providing evidence of increased net income risk created by marriage. This additional net income risk offsets the advantage of married couples compared to single individuals. In particular, Dynan *et al.* (2012) find that household income is more volatile than single income in the USA. They find that the share of households experiencing a 50 per cent plunge in income over two years climbed from about 7 per cent in the 1970s to more than 12 per cent in the early 2000s (Dynan *et* *al.*, 2012). The results indicate that household net income risk has been rising compared to individual risk.

Assortative marital choice may contribute to rising income inequality. It increases income segregation between households and decreases social mobility (Burtless, 1999; Hyslop, 2001, Chiappori *et al.*, 2020). In contrast, a recent body of work revisits the link between assortative marital choice and income inequality by considering average aggregated household income. In a decomposition analysis, Hyrshko *et al.* (2017), Eeckaut and Stanfors (2019), Eike *et al.*(2019), Dupuy and Weber (2019), and Schwartz and Mare (2005) quantify the contribution of various factors to the distribution of household income and conclude that educational assortative choice accounts for a moderate part of the cross-sectional inequality in the USA.[2]. Chiappori *et al.* (2020) shows in a recent study that changes in marital homogamy increased income inequality in the UK. Yet, the degree of this increase depends on factors such as occupation and education.

Concluding, marriage contributes to an insurance against adverse income shocks through several channels (e.g. added worker effects (e.g. see Christiansen *et al.* (2015)) or marriage premium (see, e.g. Jackson *et al.*, 2017)). It can also increase income risk e.g., fertility, divorce and the marriage gap (see e.g. Benson and McKay (2015)). All these are ex-post examinations of marriage, i.e. these studies (including this chapter) examine the effects of marriage after people formed couples. Nevertheless, marital choice itself is influenced by several factors that might be related to financial security or love or other subjective perceptions. The analysis of ex-ante factors of marital choice is an interesting but challenging exercise. This exercise requires a relatively large and long in the time dimension panel data set. The reason is that we need to have information on both "future" spouses well before individuals get married. The second challenge for this exercise is the way that the sampling procedure operates in this type of surveys; they follow most probably one of the spouses and the second spouse appears in the sample only after they get married. The likelihood of having both spouses before they get marries in a survey is very small. Administrative data though would enable such analysis, but there are not yet available for the UK (see e.g. Hryshko *et al.* (2017)). Consequently, the UKHLS dataset only enables me to examine ex-post marriage patterns.

This chapters examines the role of marital choice, post marriage, on private insurance against adverse income shocks. Based on the marriages that are observed assortative and

[2]Hryshko et al. (2017) analyse earnings-based assortative selection from 1980 to 2009 in the US; Dupuy and Weber (2019) and Eika et al. (2019) examine educational assortative selection from 1962 to 2013 in the US.

cross-group couples are split on socioeconomic status and education. These observations are used in the counterfactual exercise to test the robustness of the results based on post marriage decisions. Yet, this analysis cannot infer on the ex-ante factors that led to the marriages. The analysis strictly focuses on the patterns ex-post marital choice based on the information available in the UKHLS dataset.

The empirical literature reports several channels of insurance against adverse income shocks. These include the marriage premium, additional worker effect and income levels. Nevertheless, marriage can also introduce new risks such as divorce, fertility and the marriage gap. The link between marital choice and net income risk is not well understood. This chapter contributes to the ongoing discussion by measuring the difference in net income risk exposure based on marital choice. The UKHLS dataset enables an ex-post marriage analysis.

3.3 Data

In this section, I provide information on the variables used for the analysis, and a brief description of the sample selection and household decomposition. More details on the survey structure can be found in Chapter 1. This analysis refers to marital choice patterns. An assortative strategy reflects married couples who share the same socioeconomic or educational background. In contrast, non-assortative or cross-group married couples refer to partners who do not share the same socioeconomic or educational background. I analyse the marital choice across married couples based on the UKHLS data set. It includes information on the socioeconomic and educational background of each married couple. This enables me to analyse marital choice patterns combined with their degree of net income risk.

3.3.1 Sample Selection

To examine the link between marriage, marital choice and net income risk, I create a homogeneous data set. Only individuals with full interviews are kept, and incomplete interviews are removed. As a consequence, the sample maintains consistent information of individuals across all time periods. I concentrate on individuals and couples who are in the labour market with positive income and who are within the age range of 20 to 65

(Blundell and Etheridge, 2010; Busch *et al.*, 2018; Guvenen *et al.*, 2010; Heathcote *et al.*, 2010).

3.3.2 Household Formation

Households where both members are participating in the labour market and are working are considered. As a result, I focus on dual-earner households including high-earners and low-earners. The dual earner households give their respective incomes regardless of gender. The UKHLS maintains information on several different types of household. The key households considered in this chapter are single-person households and dual-earner households. Single households refer to individuals who live alone for example due to a divorce, being widowed or not having a partner. In contrast, dual-earner households consist of married couples. The marital status variable is pooled into a binary dummy variable based on the household status of being i) a married couple or legally binding civil partnership or ii) a single-person household. During the sample period a minority of individuals divorced and are not living together. I excluded this sub-sample from the analysis as the focus of this chapter is on income risk during marriage. It can be seen as a form of attrition across married couples.

Given that the UKHLS data set provides information on personal income, I can compare couples over time and differentiate them based on their income. The dual household members are classified as high and low earners, regardless of their gender. This approach to household formation contrasts with contemporary literature which mainly uses male earnings as the head of the household, being the primary breadwinner, and representing the entire household as one unit. To analyse the impact of marital choice on adverse income shocks, I distinguish two groups of dual-earner homes: on the one hand, households that indicate assortative marital choice and, on the other hand, couples who provide evidence of 'cross-socioeconomic' marital selection. Assortative mating refers to individuals who chose their partner from the same socioeconomic or educational background (Becker, 1973). In contrast, 'cross socioeconomic choice' refers to individuals who chose an individual from a different socioeconomic or educational group. The sample is split according how the household members have chosen their respective partners. Consequently, this chapter offers an innovative household definition and household member categorisation, which facilitates investigation of the net income risk dynamics implicit in a spouse's marital choice.

This chapter focuses on income risks during a marriage. I analyse the samples of married couples based on their marital choice. During the sample period some marriages resulted in planned divorce. Even though, a divorce constitutes a considerable adverse income shock and is associated with considerable income fluctuations, I do not consider this group as, post divorce, the married couple reflects the income risk of individuals. Further, the planned nature of these divorces does not capture the unexpected event of an adverse income shock. Thus I disregard the sample which leads to a form of attrition. This group of individuals is relatively small and does not provide meaningful results. Nevertheless, separated but legally married couples are included in the sample. This enables me to capture some of the fluctuations associated with separation.

3.3.3 Variables

To analyse the household members, I decompose each of the samples based on whether they contribute to the household and their marital choice strategy. The decomposition of the samples enables me to examine household development and the impact of marital choice on net income risk. Moreover, I construct cohort bands to account for fixed effects in the level identification scheme, and I also separate the sample into three age cohorts according to when the individuals turn 25 and enter the labour market, namely: below or equal to 1991 (Cohort 1), 1991 to 2000 (Cohort 2), and above or equal to 2001 (Cohort 3). The number of cohorts is dictated by the size of the sample.

The UKHLS provides data on personal income. These income variables express individual gross income and adjust for tax and transfers to give net income. It takes into account whether the individual is part of a household. Therefore, this chapter focuses on net income. The income is expressed in weeks, by defining it as the multiplication of typical monthly wages by 12, and then divided by 52 weeks. It is a precise measure of income, as applied in related literature (ONS, 2017; Heathcote *et al.*, 2010). Similarly, the datasets provide information on which socioeconomic background each spouse belongs too. This is based on a variable provided by the dataset. The UKHLS differentiates three categories: Higher Management and Professional Occupations, Intermediate Occupations, and Routine and Manual Occupations (see Appendix *C* for more details on the socioeconomic status variable).

3.3.4 Counterfactual Exercise: Synthetic Sample

The intensive margin of married couples influences the extent of pool income. Therefore, I create a counterfactual exercise to analyse household net income risk dynamics and create a synthetic sample based on the original sample of married couples. I consider the household income for the actual households in comparison to income changes for randomly formed couples. The key idea is to randomise the couples and the respective partners over the eight waves based on their marital choice. Thus, the spouses are matched with a new partner based on either an assortative or cross-group marital choice. Any endogenous response of household income associated with the number of hours worked by the partner is, by construction, non-existent for synthetic couples. The synthetic sample of married couples have new partners with the same attributes based on their initial marital choice. Consequently, I investigate the income risk dynamics of the synthetic sample as well, so as to compare it with the original sample.

To estimate the temporary and permanent income shock variances I include only couples with information over three consecutive waves, as the identification of one permanent income shock requires moments from three consecutive periods (waves), $t-1$, t and $t+1$. To ensure that the household is consistent over the periods, I use the head of the household provided by the survey. The advantage is that the household identifier stays the same throughout the three years for the original or the synthetic sample.

I consider randomly formed couples given their marital choice. The actual couples are randomised based on their original marital choice. In other words, married couples are matched with a partner from the same socioeconomic background and vice versa. To each synthetic couple, I apply the same selection criteria as for the actual households. In the next step, I control for some characteristics of actual household formation, as sorting along those dimensions might in part explain changes in actual household incomes. Thus, I make synthetic couples more similar to actual households, while still isolating potential endogeneity. In particular, I control for age, gender and education.

Then, I simulate 1000 synthetic samples, for each wave triplet and for each synthetic married couple based on their marital choice. For each simulation, I calculate the transitory and permanent shocks, and my results are the average over those 1000 calculations. For comparability, for the original sample, I calculate the transitory and permanent shocks for each wave triplet and each assortative mating group. Overall, I find the same ranking, but weaker effects in the synthetic sample compared to the original sample.

3.4 Methodology

3.4.1 Empirical Model

This section describes the model used in this analysis. It follows the approach by Blundell and Etheridge (2010) and Heathcote *et al.*, (2010), who analyse trends in income dynamics in the UK and the USA respectively. I focus on the UK, using panel data from the UKHLS over the time horizon from 2009 to 2018. In line with the literature, I analyse the 'residual' dispersion (Brzozowski *et al.*, 2010, Fuchs-Schündeln *et al.*, 2010, Heathcote *et al.*, 2010). Here I focus on individuals and households.

I consider individual log net income, $y^g_{h,c,t}$, for a household h, belonging to a cohort c and population subgroup g, and observed in year t. I assume the following model.

$$\ln y^g_{h,c,t} = \beta^g X_{h,c,t} + u^g_{h,c,t} \tag{3.1}$$

I also examine the individual income ($y_{i,c,t}$) for individuals i, age cohorts c and time dimension t:

$$\ln y^g_{i,c,t} = \beta^g X_{i,c,t} + u^g_{i,c,t} \tag{3.2}$$

which means that the log net income consist of a determinist (or explained by observables) linear part $\beta^g X_{i,c,t}$ and a residual (unexplained or idiosyncratic) part $u^g_{i,c,t}$. $X_{i,c,t}$ includes a constant term, a quadratic in experience approximated by age, age of spouse, dummies for region of residence, dummy for gender, dummy for marital status and time fixed effects. Following Blundell and Etheridge (2010) I also include as a regressor the logarithm of the household size. The superscript g denotes the eight subgroups defined by the combination of three variables: sex (men and women), ethnicity (White and Non-White), education (degree holders or not).[3] Moreover, I consider three cohorts. Controlling for the observables captures the idea that expected changes to income do not represent risk (see Japelli and Pistaferri, 2017). The key interest is in the income risk trends between households and individuals. I also examine the size of income shocks between married couples based on marital choice.

[3] Analytically, the eight subgroups are: i) male, degree, White; ii) male, degree, Non-White; iii) male, no degree, White; iv) male, no degree, Non-White; v) female, degree, White; vi) female, degree, Non-White; vii) female, no degree, White; viii) female, no degree, Non-White.

I further assume that the residual term, $u^g_{i,c,t}$, consists of two components, a permanent component, $p^g_{i,c,t}$, and a transitory component, $\varepsilon^g_{i,c,t}$; the permanent component is a random walk while the transitory component is a purely *i.i.d* shock. In addition, the two components are additive (in logs). The formal expression of $u^g_{i,c,t}$, can be found in Chapter 1 Section 3 and 4.

3.5 Results and Discussion

This section presents the results and discusses the implications. Section 3.5.1 shows the results of individual risk by marital status. Section 3.5.2 examines the household risk by marital choice. Section 3.5.3 presents the results of the synthetic sample. The chapter disentangles the impact of marriage and marital choice on net income risk. Income risk is expressed in the form of transitory and permanent income shock variances, in which higher income shock variances indicate a higher income instability and subsequently higher net income risk. Several key findings have been identified.

Firstly, the analysis of individual risk by marital status provides evidence for a private insurance mechanism through marriage. Single individuals face higher levels of net income risk compared to married couples. They are also more likely to face adverse income shocks compared to married individuals. Thus, the results indicate a marriage insurance mechanism expressed in lower levels of net income risk for married couples compared to single individuals (see Figure 3.1 and Table 3.1). The underlying factor is the access to income pooling for married individuals, which single individuals do not have. This finding is in line with the literature, including Antonovices and Town (2004), Christiansen *et al.*(2015), Hyslop (2001), Autor, (2014), Greenwood *et al.*(2014), Pestel (2017), and Hryshko *et al.* (2017).

Secondly, a key finding of this chapter concerns the role of marital choice in determining the magnitude of net income risk. I find that marriage reduces income volatility when married couples share the same socioeconomic characteristics, namely assortative married couples, relative to couples that do not share them. Assortative couples also face a 1.4 percentage point lower likelihood of facing an adverse income shock compared to couples who differ in these characteristics. Another contribution is my novel statistical decomposition for quantifying the effect of marital choice on net income risk. This decomposition examines the magnitude of marital insurance between married couples. A key factor of the insurance relates to the net income risk associated with the socioeconomic and educational background of married couples. Thus, the chapter contributes to the net income risk literature by providing evidence on the magnitude of marriage insurance against adverse income shocks based on marital choice. It provides a unique perspective on the dynamics between marriage and net income risk.

Thirdly, the household risk by marital choice indicates that the marriage insurance mechanism depends on marital choice. Married individuals with assortative choice show lower net income risk compared to married couples with cross-group marital choice (see Figure 3.2 and Table 3.2). In particular, the permanent income shock variances of cross-socioeconomic married couples is higher compared to household members with assortative choice. The synthetic sample supports the marital choice findings (see Table 3.5). Even though the degree of net income risk exposure is lower, the same ranking between marital choice can be identified. The lower degree of risk in the synthetic sample is related to the removal of endogeneity related to the intensive margin.

Fourthly, I calculate the risk ratio based on marital status and marital choice. The risk ratio is defined as the ratio of permanent income shocks encountered by single individuals relative to married couples. It indicates the difference between the groups and expresses the degree of income variation between the respective groups. A high risk ratio indicates a high degree of permanent income shocks resulting in higher income volatility. In contrast, a low-risk ratio indicates few permanent income shocks and, therefore, income stability. Thus, the risk ratio acts as an indicator of income variation related to permanent income shocks and endorses the economic relevance of this chapter.

This section also discusses the economic implications of the key results. These focus on the advantage married couples have compared to single individuals. The degree of private insurance through marriage is found to depend on marital choice. I also analyse the impact of an adverse permanent income shock on individuals and households. The approach follows the utility welfare loss based on standard deviations in Chapter 1 (see Section 1.5 for more details).

3.5.1 Marital Status

This section focuses on the results of individual risk by marital status, namely being single or married. Table 3.1 indicates the distinct net income risk exposure of married and single individuals. The individual income measure of married individuals is used to make the income variable comparable to single individuals. The income risk estimates show that single individuals face higher transitory and permanent income shocks with $\sigma^2_{\varepsilon_t^{SI}} = 0.0688$ and $\sigma^2_{\zeta_t^{SI}} = 0.0227$, respectively. In contrast, married individuals encounter lower income shock variances with $\sigma^2_{\varepsilon_t^{MI}} = 0.0588$ and $\sigma^2_{\zeta_t^{MI}} = 0.0199$. The time series evidence in Figure 3.1 indicates the magnitude of the difference of permanent and transitory income shock variances between married and single individuals (see Figure 2.2). Moreover, the difference in the permanent risk estimates of singles and married individuals is significantly different at the 90 per cent confidence interval. The marriage insurance mechanism is characterised by the lower levels of net income risk compared to single individuals, on average. Table 3.2 shows the distinct welfare loss between single and married individuals.

The risk ratio ($\frac{SI}{MI} = 1.1$) underpins the difference between the two groups and shows that single individuals encounter a higher risk ratio. This insurance mechanism is based on the ability of married individuals to pool their income to smooth income shocks. In addition, single individuals have higher labour market mobility compared to married ones (Becker, 1973,1974; Gardiner, 2017; Guner, Kulikova and Valladares-Esteban, 2015). Consequently, the results in Table 3.1 provide evidence for a marriage insurance mechanism.

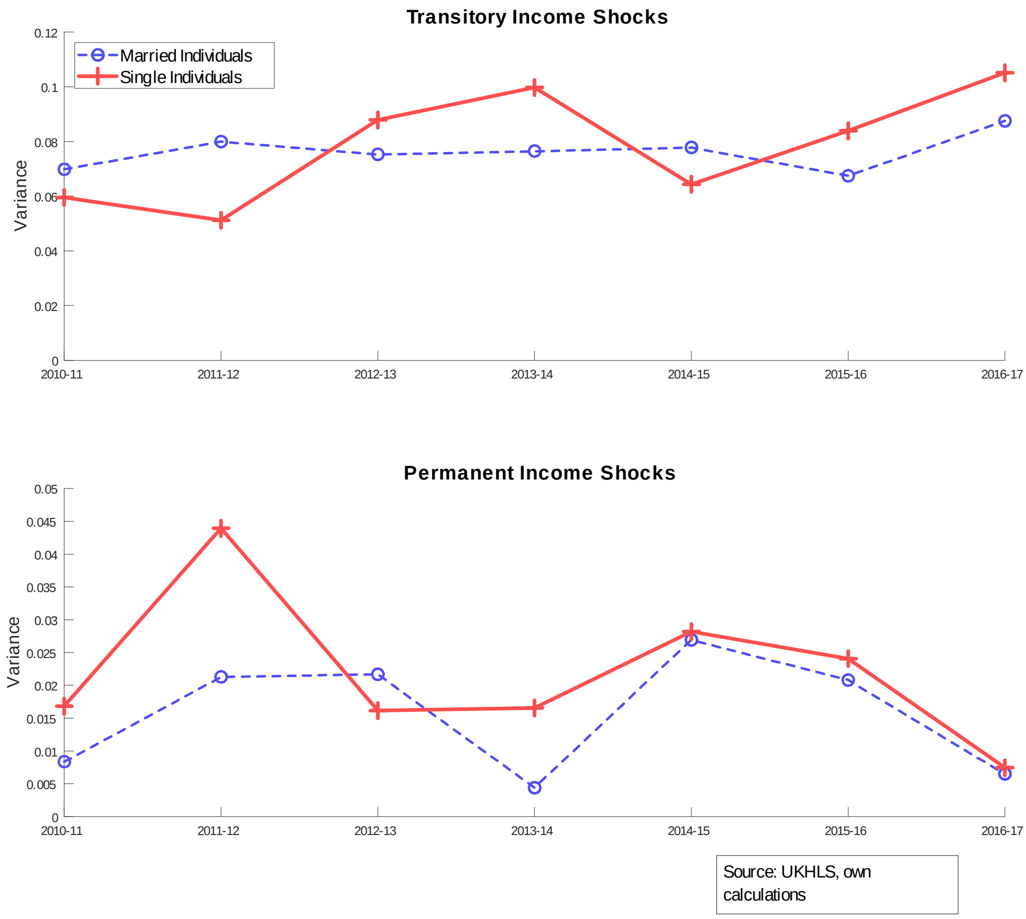
Table 3.1: Individual Income Risk, Marital Status

Subgroup	Transitory $\sigma^2_{\varepsilon_t^g}$	Permanent $\sigma^2_{\zeta_t^g}$	Risk Ratio $\frac{SI}{MI}$
Married Individuals (MI)	0.0588***	0.0199***	1.1***
s.e.	(0.0027)	(0.0021)	
Sample Size	119,761		
Single Individuals (SI)	0.0638***	0.0227***	
s.e.	(0.0047)	(0.0046)	
Sample Size	53,109		

Notes: Single individuals face higher income risk compared to married on 1000; Individual Net Income; The bootstrap standard errors are based on 1000 replications and presented in parentheses; *significant at p<0.1; **significant at p<0.05;***significant at p<0.01.
The risk ratio is based on $\sigma^2_{\zeta_t^g}$.

Figure 3.1 shows the net income risk based on marital status from 2010 to 2017. It shows that single-person households face higher levels of net income risk compared to married households.

Figure 3.1: Individual Income Risk Estimation based on Marital Status



Notes: Figure 3.1 shows that single individuals face higher levels of transitory and permanent income shock variances compared to married individuals from 2010 until 2017.

Discussion: Marital Status

In the following, I discuss the economic implications of net income risk heterogeneity in marital status in the UK (see Table 3.2). I consider the impact of a one standard deviation change in permanent income shock. The estimates in Table 3.2show that single individuals face higher net income risks and encounter a subsequently higher welfare loss with2.78 per cent, compared to 2.31 per cent by married individuals. Thus, a marriage insurance mechanism does exist in the form of lower level net income risk.

Another way to quantify permanent income shocks is by expressing them in probabilities. Table 3.3 shows the probability of encountering a 20 per cent and a 50 per cent income gain or loss based on marital status. The results indicate that single individuals are 6.92 per cent likely to face an income loss of 20 per cent due to an adverse income shock. In contrast, married couples face a 5.68 per cent likelihood to encounter a 20 per cent income loss. The considerable difference in the probabilities of adverse income shocks indicates the presence of an insurance against adverse income shocks through marriage.

The results indicate that married individuals face lower levels of income risk compared to single individuals. The findings relate to the associated commitment of a marriage, with a shared financial situation including sharing expenses, combined investments and easier access to loans (Chiappori *et al.*, 2018; Grover and Helliwell, 2017).These factors are related to the underlying advantage of income pooling which allows married couples to offset income losses. The net income risk literature has identified the insurance mechanism through several channels: for example, unemployment insurance, the added worker effect, and the marriage premium (Antonovices and Town, 2004; Chiappori *et al.*, 2012; Dynan *et al.*, 2012; Pestel, 2017). As a result, the private insurance through marriage allows married couples to pool income. This type of insurance is not accessible to single individuals. Consequently, the income pooling partially explains the difference in the level of income risk between married and single individuals.

The higher net income risk for single individuals is supported by the literature. Jensen and Shore (2015) find a systematic increase in volatility for a majority of single individuals in the U.. The increase in average volatility has been driven almost entirely by a sharp increase in the earnings volatility of single individuals, depending on occupational background. Self-employment is associated with high income volatility as it entails a stronger element of self-identity and risk-seeking compared to employed individuals. Thus, the distinct net income risk exposure is also related to the occupational background of married and single individuals.

In summary, individual risk by marital status provides evidence of a private insurance mechanism through marriage. Single individuals face higher levels of net income risk compared to married couples. They are also more likely to face adverse income shocks compared to married individuals. Consequently, the results indicate a marriage insurance mechanism as expressed in lower levels of net income risk for married couples compared to single individuals. The underlying factor is the access to income pooling for married individuals. This finding is in line with literature such as Antonovices and Town (2004), Christiansen *et al.*(2015), Hyslop (2001), Autor, (2014), Greenwood *et al.*(2014), and Pestel (2017).

