Automation Technologies and Labour Market Outcomes

A PhD Thesis
Submitted in Fulfillment of the Requirements
for the Degree of
Doctor of Philosophy in Economics

by
Kaizhao Guo
Adam Smith Business School,
College of Social Sciences,
University of Glasgow

Dissertation Director:
Professor Sayantan Ghosal
Dr Theodore Koutmeridis
Dr Zafer Kanik

September 3, 2024

Abstract

Automation Technologies and Labour Market Outcomes

Previous research has documented significant correlation between automation technologies and labour market outcomes. Little work, however, has examined regional variations of technological unemployment. This thesis made three strands of contributions. Firstly, it explores the heterogeneous effects across regions from different income groups, based on various forms of automation technologies. Analysis on regional variations of technological unemployment also complements a vast body of literature on Routine Biased Technical Change (RBTC). Secondly, this thesis extends studies of the role of skill shares and industrial structures on net job creation, causing heterogeneous employment effects from automation technologies. Thirdly, this thesis sheds light on the fact that net employment effects are mainly caused by differentials in productivity effects, and displacement effects are prevalent across regions.

This thesis is composed of five chapters. Chapter 1 introduces the research question of this thesis. The conceptual framework highlights that the key determinant behind such heterogeneous effects is the percentage of high skilled workers. With growing proportion of high skilled labour, productivity effects tend to become more pronounced in high-income regions, implying that new job vacancies could complement job destructions from displacement effects. In contrast, such non-negative employment effects are less likely in regions from low- and middle-income groups, due to strong displacement effects induced by lower percentage of high skilled workers.

Based on the conceptual framework, Chapter 2 exploits variations across US states and commuting zones, Chapter 3 explores differences across countries, and Chapter 4 analyses variations among UK workers. Leveraging shift-share IV strategies and generalised model specifications, this thesis finds that the magnitudes of employment reductions are significant and sizeable in low and middle income areas, and rising income levels could cause insignificant employment responses. Further evidence supports that these patterns can be explained by a simple net job creation channel, as displacement effects outweigh productivity effects in low income regions with lower proportion of skilled labour, and job creations are complementing job destructions with growing income levels and higher skill shares. Such technical changes are biased towards high skilled labour force, and are more pronounced in regions with manufacturing sectors.

Chapter 5 concludes, with a discussion of limitations and promising direction of future research, as well as policy implications.

JEL classification: E24, J24; O14; O33.

Keywords: Automation; Displacement Effects; Productivity Effects; Net Job Creations; Skill Shares.

Contents

List of Figures

List of Tables

Acknowledgments

As I rewind my memories, I grew interested in academic research during my undergraduate studies in Nankai University in China. Knowing that being an academic staff does not lead to wealth accumulation, my parents still chose to support me. Because they regarded me as their treasure throughout the lives. Even when my mom was seriously ill in hospital before, they still encouraged me to chase my dream without hesitations. I am appreciated for their caring and supports.

I extend my heartfelt thanks to my supervision team, including Professor Sayantan Ghosal, Dr Theodore Koutmeridis, and Dr Zafer Kanik. Suggested by my master's supervisor Professor Wiji Arulampalam, I choose University of Glasgow to continue my research work. Thanks Dr Theo for his detailed guidance, including how to find a good topic, and how to tell a good story. Also many thanks to Professor Sayantan, my Principal Supervisor, he always had regular meetings with me, to ensure that my research is in the right way. From my third year of PhD life, the addition of Dr Zafer to the PhD supervision was critical in this process, helping me to build a solid foundation.

I also would like to thank Francisca Antman, Dimitris Christelis, Thomas Drechsel, Ester Faia, Joachim Hubmer, Shoujun Huang, Elisa Keller, Petter Lundborg, Rachel Ngai, Ezra Oberfield, Erik Oberg, Barbara Petrongolo, Pascual Restrepo, Stefan Speckesser, Jan Stuhler, Yuta Takahashi, Mathieu Taschereau-Dumouchel, Alex Trew, Zhihong Yu, Joseph Zeira, Anwen Zhang, and numerous students from Brighton, Bristol, Glasgow, Oxford, Peking, Wurzburg, Zurich for excellent comments that improved the paper. I thank several participants at various seminars and conferences such as 2022 China Economist International Frontier Forum and School of Economics in Peking University 2022 International Cooperation Forum; ArmEA Annual Meetings; Asia-Pacific Conference on Economics & Finance; Asian and Australasian Society of Labour Economics 2022 Conference; Bristol PhD Seminar; Glasgow PhD Reading Group; Glasgow PhD Workshop; Glasgow Lunchtime Seminar; Knowledge, Skills, Behaviours An International Workshop; Nankai International Symposium on Economic Behaviour and Forecasting; PHD-EVS Seminar; RES Junior Symposium, etc, which provided high-quality empirical evidence to support my analysis.

I am thankful to the University of Glasgow and the Adam Smith Business School, in the form of all its members and staff, for providing such a decent research environment, and for their helpful advice. Special gratitude to my two examiners, and I appreciate the opportunity to have your helpful comments.

For my beloved parents here

Author's Declaration

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.

Printed Name: Kaizhao Guo

Signature:

Chapter 1

Introduction

1.1 Motivation

In recent years, development economists have regarded automation technologies as a potential driver of persistent economic growth (Aghion et al., 2017; PwC, 2018), and the adoption of automation could yield positive employment effects. However, a substantial body of research has expressed concerns about technological unemployment, defined as job losses within industries due to the adoption of automation technologies (Autor, 2014, 2015; Brynjolfsson and Mitchell, 2017; Dauth et al., 2021; Graetz and Michaels, 2017; Mitchell and Brynjolfsson, 2017; Sachs and Kotlikoff, 2012). This raises the question: What are the labour market impacts of automation technologies? Therefore, understanding the impacts of automation technologies on labour market outcomes at all levels of analysis, including individual workers, skill groups, metropolitan areas, and countries, is important.

Despite extensive research, the impacts of technological updating on labour market outcomes continue to be a subject of debate (Aghion et al., 2017; Autor and Salomons, 2018; Machin and Reenen, 1998), and little is known about heterogeneous effects with respect to the proportion of skilled workers, reflected by regions from different income groups. In this thesis, I leverage comprehensive macro and micro dataset across US commuting zones from 2000 to 2019, to explore the impacts of automation technologies on employment rate, from the standpoint of advanced economies. Additionally, for further discussions, generalisations to cross country evidence, along with individual level analysis based on UK context, will be provided.