Table 3.2: Utility Welfare Loss, Marital Status

Subgroup	Loss in per cent	Utility Welfare Loss in per cent
Married Individuals	14.23%	2.31%
Single Individuals	15.12%	2.78%

Notes: Table 3.2 indicates that single individuals face a higher utility welfare loss compared to married ones; Individual net income; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 3.3: Probabilities of Permanent Income Shocks, Marital Status

Probability of income gain/loss		Permanent income shock in per cent	
		Married Individuals	Single Individuals
		$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{married}}\right)$	$\zeta_{i,t} \sim N\left(0, \sigma^2_{\zeta_t^{\sin gle}}\right)$
income gain>50%:	$Pr(\zeta_{i,t} > \ln(1.50))$	0.20%	0.36%
income gain>20%:	$Pr(\zeta_{i,t} > \ln(1.20))$	9.78%	11.27%
income loss>50% :	$Pr(\zeta_{i,t} < \ln(0.50))$	0.30%	0.71%
income loss>20%:	$Pr(\zeta_{i,t} < \ln(0.80))$	5.68%	6.92%

Notes: Table 3.3 shows that single individuals are more likely to encounter an adverse permanent income shock. The probabilities of gains/losses are with respect to the level of permanent income under the mean shock. Note that $\zeta_{i,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

3.5.2 Marital Choice based on Socioeconomic Status

This section focuses on the results of household risk by marital choice based on the socioeconomic background of married couples in the UK. The results in Table 3.4 provide evidence of a stronger insurance mechanism for married couples with assortative mating compared to married couples with a cross-group choice. Assortative married couples face, on average, lower levels net income risk compared to married couples with a cross-group choice. Married individuals with an assortative choice choice face lower transitory ($\sigma^2_{\varepsilon_t^{AM}} = 0.0195$) and permanent ($\sigma^2_{\zeta_t^{AM}} = 0.0209$) income shock variances. The results show that cross-group married couples on average face higher levels of income risk. This holds for both income risk types, with transitory income shock variances of $\sigma^2_{\varepsilon_t^{CGM}} = 0.0222$ and permanent income shock variances of $\sigma^2_{\zeta_t^{CGM}} = 0.0242$. The risk ratio of $\frac{CGM}{AM} = 1.2$ emphasises the difference in net income risk. Table 3.4 indicates the distinct welfare loss between assortative and cross-socioeconomic group married couples. In addition, the difference in the permanent risk estimates between assortative and cross-group couples based on socioeconomic status is significantly different at the 90 per cent confidence interval.

Moreover, the complementary findings show that the same pattern of marital choice can be found based on the educational selection. The robustness test in Section 3.3 indicates that couples from the same educational background also have an advantage over couples from different educational backgrounds. The findings support the role of assortative marriages showing a higher insurance against adverse income shocks. This is expressed in the lower levels of income risk for assortative married couples compared to cross-group couples.

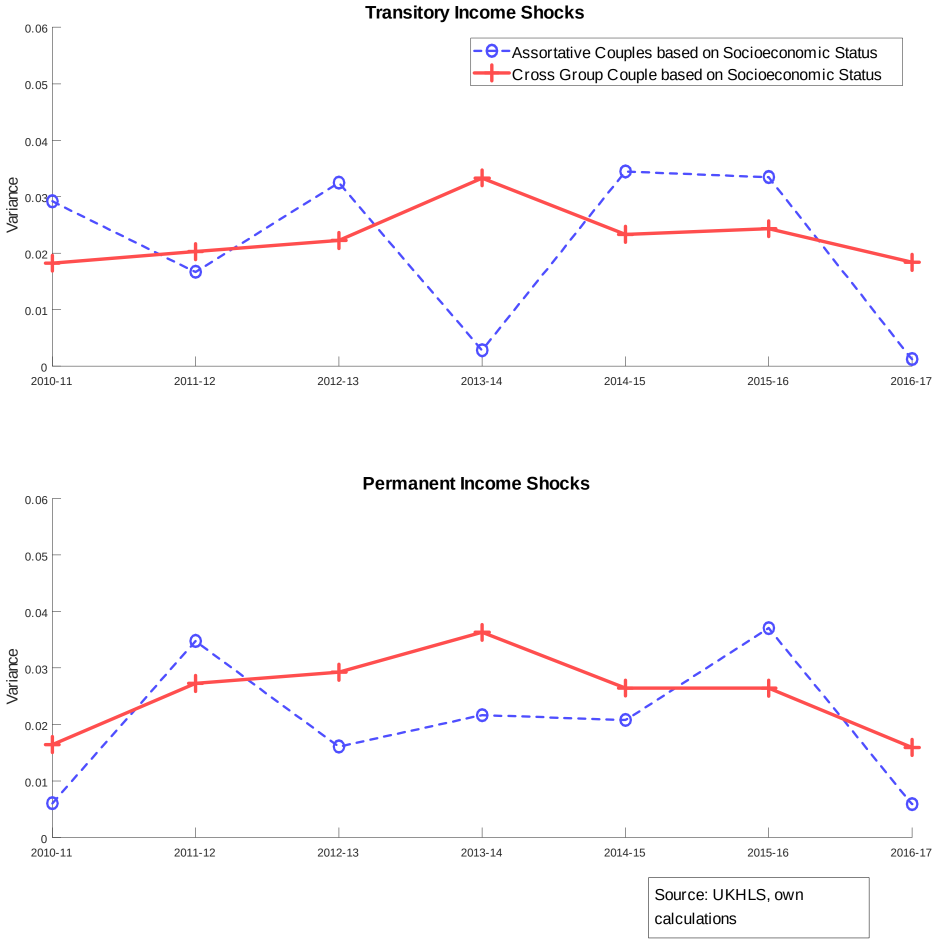
Further, Figure 3.2 reports the magnitude of the difference between permanent and transitory income shock variances for married couples based on marital choice associated with the socioeconomic status. Figure 3.2 shows the income risk estimates from 2010 to 2017. Thus, the magnitude of private insurance depends on marital choice. This finding might be related to coordination of decision making and the net income risk associated with the socioeconomic and occupational background of the spouse.

Table 3.4: Household Income Risk, Marital Choice based on Socioeconomic Status

Groups	Transitory $\sigma^2_{\varepsilon^g_t}$	Permanent $\sigma^2_{\zeta^g_t}$	Risk Ratio $\frac{CGM}{AM}$
Assortative Couples (AM)	0.0195***	0.0209***	1.2***
s.e.	(0.0019)	(0.0023)	
Sample Size	39,500		
Cross Group Couples (CGM)	0.0222***	0.0242***	
s.e.	(0.0022)	(0.0024)	
Sample Size	17,624		

Note: Cross Group Couples encounter higher transitory and permanent income shock variances compared to assortative couples; Net Household Income; The bootstrap standard errors are based on 1000 replications and presented in parentheses; *significant at $p < 0.1$; **significant at $p < 0.05$; ***significant at $p < 0.01$;The risk ratio is based on $\sigma^2_{\zeta^g_t}$.

Figure 3.2: Household Income Risk based on Marital Choice, Socioeconomic Status



Notes: Figure 3.2 shows that cross group couples based on marital choice associated with of the socioeconomic status encounter higher levels of income shock variances compared to assortative couples from 2010 until 2017.

Discussion: Marital Choice based on Socioeconomic Status

In the following, I discuss the economic implications of the net income risk heterogeneity associated with marital choice based on socioeconomic status in the UK (see Table 3.5). I consider the impact of a one standard deviation change in the permanent income shock.

The estimates in Table 3.5 show that assortative choice married couples face lower net income risks and encounter a subsequently lower welfare loss with 1.57 per cent compared to 2.71 per cent by cross-socioeconomic group married couples (see Table 3.5). The current results provide evidence that married couples with an assortative choice strategy show less income variation compared to the married couples of a cross group marital choice. Consequently, the degree of marital insurance depends on marital choice.

Table 3.6 shows the probability of encountering a 20 or 50 per cent income gain or loss. The decomposition is based on the marital choice of the married couples. The results indicate that cross-group couples are 7.57 per cent likely to face an income loss of 20 per cent due to an adverse income shock. In contrast, assortative couples face a 6.13 per cent likelihood of encountering a 20 per cent income loss. The difference indicates that assortative couples seem to have a lower income risk exposure, and thus supports the finding that marital choice plays a role in mitigating income risk.

The distinct net income risk in marital choice is a reflection of the socioeconomic and occupational background. The results in Table 3.4 indicate that cross-group married couples face higher transitory and permanent income shock variances than assortative couples. Factors that drive the net income risk heterogeneity in martial choice are related to the spouse's occupation. The UKHLS data shows that 41 per cent of cross-group married couples have a spouse who works in a routine or manual occupation. The different occupational background in cross-group marriages generates additional net income risk, which the spouse would not have encountered if they had remained single. Consequently, the income pooling results in additional income risk, which decreases the degree of private insurance for cross-group couples.

In contrast, most assortative couples are from professional and higher management occupations. This creates stronger private insurance against adverse income shocks, expressed in lower levels of income risk. A robustness test on the role of assortative choice based on socioeconomic background would be to control for industries in which the spouses of married couples work. This exercise could elicit information on the degree of insurance based on marital choice. Yet, the UKHLS data set does not provide the necessary industry level data for such an exercise. Consequently, the income levels associated with the occupation of the couples is an underlying factor that partially explains the difference in private insurance. The robustness check based on the synthetic sample that randomises the spouses based on their original marital choice confirms the findings. The synthetic income risk estimates provide the same ranking in the degree of private insurance based on marital choice. Further, complementary findings based on the educational background of the marital choice indicate similar degrees of private insurance.

Nevertheless, assortative choice contributes to segregation in a society. Frémeaux (2014), Frémeaux and Lefranc (2017) and Chiappori *et al.* (2020) find that an assortative selection strategy reinforces the trend of rising income inequality. Married individuals from the same socioeconomic background reduce social mobility, by reinforcing the concentration of wealth. The UKHLS data set indicates a similar pattern of assortative couples across professional and higher management occupations. Blanden *et al.*, (2001) compares and contrasts estimates of the extent of intergenerational income mobility. They argue that assortative choice marriage is an underlying factor that reduced social mobility between the 1970s and the late 1990s. The evidence of this analysis indicates that assortative marital choice patterns mean that individuals have married within the same socioeconomic status group during the past 10 years. As a result, the assortative marital choice may have contributed to lower social mobility within the UK.

In summary, the findings indicate differing degrees of private insurance against income risk based on marital choice. The results suggest that assortative married couples have stronger private insurance than cross-group couples in terms of lower levels of net income risk. The underlying factor that partially explains this pattern is associated with the occupations held by spouses. Further, the assortative choice strategy may have reduced social mobility, as like marries like.

Table 3.5: Utility Welfare Loss, Marital Choice based on Socioeconomic Status

Subgroup	Loss in per cent	Utility Welfare Loss in per cent
Assortative Couples	14.58%	1.57%
Cross Group Couples	15.53%	2.71%

Note: Assortative couples face lower utility welfare losses compared to cross group couples; Net Household Income; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 3.6: Probabilities of Permanent Income Shocks, Marital Choice

Probability of income gain/loss		Permanent income shock in per cent	
		Assortative Couples	Cross Group Couples
		$\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{AM}}\right)$	$\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{CGM}}\right)$
income gain>50%:	$Pr(\zeta_{h,t} > \ln(1.50))$	0.25%	0.45%
income gain>20%:	$Pr(\zeta_{h,t} > \ln(1.20))$	10.32%	12.02%
income loss>50% :	$Pr(\zeta_{h,t} < \ln(0.50))$	4.17%	8.20%
income loss>20%:	$Pr(\zeta_{h,t} < \ln(0.80))$	6.13%	7.57%

Note: Assortative couples are less likely to encounter an adverse permanent income shock.
The probabilities of gains/losses are with respect to the level of permanent income under the mean shock.
Note that $\zeta_{h,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

3.5.3 Robustness Check: Counterfactual Exercise

I create a synthetic sample to remove any endogeneity and test the robustness of the household risk by marital choice. Table 3.7 indicates the transitory and permanent income shock variances of the actual and the synthetic samples (see section 3.7 for details of its construction). The synthetic sample yields the same ranking of findings as the actual sample, yet on a different magnitude. The difference in the magnitude of the net income risk between the original and the synthetic sample implies that factors other than marital choice might be contributing to the insurance mechanism.

In the original sample cross-socioeconomic group couples face higher net income risk, expressed in the permanent income shock variance $\sigma^2_{\zeta_t^{Orig|CGM}} = 0.0061$ and the transitory income shock variance $\sigma^2_{\varepsilon_t^{Orig|CGM}} = 0.0207$. Also in the synthetic sample cross-group couples face higher permanent income shock $\sigma^2_{\zeta_t^{Sync|CGM}} = 0.0049$ and transitory income shock $\sigma^2_{\varepsilon_t^{Sync|CGM}} = 0.0192$ income shock variances. The results in Table 3.7 indicate that assortative choice households face lower permanent and transitory income shocks compared to cross-group married couples. The lower level of transitory and permanent income shock variances for assortative households can be translated as a form of insurance because they face lower net income risk. Hence, the results indicate a net income risk difference based on marital choice.

Table 3.7: Original vs. Synthetic Household Income Risk

Subgroup	Transitory $\sigma^2_{\varepsilon^g_t}$	Permanent $\sigma^2_{\zeta^g_t}$	Risk Ratio $\frac{CGM}{AM}$
	Original Survey Sample		
Assortative Couples (AM)	0.0188***	0.0055**	1.1***
s.e	(0.0022)	(0.0015)	
Cross Group Couples (CGM)	0.0207***	0.0061***	
s.e	(0.0024)	(0.0017)	
	Synthetic Marital Choice		
Assortative Couples (AM)	0.0167***	0.0030***	1.6***
s.e	(0.0011)	(0.0008)	
Cross Group Couples (CGM)	0.0192***	0.0049***	
s.e	(0.0013)	(0.0010)	

Notes: Table 3.7 shows that the same patterns of the original sample are also found in the synthetic sample; Net Household Income; The bootstrap standard errors are based on 1000 replications and presented in parentheses;*significant at $p < 0.1$;**significant p < 0.05;***significant p < 0.01; Level estimation.

Discussion Robustness Check: Counterfactual Exercise

The counterfactual exercise involves the creation of a synthetic sample in which the partners of the couples are randomised based on their initial marital choice. The counterfactual exercise supports the findings for marital choice in the original sample in Table 3.7. The reduced net income risk of households with assortative couples reflects an advantage compared to cross-group couples. In the synthetic sample cross-group couples face $\sigma^2_{\zeta^g_t} = 0.0019$;and $\sigma^2_{\varepsilon^g_t} = 0.0025$ higher income shock variances compared to assortative couples. Consequently, the synthetic sample supports the evidence of an advantage for assortative couples compared to cross-group couples based on marital choice associated with the socioeconomic status of their partner.

Further, Table 3.7 shows that the couples in the synthetic sample face lower income shocks compared to those in the original sample. This indicates that by randomising the spouse based on marital choice net income risk decreases. This reduction in net income risk reveals that other factors are playing a role in insuring couples against adverse income shocks, such as positive covariance between spouses' incomes. The lower degree of risk in the synthetic sample is probably related to the removal of a form of endogeneity.

3.5.4 Robustness Check

Marital Choice based on Education

This section focuses on the results of household risk by marital choice based on education of households across the UK. The original work of Becker (1973, 1974) focused on assortative choice across couples based on education. The similar results between socioeconomic background and education are to be expected, as highly educated individuals are likely to obtain more well paid jobs, which reflects in the occupational background of socioeconomic status. The similar patterns of results indicates that marital choice findings based on socioeconomic status are robust.

The UKHLS data set provides information on the level of educational attainment for all households and individuals. As a consequence, I use the following education categories: 'university degree', which includes those with an honours degree or equivalent; 'intermediate education' for those with A-levels or equivalent, and 'obligatory education' which covers the remainder of the sample. On the basis of this classification I test whether married couples of the same educational background have a similar advantage relative to married couples from different educational backgrounds.

The results in Table 3.8 provide evidence for a stronger insurance mechanism for assortative married households as they face lower net income risk, in terms of lower variances in transitory ($\sigma^2_{\varepsilon_t^{AM.}} = 0.0431$) and permanent ($\sigma^2_{\zeta_t^{AM}} = 0.0101$) income shocks. The results indicate a considerably higher net income risk exposure for married couples from different socioeconomic backgrounds. Married households on average face higher variances in both, transitory income ($\sigma^2_{\varepsilon_t^{CGM}} = 0.0467$)and permanent income shocks ($\sigma^2_{\zeta_t^{CGM}} = 0.0198$). The risk ratio 2 reports the difference in net income risk and indicates higher income volatility for couples who do not share the same educational background. Further, the difference in the permanent risk estimates between assortative and cross-group couples based on an educational marital choice is significantly different at the 90 per cent confidence interval. Consequently, the advantage for assortative married couples based on education is also evident, emphasising the robustness of the findings.

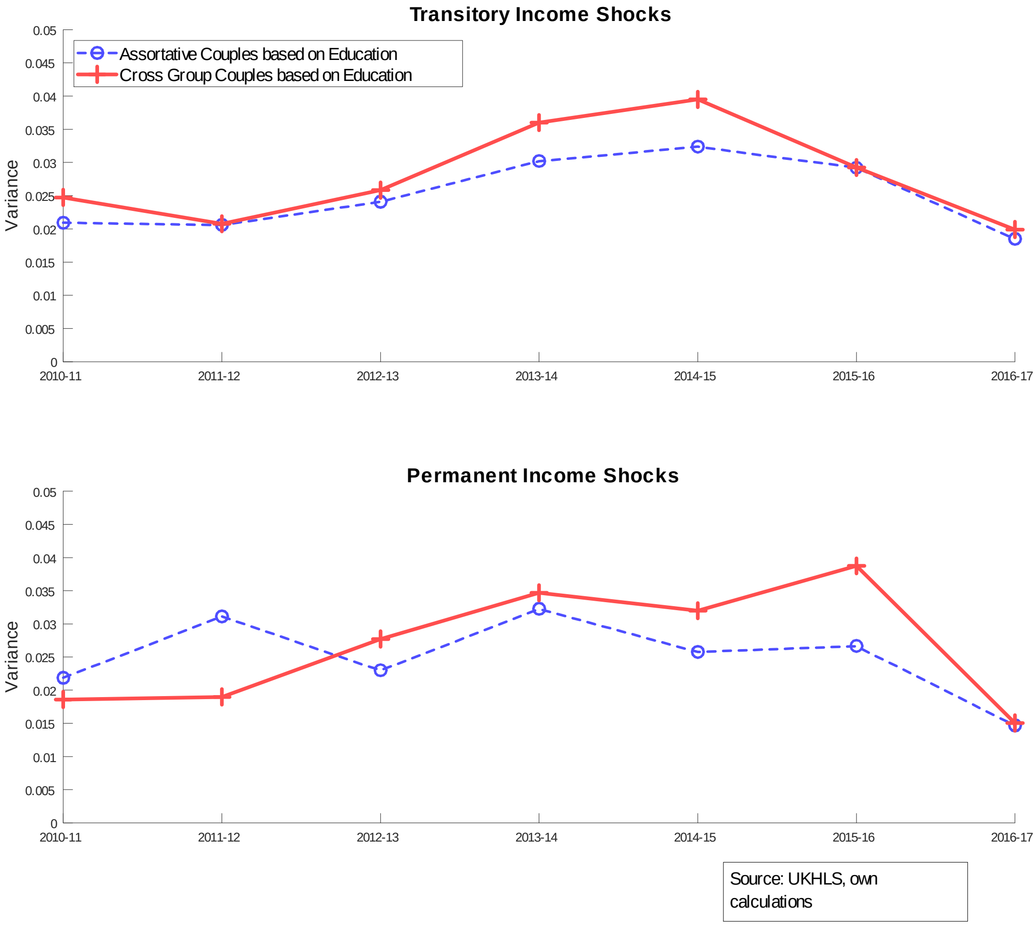
Table 3.8: Household Income Risk, Marital Choice based on Education

Subgroup	Transitory $\sigma^2_{\varepsilon^g_t}$	Permanent $\sigma^2_{\zeta^g_t}$	Risk Ratio $\frac{CGM}{AM}$
Assortative Couples (AM)	0.0431***	0.0101***	2***
s.e.	(0.0025)	(0.0017)	
Sample Size	35,124		
Cross Group Couples (CGM)	0.0467***	0.0198***	
s.e.	(0.0022)	(0.0019)	
Sample Size	21,914		

Notes: Table 3.8 shows that cross group couples encounter higher levels of income shock variances; In Net Household Income; The bootstrap standard errors are based on1000 replications and presented in parentheses; The risk ratio is based on $\sigma^2_{\zeta^g_t}$; g refers to groups.
*significant at $p < 0.1$;p < 0.05;***significant p < 0.01; Level estimation.

Figure 3.3 shows the estimation of net income risk from 2010 to 2017. The income risk distinction is based on assortative and cross-group couples categorised by level of education. It shows that couples who share the same educational background face lower transitory and permanent income shocks compared to couples where partners are from different educational backgrounds. The evidence in Figure 3.4 supports the findings in Table 3.8, confirming the findings associated with socioeconomic background. It indicates that households with the same characteristics such as education and socioeconomic background face lower income risk compared to couples from different backgrounds. In other words, assortative couples also show an advantage over cross-group couples where on marital choice is classified by education.

Figure 3.3: Household Income Risk based on Marital Choice, Education



Notes: Figure 3.3 shows that cross group couples based on marital choice associated with the education encounter higher levels of income shock variances compared to assortative couples from 2010 until 2017.

Discussion Marital Choice based on Education

In the following, I discuss net income risk associated with marital choice based on education. The evidence of educational homogamy in Table 3.9 indicates patterns similar to those for socioeconomic status. I consider the impact of a one standard deviation change in the permanent income shock. The estimates in Table 3.9 show that assortative married couples face lower net income risks and encounter a subsequently lower utility welfare loss of 1.62 per cent compared to 2.33 per cent for cross-socioeconomic married couples (see Table 3.9). The results are similar to those based on socioeconomic status. The current results provide evidence that married couples with an assortative choice strategy show less income variation than couples with a cross-group marital choice. As a result, the findings confirm the impact of marital choice on insurance against adverse income shocks, indicating that the degree of marital insurance does depend on marital choice.

Table 3.8 shows the probability of couples facing a positive or negative income shock, associated with different degrees of losses and gains. The results indicate that cross-group couples are 5.63 per cent likely to face an income loss of 20 per cent due to an adverse income shock. In contrast, assortative couples face a 1.31 per cent likelihood of encountering a 20 per cent income loss. The results indicate that non-assortative couples, based on education, have almost four times the likelihood of encountering an adverse income shock. This iterates the findings based on the role of marital choice in mitigating income risk. The results are similar to Hryshko *et al.* (2017) and Eike *et al.*(2019).

Table 3.9: Utility Welfare Loss, Marital Choice based on Education

Subgroup	Loss in per cent	Utility Welfare Loss in per cent
Assortative Couples	10.11%	1.62%
Cross Group Couples	13.88%	2.33%

Notes: Table 3.9 shows that cross group couples face higher utility welfare losses compared to assortative couples; Net Household Income; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 3.10: Probabilities of Permanent Income Shocks, Marital Choice based on Education

Probability of income gain/loss		Permanent income shock in per cent	
		Assortative Couples	Cross Group Couples
		$\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{AM}}\right)$	$\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{CGM}}\right)$
income gain>20%:	$Pr(\zeta_{h,t} > \ln(1.20))$	0.02%	0.20%
income gain>50%:	$Pr(\zeta_{h,t} > \ln(1.50))$	3.46%	9.72%
income loss>50% :	$Pr(\zeta_{h,t} < \ln(0.50))$	2.64%	3.13%
income loss>20%:	$Pr(\zeta_{h,t} < \ln(0.80))$	1.31%	5.63%

Notes:Table 3.10 shows that cross group couples are more likely to face adverse permanent income shocks. The probabilities of gains/losses are with respect to the level of permanent income under the mean shock. Note that $\zeta_{h,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

3.6 Conclusion

This chapter measures the private insurance against adverse income shocks based on marriage in the UK. It analyses the relationship between marriage, marital choice and net income risk. I find that married individuals have an income insurance advantage through income pooling compared to single individuals. Further, I find that amongst married couples the degree of private insurance depends on marital choice. I consider the socioeconomic background of the spouses within the marital choice. The analysis is based on the PIH by Friedman (1957), which separates the income process into both transitory and permanent components. The robustness test entails a counterfactual exercise in which a synthetic sample is created. This randomises the spouses of each married couple based on their marital choice which enables me to remove any endogeneity. This estimation is based on the UKHLS survey, which contains socioeconomic information from the UK between 2009 and 2018. The degree of income risk faced by individuals and married couples is an important issue in understanding economic behaviour and for developing government policies.

The main contribution lies in the findings on insurance opportunities arising from marriage, based on marital status and marital choice. Individual risk by marital status provides evidence for a private insurance mechanism through marriage. Single individuals face higher levels of net income risk compared to married couples, and are also more likely to face adverse income shocks compared to married individuals. Consequently, the results indicate a marriage insurance mechanism, as expressed in lower levels of net income risk for married couples compared to single individuals. The underlying factor is the access of married individuals to income pooling. This finding is in line with literature such as Hyslop (2001), Antonovices and Town (2004), Christiansen *et al.* (2015), Autor (2014), Greenwood *et al.* (2014), and Pestel (2017).

Moreover, the results reveal that the degree of private insurance through marriage depends on marital choice. Private insurance is expressed in terms of lower income risk for assortative married couples compared to cross-group married couples. The findings show that marriage reduces income volatility for couples sharing the same socioeconomic characteristics relative to couples who do not. Assortative married couples also face a 1.4 per cent point lower probability of facing an adverse income shock of 20 per cent compared to couples who differ across socioeconomic characteristics. The occupation associated with the couples' partners might explain the additional income risk for cross-group couples. Marital choice based on education indicates the same pattern. Consequently, the magnitude of marriage insurance depends on marital choice, a conclusion supported by the results from the synthetic sample of the counterfactual exercise.

Another key contribution is the statistical decomposition to quantify the effect of marital choice on net income risk. The marital choice decomposition is an innovative approach to examine the dynamics between marriage insurance and net income risk. The decomposition by marital choice enables the analysis of private insurance based on marriage. The robustness check entails a counterfactual exercise in which I create a synthetic sample of married couples based on their marital choice by spouses' socioeconomic status. Within this synthetic sample I randomise the partners based on their original marital choice, namely assortative or cross-group socioeconomic choice. The income risk estimates with the randomised partners indicate the same income risk pattern and support the key findings.

From a policy maker's perspective, the information on the impact of marriage related to marital choice is useful for policy design. The results indicate the advantage for married households compared to single individuals. The analysis suggests incorporating consideration of adverse income shocks in the policy design. The design of taxes and benefits should take into account the distinctive income risk exposures of married couples and single individuals.

One limitation of this research concerns the time dimension of UKHLS from 2009 until 2018. This relatively short period does not allow for investigation of the long-run factors such as the duration of marriages in the discussion of private insurance mechanisms.

Another factor that should be highlighted is the possible attrition bias due to married couples who divorce during the sample period. Further, the lack of industry level data does not allow for additional robustness tests on the degree of private insurance for married couples.

Future research should examine the duration of marriage, based on marital choice. A sufficiently large panel data set might provide insights as to whether marriages based on shared background characteristics of the spouse are more long lasting. Such a discussion could provide insight on how far marriage constitutes an insurance against adverse income shocks. Another research question could focus on a policy analysis comparing married and cohabiting couples. Consequently, there is scope for further analysis to contribute to discussion on the size of private insurance against adverse income shocks.

CHAPTER

4

SOCIAL INSURANCE POLICIES AND INCOME RISK IN THE UNITED KINGDOM

4.1 Introduction

This chapter quantifies the link between British welfare policy reform and net income risk for welfare receiving households. Targeted welfare policies conditional on household income can further supplement the need for self-insurance through a progressive welfare system. They typically help low-income households to deal with the adverse shocks to income, which are otherwise uninsurable due to incomplete markets. Therefore, changes to the welfare framework have a direct impact on the well-being of programme recipients. This is particularly relevant as the British welfare system is undergoing a major reform, replacing the Legacy System with Universal Credit, which is less generous than the former system (Brewer, 2019). In this analysis I exploit a natural experiment by examining the impact of the welfare scheme reform in the UK on the level of income risk that the households face. This contributes to the understanding of how the design of welfare policies affects the social insurance of welfare-receiving households, faced with unexpected income changes.

The main finding is of a rise in net income risk for households under Universal Credit. In contrast, the income risk for households under the Legacy System and Non-Welfare receiving households is stable. Further, households under Universal Credit are almost twice as likely to face an adverse permanent income shock of 10 per cent compared to households under the Legacy System. This likelihood increases even further if children are present in the household. This difference is explained by newly implemented policy measures such as the benefit reductions of Universal Credit. As a result, this implies a need to take account of income risks in the design of welfare policies.

This analysis contributes to the literature through its novel findings on the development of net income risk associated with a British welfare reform. Labour market earnings constitute the main source of income for most households. For low-income households, income also often includes benefits from welfare policies such as cash benefits, benefit transfers, and tax credits. These programmes reduce the after-tax, after-benefit level of income volatility for households with limited resources (Kniesner and Ziliak, 2002; Belfield, 2017; Brendler, 2020). Yet, the welfare support potentially amplifies income instability if programme receiving households face benefit reductions and depend on eligibility criteria. It is not yet well understood how changes in welfare policies affect programme receiving households. The literature provides sparse evidence on the dynamics between income risk and changes in welfare support. Consequently, this thesis contributes to the debate by measuring net income risk associated with the British welfare reform for welfare receiving households.

The process of restructuring the British welfare system is a part of the austerity package in response to the Great Financial Crisis in 2007/08. The transition of British welfare policies from the Legacy System to Universal Credit was initiated with the Welfare Reform Act in April 2012. It was launched officially in 2015 across the United Kingdom. The key aims of Universal Credit are to (i) simplify the administrative body of the Legacy System, (ii) decrease poverty and (iii) make work pay (UK government, 2020). The simplification occurs through repackaging six benefit types in the former system into one 'universal' package. The decrease in poverty and the idea of making work pay are addressed through considerable regulatory changes (Brewer, 2019). Thus, the underlying idea of the new welfare policy is to decrease the costs of welfare support while motivating progress into employment.

The regulatory changes associated with Universal Credit have led to a controversial debate. It is unclear whether the new framework addresses its key aims while providing social insurance to households under the programme. The implementation of Universal Credit is associated with considerable reductions in benefit payments compared to the former system. The decrease in payments under Universal Credit is intended to motivate households to increase their employment levels (Department for Work and Pensions, 2019). Yet, the benefit reduction also causes income variability, which decreases the social insurance provided by Universal Credit. Brewer *et al.* (2020) and DeAgostini (2017) show that households face considerable financial losses, associated with significant benefit reductions under the new programme. Consequently, the new Universal Credit framework may increase net income risk for welfare receiving households. Understanding the role of income risk is important if effective stabilisation, stimulus policies and government insurance programmes are to be formulated.

The ongoing reform offers a unique natural policy experiment. The United Kingdom Household Longitudinal Survey (UKHLS) contains welfare information of households from 2009 to 2018 under each welfare policy. Since 2015 eligible households only receive benefits by applying for Universal Credit. This phase refers to the natural migration. In a second phase from January 2019 the 'managed migration' was launched. During this second phase households from the Legacy System are transferred to the Universal Credit framework. The second phase of the managed migration is not included in this analysis. I use the first phase of the natural migration as part of the natural policy experiment. This structure enables me to create an independent sample of households under each policy from 2009 until 2018. The longitudinal structure of UKHLS permits a comparison of the size of net income risk for welfare receiving households under each policy. The comparison between both welfare policies over the same period reveals new findings on the design of welfare policies.

I follow the PIH to captures the extent to which households experience sizable unanticipated income changes. The associated uncertainty in future income can be split into two stochastic components, i) permanent and ii) transitory (Hall and Mishkin, 1982; Meghir, 2004). The nature of the two components is shaped by their characteristics (see chapter 1 for a detailed review).

The estimation method focuses on income dynamics, based on the approach by Heathcote *et al.* (2010). In particular, the idiosyncratic component of income is modelled as a sum of two sub-components, a purely transitory and a permanent one (see eq. (1.2) and (1.3)). I exploit the variance-covariance structure of the idiosyncratic income component to estimate the properties of the distribution of transitory and permanent income shocks. The idiosyncratic income component is approximated as the residual of a first step Mincerian regression, partialling out such observables as age, region, household size and year effects (Mincer, 1974). The direct comparison before and after the implementation of Universal Credit provides a natural experiment, facilitating comparison of household income risk between both social welfare policies.

This chapter comprises six sections. Section 4.2 offers a literature review, which elaborates on current empirical and theoretical evidence. Section 4.3 provides information on the dataset. Section 4.4 reflects on the methodology applied and section 4.5 provides the income risk estimates with suggestions on the implications of the results. Section 4.6 concludes.

4.2 Literature Review

4.2.1 Social Insurance Policy

This section discusses the role of conditional social insurance for welfare receiving households. The social insurance is conditional as only low-income households are eligible to apply for the welfare support associated with the Legacy System and Universal Credit. The main findings in the literature are discussed, highlighting key factors that contribute to social insurance such as the redistributive nature of the welfare system, its progressiveness, the size and type of benefit payments.

Social insurance influences the size of adverse income shocks. Government policies can supplement or partly replace the need for self-insurance, through taxes and benefits which are accessible to all households. Current empirical findings provide a consensus on income risk mitigation through policy support. Meghir and Pistaferri (2004) and Blundell *et al.* (2008) find that a key factor that blunts the transmission of adverse income shocks into consumption choice derives from government policies. As a consequence, partial self-insurance or social insurance can mitigate the impact of adverse permanent income shocks (Blundell *et al.*, 2008; Blundell and Etheridge, 2010; Heathcote *et al.*, 2010; Dolls *et al.*, 2012; Blundell *et al.*, 2013; Blundell *et al.*, 2016; Hill *et al.*, 2017; Bush *et al.*, 2020; DeNardi *et al.*,2021). In particular, during economic recessions, the government provides social insurance for individuals or households (Guvenen *et al.*, 2014; Belfield *et al.*, 2017).

This work contributes to the social insurance literature by measuring changes in net income risk based on the British welfare reform. A large part of the literature focuses on the mitigation of income risk through welfare policies. Empirical findings indicate several key channels such as the progressiveness of the welfare system, and the redistributive size of benefit payments and tax credits. In particular, during economic downturns, social insurance supports households with limited resources (Bitler *et al.*, 2017). It complements work on changes in social insurance, including Kniesner and Ziliak (2002), Hood and Oakley (2004), Gregg *et al.* (2009), Blundell *et al.* (2008), Brewer and Wren-Lewis (2012), Heathcote *et al.* (2016), Brewer *et al.* (2017), Doll *et al.* (2017), Blundell *et al.* (2018), Cribb *et al.* (2018), Avram *et al.* (2019), De Nardi *et al.* (2019) and Brendler *et al.* (2020). Yet, it is not well understood how changes in welfare support affect receiving households. The new structure of welfare programmes can amplify income instability for welfare receiving households whether through benefit reductions or stricter eligibility criteria. To date, this chapter is the first to address how welfare reforms affect household income risk and social insurance for programme recipients.

To investigate social insurance dynamics, comparative policy experiments are a standard method used in the literature. Gregg *et al.* (2005) examine the change in household expenditures following the increase in British child support in the 1990s. They find that the increase in child support increases the consumption choices of low-income households after the reform (Gregg *et al.*, 2005). Similarly, Blundell *et al.* (2016) create a policy experiment based on British welfare reforms between 1992 and 2002. In particular, they examine the impact of the reforms on female labour supply, finding considerable elasticity in labour supply amongst lone mothers. Further, Dolls *et al.* (2017) explore the fiscal responses of the Great Financial Crisis (GFS) between the European Union and the USA. They test the change and effectiveness of the welfare systems after the crisis in 2007/2008 in these economies. This work provides a unique analysis based on the natural policy experiment offered by British welfare reform. The comparison between the Legacy System and Universal Credit provides new findings on the impact of welfare reforms on net income risk. It also gives a new perspective on the economic implications of social insurance for welfare receiving households.

The redistributive nature of the welfare system induces social insurance. A progressive welfare policy redistributes resources to low-income households. In the UK, the poorest fifth receives 16 times more in benefits and taxes as a share of their net income than the highest-income fifth (Brewer *et al.*, 2019; Hudson Sharp *et al.*, 2017). The redistribution process of the British welfare framework through benefits and tax credits generates partial insurance against adverse income shocks (Blundell *et al.*, 2008; Blundell *et al.*, 2016). It enables welfare receiving households to smooth adverse income shocks across time. Further, Halvorsen *et al.* (2019), De Nardi *et al.* (2019; 2021) and Bush *et al.* (2020) report that the progressive Norwegian and Dutch welfare systems contribute towards reducing the effect of the negatively skewed labour income. In particular, government transfers are a key source of insurance against adverse income shocks. They offset some of the largest declines in income (Bush *et al.*, 2020). Thus, the empirical evidence suggests that the progressive nature of the welfare systems is a key factor in protecting households against adverse income risks. This chapter contributes to the ongoing discussion by comparing the degree of income risk under the two policies which differ in the nature of welfare support offered.

In the presence of a less generous welfare system, households resort to other insurance mechanisms. De Nardi *et al.* (2019) show that insurance through family networks plays a much larger role in the USA than in the Netherlands. The divergent trends in net income risk in the Netherlands and the USA are due to the nature of the policy regimes. Another insurance mechanism occurs through income pooling. Pruitt and Turner (2020) use administrative data from the USA and find that the probability of the spouse entering employment rises when the male experiences earnings losses. Thus, in the absence of welfare support, family networks and spousal income pooling protect against adverse income shocks.

The generosity of benefits payments contributes to the size of social insurance. Benefits are a direct tool against adverse income shocks because they support the financial liquidity of households by increasing the amount of disposable income available. This enables households to smooth consumption against adverse income shocks from one period to the next. Kniesner and Ziliak (2002) find that annual consumption variation is reduced by almost 20 per cent due to the explicit and implicit income smoothing of the welfare system. Moreover, Bitler *et al.* (2017) and Cribb (2018) emphasise the positive impact of the expansion of benefit payments, during the 1990s and 2000s. They find that the benefit expansion reduces income variation in the UK. Consequently, benefits provide explicit insurance by partially offsetting adverse income shocks for welfare receiving households.

Child tax credits are an indirect benefit to support low-income households with children. The child tax credit is a means-tested payment which is part of the new Universal Credit package and aimed at households with children, in contrast to child benefit, which is a flat rate to all households with children independent of their income. The child tax credit has been available since 2003 to low-income families irrespective of work status. It is accessible for households with a labour income below £32,000, which is paid on top of the child benefit. Thus, the child tax credit supports vulnerable households against financial challenges. Brewer *et al.* (2005) and DeNardi *et al.* (2021) emphasise the key role of the generosity of tax credits that have supported net income growth among low-wage households for benefit receiving households in the UK. Avram *et al.* (2019) show that cash benefits and income-dependent refundable tax credits reduce UK household income volatility by around a quarter. Thus, direct and indirect benefits create social insurance against adverse income shocks.

Current literature highlights the impact of financial support for children. Households under a welfare programme with children are particularly vulnerable to adverse income shocks due to their family structure. Targeted welfare support for these households such as child tax credit plays a key role in giving financial relief. Dahl and Lochner (2012) provide evidence that high levels of income instability affects a child's achievement in mathematics and reading. They use an instrumental variable approach to test how the expansion of earned income tax credit affects the child's potential in mathematics and reading. The study indicates a positive impact of the increase in household income through tax credits on children's mathematics and reading test scores[1]. As a result, child-specific welfare affects the potential health and educational development of children. Reductions in child support can amplify stress levels of both parent and child (Leete and Bania, 2009; Adams *et al.*, 2016; Wolf and Morrissey, 2017; Hardy and Hill, 2019, DeNardi *et al.*,2021). Therefore, examining the level of income risk associated with changes in child tax credit under Universal Credit provides new insight on the link between income risk and welfare

[1]Dahl and Lochner (2012) baseline estimates imply that a \$1,000 increase in income raises contemporaneous math and reading test scores by 6 percent of a standard deviation.

programmes.

Welfare policies play a key role during recessions. In an economic downturn, incomes are more likely to drop and induce financial losses than creating financial gains (Guvenen *et al.*, 2014; Wolf and Morrissey, 2017; Pruit and Turner, 2020). Therefore, welfare policy support during recessions is particularly important for households with limited resources as the likelihood of adverse income shocks increases. The social insurance created by welfare policies helps mitigate the impact of the adverse income shocks. Blundell and Etheridge (2010) and Avram *et al.* (2019) highlight that the British welfare system partially offsets the impact of recessions on the lower quintals of the income distribution. Their findings illustrate the alleviation of adverse income shocks through welfare policies.

4.2.2 Income Risk and Universal Credit

Universal Credit represents a major transformation of the British welfare framework. While the principles of social insurance, simplification and making work pay are key aims of the ongoing reform, questions remain about Universal Credit's ability to deliver on those aims. Some of the initial policy choices around Universal Credit, coupled with subsequent revisions over the last few years, have led to concerns regarding their feasibility to provide social insurance (Brewer, 2020). Therefore, this section discusses the dynamics between income risk and changes associated with Universal Credit.

The standard approach to analyse income risk is based on the PIH (Friedman, 1957). This approach assumes that the income stream consists of two components, which are characterised by the nature of income shock variances (see eq. (1.2) and (1.3)). The permanent component reflects the expected income over the life cycle and translates to permanent income differences between households. The reasons for these permanent differences can be traced (among others) to job displacement, changes in returns to education, or severe injuries. In contrast, a transitory component reflects fast mean reversion income changes such as bonus payments or unemployment spells or lottery wins (Meghir and Pistaferri, 2011). Consequently, the nature of income risk differs depending on its characteristics (see Chapter 1 for more details).

The PIH asserts that a household's consumption and savings choices respond differently to permanent income shocks compared to transitory ones. Permanent income shocks directly translate into consumption choices, while transitory income shocks may be smoothed throughout periods. An increase in the variance of permanent income shocks leads to a decrease in welfare, because households have to save more to be better prepared for income volatility and especially adverse income shocks. However, if a household cannot smooth income shocks, due to liquidity constraints, welfare losses can also arise from transitory income shocks (see Chapter 1 for an in-depth review).

This is particularly relevant for households that have limited private resources. Low-income households face financial challenges and receive financial support through the welfare system. As a result, they are vulnerable to changes in the welfare framework that is less generous as it increases the exposure to net income risk (Blundell, Pistaferri and Preston, 2008). The implementation of Universal Credit is associated with benefit reductions, which decrease net income for welfare receiving households and increase exposure to a given level of income risk. Brewer *et al.* (2018) and Bernard (2019) show that households under Universal Credit face financial losses (DeAgostini, 2017; Brewer *et al.*, 2018; Cribb, 2018; Hudson Sharp *et al.*, 2018). The new policy regulations associated with Universal Credit thus influence a household's exposure to net income risk.

This chapter contributes to the literature by measuring net income risk in the light of the transition from the Legacy System to Universal Credit. Given the lower generosity of Universal Credit, changes in net income risk can be observed in a natural policy experiment.

Further, dependency on the level of benefit payments has a direct impact on the consumption choices of households under a welfare policy. The benefit reductions associated with Universal Credit mean that households need to adjust their consumption choices and select cheaper alternatives. Thompson *et al.* (2017) and Loopstra *et al.* (2018) find that the demand for food bank donations increases in the areas where Universal Credit has been implemented. The adjustment in consumption choices in these areas might indicate the impact of permanent income risk based on the implementation of Universal Credit.

The comparison between both welfare policies over the same period reveals new insights on household net income risk associated with the implementation of Universal Credit. The new regulatory framework incorporates an employment conditionality, which drives fluctuations in worked hours per week, increases income variability and thereby induces income risk (Adam and Browne, 2013). The income variability occurs through changing employment types, for example in favour of part-time or zero-hours contracts. These policies can generate additional income risk via the reduced social insurance over labour income changes. As a consequence, income streams are more volatile under Universal Credit.

The changes associated with Universal Credit direct the British welfare structure towards a regressive system. In other words, the largest impacts are felt by those with lower incomes. Portes and Reed (2018) find that those in the bottom two deciles will lose, on average, approximately 10 per cent of net income, with much smaller losses for those higher up the income distribution. They show that adverse impacts are particularly large for households with more disabled members, and individuals with more severe disabilities, as well as for lone parents on low incomes. Key drivers for these developments lie in the freeze in working-age benefit rates, changes to disability benefits and a reduction in Universal Credit rates. Thus, the degree of social insurance is affected by Universal Credit changes.

Current studies highlight an uneven regional impact and diverse local impact of Universal Credit regulations for welfare receiving households. Betty *et al.* (2011) show the regional effects of Universal Credit. They find a difference in financial benefit loss *per capita* that is four times greater in Blackpool compared to Hampshire (Betty *et al.*, 2011). Jackson and Nixon (2013) focus on the local impact of the welfare reform in Manchester. Their estimation indicates a potential reduction of £45 million a year in the local area of Manchester (Jackson and Nixon, 2012). Similarly, Edwards *et al.* (2013) find a considerable proportion of the loss in North-East England is attributable to benefit reductions for disabled people. It is estimated that over 70,000 people in the North East are affected by the time-limiting of contribution-based Employment and Support Allowance (ESA) and the stricter eligibility criteria. This chapter contributes to the literature with a national analysis that emphasises the changes in net income risk for households under Universal Credit.

According to Goulden (2020), child poverty is at an unprecedented high in the UK, exacerbated by reductions in child tax credit. Hood and Waters (2017) show that absolute child poverty has increased by around four percentage points based on the Universal Credit regulations. They emphasise that of this increase, around three quarters is attributable to benefit and child tax credit changes, which increase the exposure to adverse income shocks for households with children. In particular, households with three or more children see particularly large losses due to the two child limit (Portes and Reed, 2018). Consequently, the design of Universal Credit regulations influences the degree of child poverty in the United Kingdom.

The empirical evidence indicates an uneven distribution of welfare support across households under Universal Credit. Brewer *et al.* (2019) and De Agostini *et al.* (2018) emphasise that under the new policies of Universal Credit low-income households with children and single parents encounter less benefit support. They estimate in a microsimulation model that households in the bottom 10 per cent of the income distribution on average lose the most due to Universal Credit (Brewer *et al.*, 2018). Lone parents, who are more likely to have low incomes, lose on average 2 per cent of their disposable income, as a consequence of the benefit reductions (De Agostini *et al.*, 2018). However, while vulnerable households face considerable financial constraints induced by Universal Credit, in contrast, the evidence indicates that dual-earner households and pensioners benefit from the new regulations (DeAgostini *et al.*, 2018).

4.2.3 British Welfare System

This section reviews the welfare policy changes in the UK and, in particular, the transformation of the welfare framework from the Legacy System to Universal Credit, including changes therein (see Appendix *D* for a detailed review of Universal Credit).

The British welfare system has been considerably expanded since the late 1990s. The characteristics of the scheme have shifted away from the three main income-related, out-of-work benefits (incapacity benefit, income support and unemployment benefit, which made up 25 per cent of welfare spending in 1987- 88 but only 9 per cent in 2017-18) and towards tax credits, housing benefit and cost-related disability benefits (Gardiner, 2019). The government increased the generosity of social assistance and tax credits from 1997 to 2010, intending to minimise child poverty (Joyce and Sibieta, 2013). However, since 2011 the British government has focused on austerity policies to address the impact of the Great Financial Crisis in 2007/2008. In 2013 the government implemented a set of reductions to means-tested working-age benefit as part of a package of post-recession fiscal consolidation measures. The reductions associated with the fiscal consolidation resulted in the welfare reform and the implementation of Universal Credit (see Appendix *D*4 for detailed review).

The fiscal austerity measures have direct implications for the generosity and reach of anti-poverty programmes and the welfare system. Along with these measures, Universal Credit was launched in 2015, as part of a package contained in the Welfare Reform Act in 2012 (Smith and Freud, 2012). Under current plans, Universal Credit is expected to be fully rolled out by December 2023. The policy is a repackaged version of the former Legacy System. It is designed to simplify the benefits system, reduce poverty and incentivises paid work, while providing a social insurance framework (Brewer *et al.*, 2019).

The simplification process means that the six benefit types of the Legacy System are combined in one 'universal' system, replacing the six-means tested benefits and tax credits with one single payment scheme. These means-tested benefits are working tax credit, child tax credit, income-based job seeker's allowance, income support, income-related employment and support allowance and housing benefit. The simplification process also aims to facilitate access to benefit payments. Furthermore, through different incentives, Universal Credit seeks to decrease poverty and increase employment stability. The key measures to achieve these aims are summarised as follows:

- Limiting the child element of Universal Credit to two children for new claims (July Budget 2015).
- Removing the family element in Universal Credit for new claims (July Budget 2015).
- Reducing the income disregards and work allowances in Universal Credit (July Budget 2015).
- Uprating the minimum income floor with the National Living Wage (Autumn Statement 2015).
- Reducing the taper rate to 63 per cent (Autumn Statement 2018).

The key measures are facilitated through financial and non-financial incentives. The financial incentives are reflected in benefit reductions. This refers to reductions in entitlements of £2 billion *per annum*, a 5-year benefit payment freeze and the two-child limit. The benefit reductions aim to encourage households to find employment or increase currently worked hours. Within the framework of financial incentives, one of the most extensive reductions focuses on the taper rate and its associated work allowance. The taper rate reflects the number of hours that a benefit recipient is allowed to work. It means that 63 pence is deducted from the work allowance for every additional hour worked. This amount is reduced from the benefit payment. In contrast, under the Legacy System, withdrawal of benefits was dependent on family and marital status and on housing status ((Department for Work and Pensions, 2019). Consequently, the welfare support under Universal Credit is considerably less generous compared to the Legacy System.

4.3 Data

4.3.1 Sample Selection

This chapter focuses on household net income risk. I construct the households based on the information provided by the UKHLS data set. Given the information on household identifiers, I obtain households with several household members. A household consists of either one person living alone, or a group of people (not necessarily related) living at the same address (UKHLS, 2019). I also include children of the respective household if they are reported. The head of the household is between 25 and 60 years of age with a positive income. To examine income risk and social insurance it is essential to create a homogeneous sample with comparable information. All imputed income variables are dropped and only households with positive income included. To account for inflation, the income variables are deflated using the retail price index (RPI). In addition, to consider possible outliers, I trim the top and bottom of the observations of income variables in any wave at 0.25 per cent. These processes enable me to create a homogeneous household sample, which maintains the same households across all waves.