This thesis employs two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on datasets from International Federation of Robotics (2021), United Nations (2021) and The Conference Board (2021). Automation technologies are defined as "any technology that enables machines, algorithms, capital to perform tasks previously allocated to humans" (Acemoglu and Restrepo, 2022). Generally speaking, they are comprised of three components, including numerical controlled machinery, industrial robots, and specialised software. For industrial robots, they refer to "an automatically controlled, reprogrammable, and multipurpose machine" (International Federation of Robotics, 2021). They could cover automation technologies that do not require human instructions and can automatically operate based on programmed codes (Acemoglu and Restrepo, 2020). While for ICT investments, they refer to "acquisition of equipment and computer software that is used in production for more than one year" (OECD, 2020). In other words, ICT investments include information technology equipment, communications equipment, and software, which have substantial overlaps with automation technologies that still require human corporations. Furthermore, this research also utilises alternative measures of automation technologies, including degree of automated equipments and computerisation complexities, to document the susceptibility to replacement by automation technologies for each UK labour force.

1.2 Related Literature

A burgeoning trend of research is focusing on the relationship between technological changes and labour market outcomes. In this section, I review the existing theoretical works on the welfare effects of automation and other advanced technologies. In addition, I present related empirical evidence, to offer an overview of how technological progress affects labour markets, productivity and economic growth.

1.2.1 Theoretical Work

A vast literature seeks to explain the sources of declining labour share in national income, and many researchers attribute this phenomenon to some forms of biased technical change.

Previous articles adopted canonical approach (Acemoglu and Restrepo, 2018b; Kogan et al., 2023), which directly posits a production function of the form $Y = F(A^K K, A^L L)$. This approach imposes that all technological change augments factors of production. However, the definitions of capital-augmenting technological change or labour-augmenting technological change suggest that facing technical changes, the relevant factor becomes universally more productive across all tasks (Acemoglu and Restrepo, 2019a). In contrast, the task-based approach focused on technologies that change task contents of production, offering a more effective framework for understanding changes in labour demand and productivity growth (Autor et al., 2003; Zeira, 1998).

According to task-based framework developed by Acemoglu and Autor (2011), robots and other forms of automation technologies, are devices designed to execute complicated and typically repetitive tasks. In other words, they directly substitute workforce previously responsible for routine tasks in industrial assembly lines (Grossman and Oberfield, 2022).

The task-based model clarifies that automation technologies operate by substituting capital for labour across an expanding array of tasks. In addition, it suggests that the welfare implications of automation may differ among occupations with different task contents (Restrepo, 2024). It is important to note that each occupation requires multiple types of tasks, a concept supported by a body of existing research including Adachi (2021). Whereas, a heterogeneous mix of tasks can be carried out by workforces from different occupations. In other words, occupations with similar task intensities may overlap (Acemoglu and Restrepo, 2019a).

Following Acemoglu and Restrepo (2022), the key economic decision for each occupation is how to perform these tasks to optimise the output

$$y_x = \Sigma_g A_g \cdot \psi_{gx} \cdot l_{gx} + A_k \cdot \psi_{kx} \cdot k_x \tag{1.1}$$

According to Equation 1.1, each occupation requires specific tasks x, which can be produced utilising a combination of labour and task specific capital. Workers are classified into heterogeneous groups $g \in \{1, \cdots, G\}$. The parameters ψ_{gx} and ψ_{gx} denote the productivity of the inputs. The terms A_k and A_g terms represent standard factor-augmenting technologies, which enhance the productivity of factors uniformly across all tasks. For the task specific component, l_{gx} is the quantity of labour required to perform task x, and l_x is the quantity of task specific capital.

In the remainder of this section, I will offer a brief review of this task-based framework, and investigate the sources of negative employment effects from automation technologies, alongside several countervailing forces.

Firstly, automation could replace labour, particularly in routine occupations where tasks can be easily codified by computer programming (Acemoglu and Restrepo, 2020; Autor, 2013, 2015; Brynjolfsson and Mitchell, 2017; Mitchell and Brynjolfsson, 2017; Sachs et al., 2015). Compared with conventional labour force, automation technologies are relatively cheaper than ordinary wages, thus firm owners prefer to use machines. The adoption of new technologies could promote reallocation between capital and labour within sectors, and accelerate the process where tasks previously conducted by labour are gradually taken over by capital, known as displacement effects.

As indicated in Equation 1.1, task specific capital and workers are perfect substitutes. In contrast to AI (Artificial Intelligence) and other forms of new task creation, in all instances of automation technologies, machines or software can replace the labour force in narrowly defined tasks (Restrepo, 2024).

To understand the displacement effects of automation technologies on labour market performance, the theoretical approach by Acemoglu and Autor (2011) can be illustrated in a simple diagram, as presented in Figure 1.1.

Figure 1.1: Displacement Effects from Automation Technologies

$N \quad N_L \quad N_H \quad N+1$

$\underbrace{N_L \quad N_H}_{\text{Displaced}}$

$N \quad N_L \quad N_H \quad N+1$

$N^* \quad N_L^* \quad N_H^* \quad N^*+1$

Notes:
The graph summarises the process of displacement effects from automation technologies (Acemoglu and Restrepo, 2019a).

In a single sector economy, the production process combines the output from a variety of tasks, which can be accomplished utilising either capital or labour. Tasks are ranked by wage percentile, and can be normalised to lie between N and $N + 1$. By definition, tasks in the range $[N, N_L]$ are not automated, because workers' reservation wages are relatively lower than the cost of machines. Therefore, the introduction of automation technologies could replace labour in tasks $[N_L, N_H]$, thereby reducing production costs[1]. If we then re-normalise the tasks into the range $[N^*, N^*+1]$, the tasks located in the middle of wage percentile $[N_L^*, N_H^*]$ are considered vulnerable to being replaced by machines during the next wave of technological advancement (Aghion et al., 2017).

Secondly, automation could also promote employment[2], and generate several countervailing forces (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a; Autor, 2015). On the one hand, the adoption of automation technologies could lower production costs where tasks are easily automated, leading to overall economic expansion and thus rising labour demand in all local sectors, particularly in non-automated local areas, known as productivity effects (Acemoglu and Restrepo, 2018a). According to Acemoglu and Restrepo (2019a,b)

$$Wage\,Bill = Value\,Added \times Labour\,Share \tag{1.2}$$

As summarised in Equation 1.2, for firms adopting automation technologies, the growth in value added will translate into changes in wage bill, thus raising labour demand in other sectors, particularly in non-automated local areas (Acemoglu and Restrepo, 2018c). For instance, smart machines are typically designed and improved by skilled workers (Sachs and Kotlikoff, 2012), which can create a significant number of labour saving jobs, thus boosting labour demand in other relevant sectors. Besides, with reduced production costs due to the widespread adoption of automation technologies, firm owners are incentivised to invest more in both labour and capital, thus raising demand for labour force.