The transition from the Legacy System to Universal Credit is shaped by two migration types. These types refer to the natural and the managed migration of programme recipients. The natural migration constitutes the launch of Universal Credit in 2015. With the official implementation of the programme new claims to the Legacy System are no longer possible. From January 2019 the government piloted the second migration: the managed migration, which refers to the movement of existing benefit claimants from the Legacy System to Universal Credit. The full managed migration was enacted in 2020. The UKHLS data set maintains information for the Legacy System from 2009 until 2018 and for Universal Credit from 2015 until 2018. The migration framework of the sample does not include information on the managed migration, which ensures that the welfare policy samples are independent and do not overlap. The phase 2 managed migration is not part of this analysis. Consequently, the natural migration process during phase 1 allows me to examine the natural policy experiment in the form of a welfare policy comparison from 2009 until 2018. This period includes the implementation of Universal Credit and the natural migration phase.

The UKHLS provides socioeconomic information on households under both British welfare schemes from 2009 until 2018. To understand the size of social insurance generated by welfare systems, it is crucial to split the data set into periods based on the implementation of Universal Credit. Consequently, this analysis considers two periods, divided by the implementation date of Universal Credit in wave 5, which translates into years 2014/2015. Period 1 covers information from wave one until wave five. While period 2 contains information from wave six to wave nine. The comparison between the two periods offers new insight onto income risk patterns and the size of social insurance for each welfare system (see Table 4.1).

The nature of the policy comparison requires samples that represent households under each welfare system. The creation of the sample depends on the accessibility of the UKHLS information. The information on Legacy System households can be accessed directly as the data set offers clear variables throughout the sample period. Consequently, I create a Legacy System sample based on the UKHLS variables (see variable section). Similarly, the UKHLS data set reports information on households under the new, Universal Credit system, in period 2. To examine the households under Universal Credit in period 1 I track the households based on the household identifier, which enables me to find the households in each period. Consequently, the 'tracked Universal Credit' sample maintains households in period 1 that receive Universal Credit in period 2 (see Table 4.1 and Appendix $D4$ for more details on the variable construction). In addition, I also include households that do not receive any welfare support under either system. The sample of non-welfare households is a baseline. Their income is too high, which excludes them from receiving additional welfare support. The creation of clear samples enables the comparison of both welfare systems.

Figure 4.1 shows the average net income of each sample from 2010 until 2017. It shows the net labour income for each welfare system and households under no welfare scheme. Households that never received any welfare payments have the highest net average income over time. A difference in net income between the Legacy System and Universal Credit can be observed. Households under the Legacy System receive higher net average income relative to households under Universal Credit.

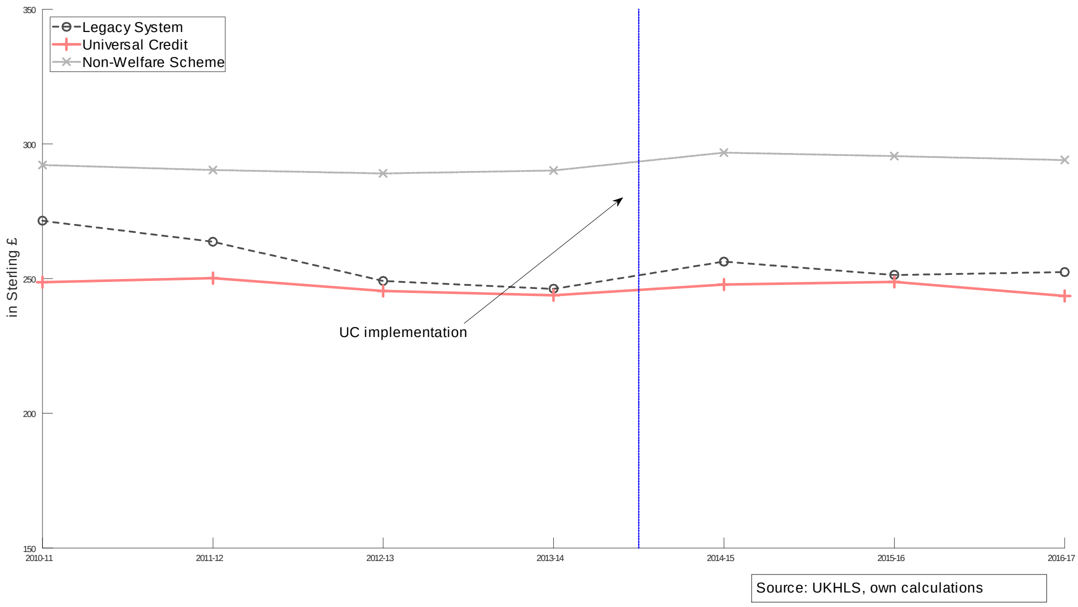
Table 4.1: Data Structure

Wave	Calendar Years	Period
1	2009-2010	1
2	2010-2011	1
3	2011-2012	1
4	2012-2013	1
5	2013-2014	1
6	2014-2015	2
7	2015-2016	2
8	2016-2017	2
9	2017-2018	2

Source: UKHLS

Notes:Table 4.1 indicates the period structure by wave.

Figure 4.1: Net Average Income based on Welfare Schemes in the UK



Notes: Figure 4.1 indicates that households under Universal Credit receive the lowest net income compared to the other groups; based on net weekly household income.

4.3.2 Variables

My benchmark measure of income is weekly net labour income because it captures key information on income volatility. Moreover, as some programme recipients might not have additional income using net labour income, the net income reflects benefit payments. I use weekly net wages as a measure for income: it is the standard approach in the literature within the UK, and therefore, for the purpose of comparability I use the same measure. The UKHLS provides income data on a monthly basis. Consequently, I calculate the weekly income variable based on the available monthly income information. In doing so, I multiply the monthly wages by 12 and then divide it by 52 weeks, which results in a measure for an average net weekly wage. It is a precise measure of income changes which is found in related literature such as Avram *et al.*(2019), Blundell and Etheridge (2010) and Heathcote *et al.*(2010).

To compare income risk patterns based on welfare schemes, it is essential to create distinct groups according to whether they are benefits recipients or not, and whether they are LS or Universal Credit recipients. The information of the Legacy System is based on six different variables that reflect the distinct benefit types. To construct the indicator variable for the 'Legacy System' I pooled information from the following benefit types: i) income support; ii) income-based jobseeker's allowance; iii) income-related employment and support allowance; iv) housing benefit; v) child tax credit and; vi) working tax credit (See Appendix $D4.1$).

The UKHLS dataset does not report emergency benefits. As a result, the analysis does not include discretionary hardship or crisis payments, which households can claim in emergencies, or schemes put in place by the governments of Scotland or Northern Ireland which currently provide some (albeit limited) financial hardship mitigation through supplementary payments.

The key samples of this chapter are households under a welfare scheme. To analyse the income risk exposure under the Legacy System and Universal Credit, I focus on net labour income of households, which represents the income after benefit payments and tax credits have been added, providing evidence of the dynamics related to the welfare schemes. As a baseline I also consider households who never have been under a welfare scheme, to provide an additional income risk comparison. Table 4.2 provides the descriptive statistics in period 1 for households under the Legacy System, future Universal Credit households (in period 2) and households under no welfare scheme.

Table 4.2: Descriptive Statistics of Income in Period 1

Variables	Mean	SD	Max.	Min.
Non-Welfare Scheme Households (NWS)				
Net Labour Income NWS	341.88	179.02	1571.82	3.60
Benefit receiving Households (BRH)				
Legacy System	288.80	126.00	1231.86	6.16
Tracked Universal Credit	279.60	122.93	972.02	44.01

Notes: Table 4.2 highlights that NWS have the highest net income in period 1. Income based on net weekly household income; Tracked Universal Credit households are households that receive Universal Credit in period 2; Period 1 refers to 2009 until 2015.

Table 4.3 provides the descriptive statistics of net labour income for period 2. It shows how Universal Credit recipients on average receive considerably less income compared the households under the Legacy System. Households under no welfare scheme earn the highest net income.

Table 4.3: Descriptive Statistics of Income in Period 2

Variables	Mean	SD	Max.	Min.
Non-Welfare Scheme Households (NWS)				
Net Labour Income NWS	346.28	180.35	1377.24	1.170
Benefit receiving Households (BRH)				
Legacy System	288.56	124.18	1377.24	17.54
Universal Credit	246.55	119.87	1015.32	6.31

Notes: Table 4.3 highlights that NWS have the highest net income in. in period 2; Income based on net weekly household income; Period 2 refers to 2015 until 2018.

4.4 Methodology

4.4.1 Empirical Model

This section describes the model used in this analysis. It follows the approach by Blundell and Etheridge (2010) and Heathcote *et al.*, (2010), who analyse trends in income dynamics in the UK and the USA respectively. I focus on the UK and use the panel data from the UKHLS over the time horizon from 2009 to 2018. In line with the literature, I analyse the 'residual' dispersion based on the level identification scheme seen also in Brzozowski *et al.*, (2010), Fuchs-Schündeln *et al.*, (2010), Heathcote *et al.*, (2010). In this chapter, the focus is on welfare receiving households.

I consider household log weekly net income, $y^g_{h,c,t}$, for a household h, belonging to a cohort c and population subgroup g, and observed in year t. I assume the following model

$$\ln y^g_{h,c,t} = \beta^g X_{h,c,t} + u^g_{h,c,t} \tag{4.1}$$

which means that the log net income consist of a determinist (or explained by observables) linear part $\beta^g X_{h,c,t}$ and a residual (unexplained or idiosyncratic) part $u^g_{h,c,t}$. $X_{h,c,t}$ includes a constant term, a quadratic in experience approximated by age, dummies for region of residence, dummy for gender, dummy for marital status and time fixed effects. Following Blundell and Etheridge (2010) I also include as a regressor the logarithm of the household size. The superscript g denotes the four subgroups defined by the combination of three variables: sex (men and women), education (degree holders or not)[2]. Moreover, I consider three cohorts. Controlling for the observables captures the idea that expected changes to income do not represent risk (see Japelli and Pistaferri, 2017). Of key interest are the income risk patterns between the welfare receiving households under the Legacy System and Universal Credit.

I further assume that the residual term, $u^g_{h,c,t}$, consists of two components, a permanent component, $p^g_{h,c,t}$, and a transitory component, $\varepsilon^g_{h,c,t}$; the permanent component is a random walk while the transitory component is a purely *i.i.d* shock. In addition, the two components are additive (in logs). The formal expression of $u^g_{h,c,t}$, can be found in Chapter 1 Section 3 and 4.

[2] Analytically, the four subgroups are: i) male, degree; ii) male, no degree; iii) female, degree; iv) female, no degree.

4.5 Results and Discussion

This section outlines the estimates and economic implications of the natural policy experiment. The main finding indicates a rise of net income risk for households under Universal Credit. In contrast, the income risk for households under the Legacy System households and non welfare receiving households is stable. Further, households under Universal Credit are more exposed to income risk. They are almost twice as likely to face an adverse permanent income shock of 10 per cent compared to households under the Legacy System. The likelihood increases even further if children are in the household. This difference is explained by the newly implemented policy measures such as benefit reductions through Universal Credit. Consequently, welfare receiving households encounter higher net income risk under Universal Credit compared to the Legacy System.

The ongoing reform offers a unique natural policy experiment, to compare income risk under the Legacy System and Universal Credit. To this end I separate the sample into two periods based on the implementation of Universal Credit in 2015. This allows examination of the development of income risk before and after the policy reform. The income risk is expressed in the form of permanent and transitory income shock variances. Given the considerable change in the policy framework between the Legacy System and Universal Credit it is expected that income risk will be affected.

Within this chapter I focus on the of 10 per cent, 20 per cent and 30 per cent likelihood of encountering a labour income gain/loss. The change in the probabilities is based on the low income of the households who receive support either under the Legacy System or Universal Credit. Consequently, I focus on different probabilities of permanent income shocks.

Moreover, I calculate the risk ratio based on the type of policy support. The risk ratio is defined as the ratio of the permanent income shocks based on Universal Credit and Legacy System households. It expresses the differences and the degree of income variation between the respective households receiving policy support. A high level of risk ratio indicates a high degree of permanent income shocks resulting in higher income variation. In contrast, a low risk ratio indicates few permanent income shocks indicating income stability. It is an indicator of income variability related to permanent income shocks and supports the economic relevance of this chapter. The impact of an adverse income shock on welfare receiving households is also analysed. The approach follows the utility welfare loss based on standard deviations in Chapter 1 (see 1.5 for more details). The well-being analysis is complemented by a probability exercise.

4.5.1 Social Insurance Policy Results

Table 4.3 shows the net income risk estimates of each welfare system during period 1. It reports net income risk for households under the Legacy System and the tracked households under Universal Credit in period 1: year 2009 until 2015. The net income risk is expressed in transitory and permanent income shock variances. The group 'tracked households' refers to the sample of households in period 1 who receive Universal Credit in the future. Through the household identifier code it is possible to track the households in both periods. The results in Table 4.4 indicate that tracked Universal Credit households face lower permanent income shock variance, with a difference of $\sigma^2_{\zeta^g_t} = 0.0086$ compared to Legacy System households. The difference in permanent risk estimates between the households under the Legacy System and Universal Credit is significantly different at the 90 per cent confidence interval. Households that do not receive any benefits face the highest net income risk exposure $\sigma^2_{\zeta^g_t} = 0.0143$.

In period 1 tracked Universal Credit households have not yet applied for the new welfare scheme. Hence, these estimates represent households in employment, which explains the lower net income risk exposure compared to households under the Legacy System. During period 1 tracked Universal Credit households were mainly in semi-skilled and routine jobs based on the data set (UKHLS, 2019).

Table 4.4: Household Net Income Risk in Period 1

Welfare Policy	Transitory $\sigma^2_{\varepsilon^g_t}$	Permanent $\sigma^2_{\zeta^g_t}$	Risk Ratio $\frac{TUC}{LS}$
Legacy System Households (LS)	0.0722***	0.0107***	0.1***
s.e.	(0.0022)	(0.0011)	
Sample Size	24,447		
Tracked Universal Credit Households (TUC)	0.0719***	0.0089***	
s.e.	(0.0062)	(0.0003)	
Sample Size	1,467		
Non-Welfare Scheme Households (NWS)	0.0977***	0.0141***	
s.e.	(0.0036)	(0.0013)	
Sample Size	27,066		

Notes: Table 4.4 reports that NWS encounter the highest level of permanent income shock variance; TUC sample are households that receive Universal Credit in period 2; *** indicates p-value<0.01; **indicates p-value<0.05; *indicates p-value <0.1. The bootstrap standard errors are based on 1000 replications and are presented in parentheses;Period 1 refers to 2009 until 2015; g refers to groups.

Table 4.5 provides information on net income risk exposure based on the two welfare policies in period 2 from 2015 until 2018. It shows a increase in net income risk exposure for households under Universal Credit. This increase translates into a lower net income risk mitigation effect under Universal Credit. The permanent income shock variance of Universal Credit households is $\sigma^2_{\zeta^g_t} = 0.0190$ higher compared to Legacy System households in period 2. The permanent risk estimates between the households under the two systems are significantly different at the 90 per cent confidence interval. The permanent income shock more than doubles for households under Universal Credit across the two periods. A comparison between period 1 and period 2 indicates that the permanent income shock variance for households under the Legacy System changes only marginally. Further, the marginal change in net income risk exposure for households under the Legacy System across period 1 and 2 provides evidence of lower income variation, as the risk has not changed considerably.

To create a baseline I also consider the net income risk of non-welfare policy households. These households are not receiving welfare benefits under either system. Considering the net income risk estimates between period 1 and period 2 the results show that net income risk does not change (see Table 4.4 and 4.5). It is relatively stable compared to the welfare receiving households. Figure 4.3 supports the estimates.

Consequently, the increase in net income risk observed for households under Universal Credit is associated with the regulations under the new welfare system such as benefit reductions and changes in the work allowance (Brewer *et al.*, 2019; Cribb *et al.*, 2018). The considerable rise in net income risk exposure is related to the change in the financial framework associated with the new regulations of Universal Credit. The results in Table 4.5 can be interpreted as a decrease in the net income risk mitigation effect through the implementation of Universal Credit.

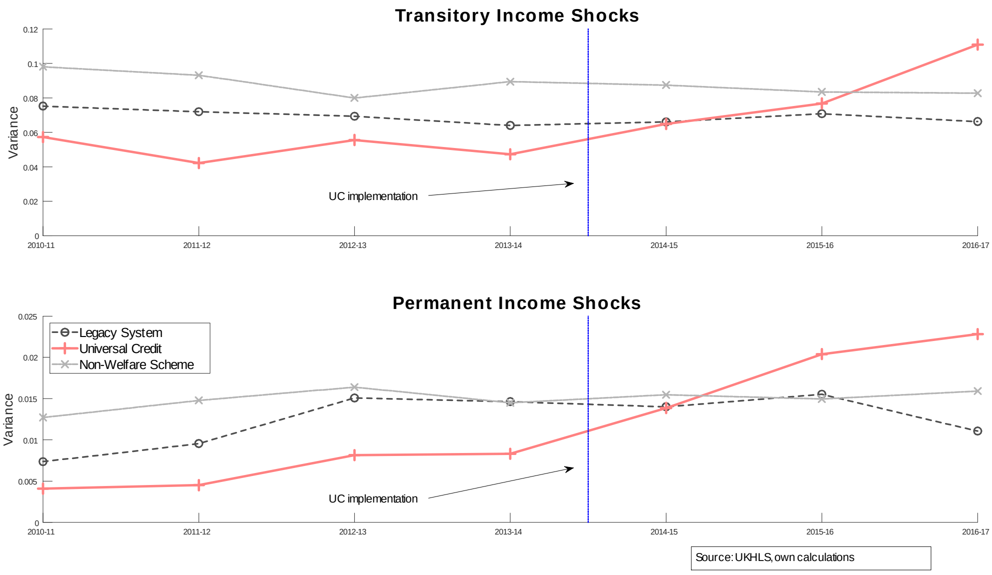
Table 4.5: Household Net Income Risk in Period 2

Welfare Policy	Transitory $\sigma^2_{\varepsilon^g_t}$	Permanent $\sigma^2_{\zeta^g_t}$	Risk Ratio $\frac{UC}{LS}$
Legacy System Households	0.0685***	0.0080***	2.3***
s.e.	(0.0033)	(0.0019)	
Sample Size	10,301		
Universal Credit Households	0.0841***	0.0190***	
s.e.	(0.0012)	(0.0057)	
Sample Size	1,366		
Non-Welfare Scheme Households	0.0731***	0.0139***	
s.e.	(0.0036)	(0.0028)	
Sample Size	14,504		

Notes: Table 4.5 reveals the higher levels of permanent income shock variance compared to the other groups;*** indicates p-value<0.01; **indicates p-value<0.05.;*indicates p-value <0.1; The bootstrap standard errors are based on 1000 replications and are presented in parentheses; g refers to groups; Period 2 refers to 2015 until 2018.

Figure 4.2 reports the permanent income shock variance based on both welfare schemes. It indicates a considerable increase in net income risk after 2015, which reflects the implementation of Universal Credit, whereas, the permanent income shock variance for households under the Legacy System is relatively constant throughout both sample periods. Consequently, Figure 4.3 reflects the results in Table 4.4 and 4.5.

Figure 4.2: Income Risk based on Welfare Policies



Notes: Figure 4.2 reports that households under Universal Credit encounter considerably higher levels of permanent income shock variances after the welfare scheme implementation compared to the other groups.

Discussion Welfare Policies

This discussion focuses on the economic implications of the difference in net income risk exposure based on the British welfare schemes. The findings in Table 4.6 emphasise the utility welfare loss associated with the net income risk exposure of Universal Credit compared to the Legacy System. I consider the impact of a one standard deviation change in the permanent income shock variance. The estimates show that the utility welfare loss for households under Universal Credit is 1.32 percentage points higher compared to households under the Legacy System. Households under Universal Credit face a higher net income risk exposure associated with a higher utility welfare loss.

Table 4.7 shows the probability of households facing an income gain or loss of 10 per cent, 20 per cent or 30 per cent, based on the policy type. The results indicate that Universal Credit households are 24.23 per cent likely to face an income loss of 10 per cent due to an adverse income shock. In contrast, households under the Legacy System face a 12.37 per cent likelihood of encountering a 10 per cent income loss. Households under the Universal Credit programme are almost twice as likely to encounter an adverse income shock of 10 per cent. The findings further underpin the evidence of increased income risk for households under Universal Credit.

The utility welfare loss for households under Universal Credit can be translated into monetary terms. The results show that the utility welfare loss translates into a weekly loss of £22.64 for households under Universal Credit with a weekly income of around £246.55. This indicates considerable utility welfare and monetary loss for households under Universal Credit.

The utility welfare loss induced by Universal Credit has an impact on the household consumption choice. These losses result in a lower ability to smooth net income risks from one period to the next. Evidence from the National Audit Office (NAO) showed that households under Universal Credit did not have enough savings to last until their first payment was made (Gardiner, 2020). Furthermore, households under Universal Credit indicate problems with monthly budgeting due to fluctuating benefit payments under Universal Credit (Leete and Bania, 2009; Gardiner *et al.*, 2020). The evidence of the NAO combined with the findings of increased net income risk, confirm that households are worse off under the new welfare scheme. Complementing these findings, Thompson *et al.*(2019) find that the demand for food bank donations increased considerably in areas where Universal Credit was rolled out. They show that twelve months after the implementation of Universal Credit an increase of 30 per cent in the demand for local food bank donations was observed. In contrast, Thompson *et al.*(2019) find a rise of 13 per cent in non-Universal Credit areas based on data from 2015 until 2017. Hence, the implementation of Universal Credit is associated with a change in household consumption behaviour, that is, the choice shifts towards food bank donations. The net income risk results in Table 4.4 complement findings in the literature that emphasise financial losses for households receiving welfare under Universal Credit.

However, the structure of Universal Credit might stimulate net income risk through its non-financial incentives. A key aim of Universal Credit is to reduce poverty by motivating households to progress into work through a 'work commitment' policy. Yet, this also increases the variability of household income. Tucher (2017) finds that the monthly payments to households vary considerably through changes in benefit entitlements. The income variability is associated with employment transitions, for example extra hours worked. Thus, the new regulations associated with Universal Credit such as the work allowances and work commitment create a framework that exacerbates income variability, and hence the increase in net income risk observed in Table 4.3 and Figure 4.2 might also reflect the new policy structure.

A new policy structure can be developed by expanding the redistributive power of the tax and benefit system in the UK. The British tax and benefit system has been transformed into a less progressive system during the past 50 years. Thus, perhaps a way to finance a more generous welfare scheme is to revert back to a more progressive tax system (Adam, 2011). In addition, other ways to finance a more fair welfare scheme have been suggested such as increases in taxing of corporate and estate rents or regulating the functioning of tax havens (see e.g. Zucman, 2021). This topic deserves a separate and thorough analysis and is left for future research.

In summary, the results indicate a considerable difference in income risk between the two welfare schemes. The results indicate that households under Universal Credit face considerably higher income risk compared to households under the Legacy System. This is combined with evidence of an increased demand for food bank donations in the areas where Universal Credit has been rolled out. One way to address the issue is to implement a more progressive taxes and benefit system in order to raise funds that facilitate the implementation of a more generous Universal Credit.

Table 4.6: Utility Welfare Loss by Policy in Period 2

Welfare Policy	Loss in per cent	Utility Welfare Loss in per cent	Loss in £
Universal Credit	1.31%	3.11%	22.64£
Legacy System	0.90%	1.79%	16.18£

Notes: Table 4.6 indicates the higher utility welfare loss for households under Universal Credit; The loss indicates a one standard deviation change in the utility welfare.
of a negative permanent income shock from one period to the next.
Period 2 refers to 2015 until 2018.

Table 4.7: Probabilities of Permanent Income Shocks, Policy Type in period 2

Probability of income gain/loss		Permanent income shock in per cent	
		Legacy System	Universal Credit
		$\eta\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{LS}}\right)$	$\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{UC}}\right)$
income gain>30%:	$Pr(\zeta_{h,t} > \ln(1.30))$	0.20%	2.84%
income gain>20%:	$Pr(\zeta_{h,t} > \ln(1.20))$	2.25%	9.26%
income gain>10%:	$Pr(\zeta_{h,t} > \ln(1.10))$	14.7%	22.40%
income loss>10% :	$Pr(\zeta_{h,t} < \ln(0.90))$	12.37%	24.23%
income loss>20% :	$Pr(\zeta_{h,t} < \ln(0.80))$	0.71%	5.30%
income loss>30%:	$Pr(\zeta_{h,t} < \ln(0.70))$	0.00%	0.48%

Notes: Table 4.7 reports that households under Universal Credit are more likely to encounter an adverse permanent income shock compared with households under the Legacy System.
The probabilities of gains/losses are with respect to the level of permanent income under the mean shock.
Note that $\zeta_{h,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

4.5.2 Child Tax Credit Decomposition

The natural policy experiment focuses on the development of net income risk for welfare receiving households under the British welfare reform. This part of the analysis focuses on the role of child tax credit. A household with children and an income below about £32,200 could claim child tax credit on top of child benefit. The tax credit is "non-wastable" and is paid independently of employment status. It is integrated with the working tax credit, which also provides support for child care costs. Thus, the child tax credit is a form of guardians' allowance and indirect child benefit. Currently, the child tax credit is part of the Universal Credit structure. Incorporating the child tax credit decomposition in this analysis enables a new perspective on the distribution of net income risk based on the nature of each welfare policy. Tables 4.8 and 4.9 show net income risk for households with and without children under each welfare policy.

Table 4.8 compares households receiving allowances under the legacy system and the tracked Universal Credit households with and without children in period 1. The Legacy System net income risk estimates indicate that households without children face a higher variance of $\sigma^2_{\zeta,t} = 0.014$ permanent income shocks compared to households with children. It indicates that the benefits associated with the Legacy System mitigate some of the net income risk. Tracked Universal Credit households are not yet under a welfare policy. Yet, under the tax credit system households with children are eligible for a child tax credit. Consequently, tracked Universal Credit households face a lower income risk with a difference of $^2_{\zeta,t} = 0.0042$. The ratio of the risk ratio for benefit recipients indicates that households with children encounter higher income variation than households without children under a welfare scheme.

Table 4.8: Household Average Net Income Risk, Child Tax Credit, Period 1

Welfare Policy	Children		No Children	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{BRH}}$	$\sigma^2_{\zeta_t^{BRH}}$	$\sigma^2_{\varepsilon_t^{BRH}}$	$\sigma^2_{\zeta_t^{BRH}}$
Legacy System	0.0726***	0.0028***	0.0978***	0.0168***
s.e.	(0.0025)	(0.0015)	(0.0046)	(0.0014)
Sample Size	8,835		19,000	
Tracked Universal Credit	0.0657***	0.0048***	0.0406***	0.0090***
s.e.	(0.0036)	(0.0019)	(0.0030)	(0.0004)
Sample Size	9,066		400	
Risk Ratio $(\frac{UC}{LS})$		1.7***		0.5***

Notes: Table 4.8 reports that the income shock variances for households receiving allowances in period 1;*** indicates p-value<0.01;**indicates p-value<0.05.; *indicates p-value<0.1.; The bootstrap standard errors are based on 1000 replications and are presented in parentheses. In Period 1, which refers to 2009 until 2015; Net household income ; The sample refers to benefit receiving households (BHR).

Table 4.9 shows the net income risk estimates with the Universal Credit implementation in Period 2. The results for the Legacy System show a similar pattern as in Period 1. Households with children encounter lower net income risk. In contrast, households with children under Universal Credit face higher net income risk compared to households with no children, with a difference $\sigma_{\zeta,t} = 0.0256$. Figure 4.3 highlights the difference between permanent income shocks under each system. Thus, the transition from the Legacy System to Universal Credit indicates that the benefit reductions affect child tax credits. The main finding in Table 4.9 and Figure 4.3 is of a shift in welfare targeting. Permanent risk estimates for households with children under the Legacy System and under Universal Credit are significantly different at the 90 per cent confidence interval. The same holds for households without children, where permanent risk estimates are also significantly different at the 90 per cent confidence interval.

The estimates for Universal Credit show that the net income risk has increased for households with children, while it has decreased for childless households. Consequently, the estimates provide evidence of a change in social insurance associated with the implementation of Universal Credit. The ratio of the risk ratio for benefit recipients indicates that welfare receiving households with children encounter considerably higher income variation than households receiving support without children.

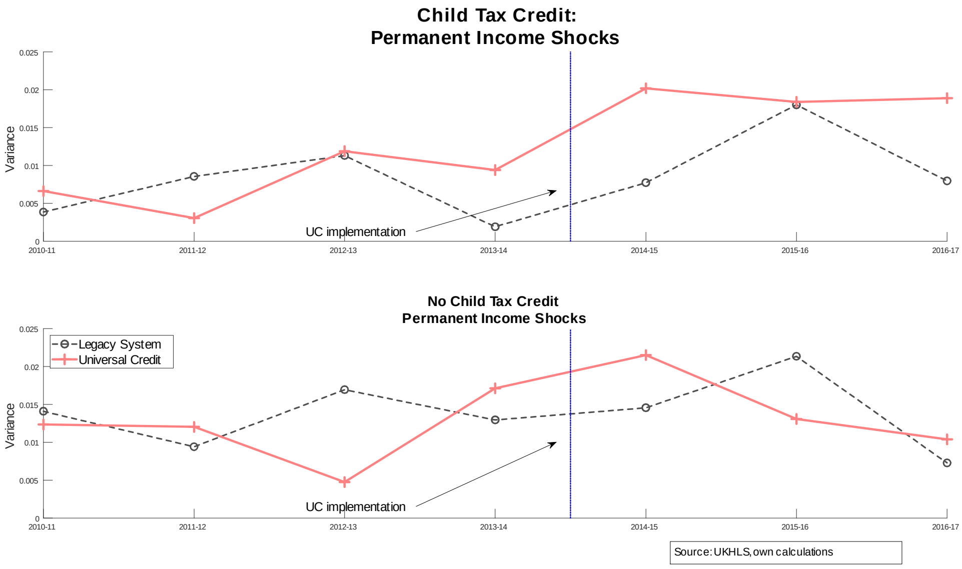
Table 4.9: Household Average Net Income Risk, Child Tax Credit, Period 2

Welfare Policy	Children		No Children	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{BRH}}$	$\sigma^2_{\zeta_t^{BRH}}$	$\sigma^2_{\varepsilon_t^{BRH}}$	$\sigma^2_{\zeta_t^{BRH}}$
Legacy System	0.0728***	0.0031***	0.0900***	0.0185***
s.e.	(0.0028)	(0.0014)	(0.0036)	(0.0022)
Sample Size	2,807		7,501	
Universal Credit	0.0572***	0.0459***	0.1161***	0.0203***
s.e.	(0.0033)	(0.0029)	(0.0057)	(0.0039)
Sample Size	1,066		300	
Risk Ratio ($\frac{UC}{LS}$)		14.8***		1.2***

Notes: Table 4.9 reports that the income shock variances for households receiving allowances in period 2;*** indicates p-value<0.01;**indicates p-value<0.05.; *indicates p-value<0.1.; The bootstrap standard errors are based on 1000 replications and are presented in parentheses. In Period 2, which refers to 2015 until 2018; Net household income ; The sample refers to benefit receiving households (BHR).

Figure 4.3 shows the permanent income shocks under each welfare policy considering child tax credit. It confirms the average permanent income shock estimates and shows that households with children under Universal Credit face higher net income risk relative to childless households. The net income risk patterns for the Legacy System are not influenced by presence of children in the household.

Figure 4.3: Income Risk Estimation based on Child Tax Credit



Notes: Figure 4.3 shows that households under the new child tax credits encounter considerably higher levels of permanent income shock variances.

Discussion Child Tax Credit

This discussion focuses on the economic implications of net income risk based on the presence of children for households under different welfare schemes. The findings in Table 4.10 emphasise the utility welfare loss associated with the net income risk exposure under Universal Credit compared to the Legacy System. I consider the impact of a one standard deviation change in the permanent income shock variance. Universal Credit receiving households face a higher net income risk accompanied by a higher utility welfare loss of 3.85 per cent. The estimates show that the utility welfare loss for households under Universal Credit is 1.32 percentage points higher compared to households under the Legacy System.

This utility welfare loss can be translated into monetary terms, and is equivalent to a weekly loss of £31.72 for households under Universal Credit with a weekly income of around £249.55 (see Table 4.10). Consequently, another key finding is the considerable utility welfare and monetary loss for households with children who receive benefits under Universal Credit. In contrast, households with children under the Legacy System encounter considerably less

Another way to quantify permanent income shocks is by expressing them in terms of probabilities. Table 4.11 shows the likelihood of a welfare receiving household with children encountering a 10 per cent, 20 per cent or 30 per cent income gain or loss. The results indicate that Universal Credit households with children are 32.14 per cent likely to face an income loss of 10 per cent due to an adverse permanent income shock. In contrast, households with under the Legacy System face a 2.92 per cent likelihood of encountering a 10 per cent income loss. Consequently, households with children under Universal Credit face a considerably higher probability to facing an adverse permanent income shock of 10 per cent.

Child tax credits are an indirect benefit to support low-income households with children. Brewer *et al.*(2005) emphasise the key role of the generosity of benefits and tax credits in supporting net income growth among low-wage benefit receiving households in the UK (Brewer *et al.*, 2005; Blundell *et al.*, 2016). Thus, both direct and indirect benefits create social insurance against adverse income shocks. Between 1998 and 2003 reducing child poverty was made a government priority. The empirical evidence indicates that increases in benefits directly influence a household's consumption choices. The role of the rise in child support is a key example of the impact of benefits on consumption choice (Gregg *et al.*,2005; Waldfogel, 2008), supporting an increase in consumption spending. Waldfogel (2008) compares the effects between the UK and the US and finds that low-income households in both countries who are affected by the reforms increase spending. Consequently, the empirical evidence shows that household spending increases with the generosity of benefit payments.

However, Universal Credit is characterised by considerable austerity features. Child support is at a record low in terms of generosity, with lower rates than those offered under the Legacy System. The implementation process for Universal Credit includes several key austerity features to reduce the child tax credit support, such as lower rates, the removal the first child premium and the two-child limit (Brewer *et al.*, 2016). These features result in a considerable decrease in child tax credits for Universal Credit recipients (Tucker, 2019). The results in Table 4.7 and Figure 4.3 indicate a shift in welfare support for households under this programme, including a welfare loss for households with children (see Table 4.10). Consequently, the findings indicate that social insurance has decreased under Universal Credit. While this makes it a more cost efficient welfare policy, as a consequence of the austerity features in Universal Credit, receiving households with children face higher levels of income risk.

Moreover, the welfare policy reform has changed the nature of child tax credits. Under Universal Credit the child tax credit is shaped by means-testing. As a result, the child tax credit varies based on the income level of the welfare receiving households, complementing the findings in Table 4.10. Consequently, the nature of the child tax credit generates more income volatility, which translates into higher income risk for households with children under Universal Credit.

Higher levels of income risk can affect the development of the children. Too much change in income and economic circumstances can disrupt investment in children and parenting practices, particularly when the income changes are unanticipated. Adams *et al.*(2016), and Hardy and Hill (2019), argue that income changes affect stress levels of both parent and child. Moreover, Dahl and Lochner (2012) provide evidence that income variation associated with high levels of income risk affects a child's mathematics and reading achievement. They use an instrumental variable approach to test how the expansion of earned income tax credit affects a child's potential mathematics and reading ability. The study indicates a positive impact of an increase in household income through tax credits on children's mathematics and reading test scores [3].

Overall, the results indicate a considerable difference in income risk considering the child tax credit. It shows that households with children under Universal Credit face considerably higher income risk compared with households under the Legacy System. In addition, the empirical findings of the literature highlight the importance of long-lasting impact of welfare support on a child's health and educational development (Dahl and Lochner, 2012; Hardy and Hill, 2019). Consequently, the findings of this analysis combined with the evidence of the empirical literature highlight the importance of maintaining child-specific welfare support that induces income stability.

[3] Dahl and Lochner's (2012) baseline estimates imply that a $1,000 increase in income raises contemporaneous maths and reading test scores by 6 percent of a standard deviation.

Table 4.10: Utility Welfare Loss, Child Tax Credit, Period 2

Welfare Policy	Loss in per cent	Utility Welfare Loss in per cent	Loss in £
Universal Credit	1.61%	3.85%	31.72£
Legacy System	0.50%	1.05%	13.83£

Table 4.10 shows that households under UC face a higher utility welfare loss. Period 2 refers to 2015 until 2018; The loss indicates a one standard deviation change in the utility welfare of a negative permanent income shock from one period to the next.

Table 4.11: Probabilities of Permanent Income Shocks, Child Tax Credit, Period 2

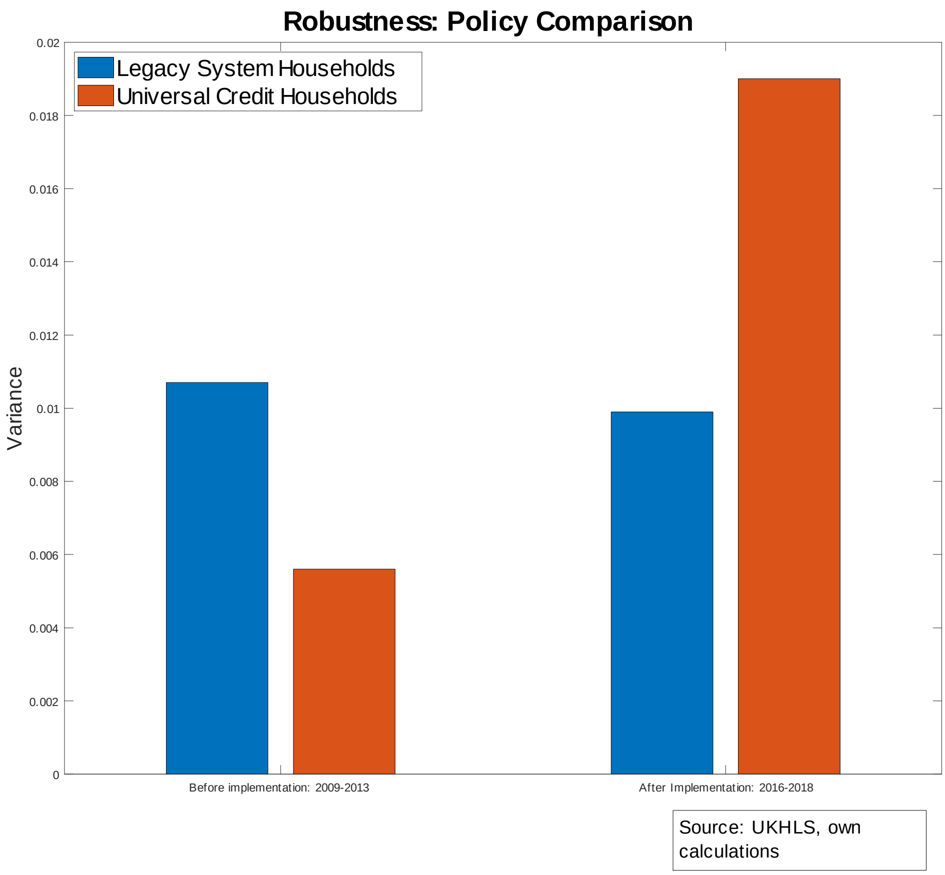
Probability of income gain/loss		Permanent income shock in per cent	
		Legacy System with children	Universal Credit with children
		$\eta\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{LS}}\right)$	$\zeta_{h,t} \sim N\left(0, \sigma^2_{\zeta_t^{UC}}\right)$
income gain>30%:	$Pr(\zeta_{h,t} > \ln(1.30))$	0.12%	11.02%
income gain>20%:	$Pr(\zeta_{h,t} > \ln(1.20))$	0.05%	19.70%
income gain>10%:	$Pr(\zeta_{h,t} > \ln(1.10))$	4.30%	31.77%
income loss>10% :	$Pr(\zeta_{h,t} < \ln(0.90))$	2.92%	32.14%
income loss>20% :	$Pr(\zeta_{h,t} < \ln(0.80))$	0.20%	14.87%
income loss>30%:	$Pr(\zeta_{h,t} < \ln(0.70))$	0.23%	4.80%

Table 4.11 reports that households under Universal Credit are more likely to encounter an adverse permanent income shock compared with households under the Legacy System. The probabilities of gains/losses are with respect to the level of permanent income under the mean shock. Note that $\zeta_{h,t}$ refers to the natural logarithm of permanent shocks to labour income, and has zero mean.

4.5.3 Robustness Check: Exclusion Implementation Period

This section focuses on the robustness of the results. Figure 4.4 shows the permanent income shock variance without the implementation period of Universal Credit for welfare receiving households. These estimates do not include the implementation period in wave 5, which translates to the years 2014-2015. By excluding the transition period any associated risks are removed, which highlights the robustness of the findings. It shows a difference of $\sigma^2_{\zeta_t^{BRH}} = 0.0091$ in permanent income risk after the implementation for households receiving Universal Credit. Consequently, the robustness test supports the evidence that Universal Credit receiving households face higher income risk compared to households under the Legacy System.

Figure 4.4: Robustness Check Household Income Risk excluding UC implementation period



Notes: Figure 4.4 shows the same income risk patterns when excluding the implementation period of Universal Credit.

4.6 Conclusion

This chapter focuses on the size of social insurance generated by the welfare policies for programme recipients in the UK, using the ongoing welfare reform there as a natural policy experiment. Social insurance creates a lower exposure to labour income risk through policies such as benefit payments. In other words, it influences the net income risk that welfare receiving households face. The findings indicate a higher net income risk under Universal Credit. The chapter expresses net income risk in the form of a permanent and a transitory component, based on the PIH (see Chapter 1 for a detailed review). The UKHLS data set maintains information on welfare receiving households for this analysis from 2009 to 2018. In particular, it contains information on income variables of each welfare policy within the period. It enables a comparison of net income risk and social insurance and shows the change in household net income risk associated with the welfare reform.

The work contributes to the literature with a unique analysis of this natural policy experiment and its impact on social insurance in the UK. It compares social insurance against adverse income shocks under both the Legacy System and Universal Credit. The natural policy experiment enables a direct comparison between the two welfare policies. Moreover, the implementation date of the British welfare reform in 2015 enables a 'before and after' comparison of net income risk over the same time period for both policies. This approach shows the change in net income risk after the implementation of Universal Credit. It provides evidence of the different size of social insurance under Universal Credit compared to the Legacy System. Consequently, the higher income risk under Universal Credit could create an incentive to progress in employment due to the lower social insurance provided to programme recipients.

The analysis provides new insights regarding the size of social insurance in the UK. Households under Universal Credit encounter higher income risk compared to households under the Legacy System. Universal Credit recipients are almost twice as likely to face an adverse permanent income shock of 10 per cent compared to households under the Legacy System. The probability of encountering an adverse income shock is even higher for welfare receiving households with children. This difference is associated with the newly implemented policy measures such as benefit reductions through Universal Credit. Consequently, these findings confirm the lower size of social insurance provided by Universal Credit, which in turn leads to lower household well-being, combined with a higher probability of experiencing an adverse income shock. In other words, the net income risk mitigation effect of social insurance has decreased under Universal Credit compared to the Legacy System.

In contrast, for the Legacy System the natural policy experiment indicates that net income risk is stable. The results show a marginal change in the income risk between period 1 and period 2. Consequently, this chapter provides new evidence of the increase in net income risk combined with lower social insurance resulting from the implementation of Universal Credit. The findings complement literature indicating financial losses due to the new Universal Credit policy framework, such as De Agostini *et al.* (2017), Brewer *et al.* (2018), and Cribb (2018).

The British government should consider the effects of net income risk on social insurance in their policy design. The findings of this research indicate higher net income risk for households, and consequently a lower net income risk mitigation effect of social insurance under Universal Credit compared to the Legacy System. In particular, within the development of Universal Credit policymakers should focus on mitigating losses in well-being associated with adverse income shocks. The higher net income risk under Universal Credit could be associated with its recently implemented tools such as benefit reductions, changes in work allowances and changing entitlement levels. In particular, welfare policy should stimulate a supportive economic framework for welfare receiving households with children, as these are especially exposed to net income risk. Social policy design can be improved with better knowledge of the size of income risk and its distribution across the welfare programme receiving population. From a policymaker's perspective, this chapter provides new evidence suggesting that future welfare policy design should take income risk into account.

One limitation of this research concerns the time dimension of UKHLS and the roll-out of the social policies. Currently, information is available from 2009-2018. The short period does not allow for a long-run examination. Also the roll-out of the welfare reform is unfinished. Currently, the it is estimated to be finalised in 2023. Once the Universal Credit roll-out is complete there will be a larger sample of households receiving welfare, allowing a deeper insight into the dynamics between net income risk and social insurance for programme recipients. Another, shortcoming is that the analysis does not allow the use of gross labour income, as some of welfare receiving households have no income according to this metric. Consequently, I focus on the net income for programme recipients. This initial limitation, however, has the benefit that households base their choices on net income.

Future research should focus on the effects of non-financial policies in the welfare system. Changes in non-financial policy measures such as work commitment are likely to be important in the development of social insurance as they contribute to households' progress in work. In addition, this chapter lays the foundation for future research into family classifications of the household under Universal Credit. The analysis by family type could further indicate how the Universal Credit support is distributed across households.

CHAPTER

5

APPENDICES

5.1 Appendix Chapter A1

5.1.1 Appendix A1: Variable Overview

This section reflects on the Chapter 1. Table $A1.1$ provides the descriptive statistics for net income based on weekly wages across for the entire sample of the UKHLS.

Table $A1.1$: Summary Statistics of Weekly Wage, UK

Subgroup	Mean	S.D.	Min.	Max.
Entire Sample	281.92	188.18	2.38	2402.62

Source: UKHLS.

Table $A1.2$: Variable Information

Income	Definition	Variables
Net Individual Income	Net Personal weekly income.	fimnnet_dv

Source: UKHLS

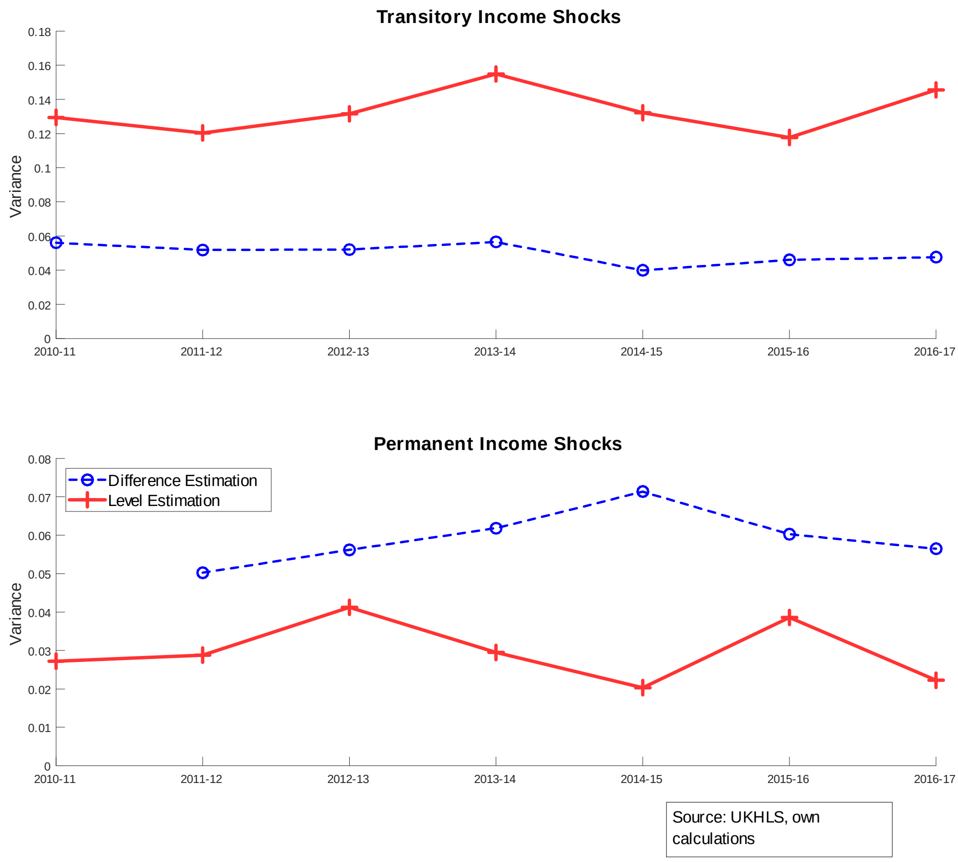
5.1.2 Appendix A2: Identification Scheme Puzzle

A body of work in the income risk literature focuses on estimating the stochastic processes of earnings for individuals (or households). The literature is shaped by a debate on two types of identification scheme. Currently, income shocks can be identified through using i) a level approach or ii) a first differences approach. Both schemes are used in the literature (Heathcote *et al.*,2010). The first, more common in macroeconomic applications (e.g., Storesletten *et al.*, 2004b; Guvenen, 2007; Heathcote *et al.*, 2008), uses moments in log income levels, although either approach can be used to estimate the permanent-transitory model. The second, common in labour economics (e.g., Abowd and Card, 1989; Meghir and Pistaferri, 2004; Blundell *et al.*, 2008), uses moments based on income growth rates, or first differences in log income.