In a multi-industry economy, the development of automation technologies could also affect aggregate labour demand through composition effects, as improved efficiency in cer-

[1] It is observed that labour inputs have comparative advantages in non-routine tasks in the range of $[N_H, N+1]$, which cannot be easily replaced by machines (Acemoglu and Restrepo, 2018c).

[2] Here I use "promote employment" instead of complementary effects, as automation technologies could only replace labour force rather than complement labours. What "complementary effects" refers to is reinstatement effects, which will be illustrated later in this section

tain tasks may change the demand for downstream products (Agrawal et al., 2019; Jackson and Kanik, 2019). Driven by general equilibrium effects, industries utilising complementary inputs and tasks in their production processes will also experience a rise in labour demand (Dauth et al., 2021).

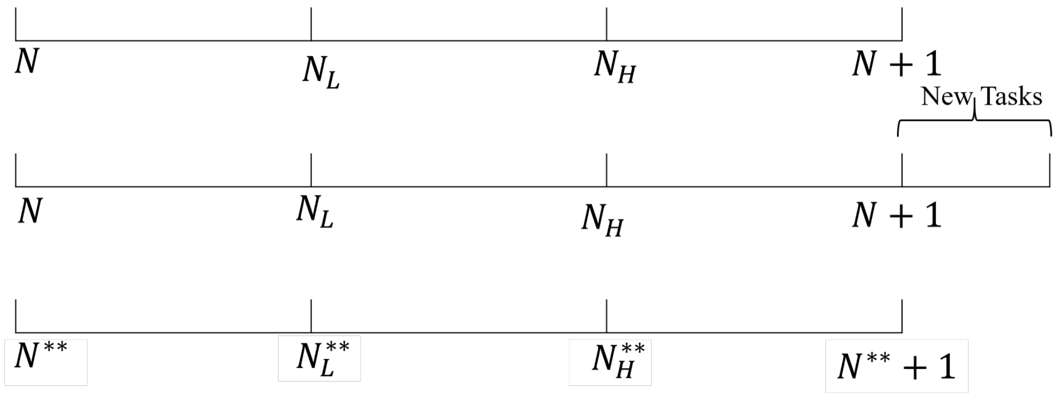
Taking input-output networks among firms into accounts, in sectors where high skilled labour force can also perform simple tasks, those low skilled workers face risks of displacement, often termed ripple effects (Acemoglu and Restrepo, 2022; Jackson and Kanik, 2019). In other words, they are likely to experience job losses, as an indirect consequence of automation technologies.

On the other hand, technological advancement also generates new tasks where labour maintains comparative advantages (Acemoglu and Restrepo, 2019b), and raises corresponding labour demand through the rise of AI platforms, a phenomenon known as reinstatement effects. For example, by minimising prediction uncertainties, artificial intelligence has the potential to reduce both search and production costs, hence increases relative returns of decision tasks and boosts labour demand for those specialised in new communication tasks (Agrawal et al., 2019; Brynjolfsson et al., 2019). It is important to recognise that reinstatement effects are limited to the effects of AI, rather than automation technologies. This is because only artificial intelligence has the capacity to create new jobs, and automation technologies can only promote employment through productivity effects.

In the case of generative AI, the capital deepening of automation technologies can also occur (Acemoglu, 2024). For example, an already-automated IT security task may be executed more effectively by generative AI. By raising the task complementarity, the productivity of capital can also increase, while at the same time enabling workers to specialise and raise their productivity in other aspects of their jobs (Acemoglu and Restrepo, 2019a).

Acemoglu et al. (2001) offer a theoretical notion for understanding how technological changes affect labour market performance through reinstatement effects. This framework is illustrated in Figure 1.2.

Figure 1.2: Reinstatement Effects from Automation Technologies



Notes:
The graph presents the process of reinstatement effects from automation technologies (Acemoglu and Restrepo, 2019a).

Similar to the analysis of Figure 1.1, each product in Figure 1.2 requires the completion of a sequence of tasks, which is achievable through the utilisation of capital or labour. These tasks are ranked according to wage percentile, and can be normalised to lie between N and $N+1$. By definition, the creation of new tasks is not observable at the tasks with lower wage level, due to relatively lower labour cost compared with price of machines. Therefore, the introduction of new labour-intensive tasks or new capital-intensive tasks corresponds to expansion of task range above N. Then if we re-normalise the tasks into the range $[N^{**}, N^{**}+1]$, an increase in $N^{**}+1$ translates to the introduction of new tasks, triggered by AI platforms or other advanced technologies. The impacts on equilibrium wage are uncertain, and are potentially determined by trade-offs between productivity gains and reductions in labour inputs (Acemoglu and Restrepo, 2018b; Jackson and Kanik, 2019).

In summary, the heterogeneous effects of automation adoption on labour market outcomes are determined by net job creations, induced by displacement effects and other countervailing forces.

1.2.2 Empirical Work

Much of the public attention paid to technological updating concerns the effects on jobs. Understanding these effects requires comprehending the capabilities of this technology. This section begins by reviewing the sources of skill premium. Then I will offer some empirical evidence on impacts from automation technologies, including job polarisation across regions and occupations. In addition, I will summarise existing empirical studies based on US evidence, cross country evidence, and UK evidence. Finally, I will highlight some challenges, such as task contents and skill measures, as well as influences from international trade.

Over the last two decades, shifts in skill demand, such as episodic events or changes in labour force composition, have played an increasingly important role in wage structure variations among different education groups (Autor et al., 2008; Beaudry et al., 2016; Zimmerman, 2019). An analysis of wage structure based on US census in the late 20th century indicates that firms strongly favoured college graduates and females (Carneiro and Lee, 2011; Katz and Murphy, 1992). The findings by Zimmerman (2019) suggest that education and peer ties formed at elite colleges could help students to reach top positions in the economy in the future, leading to rising wage levels for high skilled workers. Moreover, increases in college enrolment may have contributed to a declining college premium throughout US history, due to lower average quality of college educated workers (Carneiro and Lee, 2011).

Given exogenous relative supply of skilled workers, one of the key factors that could contribute to changes in wage inequality, is skill-biased technical change (Card and DiNardo, 2002; Jones and Yang, 2016; Kaplan and Rauh, 2013). And studies using World Health and Income database also described a Pareto distribution of skill alongside increasing skill returns (Jones and Kim, 2018). Besides, a significant body of empirical research evaluates the connection between wage gap and technical changes, measured by the adoption of “white-collar” tools (Krueger, 1993).

The results of this thesis also complement the theory of skill biased technical change, and confirm that technological changes driven by automation technologies are biased towards high skilled workers with advanced qualifications.

Regarding the influence of information technology on overall wage differentials between college students and non-college students, the expansion of computer use could explain approximately 60% of increasing education return (Krueger, 1993), and the effects could vary across different fields of study (Moreno-Galbis and Wolff, 2011). Based on NCDS data in UK, Dolton and Makepeace (2004) observed a significant premium associated with computer use for some British people, and the coefficients differ across individuals. In addition, based on German data, people found statistically significant associations between wage differentials and the use of other “white-collar” tools, such as calculators, telephones and manual writing materials, and the magnitude of the correlations was similar to that observed between computer use and wage gaps (DiNardo and Pischke, 1997).

With the development of automation technologies, such as robotic machines and computerised equipments, their strong computing power could easily assist humans in performing prediction tasks. This has greatly enhanced the efficiency of decision-making (Agrawal et al., 2019), thereby improving productivity of work currently performed by labour. Simultaneously, these technologies are changing the task contents of productions, which has significant effects on labour market outcomes (Acemoglu and Restrepo, 2019a).

As noted by Montobbio et al. (2024), previous research has primarily employed two alternative methodologies to appraise the implications of automation technologies on labour markets, in terms of occupational level employments and wages. The first approach, which was introduced by Frey and Osborne (2017), developed an index to represent the likelihood of automation technologies, based on subjective evaluation of job displacement vulnerability. This method has been widely adopted in recent papers that focused on artificial intelligence. Webb (2019) proposed a direct measure, leveraging machine learning techniques to calculate the similarity between verb-noun pairs found in the titles of AI patents and O*NET tasks. The second approach relies on the dataset of robotic usage by International Federation of Robotics (2021), or other datasets about automation technologies such as The Conference Board (2021). For instance, Acemoglu et al. (2023) discovered that findings in the Netherlands closely aligned with the evidence in Germany by Dauth et al. (2021). In contrast to the US analysis, robots did not lead to a significant decrease in overall employment in Europe, but the proportion of low skilled workers in the workforce declined over the study period, particularly in the manufacturing sector.

Table 1.1: Summary of Relevant Literature on Measures of Automation

Contribution	Measure (Automation and AI)	Level of analysis
Frey and Osborne (2017)	Delphi method and machine-learning algorithm	Occupations
	to identify exposed occupations to automation	Occupations
Acemoglu and Restrepo (2020)	Share of robot adoption	Industry
Felten et al. (2018)	Questionnaire on 10 AI application	Jobs
Webb (2019)	Co-occurrence of verb-noun pairs in AI patents and O*NET tasks	Jobs
Kogan et al. (2023)	Term frequency-inverse document frequency matrix of the patent text and DOT	Jobs
Montobbio et al. (2024)	Term frequency-inverse document frequency matrix of CPCs and O*NET	Jobs

Notes:
This table presents a summary of relevant literature on measurement of automation technologies, with their methodologies and levels of analysis (Montobbio et al., 2024). Jobs refer to tasks aggregated at the occupational levels.

This research employs two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on datasets from International Federation of Robotics (2021); United Nations (2021); The Conference Board (2021). Moreover, the study utilises alternative measures of automation technologies, including degree of automated equipments and computerisation complexities, to determine the vulnerability of each segment of the UK labour force to displacement by automation technologies..

Conventional economic models often formalise technological change as factor augmentation. These models suggest that, in the face of exogenous technological shocks, both labour demand and equilibrium wage should rise, regardless of whether the technological change is capital-augmenting or labour augmenting (Acemoglu and Restrepo, 2018b). Combining such complementary effects with another distinctive feature named displacement effects, an alternative task-based framework was developed by Acemoglu and Autor (2011). Endogenising the direction of technological change, this framework uncovers both productivity effects and displacement effects from automation technologies.

Technological unemployment and job polarisation have been widely examined in western developed countries. A wealth body of case-study analysis draws upon US data sources such as Current Population Survey (CPS) Census Integrated Public Use Micro Samples, American Community Survey (ACS) and Dictionary of Occupational Titles (DOT) (Antonczyk et al., 2018; Autor et al., 2003; Autor and Dorn, 2009, 2013; Murphy and Welch, 1993). These studies illustrate a shift in labour inputs towards non-routine occupations accompanied by skill upgrading in the 20th century. This shift is primarily attributed to industry task changes driven by technological updating (Autor et al., 2003; Autor and Dorn, 2009, 2013; Berman et al., 1994). Younger college-educated workers and new entrants are more likely to move to nonroutine jobs with high skill demand, while those older workers with higher costs of occupational mobility are more likely to remain in their existing roles or flow to low-skill nonroutine occupations, even when controlling for occupation and demographic characteristics. Those patterns of shrinking workforce in middle occupations have persisted across demographic, regional and industry groups since late 1970s (Bluestone and Harrison, 1988). Using Natural Language Processing to characterise high skilled occupations, Acemoglu et al. (2022b) found that these occupations have become more accommodating to the preferences of older workers. The results are consistent with findings by Autor and Dorn (2009); Mohnen (2024), who observed a concentration of older workers in high skilled jobs, noting that these occupations are ”getting old”.

A significant volume of the existing research on technological unemployment focused on

US. Acemoglu and Restrepo (2020) provided evidence on large negative effects of robot adoption on employment and wages in the US. Utilising textual analysis techniques, Kogan et al. (2021) calculated the probability of automation adoptions, measured by similarity between descriptions of automation patent innovations and occupation listed in ONET. Their findings, based on NBER-CES manufacturing data, reveal positive association between technological changes and labour productivity. For the patterns across different sectors, Acemoglu and Restrepo (2022) showed that negative employment effects are mainly observed in manufacturing sectors with greater exposure to automation technologies, and those with higher adoptions of equipment and software (Hubmer, 2023). Building on these US-focused studies, Chapter 2 will provide novel evidence on regional variations of such technological unemployment, and explore potential mechanisms about net job creations.

For cross country evidence, evidence of widespread job polarisation can also be observed in other European countries. Studies utilising German social security records from IABS dataset align with US findings, suggesting a technology-driven polarisation in the European labour market (Antonczyk et al., 2018; Goos et al., 2009). Because of the unionisation rate, technology effects alone cannot fully account for the empirical findings in European countries (Dauth et al., 2021). Taking labour market institutions into accounts, Acemoglu et al. (2023) estimated the effects of robot adoption on firm level and worker level outcomes in the Netherlands and other European countries. Their research indicates that, despite the rigidity of the labour market and constraints on firms' ability to adjust both employment and wages, workers directly exposed to automation technologies experience lower earnings and employment rates. However, there is only limited evidence regarding phenomenon of job polarisation and other forms of technological unemployment in emerging economies. Chapter 3 aims to address this gap in the literature.