Given the availability of data and the research approach both methods can be used to identify the permanent-transitory model. The key distinction between the schemes are the structural parameters that can be identified. The level identification scheme enables me to exploit more data observations compared to the first difference approach. Further, examining the same data, the estimates of the income process in Chapter 1 Section 1.4, when targeting the moments in log-wages, the size between the transitory and permanent income shocks flips between the identification schemes. Although this discrepancy was first documented using survey-based data it is also identified when using administrative data. They nature of this discrepancy is inconclusive and identified by Brzozowski *et al.*, (2010) for Canada, Domeij and Flodén, (2010) for Sweden, Fuchs-Schündeln *et al.*, (2010) for Germany, Heathcote *et al.*, (2010) for the USA and Hryshko *et al.*, (2018) for Germany and Denmark.

The evidence of the UKHLS reflects the identification scheme puzzle. Figure $A2.1$ shows an inflated variance in the permanent income shock in first differences but a deflated permanent income shock in levels. In contrast, the variance of the transitory income shock is inflated in levels, whilst the first difference estimates indicate a deflated variance of the permanent income shock. To date, it is unclear what drives the differences in the size of the permanent and transitory income shocks between both identification schemes. Comparing the income risk ranking based on the group decomposition indicates the same income risk heterogeneity based on ethnicity and gender. Consequently, the identification in first differences is a robustness test for the results found in the level identification process.

Figure $A2.1$: Identification Puzzle



Notes: Figure A2.1 shows the income risk based on each identification puzzle.

5.2 Appendix Chapter B2

5.2.1 Appendix B2: Variable Overview

Income Variables

Appendix B2 gives the descriptive statistics in Chapter 2. This chapter focuses on the individual income risk. The key income variable is net income, which includes labour market income, miscellaneous income, taxation deductions, benefits and personal income. The gross income variables reflect gross labour income before taxes and benefits. Table 2.1 lists the respective variables from the dataset.

Table B2.1: Definition of Income Types

Income	Definition	Variables
Gross Individual Income	Gross personal weekly labour income.	fimnlabgrs_dv
Individual Benefits	Private personal benefit income.	fimnprben_dv
Miscellaneous income	Miscellaneous personal income.	fimnmisc_dv
Net Individual Income	Net Personal weekly income.	fimnnet_dv

Notes: Table B2.1 provides a list of income types.

Source: UKHLS

Table B2.2 summarises statistics of weekly wages in the UK. In contrast, part-time workers earn on average the lowest weekly wage with £122.31. Considering only full-time workers Table C2.1 shows that women earn the lowest weekly wage, £220.90.

Table B2.2: Summary Statistics Net Individual Income

Subgroup	Mean	S.D.	Min.	Max.
		Gender		
Women	220.90	162.42	0.0093	2250.36
Men	331.31	214.76	0.0093	2402.62
		Ethnicity		
White	277.77	198.22	0.0093	2402.62
Non-White	254.21	193.38	0.0095	2005.62
		Marital Status		
Married	284.88	204.69	0.0093	2402.62
Single	240.49	167.20	0.0093	2402.62
		Parenthood		
Parent	272.19	207.46	0.0095	2296.24
Non-Parent	276.77	188.49	0.0093	2402.62
		Urban-Rural Classification		
Urban	272.70	272.70	0.0094	2296.24
Rural	296.24	2296.24	0.0095	2402.625
		Employment Status		
Full-time	318.51	318.51	0.0093	2402.62
Part-Time	122.31	115.00	0.0093	2112.58
Employed	277.34	187.47	0.0096	2402.62
Self-Employed	259.24	277.83	0.0093	2402.62

Notes: Table B2.2 provides the summary statistics on income; Source: UKHLS.

Table B2.3 shows the sample sizes of each group. It indicates a larger sample for women compared to men.

Table B2.3: Sample Size by group, UK

Subgroup	Sample Size	Women	Men	White	Non-White
		Gender			
Women	94,785	-	-	78,801	15,331
Men	78,327	-	-	65,947	11,680
		Ethnicity			
White	144,748	78,801	65,947	-	-
Non-White	27,011	15,331	11,680	-	-
		Marital Status			
Married	119,761	63,657	56,104	101,807	17,411
Single	53,109	30,983	22,126	42,744	9,558
		Education			
University Degree	47,427	26,113	21,314	38,720	8,520
High School Degree	80,951	44,144	36,807	71,212	9,417
		Parenthood			
Parent	79,185	46,386	32,781	62,890	15,719
Non-Parent	93,945	48,399	45,546	81,858	11,292
		Urban-Rural Classification			
Urban	135,196	74,095	61,101	107,871	26,427
Rural	37,916	20,690	17,226	36,877	5844
		Employment Status			
Full-time	101,121	43,350	57,771	87,622	12,747
Part-Time	29,733	24,135	5,598	25,069	4,446
Employee	117,905	62,861	55,044	91,206	13,427
Self-Employed	13,754	5,080	8,674	8,710	19,354

Note: Figure B2.3 shows the sample sizes of each group;

Source: Data is based on the UKHLS.

Table B2.4. provides information on the level of education by gender and ethnicity. The education level distinguishes three groups: 'University degree', 'A-levels, O-levels or apprenticeship', and 'No degree'. The sample sizes show that men and White individuals hold the majority of university degrees. In contrast, Non-White individuals hold most of the A-levels, O-levels and apprenticeships.

Table B2.4: Education Decomposition, Sample Size

Subgroup	Women	Men	White	Non-White
University Degree	26,113	21,314	38,720	8,520
Non-University Degree	56,096	47,049	89,209	13,536
Total	82,209	68,363	127,929	22,056

Notes: Table B2.4 indicates the sample size by education qualification.

Source: UKHLS

Further, Table B2.5 provides evidence of employment status across gender and ethnicity. The distribution of the sample indicates that women are more likely to be self-employed, while men hold more full-time positions. Considering different ethnic backgrounds the sample shows that Non-White individuals are more likely to be self-employed, while White individuals are more likely to be employed.

Table B2.5: Employment Status Decomposition, Sample Size

Subgroup	Women	Men	White	Non-White
Full Time	43,350	57,771	87,622	12,747
Part Time	24,135	5,598	25,069	4,446
Self-Employed	8,674	5,080	11,766	15,340
Employed	62,861	55,044	101,625	1,955

Notes: Table B2.5 indicates the sample size by employment status.

Source: UKHLS

5.2.2 Appendix B2: Net Income Risk Results in First Differences

UK Results

This section focuses on the income risk estimation based on first differences using individual net income. Tables B2.6 and B2.7 report the transitory and permanent income shock variances for individuals in the UK. I follow the same group decomposition approach and differentiate the individuals based on certain characteristics. The size of the transitory and permanent income shocks differs based on the first difference identification scheme compared to the level approach. Yet, the income risk heterogeneity patterns hold across both identification schemes, which indicates robustness. The permanent income shocks are considerably higher for women, with the respective differences of $\sigma^2_{\varepsilon,t} = 0.0146$ and $\sigma^2_{\zeta,t} = 0.0046$ compared to the income risk faced by men. Similarly, Non-White individuals encounter higher income risk than White individuals, with the difference of $\sigma^2_{\varepsilon,t} = 0.0065$ and $\sigma^2_{\zeta,t} = 0.0139$. Consequently, the income risk estimates in Tables B2.5 and B2.6 support the evidence of income risk heterogeneity based on gender and ethnicity. The income risk inequalities are further confirmed in Tables B2.9 to B2.10, which examine the group income risk in more detail.

Table B2.6: Net Individual Income Risk Estimation, UK, First Diff.

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
Entire Sample	0.0646***	0.0360***
s.e.	(0.0032)	(0.0017)
	Gender	
Women	0.0793***	0.0407***
s.e.	(0.0039)	(0.0024)
Men	0.0647***	0.0361***
s.e.	(0.0032)	(0.0017)
	Ethnicity	
White	0.0639***	0.0346***
s.e.	(0.0035)	(0.0019)
Non-White	0.0704***	0.0485***
s.e.	(0.0048)	(0.0016)

Notes: Table B2.6 shows the income risk heterogeneity across groups. Individual Net income; The estimation is based on the differences identification scheme. *significant at $p < 0.1$;**significant $p < 0.05$;***significant at $p < 0.01$;The bootstrap standard errors are based on 1000 replications and presented in in parentheses.

Table B2.6 continues to document income risk based on the first difference estimation. The group decomposition focuses on marital status, parenthood, urban-rural classification and employment status. In particular, part-time workers and self-employed individuals face higher income risk. The sample sizes of each group are reported in Table B2.3.

Table B2.7: Net Individual Income Risk Estimation, UK, First Diff.

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
	Marital Status	
Married	0.0633***	0.0352***
s.e.	(0.0034)	(0.0018)
Single	0.0684***	0.0413***
s.e.	(0.0082)	(0.0045)
	Parenthood	
Parent	0.0595***	0.0438***
s.e.	(0.0084)	(0.0034)
Non-Parent	0.0705***	0.0263***
s.e.	(0.0044)	(0.0024)
	Urban-Rural Classification	
Urban	0.0797***	0.0301***
s.e.	(0.0035)	(0.0018)
Rural	0.0606***	0.0368***
s.e.	(0.0069)	(0.0042)
	Employment Status	
Full-time	0.0459***	0.0440***
s.e.	(0.0029)	(0.0014)
Part-Time	0.0574***	0.2614***
s.e.	(0.0030)	(0.0028)
Employed	0.0388***	0.0261***
s.e.	(0.0016)	(0.0012)
Self-Employed	0.3001***	0.1288***
s.e.	(0.0029)	(0.0017)

Notes: Table B2.7 shows the income risk heterogeneity across groups; The estimation is based on first differences . *significant at $p < 0.1$; **significant; $p < 0.05$;***significant at $p < 0.01$;The bootstrap standard errors are based on 1000 replications and presented in parentheses.

Gender Decomposition First Differences

Tables B2.8 and B2.9 report the transitory and permanent income shock variances for each wave based on gender. The group heterogeneity patterns are robust between the estimation methods. The results based on differences show the same ranking between the groups as the estimation in levels. The results indicate a difference based on gender, with women facing higher net income risk than men. The sample sizes of each group are reported in Table B2.3.

Table B2.8: Net Individual Income Risk Estimation, UK, First Diff., Gender

Subgroup	Women		Men	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{Women}}$	$\sigma^2_{\zeta_t^{Women.}}$	$\sigma^2_{\varepsilon_t^{Men}}$	$\sigma^2_{\zeta_t^{Men}}$
		Marital Status		
Married	0.0532***	0.0261***	0.0633***	0.0352***
s.e.	(0.0034)	(0.0018)	(0.0034)	(0.0018)
Single	0.0784***	0.0512***	0.0684***	0.0413***
s.e.	(0.0032)	(0 .0025)	(0.0032)	(0 .0045)
		Urban Rural Classification		
Urban	0.0601***	0.0343***	0.0797***	0.0301***
s.e.	(0.0025)	(0.0028)	(0.0035)	(0.0018)
Rural	0.0636***	0.0389***	0.0606***	0.0368***
s.e.	(0.0059)	(0.0032)	(0.0069)	(0.0042)
		Ethnicity		
White	0.0711***	0.0406***	0.0639***	0.0345***
s.e.	(0.0035)	(0.0014)	(0.0035)	(0.0019)
Non-White	0.0813***	0.0459***	0.0704***	0.0485***
s.e.	(0.0041)	(0.0039)	(0.0068)	(0.0036)

Notes: Table B2.8 shows the income risk heterogeneity based on gender; Individual Net income; The estimation is based on first differences identification scheme. *significant at $p < 0.1$;**significant $p < 0.05$;***significant at $p < 0.01$;The bootstrap standard errors are based on 1000 replications and presented in in parentheses.

Table B2.9 shows income risk heterogeneity by gender. The income risk estimation is based on first differences, and supports the findings on income risk heterogeneity based in gender. Women across all subgroups face higher income risk compared to men, particularly when they work part-time or are a parent. The estimates in Table B2.9 also suggests that age cohort plays a role complementing the evidence in Chapter 1. The sample sizes of each group are reported in Table B2.3.

Table B2.9: Net Individual Income Risk Estimation, UK, First Diff., Gender

Subgroup	Women		Men	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{Women}}$	$\sigma^2_{\zeta_t^{Women.}}$	$\sigma^2_{\varepsilon_t^{Men}}$	$\sigma^2_{\zeta_t^{Men}}$
		Parenthood		
Parent	0.0411***	0.0201***	0.0388***	0.0261***
s.e.	(0.0035)	(0.0024)	(0.0034)	(0.0034)
Non-Parent	0.0511***	0.0537***	0.0595***	0.0438***
s.e.	(0.0044)	(0.0004)	(0.0043)	(0.0024)
		Employment Status		
Full-time	0.0459***	0.0440***	0.0459***	0.0340***
s.e.	(0.0039)	(0.0019)	(0.0029)	(0.0014)
Part-Time	0.2074***	0.3214***	0.1074***	0.2614***
s.e.	(0.0027)	(0.0011)	(0.0306)	(0.0289)
Employed	0.0288***	0.0361***	0.0388***	0.0261***
s.e.	(0.0031)	(0.0016)	(0.0016)	(0.0012)
Self-Employed	0.0300***	0.2288***	0.3006***	0.1288***
s.e.	(0.0037)	(0.0067)	(0.0081)	(0.0077)

Notes: Table B2.9 shows the income risk heterogeneity based on gender; Individual Net income; The estimation is based on the differences identification scheme. *significant at $p < 0.1$;**significant $p < 0.05$;***significant at $p < 0.01$;The bootstrap standard errors are based on 1000 replications and presented in in parentheses.

Ethnicity Decomposition First Differences

Tables B2.10 and B2.11 show income risk heterogeneity by ethnicity. The income risk estimation is based on first differences. Non-White individuals across all subgroups face higher income risk compared to White individuals, particularly when they are self-employed or working in part-time positions. Thus, the income risk estimates support the findings on income risk heterogeneity based in ethnicity. The sample sizes of each group are reported in Table B2.3.

Table B2.10: Net Individual Income Risk Estimation, UK, First Diff., Ethnicity

Subgroup	White		Non-White	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{White}}$	$\sigma^2_{\zeta_t^{White.}}$	$\sigma^2_{\varepsilon_t^{Non-White}}$	$\sigma^2_{\zeta_t^{Non-White}}$
Entire Sample	0.0639***	0.0346***	0.0704***	0.0485***
s.e.	(0.0035)	(0.0019)	(0.0078)	(0.0036)
		Marital Status		
Married	0.0621***	0.0352***	0.0731***	0.0350***
s.e.	(0.0038)	(0.0020)	(0.0082)	(0.0042)
Single	0.0712***	0.0300***	0.1298***	0.0473***
s.e.	(0.0032)	(0.0051)	(0.0091)	(0.0045)
		Urban Rural Classification		
Urban	0.0804***	0.0294***	0.0716***	0.0470***
s.e.	(0.0039)	(0.0020)	(0.0080)	(0.0038)
Rural	0.0588***	0.0351***	0.0292***	0.1024***
s.e.	(0.0027)	(0.0043)	(0.0060)	(0.0049)
		Gender		
Women	0.0711***	0.0406***	0.0639***	0.0345***
s.e.	(0.0035)	(0.0014)	(0.0035)	(0.0019)
Men	0.0639***	0.0345***	0.0704***	0.0485***
s.e.	(0.0035)	(0.0019)	(0.0048)	(0.0036)

Notes: Table B2.10 shows the income risk heterogeneity based on ethnicity; Individual net income; The estimation is based on the differences identification scheme; *significant at $p < 0.1$;**significant $p < 0.05$;***significant at $p < 0.01$;The bootstrap standard errors are based on 1000 replications and presented in in parentheses. $\sigma^2_{\varepsilon,t}$= transitory income shock variance; $\sigma^2_{\zeta,t}$= permanent income shock variance.

Table B2.11: Net Individual Income Risk Estimation, UK, First Diff., Ethnicity

Subgroup	White		Non-White	
	Transitory Income Shock	Permanent Income Shock	Transitory Income Shock	Permanent Income Shock
	$\sigma^2_{\varepsilon_t^{White}}$	$\sigma^2_{\zeta_t^{White.}}$	$\sigma^2_{\varepsilon_t^{Non-White}}$	$\sigma^2_{\zeta_t^{Non-White}}$
		Parenthood		
Parent	0.0604	0.0401	0.0509***	0.0833***
s.e.	(0.0040)	(0.0035)	(0.0037)	(0.0048)
Non-Parent	0.0684	0.0264	0.0832***	0.0273***
s.e.	(0.0036)	(0 0025)	(0.0040)	(0.0019)
		Employment Status		
Full-time	0.0452***	0.0420	0.0516***	0.0613***
s.e.	(0.0023)	(0.0022)	(0.0025)	(0.0032)
Part-Time	0.1208***	0.2231***	0.0477***	0.2738***
s.e.	(0.0051)	(0 0025)	(0.0029)	(0.0018)
Employed	0.0381***	0.0254***	0.0445***	0.0319***
s.e.	(0.0017)	(0.0012)	(0.0024)	(0.0016)
Self-Employed	0.3012***	0.1215***	0.3039***	0.2142***
s.e.	(0.0041)	(0.0015)	(0.0049)	(0.0031)

Notes: Table B2.11 shows the income risk heterogeneity based on ethnicity; Individual Net income; The estimation is based on first differences identification scheme.
*significant at $p < 0.1$;**significant $p < 0.05$;***significant at $p < 0.01$;
The bootstrap standard errors are based on 1000 replications and presented in in parentheses.
$\sigma^2_{\varepsilon,t}$= transitory income shock variance; $\sigma^2_{\zeta,t}$= permanent income shock variance

5.2.3 Appendix B2: Gross Income Risk Results in Levels

UK Results

This section presents the gross income risk estimates for the subgroups of the entire sample of the UKHLS in Table B2.12 $- B2.13$. It focuses on income risk dispersion based on the subgroups of gender, ethnicity, marital status, parenthood, urban-rural classification and employment status, as seen in Chapter 2. The estimates in Table B2.12 indicate that particularly women and Non-white individuals face higher levels of income risk. Table B2.13 reports that married individuals, parents, individuals living in rural areas and individuals who a part-time working and self-employed encounter higher levels of income risk. The heterogeneity of income risk reflects the main findings in Chapter 2. Consequently, the exercise on gross income risk provides evidence that the income risk heterogeneity patterns translate from gross income to net income (see Chapter 2 for net income risk estimates). Further, Table $B2.14 - B2.17$ lists the gross income risk by gender and ethnicity decomposition. Also here the same patterns as in Chapter 2 can be observed. The sample sizes of each group are reported in Table B2.3.

Table B2.12: Gross Individual Income Risk , UK in Levels

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
	Marital Status	
Women	0.1316***	0.0454***
s.e.	(0.0061)	(0.0059)
Men	0.0993***	0.0231***
s.e.	(0.0056)	(0.0043)
	Parenthood	
White	0.1031***	0.0212***
s.e.	(0.0080)	(0.0042)
Non-White	0.1081***	0.0248***
s.e.	(0.0065)	(0.0051)

Notes: Table B2.12 shows the income risk heterogeneity across groups; Individual Gross income; The estimation is based on the differences identification scheme; $\sigma^2_{\varepsilon,t}$= transitory income shock variance; $\sigma^2_{\zeta,t}$= permanent income shock variance; *significant at p<0.1;.**significant at p<0.05;***significant at p<0.01

Table B2.13: Gross Individual Income Risk , UK in Levels

Subgroup	Transitory $\sigma^2_{\varepsilon_t^{UK}}$	Permanent $\sigma^2_{\zeta_t^{UK}}$
	Marital Status	
Married	0.0931***	0.0375***
s.e.	(0.0057)	(0.0069)
Single	0.0893***	0.0278***
s.e.	(0.0059)	(0.0051)
	Parenthood	
Parent	0.1320***	0.0312***
s.e.	(0.0050)	(0.0056)
Non-Parent	0.0924***	0.0239***
s.e.	(0.0049)	(0.0029)
	Urban-Rural Classification	
Urban	0.0930***	0.0253***
s.e.	(0.0081)	(0.0029)
Rural	0.1417***	0.0389***
s.e.	(0.0061)	(0.0049)
	Employment Status	
Full-time	0.0673***	0.0201***
s.e.	(0.0075)	(0.0058)
Part-Time	0.1641***	0.0396***
s.e.	(0.0092)	(0.0061)
Employed	0.0511***	0.0187***
s.e.	(0.0063)	(0.0019)
Self-Employed	0.0830***	0.0418***
s.e.	(0.0086)	(0.0055)

Notes: Table 2.13 shows the income risk heterogeneity; differences identification scheme; $\sigma^2_{\varepsilon,t}$= transitory income shock variance; $\sigma^2_{\zeta,t}$= permanent income shock variance; *significant at p<0.1;.**significant at p<0.05;***significant at p<0.01

Gender Decomposition

Table B2.14: Gross Individual Income Risk, Gender in Levels

Groups	Women		Men	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{Women}}$	$\sigma^2_{\zeta_t^{Women}}$	$\sigma^2_{\varepsilon_t^{Men}}$	$\sigma^2_{\zeta_t^{Men}}$
		Marital Status		
Married	0.1221***	0.0460***	0.1893***	0.0259***
s.e.	(0.0071)	(0.0063)	(0.0055)	(0.0048)
Single	0.1030***	0.0326***	0.1767***	0.0247***
s.e.	(0.0062)	(0.0042)	(0.0074)	(0.0049)

Notes: Table B2.14 shows the income risk heterogeneity based on gender; Individual Gross Income; The estimation is based on the level identification scheme; The bootstrap standard errors are based on 1000 replications and presented in parentheses; The risk ratio is based on $\sigma^2_{\zeta,t}$;
*significant at $p < 0.1$;**significant at $p < 0.05$;***significant at $p < 0.01$.

Table B2.15: Gross Individual Income Risk, Gender in Levels

Groups	Women		Men	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{Women}}$	$\sigma^2_{\zeta_t^{Women}}$	$\sigma^2_{\varepsilon_t^{Men}}$	$\sigma^2_{\zeta_t^{Men}}$
		Parenthood		
Parent	0.1829***	0.0421***	0.1577***	0.0337***
s.e.	(0.0051)	(0.0051)	(0.0086)	(0.0093)
Non-Parent	0.1224***	0.0216***	0.0904***	0.0243***
s.e.	(0.0068)	(0.0043)	(0.0042)	(0.0045)
		Urban-Rural Classification		
Urban	0.1517***	0.0240***	0.1307***	0.0265***
s.e.	(0.0046)	(0.0048)	(0.0065)	(0.0048)
Rural	0.1985***	0.0262***	0.1879***	0.0297***
s.e.	(0.0059)	(0.0052)	(0.0072)	(0.0082)
		Employment Status		
Full-time	0.0557***	0.0249***	0.0762***	0.0151***
s.e.	(0.0055)	(0.0039)	(0.0053)	(0.0046)
Part-Time	0.0906***	0.0591***	0.0898***	0.0418***
s.e.	(0.0057)	(0.0058)	(0.0057)	(0.0076)
Employed	0.0638***	0.0210***	0.0701***	0.0191***
s.e.	(0.0066)	(0.0042)	(0.0051)	(0.0053)
Self-Employed	0.1650***	0.0559***	0.1995***	0.0446***
s.e.	(0.0096)	(0.0081)	(0.0084)	(0.0083)

Notes: Table B2.15 shows the income risk heterogeneity based on gender;
Individual Gross Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
1000 replications and presented in parentheses; The risk ratio is based on $\sigma^2_{\zeta,t}$;
*significant at $p < 0.1$;**significant at $p < 0.05$;***significant at $p < 0.01$.