Unlike previous occupational level analysis, this thesis offers original insights into RBTC across regions, and highlights that the job displacement due to automation is likely to be more harmful in middle income regions compared with low income regions. This difference is attributed to the concentration of routine occupations in middle-income regions, leading to relatively larger job losses.

UK evidence based on New Earnings Survey (NES) and Labour Force Survey (LFS) documents a U-shaped relationship between employment growth and initial log median wage levels (Goos and Manning, 2007; Goos et al., 2009; Graetz and Michaels, 2017), implying a rapid increase at both extremes of the skill distribution, namely lovely jobs at the top and lousy jobs at the bottom. Utilising R&D intensity as a directly observed measure of technical change, analysis by Machin and Reenen (1998) uncovered significant association between skill upgrading and technical change, leading to rising relative demand for high skilled workers. These results are consistent with Dolton and Makepeace (2004), suggesting that technological updating could account for one third of the rise in wage premium. In Chapter 4, I will provide individual level analysis based on UK context, and further explore the heterogeneous effects from automation technologies across regions and skill groups.

Research into the effects of technological changes on labour market outcome usually confronts with substantial challenges, such as defining task contents and measuring skills (Autor, 2013). Conventional identification strategies, using median wages paid to skill group based on education or occupation, ignore the wage dispersion across groups and individual heterogeneities (Autor, 2013; Berman et al., 1994; Goos and Manning, 2007; Murphy and Welch, 1993). Therefore, Autor and Dorn (2013); Graetz and Michaels (2018) instead implement estimations weighted by Census sampling weights and annual working hours, to reflect industrial heterogeneities within given areas, which would be easily affected by labour supply elasticities. Combining micro data and macro technology, Oberfield and Raval (2021) utilised micro data on the cross-section of plants to assess the relative importance of capital intensity, and found that skill biased technical change would lead to declining share of labour income in the U.S. manufacturing sector.

In addition, for open economies with trade interactions, the intensive use of automation technologies could also trigger some variations in labour market outcomes through free flow of production factors, such as labour force immigration (Acemoglu and Restrepo, 2020). Also, automation reshapes the relative labour costs, which are the determinants of international competitiveness (Rodrik, 2018). Moreover, decisions about the adoption of automation technologies may be correlated with capital intensity or ICT (Information and Communication Technology) investment, which also have direct impacts on labour participation (Graetz and Michaels, 2017, 2018).

As demonstrated, a vast body of literature seeks to study the association between automation technologies and labour market outcomes. In the following section, I will offer conceptual framework for this thesis.

1.3 Conceptual Framework

In this section, I illustrate conceptual framework relating regional variations of productivity effects and displacement effects arising from automation technologies, and provide guidance for interpreting empirical results.

Firstly, automation has the potential to substitute for labour, particularly in routine occupations (Acemoglu and Restrepo, 2020; Autor, 2013, 2015; Brynjolfsson and Mitchell, 2017; Mitchell and Brynjolfsson, 2017; Sachs et al., 2015). Automation technologies often present a more cost-effective option than conventional labour force, making machines preferable for firm owners. The process is known as displacement effects.

The replacement of jobs is widespread and occurs across regions with different income levels[3]. In advanced economies, the positive association between educational attainment

[3] The uneven distribution of displacement effects are also documented in Autor et al. (1998); Acemoglu and Restrepo (2022); Acemoglu and Loebbing (2022). Driven by declining price of capital goods, which can be treated as an exogenous factor, the workers exposed to industries at the early stages of automation process would face larger risks of job replacement.

and wage levels, could provide great opportunities for the adoption of automation technologies to replace high skilled labour force with advanced education (Acemoglu and Restrepo, 2021)[4]. However, most skilled labour is engaged in analytical or interpersonal tasks, and such non-routine tasks are not easily codified by computer programming, thus limiting the ability of machines to replace these workers (Acemoglu and Restrepo, 2020; Acemoglu et al., 2022a; Agrawal et al., 2019). In addition, when displacement occurs, specific institutional settings may require these high skilled production workers to spend significantly more time on transition to new jobs, potentially contributing to the low growth of jobless recoveries in developed countries (Acemoglu and Restrepo, 2018a; Graetz and Michaels, 2017). Therefore, such labour market frictions reduce the likelihood of job losses for high skilled labour.

Alternatively, in emerging markets and developing economies, extensive use of cheap labour suggests higher likelihood of enormous job losses for workers engaged in tasks currently performed by humans, as such routine tasks could also be performed by other computerised equipments (Agrawal et al., 2019). However, this is not the complete picture. Facing exposure to automation technologies, low skilled workers who are still productive elsewhere could easily switch to other occupations with similar task requirements, while those with limited labour alternative use are unable to conduct other tasks[5]. In order to secure employment, this latter group may have to accept relatively lower reservation wage (Jackson and Kanik, 2019). Compared with workers in high income areas, who are endowed with alternative labour use, those in low-income regions have no choice but to become "re-employed" at lower wage levels[6]. This could present a barrier to the adoption

[4]Recent articles such as Acemoglu and Restrepo (2022) also examined widening wage inequalities driven by automation, and highlighted that high skilled workers who are not susceptible of job replacement will enjoy wage gains. Therefore, the firm owners would make further decisions based on rising wages for high skilled labour and relatively low price of machines.

[5]Previous literature identified the importance of task dissimilarity from the costs of occupational transition (Autor and Dorn, 2009; Cortes and Gallipoli, 2017; Cortes et al., 2020; Gathmann and Schonberg, 2010; Poletaev and Robinson, 2008; Yamaguchi, 2012). Facing susceptibilities of job replacement by automation technologies, experienced workers endowed with firm specific human capital prefer to switch to other occupations within the same establishment which have similar task intensities, due to low training costs, while other people may switch across occupation to avoid high transition costs. This is also consistent with Autor and Dorn (2009), which observed that the degree of upward reallocation is strongly negatively correlated with age, as old workers are more likely to accumulate firm specific human capital.

[6]Recent papers such as Braxton and Taska (2023) also discussed situations where those low skilled workers switch to other

of automation technologies (Acemoglu and Restrepo, 2021), as economic cost remains a key factor even when the technological feasibility could support automation of specific tasks (Autor, 2013). As a consequence, the narrowing gap in job losses induced by more substantial "re-employed" workers in low income areas, results in more widespread displacement effects across both high- and low-income regions.

Secondly, automation could also generate several countervailing forces, and have positive employment effects[7] (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a; Autor, 2015). On the one hand, automation adoptions could reduce production costs, leading to overall economic expansion and thus rising labour demand across local sectors, particularly in areas relevant to non-automated tasks, known as productivity effects (Acemoglu and Restrepo, 2018a, 2019b; Sachs and Kotlikoff, 2012). On the other hand, technological updating creates new tasks where labour has comparative advantages (Acemoglu and Restrepo, 2019b), This, along with the rise of AI platforms, increases labour demand, or more formally known as reinstatement effects[8].

Among those countervailing forces, this thesis primarily considers productivity effects, namely rising high skilled labour demand in other sectors, particularly in industries that exhibit gross complementarity in their production processes. This pattern of response is expected to be more sizeable in high income economies. In these contexts, there is a rapid take-off in labour demand for high skilled occupations[9], triggered by rising consumer demand for final products, and an expanding pool of skilled labour (Acemoglu et al., 2022a; Akerman et al., 2015; Webb, 2019). In contrast, insufficient supply of such skilled

occupations. For labour forces with limited alternative uses, they are likely to suffer from earning losses after displacement.

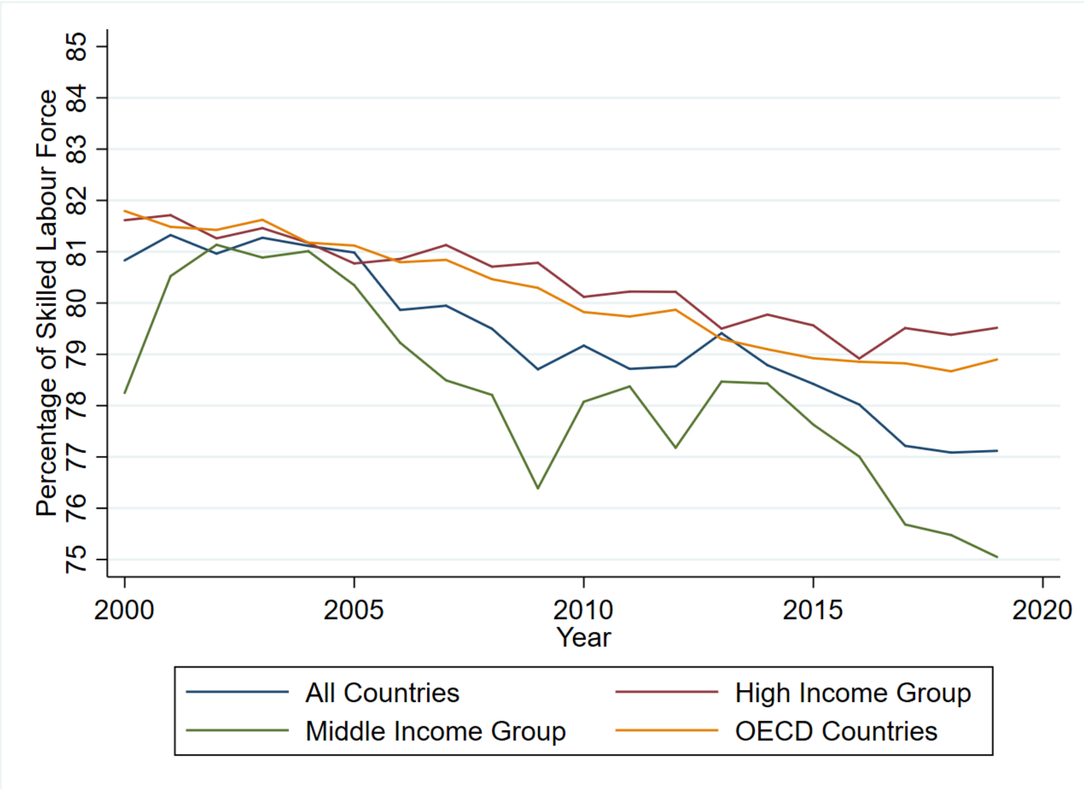
[7]Here I use "positive employment effects" instead of complementary effects, as automation technologies could only replace labour force rather than complement labours. What "complementary effects" refers to is reinstatement effects, which will be illustrated later in this section

[8]It should be noted that reinstatement effects only refer to those by AI rather than automation technologies, as only artificial intelligence could create new jobs, and automation technologies can only promote employment through productivity effects

[9]Another interpretation would be: facing depressed production costs triggered by widespread adoption of automation technologies, firm owners gain incentives to devote much inputs for both labour and capital into productions, thus raising demand for labour force. However, it is hard to distinguish the characteristics of high skilled firms conducting technology intensive products. Also, the difference between high income regions and low and middle income regions lay in consumer demand for high tech products. For emerging market and developing economies, the firm owners may not have tendencies to expand economy even if production costs are lower, as consumers do not have sufficient demand for those high quality products.

labour force in less developed economies limits the capacity of automation technologies to create similar job opportunities.

Figure 1.3: Evolution of Labour Force with Advanced Education, 2000-2019



Notes:
The graph presents proportion of skilled labour force, defined as those who received tertiary education, for countries from different income groups - using data from World Bank (2021). Classification of high income countries and middle income countries are defined by World Bank (2021), and the sample economies of OECD countries are obtained from OECD (2020).

Furthermore, as Figure 1.3 shows, the widening gap of skill shares across economies from different income groups, measured by proportion of skilled workers with tertiary education, reveals that equilibrium employment is likely to be lower in less developed regions. In contrast, strong productivity effects in economically advanced areas may reduce the likelihood of welfare deterioration.

In summary, this analysis indicates that the heterogeneous effects of automation adoption on employment are determined by net job creations between displacement effects and productivity effects. With growing proportion of high skilled labour, productivity effects tend to become more pronounced and could contribute to job creations in high income regions. This suggests that new job vacancies could complement job destructions from displacement effects. While such non-negative employment effects are less likely to occur in regions from low- and middle-income groups, induced by strong displacement effects by lower percentage of high skilled labours.

Based on the conceptual framework outlined above, this thesis proposes the research questions: What are the impacts of automation technologies on employment rate? And what are the mechanisms behind heterogeneous effects across regions from different income groups?

The hypotheses are as follows:

Hypothesis 1: In low and middle income economies, the impacts of automation technologies on employment rate are negative, as the job destructions induced by displacement effects outweigh job creations driven by productivity effects.

Hypothesis 2: In high income economies, automation technologies tend to have positive or non-negative effects on employment rate, as newly generated job vacancies induced by productivity effects, could compensate for job losses driven by displacement effects.

Hypothesis 3: Overall automation technologies destroy more jobs than they create.

To verify the hypothesis, Chapter 2 draws upon comprehensive macro and micro dataset across US states and commuting zones from 2000 to 2019. This analysis explores the impacts of automation technologies on employment rate in advanced economies. Chapter 3 expands the scope to consist of cross-country evidence, and evaluates how the heterogeneous effects of automation technologies on employment rate vary across countries at different stages of economic development. Finally, Chapter 4 presents individual level analysis based on UK workers, to show that these findings hold true for this group as well, and such technical changes are biased towards high skilled workers and those living in manufacturing intensive regions.