Ethnicity Decomposition

Table 2.16:Gross Individual Income Risk, Ethnicity in Levels

Groups	White		Non-White	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{White}}$	$\sigma^2_{\zeta_t^{White}}$	$\sigma^2_{\varepsilon_t^{Non-White}}$	$\sigma^2_{\zeta_t^{Non-White}}$
		Marital Status		
Married	0.0919***	0.0243***	0.1323***	0.0299***
s.e.	(0.0046)	(0.0041)	(0.0081)	(0.0055)
Single	0.1133***	0.0276***	0.1217***	0.0326***
s.e.	(0.0056)	(0.0047)	(0.0094)	(0.0054)

Notes: Table B2.16 shows the income risk heterogeneity based on ethnicity;
Individual Net Income; The estimation is based on the level identification scheme;
The bootstrap standard errors are based on 1000 replications and presented in parentheses;
The risk ratio is based on $\sigma^2_{\zeta,t}$;*significant at $p < 0.1$;**significant at $p < 0.05$;
***significant at $p < 0.01$

Table B2.17: Gross Individual Income Risk, Ethnicity in Levels

Groups	White		Non-White	
	Transitory	Permanent	Transitory	Permanent
	$\sigma^2_{\varepsilon_t^{White}}$	$\sigma^2_{\zeta_t^{White}}$	$\sigma^2_{\varepsilon_t^{Non-White}}$	$\sigma^2_{\zeta_t^{Non-White}}$
		Parenthood		
Parent	0.0927***	0.0399***	0.1556***	0.0467***
s.e.	(0.0044)	(0.0047)	(0.0058)	(0.0068)
Non-Parent	0.0883***	0.0281***	0.1389***	0.0284***
s.e.	(0.062)	(0.0053)	(0.0054)	(0.0057)
		Urban-Rural Classification		
Urban	0.0946***	0.0194***	0.1234***	0.0244***
s.e.	(0.0068)	(0.0051)	(0.0070)	(0.0045)
Rural	0.0965***	0.0298***	0.1429***	0.0308***
s.e.	(0.0073)	(0.0083)	(0.0083)	(0.0054)
		Employment Status		
Full-time	0.0852***	0.0199***	0.1013***	0.0242***
s.e.	(0.0031)	(0.0059)	(0 .0065)	(0.0081)
Part-Time	0.1872***	0.0345***	0.1934***	0.0468***
s.e.	(0.0038)	(0.0085)	(0.0023)	(0.0085)
Employed	0.0518***	0.0119***	0.0583***	0.0288***
s.e.	(0.0078)	(0.0051)	(0.0081)	(0.0063)
Self-Employed	0.2234***	0.0335***	0.2421***	0.0508***
s.e.	(0.0095)	(0.0034)	(0.0093)	(0.0083)

Notes: Table B2.17 shows the income risk heterogeneity based on ethnicity; Individual Gross Income; The estimation is based on the level identification scheme; The bootstrap standard errors are based on 1000 replications and presented in parentheses The risk ratio is based on $\sigma^2_{\zeta,t}$; *significant at $p < 0.1$;**significant at $p < 0.05$;***significant at $p < 0.01$

5.3 Appendix Chapter C3

5.3.1 Appendix C3: Variable Overview

Income Variables

This section focuses on the main variables in Chapter 3. The key income variable is net income, which includes labour market income, miscellaneous income, taxation deductions, benefits and personal income. The sample of marital status refers to married and single individuals. Married individuals are all those who are either cohabiting or legally married. Single individuals are singles, widowed or divorced. Marital choice refers to the socioeconomic status of the partner. Assortative couples are married to a partner from the same socioeconomic background, while cross-group couples have married someone from a different socioeconomic background. Further in Table C3.2 $-C$3.4 I describe the variables that are relevant to Chapter 3.

Table C3.1: Net Income Variables, Couple Type

Subgroup	Mean	SD	Min.	Max.
Assortative Couples	586.94	307.0	391.89	8516.94
Cross Group Couples	554.82	343.11	321.65	3363.71
Married Individuals	590.75	329.71	241.24	8516.93
Single Individuals	377.93	343.11	195.47	1572.94

Notes: Table C3.1 shows income variables by Couple Type
Source: UKHLS

Table C3.2: Marital Status Variables

Group Classification	Description	Variables
Married	Married Couples and civil partnerships	mastat_dv
Single	Singles, divorced, separated and widowed individuals	mastat_dv

Notes: Table C3.2 reports the definitions of marital status.
Source: UKHLS

Table: C3.3: Socioeconomic Group Classifications

Group Classification	Description	Variable
1. Higher Management and Professional Occupations	Employers in large establishments. Higher managerial and administrative occupations. Higher professional occupation.	jbseg_dv
2.Intermediate Occupations	Intermediate clerical and administrative occupations. Intermediate sales and service occupations. Intermediate technical and auxiliary occupations. Intermediate engineering occupations. Own account workers (non-professional). Own account workers (agriculture). Small Employers in small establishments. in industry, commerce, services Small Employers in small establishments in agriculture.	jbseg_dv
3.Routine and Manual Occupations	Lower supervisory and Technical occupations. Semi-routine occupations.	jbseg_dv

Notes: Table C3.3 reports the definitions of socioeconomic group classifications.

Source: UKHLS

Table: C3.4: Education Level Classifications

Group Classification	Description	Variable
Past 18	University Degree	hiqual_dv
A-levels	A-Level degree	hiqual_dv
O-levels or apprenticeship	O-Levels or below or apprenticeship	hiqual_dv

Notes: Table C3.4 reports the education level classifications.

Source: UKHLS

5.4 Appendix Chapter D4

5.4.1 Appendix D 4: Descriptive Statistics

This section focuses on the descriptive statistics in Chapter 4. Table D4.1 provides information on the construction of both welfare scheme variables: the Legacy System and Universal Credit. The UKHLS dataset reports the variables differently. The variable for Universal Credit households is directly reported as income support '*benbase 4*' for the respective households. In contrast, the Legacy System is reported in its six benefit types, which differ by period 1 and period 2. The variable Legacy System has been constructed on the basis of the individual reported benefit types. Table D4.1 shows the benefit types under the Legacy System between the different time periods. To analyse the patterns in net income risk I created two key Legacy System variables based on the implementation date of Universal Credit in wave 5. Hence, the variable *Legacy_System_Pre* maintains the six benefit types in period 1. while the variable *Legacy_System_Post* implies the six benefit types in Period 2.

Table D4.1: Benefit Variable Construction, Welfare Schemes

Variables	Legacy_System_Pre	Legacy_System_Post
Periods	Period 1: wave 1-5	Period 2: wave 6-9
	Legacy System	
Income Support	btype2	benbase1
Income based Jobseeker's Allowance	benunemp1	benbase2
Income based employment and Support Allowance	bendis2	bendis2
Housing Benefit	btype8	renthb
Child Tax Credit	btype5	benbase3
Working Tax Credit	btype6	etnben5
	Universal Credit	
Income Support	-	benbase4

Notes: Table D4.1 reports the variable construction for the benefits under the welfare schemes.

Source: UKHLS

Table D4.2 presents the income summary statistics under each welfare policy.

Table D4.2: Descriptive Statistics Income Variables Period 2

Variables	Mean	SD	Max.	Min.
Legacy System	288.56	124.18	1377.24	17.54
Universal Credit	246.55	119.87	1015.32	6.31

Notes: Descriptive statistics for welfare scheme income
in period 2.; Age Range: 25 to 60 with. net household income.
Source: UKHLS based on wave 6 to 9.

5.4.2 Appendix D4: Welfare Schemes in the United Kingdom

Universal Credit

The flagship reform of the British benefits system is the introduction of Universal Credit (UC). The key aims of Universal Credit are to simplify the benefits system, reduce poverty and increase employment stability. The benefits system is undergoing radical reform, with six-means tested benefits and tax credits being replaced by a single payment. It is part of a policy package in the Welfare Reform Act in 2012, which received Royal Assent in March 2012. The Act sets out the working regulations of Universal Credit, which, under current plans, is expected to be fully rolled out and replace the Legacy System by 2023/2024. Universal Credit will be administered by the Department for Work and Pensions (DWP) in Great Britain and by the Department for Communities in Northern Ireland. For claimants dealing with the DWP, this will mean that out-of-work and in-work claims will be administered by one institution rather than the present mix of three: the DWP for most out-of-work benefits, HM Revenue and Customs for tax credits and their local authority for housing benefit. This section provides information on the key policies and its administrative framework.

The implementation of Universal Credit has had two stages, known as Live Service and Full Service. The Live Service was first introduced in 2013 to a limited client base as a trial. Universal Credit Full Service, the fully digital service, was introduced in South London in November 2014 and continues to be rolled out. After this process has finished, all remaining benefit claimants will be transferred to the Universal Credit Full Service. This migration process started in 2018. The UKHLS has information on Universal Credit households from January 2015. Currently, 2.3 million households have moved onto the Universal Credit system (Department for Work and Pensions, 2020). By 2022, an estimated 7.2 million families in the UK will have received Universal Credit, of which 3.9 million are in-work households.

The transition between the welfare systems and the implementation of Universal Credit means considerable investment. The Office for Budget Responsibility (2020) estimates that actual spending on Universal Credit reached around £3 billion in 2017-18. An initial forecast of actual expenditure in 2018-19 is around £8 billion, reflecting the gathering pace of the roll-out. The marginal saving from the introduction of Universal Credit – representing much higher costs and offsetting savings – is forecast to be around £0.2 billion in 2018-19. It rises to £1.0 billion in 2022-23, which comprises a £2.5 billion net saving, due to differences between Universal Credit and the Legacy System being partly offset by the £1.5 billion cost of transitional protection payments to cases that are migrated to Universal Credit at the Department for Work and Pensions's discretion and that would otherwise lose out when they move onto Universal Credit (OBR, 2020).

The implementation of Universal Credit induces more employment. According to the Department for Work and Pensions (2020), it is estimated that Universal Credit leads to an increase of approximately 200,000 individuals in work as a result of financial and non-financial incentives, additional employment conditionality and the simplicity of the system. The underlying mechanism is based on benefit cuts to motivate unemployed households to find work, while the employment conditionality ensures employment security and income stability Currently, 74 per cent of Universal Credit households are either in employment (760,000 or 33per cent) or searching for work (930,000 or 41per cent) based on the conditionality mechanism. The majority (62per cent) of in-work households are in the 25 - 49 years age group (Department for Work and Pensions, 2019). Given Universal Credit's aim to ensure employment stability, this analysis focuses on net income risk exposure for in-work benefit households.

The financial incentive is reflected in benefit reductions and changes in the work allowance. The introduction of Universal Credit is associated with entitlements cuts amounting to £2 billion *per annum* in several forms. In addition, most working-age benefits were frozen in cash terms from April 2015 to March 2020, ignoring the change in living standards. One of the most extensive reductions regards the work allowance, resulting in workers seeing a decrease in the number of hours they can work before their Universal Credit payment starts to decrease. The Universal Credit system maintains a so-called taper rate, which means that households see their total entitlement withdrawn at a rate of 63 pence for every pound of net earnings that they earn above their work allowance (Department for Work and Pensions, 2019) [1]. The financial distress based on the benefit cuts leads to a rise in net income risk for the households. This might lead to increased employment, combined with increased income stability. Yet, lone parents and single-earner couples are likely to lose out the most from this change as they may choose not to work or move to shorter hours based on the cut in work allowance. Consequently, the mechanism of a reduced taper rate might induce less willingness to work and result in financial distress due to the change in hours entitlement for in-work households. Moreover, the level of the taper rate influences the hours worked per week and subsequently

[1] The taper sets the speed with which benefits are withdrawn once earnings exceed the work allowance. If the taper is set at 0.63, this means that for every extra pound earned after the work allowance has been met, the total benefit amount received is reduced by 63p.

affects the variability of household income. Hence, Universal Credit might induce net income risk for in-work benefit households by the nature of its construction.

To ensure employment stability Universal Credit uses non-financial incentives, As a non-financial tool, Universal Credit measures use a claimant work commitment to increase worked hours. All Universal Credit claimants need to comply with a 'claimant commitment', which forms the basis of the conditions attached to receiving Universal Credit. This extends the existing conditionality regime under jobseeker's allowance and ESA to in-work recipients and to partners in couples. Out of work claimants will be required to spend 35 hours a week searching for work, while in work claimants will be required to seek more hours if they are deemed to be working too few. Self-employed claimants must seek to increase their earnings if they are deemed too low. Sanctions will apply to claimants that do not meet the terms of their claimant commitment, removing some or all of their entitlement for a specified period.

Self-employed households face changes under the new welfare system. In contrast to the Legacy System, Universal Credit applies a 'minimum income floor' (MIF) for self-employed people. If a claimant's self-employed earnings are below the MIF, the government calculates their Universal Credit award on the assumption that they earned an amount equal to the MIF. For most people, the MIF is equivalent to 35 hours a week at the National Living Wage (i.e. broadly speaking, the minimum they would earn if working full-time as an employee). Couples in which one partner is below pension credit age, and the other above were, under the Legacy System, able to receive pension credit (typically higher than working-age benefits), but under Universal Credit they cannot. Moreover, the entitlements for individuals with disabilities vary considerably.

Families with more than two children encounter new regulations. Since April 2017, the 'two-child limit' means that families will not be eligible for the child entitlement of tax credits or Universal Credit for third or subsequent children born after that date. In addition, child tax credit is withdrawn where someone in the household has a taxable annual income of more than £50,000. An investigation by the Institute for Fiscal Studies (IFS) shows that around 36 per cent, or 370,000, more families in the UK lost some child tax credit in 2019-20 than in 2013-14. This is mostly due to the new threshold, which has not been price or earnings-indexed. Newborn first children stopped receiving a higher entitlement and newborn third and subsequent children stopped receiving any support at all. It is estimated that by 2022 more than one in five households with children will face a reduction in their child tax credit.

Legacy System

The British welfare system has undergone several expansions and reforms since its creation. The most notable reforms took place from the 1960s to 1970 and the 1980s to 1990s. The main focus of this reform was based on increasing the government's managerial efficiency and economic planning. To this end, the Treasury created a system which allocated resources to departments and departments to services. The second phase, however, during the 1980s and 1990s focused on reforming the civil service and the administration of welfare support. During the second reform, the current Legacy System was set in place in 1984.

The Legacy System comprises six different means-tested benefits. These can be differentiated based on the eligibility requirements, namely the claimant's household income combined with the household background and personal characteristics. The benefits under the Legacy System include income-based jobseeker's allowance, income support, income-related employment and support allowance, child tax credit, housing benefit and working tax credit. This section describes the nature of each benefit type under the Legacy System.

Income Support refers to a benefit type which is only accessible to claimants if they are one of the following: a carer, pregnant or a lone parent of a child under five years old. Claimants are only eligible if they meet one of these criteria (Department for Work and Pensions, 2019).

Income Jobseeker's Allowance is a benefit for households who are actively seeking employment and are capable of work. The respective claimant has to be above 18 years of age and under State Pension age to claim this benefit. In addition, it is understood that the claimant is not in full-time employment and works no more than 16 hours a week to claim this benefit. The benefit is means-tested, which means that the amount of benefit depends on the level of earned income (Department for Work and Pensions, 2019).

The Employment and Support Allowance (ESA) is a benefit for people who have limited capability for work due to an illness or disability and are not in receipt of Statutory Sick Pay. Also in this case, the recipient has to be over 16 years old and under State Pension age. This benefit is also means-tested. In contrast, contribution-based ESA, is non-means-tested and dependent on the National Insurance Contributions of the claimant (Department for Work and Pensions, 2019).

Housing Benefit contributes to the rental costs for households with a low income.

It is means-tested and takes into consideration income and capital in the framework determining eligibility (Department for Work and Pensions, 2019).

Under the Legacy System, there are two types of tax credits: (i) Working Tax Credit and (ii) Child Tax Credit. The term 'tax credits' in Britain is in fact used to describe two forms of benefit support: a work-contingent benefit, currently named Working Tax Credit, and an additional means-tested element precisely for families with children. Child Tax Credit has been available since 2003 to low-income families irrespective of work status. The Child Tax Credit is a benefit to assist with the costs of raising a child. To claim this tax credit, the claimant needs to be responsible for a child and in receipt of a low income. Also, in this case, the employment status is not being considered. Working Tax Credit is a benefit that is available to households that are in employment with a low income. Eligibility takes into account hours worked, the presence of a disability and the number of children with the associated child tax credit costs provided by approved child tax credit services (Department for Work and Pensions, 2019).

In addition, to the set of benefits under the Legacy System, the welfare policies also maintain contributory benefits. The requirement to be eligible for this benefit includes regular payments of National Insurance Contributions by the claimant (Department for Work and Pensions, 2019). The contributions are made by employees whose earnings are above a threshold, which was £155 per week in 2018. However, some welfare support, such as disability living allowance or child benefit, are neither contributory nor means-tested. These are accessible to anyone who meets the eligibility requirements independently of their income. These benefits are not included in the design of the new Universal Credit policy (Department for Work and Pensions, 2019).

Child Tax Credit

The child tax credit introduced in 2003 aims to support low-income households with children, independent of their employment status. It was available to households in and out of employment and replaced the child additions to other child benefits. Child tax credits are based on gross annual income, jointly assessed for a couple. Entitlement is not directly affected by a family's savings, as happens in means-tested benefits. Instead, non-earned income above the first £300 p.a. will be taken into account when calculating awards (Brewer, 2003). The child tax credit consists of two components:

- a family element of £545 p.a. (approximately £10.45 a week), doubled in the financial year of a child's birth;
- an amount per dependent child of £1,445 p.a. approximately £27.75 a week, and higher for disabled children).

Under the Universal Credit transformation, the child tax credit faces considerable changes. Under Universal Credit, the child tax credit is a means-tested payment to which households with children are eligible (Brewer *et al.*, 2016). Further, it is accessible for households with a labour income below £32,000, which is paid on top of the child benefit. This contrasts with the general child benefit, which is a flat rate for all households with children, independent of their income.

5.4.3 Appendix D4: Households under Non-Welfare Scheme

This section provides information on the degree of income risk by comparing gross and net income risk for households under no welfare scheme. To provide a comparative view on net income risk patterns households under no welfare system are also analysed. I create a sample of households that never received any type of welfare benefits, 'non-welfare scheme households'. The non-welfare system households are a baseline sample to contextualise the findings of net income risk patterns under a welfare scheme.

Table D4.1 shows the permanent and transitory income shock variance from wave 1 to 5, which translates into years 2010 until 2017. The key finding of Table D4.1 is the reduction of net income risk based on automatic stabilisers. The permanent income shock variance decreases by $\sigma_{\zeta,t} = 0.005$ when comparing households' gross and net permanent income shock variance. The difference between the permanent and transitory income shock variance may be linked to the taxes paid and general benefits received for example child benefit for Non-Welfare Scheme households.

The second part of Table D4.1 focuses on the degree of insurance through taxes and benefits from 2010 to 2017. The results in Table D4.2 show that tax and benefits reduce the income shock variance by $\sigma_{\zeta,t} = 0.0054$.Table $E4.1$ also provides evidence of a reduction in net income risk, which constitutes a net income risk mitigation effect. Consequently, the automatic stabilisers reduce exposure to net income risk for households. The results in Table D4.1 provide evidence of the net income risk mitigation effect, complementing evidence by Avram *et al.*(2019) and Blundell el al. (2018).

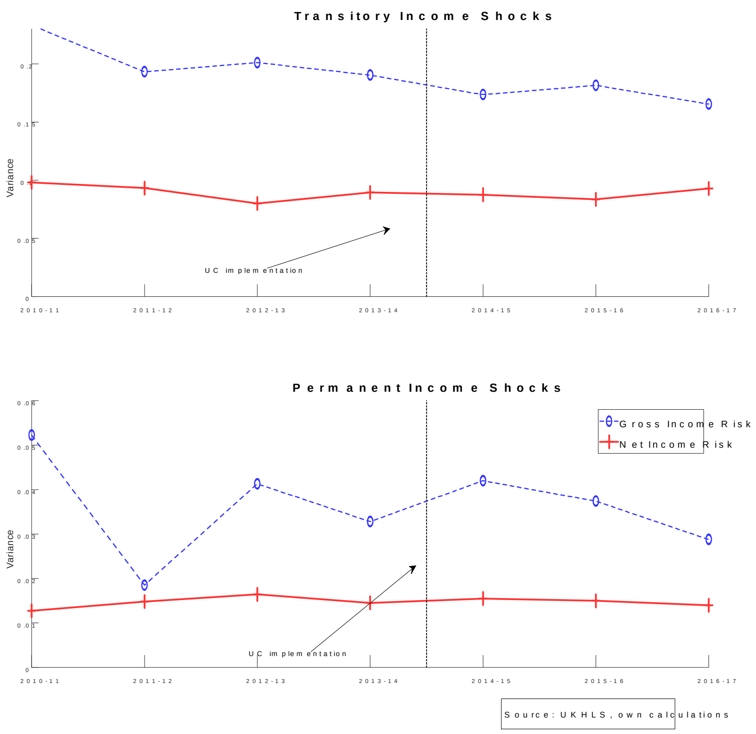
Table D4.3: Household Income Risk Estimation

Subgroup	Transitory $\sigma^2_{\varepsilon,t}$	Permanent $\sigma^2_{\zeta,t}$
Sample Period 1: Wave 1-5		
Non-Welfare Scheme HH (Gross)	0.1422***	0.0303***
s.e	(0.0043)	(0.0029)
Non-Welfare Scheme HH (Net)	0.0977***	0.0143***
s.e.	(0.0036)	(0.0013)
Sample Size	27,066	
Sample Period 2: Wave 6-9		
Non-Welfare Scheme HH (Gross)	0.1365***	0.0292***
s.e	(0.0039)	(0.0023)
Non-Welfare Scheme HH (Net)	0.0731***	0.0139***
s.e.	(0.0036)	(0.0028)
Sample Size	14,504	

Notes: Table D4.3 indicates income risk based on welfare schemes;*** indicates p-value<0.01;**indicates p-value<0.05.; *indicates p-value<0.1;The bootstrap standard errors are based on 1000 replications and are presented in parentheses. $\sigma^2_{\varepsilon,t}$= transitory income shock variance; $\sigma^2_{\zeta,t}$= permanent income shock variance. Level estimation.

Figure D4.1 shows the development of the transitory and permanent income shock variance for gross and net estimates. It supports the evidence in Table D4.1, highlighting the lower net income risk for the net estimates compared to the gross estimates. It provides evidence of the redistributive impact of the tax and transfer system.

Figure D4.1: Gross and Net Income Risk, Non-Welfare Households



Notes: Figure D4.1 indicates the household income risk from 2010 until 2017.

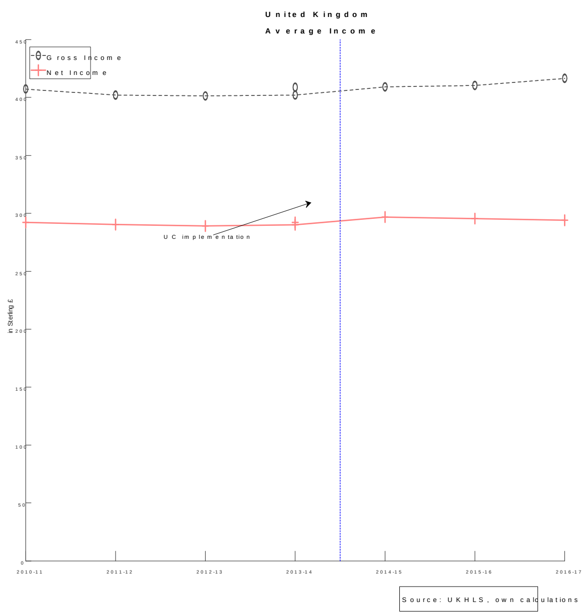
Discussion Non-Welfare Households

Tables D4.1 and Figure D4.1 provide evidence of the net income risk mitigation effect through automatic stabilizers. The degree of insurance for households against adverse income shocks can be shown by comparing gross and net income risk estimates.

Recent literature highlights the existence of welfare insurance in the UK. The results in Table D4.3 and D4.4 are in line with findings in the literature. Avram *et al.*(2019) examine household income volatility in the UK and find a redistributive factor in the British welfare system by comparing gross and net income. They show that the redistributive factor is expressed through automatic stabilisers. In particular, Cribb (2018) finds evidence that the expansion of benefit payments, during the 1990s and 2000s, enabled a direct response to the fall in earnings in the UK. The current literature indicates that automatic stabilisers contribute to welfare insurance through their redistributive effect. Currently, the majority of the literature focuses on the relationship between the income levels and the welfare system's automatic stabilisers. The findings indicate that automatic stabilisers also contribute to mitigating net income risk. In particular, Figure D4.2 shows that the permanent income shock variance of net income is lower compared to gross income.

Figure D4.2 provides information on permanent income shock variances between gross and net income risk estimates from 2010 to 2017. It highlights the difference in net income risk of the net and gross estimates. Figure D4.2 also shows the considerably lower income variability for the net permanent net income risk estimates. Thus, taxes and benefits partially decrease income risk comparing both gross and net income. This is similar to the finding on the individual level in Chapter 2.

Figure D4.2: Gross and Net Average Income, Non-Welfare Households



Notes: Figure D4.1 indicates the gross and net household income from 2010 until 2017.