1.4 Contribution

Among existing works of literature, this research is related to several empirical studies on the effects of technological adoption on labour market outcomes. It makes three strands of contributions.

The first main contribution is the exploration of the heterogeneous effects across regions from different income groups. Early works focusing on general measures of technological updating such as TFP (total factor productivity) growth and patent awards across different countries are closely related (Autor and Salomons, 2018; Autor et al., 2020). This study utilises two complementary indicators, namely robotic density and ICT intensity. Therefore, this approach allows for a more accurate differentiation between productivity growth originating from automated and non-automated sectors.

In addition, the analysis on regional variations of technological unemployment also complements a vast body of literature on RBTC (Routine Biased Technical Change). Studies by Autor and Dorn (2013); Goos et al. (2014); Graetz and Michaels (2017) and others discovered the phenomenon of job polarisation in western developed countries. They demonstrated how automation could replace labour forces in occupations located at the middle of skill percentiles with routine tasks, and cause positive employment and wage effects in other occupations. Unlike previous occupational level analysis, this thesis offers original insights into RBTC across regions. It highlights that the job displacement due to automation is likely to be more harmful in middle income regions compared with low income regions. The relatively large job losses in middle income regions are attributed to concentration of routine occupations.

For the second main contribution, this thesis complements studies of the role of skill shares, industrial structures, and net job creations, causing heterogeneous employment effects from automation technologies. Recent work by Acemoglu and Restrepo (2021) estimated the impacts of educational upgrading on the adoption of automation, arguing that a larger proportion of highly educated workers could result in scarcity of production workers in blue collar jobs. The rising wages for manufacturing workers, along with the declining participation rate, will finally provide great opportunities for automation. This thesis differs from previous studies since, rather than focusing on workers with low educational attainment, I show that the channel for high skilled labour force could be different. With intensive growth of highly educated workers, supply effect appears to generate stronger productivity effects, and act as the main driver of employment growth in advanced economies, particularly in manufacturing industries.

For the third main contribution, this thesis sheds light on the fact that net employment effects are mainly caused by differentials in productivity effects measured by job creations. And job destructions, a good proxy of displacement effects, are prevalent across different regions. In terms of the mechanisms, this study supports the findings of Acemoglu and Restrepo (2020, 2022); Bonfiglioli et al. (2021); Dauth et al. (2021). It confirms that job creations[10] often favour high skilled workers completing advanced education, while the negative welfare consequences of unemployment disproportionately affect low skilled workers.

1.5 Main Findings

The first result is that automation technologies could affect labour market differently, conditional on regional income levels. For US evidence, employment rate did not experience significant changes in high income CZs, and 1000 unit increase in robotic stocks per worker will lead to a drop of 0.87 percentage points in employment rate for low income commuting zones between 2000 and 2019. In general, a rise of 1 unit robot per thousand labour force could generate job losses by 0.67 percentage points. This coefficient

[10] Here ”job creation” refers to rising job vacancies in incumbent occupations, rather than creation of new occupations or new tasks, as the latter only applies to the field of artificial intelligence.

is similar to the estimation of employment reductions about 0.45 by Acemoglu and Restrepo (2020)[11]. The findings remain consistent when employing alternative measures of automation technologies using ICT and automation trade volumes, which align with other evidence using automation patent data (Acemoglu and Restrepo, 2021).

For cross country analysis, it is discovered that one additional robot per thousand workers tends to reduce employment rate by 1.42 percentage points, and growing GNI per capita could lead to complementary effects of 0.07 percentage points. While for individual analysis based on UK data, 1 unit increase of importance of automated equipment is associated with 2.29 hours increase of actual working time. Specifically, with each additional pound in gross earnings, the impacts of degree of automated equipments on actual working time will be flattened by 0.36 hours. This result is consistent with EU evidence by Graetz and Michaels (2018), which showed that one additional robot per thousand labour force could reduce working time by 1.22 hours for high skilled workers, and 8.59 hours for low skilled workers[12].

The second result is that 1000 unit increase in robotic stocks per worker will lead to a drop of 1.37 percentage points in the employment rate in middle income US CZs, and the magnitudes are larger than those in low income CZs. This difference arises because routine occupations, whose tasks are easily codified by machines, are concentrated in middle income regions. This is a significant extension, compared with Autor and Dorn (2013); Goos and Manning (2007); Goos et al. (2014).

Regarding the third result, leveraging comprehensive data about job creations, I found that the impacts of robotic adoptions and ICT trade volumes on job destructions are insignificant. The finding is consistent with the conceptual framework in Section 1.3. Therefore, the heterogeneous employment effects are driven by differentials in job creations, as a rise

[11]The reason why the magnitudes of the coefficient in this thesis is larger than Acemoglu and Restrepo (2020), is that their analysis is based on sample period of 1990-2007. It is uncovered that after the financial crisis in 2008-2009, the rate of technological replacement is accelerating (Sachs and Kotlikoff, 2012; Sachs et al., 2015; Brynjolfsson and Mitchell, 2017).

[12]As suggested in Chapter 4, the development of automation technologies in UK is lower than average value of automation adoptions in Europe, therefore, the results of displacement effects for UK are slightly lower than those for European Union.

of robotic stocks per thousand workers could lower job creation rate by 1.35 percentage points. The effects of ICT and automation trade volumes are similarly and significantly negative. The growing income level could mitigate job losses by 0.15 percentage points in net job creation rate.

Regarding the fourth result, further studies reveal that such technical changes are biased against low skilled workers, and are more pronounced for manufacturing sectors. From US evidence, automation technologies represented by robotic adoptions and ICT trade volumes, are negatively associated with low skilled employment for workers without high school degrees, and bring welfare improvements for high skilled workers with tertiary and university education. And new occupations are mainly created for high skilled workers. Heterogeneous analysis based on cross country evidence also confirms this finding, indicating that the negative employment effects from automation adoptions are more pronounced in OECD countries, characterised by a concentration of manufacturing activities. Similarly, from individual level analysis based on UK context, the impacts of automation technologies on labour supply are solely observable among college educated workers, which is consistent with theory of SBTC (Skill Biased Technical Change). Considering the contribution of manufacturing industry to GDP growth, such technical changes are more pronounced within London.

1.6 Thesis Structure

The remainder of the paper is as follows.

Chapter 2 provides US evidence. Following descriptions of data sources and stylised facts, I develop empirical models and econometric specifications, present preliminary results based on US state level data, along with baseline regression results in US commuting zones. This chapter also explains potential identification challenges, and employs shift share IV approach to address these identification concerns. Besides, US evidence using both robotic adoptions and alternative measures of automation technologies will be provided. In the last section, I investigate the mechanisms through net job creations, driven by differentials in job creations and job destructions.