5.5 Method Appendix E

5.5.1 Identification Schemes

Level Identification Scheme: Moments

The residuals decomposition:

$$u_{i,c,t} = p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t} \tag{5.1}$$

Key moments:

The variance at time t:

$$\begin{aligned}
var_c(u_{i,c,t}) &= E[(u_{i,c,t} - E(u_{i,c,t}))^2] \\
&= Var[(p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t})(p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t})] \\
&= E\begin{pmatrix} (p_{i,c,t-1} \times p_{i,c,t-1}) + (p_{i,c,t-1} \times \zeta_{i,c,t}) + (p_{i,c,t-1} \times \varepsilon_{i,c,t}) \\ +(\zeta_{i,c,t} \times p_{i,c,t-1}) + (\zeta_{i,c,t} \times \zeta_{i,c,t}) + (\zeta_{i,c,t} \times \varepsilon_{i,c,t}) \\ +(\varepsilon_{i,c,t} \times p_{i,c,t-1}) + (\varepsilon_{i,c,t} \times \zeta_{i,c,t}) + (\varepsilon_{i,c,t} \times \varepsilon_{i,c,t}) \end{pmatrix} \\
&= E[(p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t})^2] \\
&= var(p_{t-1}) + \sigma_{\zeta_t} + \sigma_{\varepsilon_t}
\end{aligned} \tag{5.2}$$

Covariance Structure:

The identification process is the same as in the previous section. I use the residual term in eq. (5.1) to exploit the covariance structure of the residual term ($u_{i,c,t},$) at time t and $t-1$. Given that the cross products are zero, the terms cancel out , which results in $var(p_{t-1})$.

Covariance at time $t-1$:

$$\begin{aligned}
cov_c(u_{i,c,t}, u_{i,c,t-1}) &= E[(u_{i,c,t} - E(u_{i,c,t}))(u_{i,c,t-1} - E(u_{i,c,t-1}))] \\
&= E[(p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t})(p_{i,c,t-1} + \varepsilon_{i,c,t-1})] \\
&= E\begin{pmatrix} (p_{i,c,t-1} \times p_{i,c,t-1}) + (p_{i,c,t-1} \times \varepsilon_{i,c,t-1}) \\ +(\zeta_{i,c,t} \times p_{i,c,t-1}) + (\zeta_{i,c,t} \times \varepsilon_{i,c,t-1}) \\ +(\varepsilon_{i,c,t} \times p_{i,c,t-1}) + (\varepsilon_{i,c,t} \times \varepsilon_{i,c,t-1}) \end{pmatrix} \\
&= E\left[(p_{i,c,t-1})^2\right] \\
&= var(p_{t-1})
\end{aligned} \tag{5.3}$$

I follow the same steps of derivation throughout this section.

Covariance at time $t + 1$:

$$
\begin{aligned}
cov_c(u_{i,c,t+1}, u_{i,c,t}) &= E[(u_{i,c,t+1} - E(u_{i,c,t+1}))(u_{i,c,t} - E(u_{i,c,t}))] \\
&= E[(p_{i,c,t-1} + \zeta_{i,c,t+1} + \zeta_{i,c,t} + \varepsilon_{i,c,t+1})(p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t})] \\
&= var(p_{t-1}) + \sigma_{\zeta_t} \qquad (5.4)
\end{aligned}
$$

Covariance at time $t + 2$:

$$
\begin{aligned}
cov_c(u_{i,c,t+2}, u_{i,c,t}) &= E[(u_{i,c,t+2} - E(u_{i,c,t+2}))(u_{i,c,t} - E(u_{i,c,t}))] \\
&= E[(p_{i,c,t-1} + \zeta_{i,c,t+2} + \zeta_{i,c,t+1} + \zeta_{i,c,t} + \varepsilon_{i,c,t+2})(p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t})] \\
&= var(p_{t-1}) + \sigma_{\zeta_t} \qquad (5.5)
\end{aligned}
$$

Level Identification Scheme continued: Moments

Covariance at $t = t + 1$:

$$cov_c(u_{i,c,t+1}, u_{i,c,t}) = var(p_0) + \sum_{j=1}^{t} \sigma_{\zeta_j} \tag{5.6}$$

$$\begin{aligned}
cov_c(u_{i,c,2}, u_{i,c,1}) &= var(p_0) + \sigma_{\zeta_1} \\
cov_c(u_{i,c,3}, u_{i,c,2}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} \\
cov_c(u_{i,c,4}, u_{i,c,3}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_{,2}} + \sigma_{\zeta_3} \\
cov_c(u_{i,c,5}, u_{i,c,4}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} \\
cov_c(u_{i,c,6}, u_{i,c,5}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} \\
cov_c(u_{i,c,7}, u_{i,c,6}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} \\
cov_c(u_{i,c,8}, u_{i,c,7}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\zeta_7} \\
cov_c(u_{i,c,9}, u_{i,c,8}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\zeta_7} + \sigma_{\zeta_8}
\end{aligned}$$

The respective variances:

$$var_c(u_{i,c,t}) = var(p_0) + \sum_{j=1}^{t} \sigma_{\zeta_j} + \varepsilon_t \tag{5.7}$$

$$\begin{aligned}
var_c(u_{i,c,1}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\varepsilon 1} \\
var_c(u_{i,c,2}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\varepsilon 2} \\
var_c(u_{i,c,3}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\varepsilon 3} \\
var_c(u_{i,c,4}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\varepsilon 4} \\
var_c(u_{i,c,5}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\varepsilon 5} \\
var_c(u_{i,c,6}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\varepsilon 6} \\
var_c(u_{i,c,7}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\zeta_7} + \sigma_{\varepsilon 7} \\
var_c(u_{i,c,8}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\zeta_7} + \sigma_{\zeta_8} + \sigma_{\varepsilon 8} \\
var_c(u_{i,c,9}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\zeta_7} + \sigma_{\zeta_8} + \sigma_{\zeta_9} + \sigma_{\varepsilon 9} \qquad (5.8)
\end{aligned}$$

Covariance $t = t + 2$:

$$cov_c(u_{i,c,t+2}, u_{i,c,t}) = var(p_0) + \sum_{j=1}^{t} \sigma_{\zeta_j} \tag{5.9}$$

$$\begin{aligned}
cov_c(u_{i,c,3}, u_{i,c,1}) &= var(p_0) + \sigma_{\zeta_1} \\
cov_c(u_{i,c,4}, u_{i,c,2}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_{i2}} \\
cov_c(u_{i,c,5}, u_{i,c,3}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} \\
cov_c(u_{i,c,6}, u_{i,c,4}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} \\
cov_c(u_{i,c,7}, u_{i,c,5}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} \\
cov_c(u_{i,c,8}, u_{i,c,6}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} \\
cov_c(u_{i,c,9}, u_{i,c,7}) &= var(p_0) + \sigma_{\zeta_1} + \sigma_{\zeta_2} + \sigma_{\zeta_3} + \sigma_{\zeta_4} + \sigma_{\zeta_5} + \sigma_{\zeta_6} + \sigma_{\zeta_7} \qquad (5.10)
\end{aligned}$$

Level Identification Scheme continued: Moments

Identification of the transitory income shock parameters from $t = 1, .., 9$:

$$var_c(u_{i,c,t}) - cov_c(u_{i,c,t+1}, u_{i,c,t}) = \sigma_{\varepsilon_t} \tag{5.11}$$

I use eq. (5.11) corresponding to the time periods:

$$\begin{aligned}
var_c(u_{i,c,1}) - cov_c(u_{i,c,2}, u_{i,c,1}) &= \sigma_{\varepsilon_1} \\
var_c(u_{i,c,2}) - cov_c(u_{i,c,3}, u_{i,c,2}) &= \sigma_{\varepsilon_2} \\
var_c(u_{i,c,3}) - cov_c(u_{i,c,4}, u_{i,c,3}) &= \sigma_{\varepsilon_3} \\
var_c(u_{i,c,4}) - cov_c(u_{i,c,5}, u_{i,c,4}) &= \sigma_{\varepsilon_4} \\
var_c(u_{i,c,5}) - cov_c(u_{i,c,6}, u_{i,c,5}) &= \sigma_{\varepsilon_5} \\
var_c(u_{i,c,6}) - cov_c(u_{i,c,7}, u_{i,c,6}) &= \sigma_{\varepsilon_6} \\
var_c(u_{i,c,7}) - cov_c(u_{i,c,8}, u_{i,c,7}) &= \sigma_{\varepsilon_7} \\
var_c(u_{i,c,8}) - cov_c(u_{i,c,9}, u_{i,c,8}) &= \sigma_{\varepsilon_8} \\
var_c(u_{i,c,9}) - cov_c(u_{i,c,10}, u_{i,c,9}) &= \sigma_{\varepsilon_9}
\end{aligned}$$

Identification of the variance of the permanent income shock parameters from $t = 2, ..., 9$:

$$var_c(u_{i,c,t}) - cov_c(u_{i,c,t}, u_{i,c,t-1}) - \sigma_{\varepsilon} = \sigma_{\zeta_t} \tag{5.12}$$

I use eq. (5.12) corresponding to the time periods:

$$\begin{aligned}
var_c(u_{i,c,1}) - cov_c(u_{i,c,1}, u_{i,c,0}) - \sigma_{\varepsilon_2} &= \sigma_{\zeta_1} \\
var_c(u_{i,c,2}) - cov_c(u_{i,c,2}, u_{i,c,1}) - \sigma_{\varepsilon_2} &= \sigma_{\zeta_2} \\
var_c(u_{i,c,3}) - cov_c(u_{i,c,3}, u_{i,c,2}) - \sigma_{\varepsilon_3} &= \sigma_{\zeta_3} \\
var_c(u_{i,c,4}) - cov_c(u_{i,c,4}, u_{i,c,3}) - \sigma_{\varepsilon_4} &= \sigma_{\zeta_4} \\
var_c(u_{i,c,5}) - cov_c(u_{i,c,5}, u_{i,c,4}) - \sigma_{\varepsilon_5} &= \sigma_{\zeta_5} \\
var_c(u_{i,c,6}) - cov_c(u_{i,c,6}, u_{i,c,5}) - \sigma_{\varepsilon_6} &= \sigma_{\zeta_6} \\
var_c(u_{i,c,7}) - cov_c(u_{i,c,7}, u_{i,c,6}) - \sigma_{\varepsilon_7} &= \sigma_{\zeta_7} \\
var_c(u_{i,c,8}) - cov_c(u_{i,c,8}, u_{i,c,7}) - \sigma_{\varepsilon_8} &= \sigma_{\zeta_8} \\
var_c(u_{i,c,9}) - cov_c(u_{i,c,8}, u_{i,c,8}) - \sigma_{\varepsilon_8} &= \sigma_{\zeta_9}
\end{aligned}$$

Hence the set of moments for the identification scheme in levels are:

$$var_c(u_{i,c,t}) - cov_c(u_{i,c,t+1}, u_{i,c,t}) = \sigma_{\varepsilon t} \quad (5.13)$$

$$var_c(u_{i,c,t}) - cov_c(u_{i,c,t}, u_{i,c,t-1}) = \sigma_{\zeta_t} + \sigma_{\varepsilon t} \quad (5.14)$$

The entire set of parameters, which can theoretically be identified: $\sigma_{\varepsilon 1}, \sigma_{\varepsilon 2,}, \sigma_{\varepsilon 3}, \sigma_{\varepsilon 4}, \sigma_{\varepsilon 5}, \sigma_{\varepsilon 6}, \sigma_{\varepsilon 7}, \sigma_{\varepsilon 8}, \sigma_{\varepsilon 9}; \sigma_{\zeta_1}, \sigma_{\zeta_2}, \sigma_{\zeta_3}, \sigma_{\zeta_4}, \sigma_{\zeta_5}, \sigma_{\zeta_6}, \sigma_{\zeta_7}, \sigma_{\zeta_8}, \sigma_{\zeta_9},$.

Yet, given the restrictions of the dataset I use the covariance structure to obtain the following data parameters: $\sigma_{\varepsilon 2}, \sigma_{\varepsilon 3}, \sigma_{\varepsilon 4}, \sigma_{\varepsilon 5}, \sigma_{\varepsilon 6}, \sigma_{\varepsilon 7}, \sigma_{\varepsilon 8}; \sigma_{\zeta_2}, \sigma_{\zeta_3}, \sigma_{\zeta_4}, \sigma_{\zeta_5}, \sigma_{\zeta_6}, \sigma_{\zeta_7}, \sigma_{\zeta_8}$.

5.5.2 First Differences Identification

This section reports the variance and covariance structure for the two identification schemes in differences and levels and applies it to the time framework of the UKHLS.

First Differences Identification Scheme: Moments

Residual decomposition in a permanent and transitory component.

$$u_{i,c,t} = p_{i,c,t-1} + \zeta_{i,c,t} + \varepsilon_{i,c,t} \tag{5.15}$$

First difference of the residual term:

$$\begin{aligned} \Delta u_{i,c,t} &= u_{i,c,t} - u_{i,c,t-1} \\ &= \zeta_{i,c,t} + \varepsilon_{i,c,t} - \varepsilon_{i,c,t-1} \end{aligned} \tag{5.16}$$

Key moments:
Variance at time t:

$$\begin{aligned} var_c(\Delta u_{i,c,t}) &= E[(\Delta u_{i,c,t} - E(\Delta u_{i,c,t})^2] \\ &= E[(\zeta_{i,c,t} + \varepsilon_{i,c,t} - \varepsilon_{i,c,t-1})(\zeta_{i,c,t} + \varepsilon_{i,c,t} - \varepsilon_{i,c,t-1})] \\ &= E\begin{pmatrix} (\zeta_{i,c,t} \times \zeta_{i,c,t}) + (\zeta_{i,c,t} \times \varepsilon_{i,c,t}) - (\zeta_{i,c,t} \times \varepsilon_{i,c,t-1}) \\ +(\varepsilon_{i,c,t} \times \zeta_{i,c,t}) + (\varepsilon_{i,c,t} \times \varepsilon_{i,c,t}) + (\varepsilon_{i,c,t} \times \varepsilon_{i,c,t-1}) \\ -(\varepsilon_{i,c,t-1} \times \zeta_{i,c,t}) - (\varepsilon_{i,c,t-1} \times \varepsilon_{i,c,t}) - (\varepsilon_{i,c,t-1} \times \varepsilon_{i,c,t-1}) \end{pmatrix} \\ &= E\left[(\zeta_{i,c,t} + \varepsilon_{i,c,t} - \varepsilon_{i,c,t-1})^2\right] \\ &= var(\sigma_{\zeta_t} + \sigma_{\varepsilon_t} + \sigma_{\varepsilon_{t-1}}) \\ &= \sigma_{\zeta_t} + \sigma_{\varepsilon_t} + \sigma_{\varepsilon_{t-1}} \end{aligned} \tag{5.17}$$

Covariance Structure:

Using the variance in eq. (5.15) I am able to disentangle the theoretical transitory income shock. I use the residual term ($\Delta u_{i,c,t}$) in the covariance structure at time period $t+1$ and t. Given that the cross products are zero, the terms cancel out , which results in $-\sigma_{\varepsilon_t}$.

Covariance at time $t+1$:

$$\begin{aligned} cov_c(\Delta u_{i,c,t+1}, \Delta u_{i,c,t}) &= E[(\Delta u_{i,c,t+1} - E(\Delta u_{i,c,t+1}))(\Delta u_{i,c,t} - E(\Delta u_{i,c,t})] \\ &= E[(\zeta_{i,c,t+1} + \varepsilon_{i,c,t+1} - \varepsilon_{i,c,t})(\zeta_{i,c,t} + \varepsilon_{i,c,t} - \varepsilon_{i,c,t-1})] \\ &= E\begin{pmatrix} (\zeta_{i,c,t+1} \times \zeta_{i,c,t}) + (\zeta_{i,c,t+1} \times \varepsilon_{i,c,t}) - (\zeta_{i,c,t+1} \times \varepsilon_{i,c,t-1}) \\ +(\varepsilon_{i,c,t+1} \times \zeta_{i,c,t}) + (\varepsilon_{i,c,t+1} \times \varepsilon_{i,c,t}) + (\varepsilon_{i,c,t+1} \times \varepsilon_{i,c,t-1}) \\ -(\varepsilon_{i,c,t} \times \zeta_{i,c,t}) - (\varepsilon_{i,c,t} \times \varepsilon_{i,c,t}) - (\varepsilon_{i,c,t} \times \varepsilon_{i,c,t-1}) \end{pmatrix} \\ &= -E\left[(\varepsilon_t)^2\right] \\ &= -var(\varepsilon_t) \\ &= -\sigma_{\varepsilon_t} \end{aligned} \tag{5.18}$$

I follow the same steps of derivation throughout this section.

Covariance at time $t-1$:

$$\begin{aligned} cov_c(\Delta u_{i,c,t}, \Delta u_{i,c,t-1}) &= E[(\Delta u_{i,c,t} - E(\Delta u_{i,c,t}))(\Delta u_{i,c,t-1} - E(\Delta u_{i,c,t-1})] \\ &= -\sigma_{\varepsilon_{t-1}} \end{aligned} \tag{5.19}$$

First Differences Identification Scheme continued: Moments

Identification of transitory income shock parameters for $t = 2, .., 9$:

$$cov_c(\Delta u_{i,c,t+1}, \Delta u_{i,c,t}) = -\sigma_{\varepsilon_t} \tag{5.20}$$

I use eq. (5.20) corresponding to the time periods:

$$\begin{aligned}
cov_c(\Delta u_{i,c,2}, \Delta u_{i,c,1}) &= -\sigma_{\varepsilon_1} \\
cov_c(\Delta u_{i,c,3}, \Delta u_{i,c,2}) &= -\sigma_{\varepsilon_2} \\
cov_c(\Delta u_{i,c,4}, \Delta u_{i,c,3}) &= -\sigma_{\varepsilon_3} \\
cov_c(\Delta u_{i,c,5}, \Delta u_{i,c,4}) &= -\sigma_{\varepsilon_4} \\
cov_c(\Delta u_{i,c,6}, \Delta u_{i,c,5}) &= -\sigma_{\varepsilon_5} \\
cov_c(\Delta u_{i,c,7}, \Delta u_{i,c,6}) &= -\sigma_{\varepsilon_6} \\
cov_c(\Delta u_{i,c,8}, \Delta u_{i,c,7}) &= -\sigma_{\varepsilon_7} \\
cov_c(\Delta u_{i,c,9}, \Delta u_{i,c,8}) &= -\sigma_{\varepsilon_8}
\end{aligned}$$

The respective variances

$$var_c(\Delta u_{i,c,t}) = \sigma_{\zeta_t} + \sigma_{\varepsilon_t} - \sigma_{\varepsilon_t} \tag{5.21}$$

applied to the corresponding to the time periods:

$$\begin{aligned}
var_c(\Delta u_{i,c,1}) &= \sigma_{\zeta_1} + \sigma_{\varepsilon_1} - \sigma_{\varepsilon_0} \\
var_c(\Delta u_{i,c,2}) &= \sigma_{\zeta_2} + \sigma_{\varepsilon_2} - \sigma_{\varepsilon_1} \\
var_c(\Delta u_{i,c,3}) &= \sigma_{\zeta_3} + \sigma_{\varepsilon_3} - \sigma_{\varepsilon_2} \\
var_c(\Delta u_{i,c,4}) &= \sigma_{\zeta_4} + \sigma_{\varepsilon_4} - \sigma_{\varepsilon_3} \\
var_c(\Delta u_{i,c,5}) &= \sigma_{\zeta_5} + \sigma_{\varepsilon_5} - \sigma_{\varepsilon_4} \\
var_c(\Delta u_{i,c,6}) &= \sigma_{\zeta_6} + \sigma_{\varepsilon_6} - \sigma_{\varepsilon_5} \\
var_c(\Delta u_{i,c,7}) &= \sigma_{\zeta_7} + \sigma_{\varepsilon_7} - \sigma_{\varepsilon_6} \\
var_c(\Delta u_{i,c,8}) &= \sigma_{\zeta_8} + \sigma_{\varepsilon_8} - \sigma_{\varepsilon_7} \\
var_c(\Delta u_{i,c,9}) &= \sigma_{\zeta_9} + \sigma_{\varepsilon_9} - \sigma_{\varepsilon_8}
\end{aligned}$$

Identification of permanent income shock parameters for $t = 3, .., 9$:

$$var_c(\Delta u_{i,c,t}) - cov_c(\Delta u_{i,c,t+1}, \Delta u_{i,c,t+1}) - cov_c(\Delta u_{i,c,t}, \Delta u_{i,c,t}) = \sigma_{\zeta_t} \tag{5.22}$$

I use eq. (5.22) corresponding to the time periods:

$$\begin{aligned}
var_c(\Delta u_{i,c,1}) - cov_c(\Delta u_{i,c,2}, \Delta u_{i,c,1}) - cov_c(\Delta u_{i,c,1}, \Delta u_{i,c,0}) &= \sigma_{\zeta_1} \\
var_c(\Delta u_{i,c,2}) - cov_c(\Delta u_{i,c,3}, \Delta u_{i,c,2}) - cov_c(\Delta u_{i,c,2}, \Delta u_{i,c,1}) &= \sigma_{\zeta_2} \\
var_c(\Delta u_{i,c,3}) - cov_c(\Delta u_{i,c,4}, \Delta u_{i,c,3}) - cov_c(\Delta u_{i,c,3}, \Delta u_{i,c,2}) &= \sigma_{\zeta_3} \\
var_c(\Delta u_{i,c,4}) - cov_c(\Delta u_{i,c,5}, \Delta u_{i,c,4}) - cov_c(\Delta u_{i,c,4}, \Delta u_{i,c,3}) &= \sigma_{\zeta_4} \\
var_c(\Delta u_{i,c,5}) - cov_c(\Delta u_{i,c,6}, \Delta u_{i,c,5}) - cov_c(\Delta u_{i,c,5}, \Delta u_{i,c,4}) &= \sigma_{\zeta_5} \\
var_c(\Delta u_{i,c,6}) - cov_c(\Delta u_{i,c,7}, \Delta u_{i,c,6}) - cov_c(\Delta u_{i,c,6}, \Delta u_{i,c,5}) &= \sigma_{\zeta_6} \\
var_c(\Delta u_{i,c,7}) - cov_c(\Delta u_{i,c,8}, \Delta u_{i,c,7}) - cov_c(\Delta u_{i,c,7}, \Delta u_{i,c,6}) &= \sigma_{\zeta 7} \\
var_c(\Delta u_{i,c,8}) - cov_c(\Delta u_{i,c,9}, \Delta u_{i,c,8}) - cov_c(\Delta u_{i,c,8}, \Delta u_{i,c,7}) &= \sigma_{\zeta 8} \\
var_c(\Delta u_{i,c,9}) - cov_c(\Delta u_{i,c,10}, \Delta u_{i,c,9}) - cov_c(\Delta u_{i,c,9}, \Delta u_{i,c,8}) &= \sigma_{\zeta 9}
\end{aligned}$$

Hence the set of moments for the identification scheme in differences are:

$$\begin{aligned}
cov_c(\Delta u_{i,c,t}, \Delta u_{i,c,t-1}) &= E[(\Delta u_{i,c,t} - E(\Delta u_{i,c,t}))(\Delta u_{i,c,t-1} - E(\Delta u_{i,c,t-1})] \\
&= -\sigma_{\varepsilon_{t-1}} \qquad (5.23)
\end{aligned}$$

$$\begin{aligned}
var_c(\Delta u_{i,c,t}) - cov_c(\Delta u_{i,c,t+1}, \Delta u_{i,c,t}) \\ -cov_c(\Delta u_{i,c,t}, \Delta u_{i,c,t-1}) &= \sigma_{\zeta_{i,c,t}} + \sigma_{\varepsilon_{i,c,t}} + \sigma_{\varepsilon_{i,c,t-1}} - \sigma_{\varepsilon_{i,c,t}} - \sigma_{\varepsilon_{i,c,t-1}} \\
&= \sigma_{\zeta_t} \qquad (5.24)
\end{aligned}$$

The entire set of parameters, which can theoretically be identified: $\sigma_{\varepsilon_1}, \sigma_{\varepsilon_2,}, \sigma_{\varepsilon_3}, \sigma_{\varepsilon_4}, \sigma_{\varepsilon_5}, \sigma_{\varepsilon_6}, \sigma_{\varepsilon_7}, \sigma_{\varepsilon_8}, \sigma_{\varepsilon_9}; \sigma_{\zeta_1}, \sigma_{\zeta_2}, \sigma_{\zeta_3}, \sigma_{\zeta_4}, \sigma_{\zeta_5}, \sigma_{\zeta_6}, \sigma_{\zeta_7}, \sigma_{\zeta_8}, \sigma_{\zeta_9},$.

Yet, given the restrictions of the dataset I use the covariance structure to obtain the following data parameters: $\sigma_{\varepsilon_2}, \sigma_{\varepsilon_3}, \sigma_{\varepsilon_4}, \sigma_{\varepsilon_5}, \sigma_{\varepsilon_6}, \sigma_{\varepsilon_7}, \sigma_{\varepsilon_8}; \sigma_{\zeta_3}, \sigma_{\zeta_4}, \sigma_{\zeta_5}, \sigma_{\zeta_6}, \sigma_{\zeta_7}, \sigma_{\zeta_8}$.

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