Chapter 3 provides cross country evidence. Utilising different data sources, this chapter presents stylised facts, alongside regression results for all sample countries. Employing shift share IV approach, I construct different instrumental variables, and present IV estimates across countries. In addition, this chapter examines heterogeneous effects across OECD countries and non-OECD countries, highlighting the importance of manufacturing sectors.

Chapter 4 provides individual level evidence. Based on UK context, this chapter extends US and cross country analysis to worker level analysis, and conducts regressions using static and dynamic panel data models. To address endogeneity concerns arising from unobserved intrinsic abilities, I employ advanced econometric techniques such as Arellano-Bond estimation method, and present IV estimates across UK workers. Moreover, heterogeneous analysis based on workers with varying educational backgrounds and those with different living regions are also performed, confirming that such technical changes are biased towards high skilled workers, and are more prominent in manufacturing sectors.

Chapter 5 concludes, and points out limitations and potential future extensions, along with policy implications.

Chapter 2

US Evidence

This chapter provides econometric analysis based on US context. Informed by the conceptual framework outlined in Chapter 1, the research question of this chapter is to explore the impacts of automation technologies on employment rate, and to investigate mechanisms behind heterogeneous effects across regions from different income groups.

2.1 Introduction

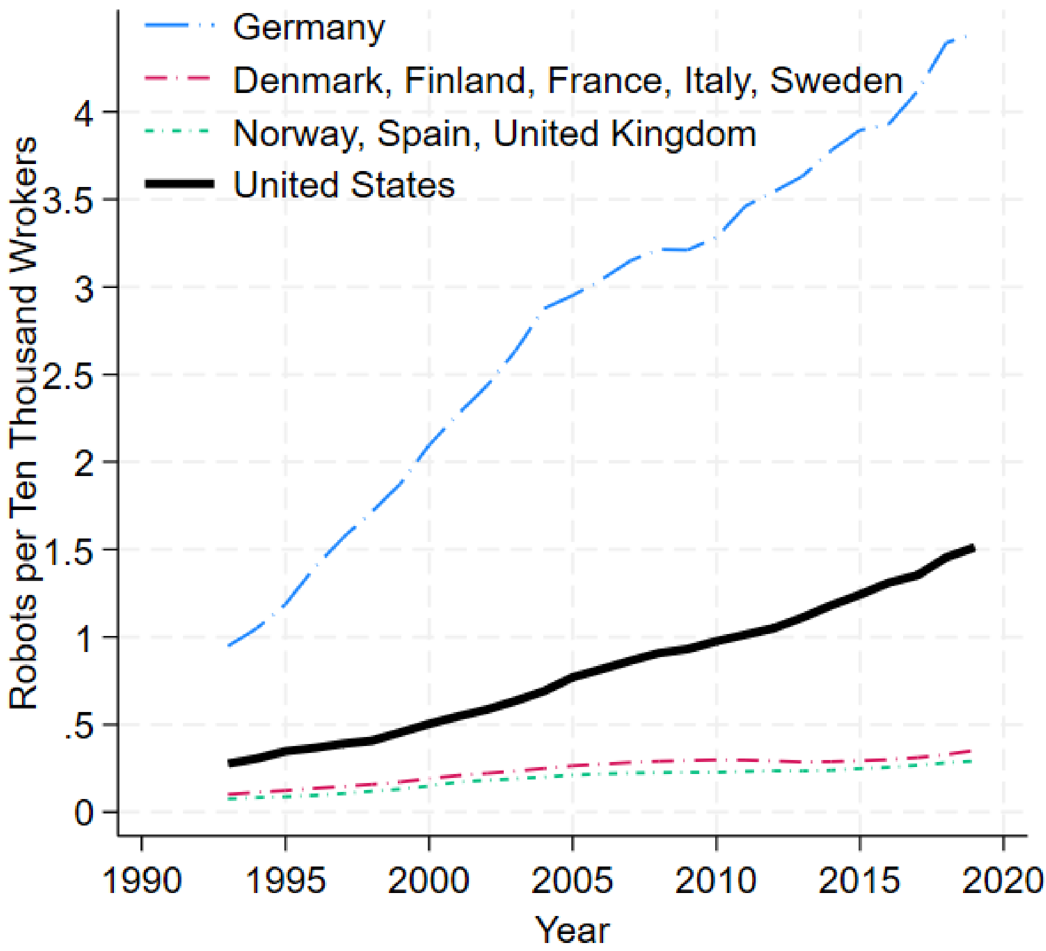
This section presents introduces the US analysis, with a focus on the motivation, hypothesis, and contribution of this chapter.

2.1.1 Motivation

The reasons for choosing the US to perform empirical analysis are as follows.

Firstly, as discussed in Chapter 1, understanding the impacts of automation technologies on labour market outcomes at all levels of analysis, including individual workers, skill groups, metropolitan areas, and countries, is important. It is also necessary to investigate mechanisms behind such technological unemployment in US, one of the leading global economies in technological advancements. Accordingly, this chapter offers an analysis across US metropolitan areas, and focuses on state level data and commuting zone level data.

Figure 2.1: Robot Adoption in US and European Countries, 1993-2019



Notes:
The data about operational stocks of robots are based on International Federation of Robotics (2021). Robot density refers to refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020), and the data is from World Bank (2021).

Secondly, the United States is the most advanced economy all over the world.[1] As Figure 2.1 shows, robotics technology the US and Western European countries progressed significantly throughout the 1990s and 2000s. Among these countries, US and Germany have relatively higher robotic densities, measured by robotic stocks per thousand workers, reflecting their leading role in global automation techniques. In addition, people can get access to high quality data across all US regions with no missing values, making it possi-

[1] According to World Bank (2021), the US GDP per capita in 2019, measured in current US dollars, is approximately $65548, and the United States is the most advanced economy. To avoid the influence of COVID 19 on economic growth, here I use the data in 2019.

ble to investigate regional variations of technological unemployment[2]. Therefore, further analysis in the US is interesting, and it proves valuable in understanding the mechanisms in high income regions.

Thirdly, previous studies about automation technologies such as Acemoglu and Restrepo (2020, 2021, 2022); Autor and Dorn (2013) primarily focused on US evidence. This chapter offers a more accurate depiction of automation adoptions across US regions from different income groups. In addition, the availability of unique data on job creations makes it feasible to investigate the mechanisms. Therefore, empirical analysis based on US context enables a clear comparison with previous research[3].

2.1.2 Hypothesis

The hypotheses are as follows:

Hypothesis 1: Automation technologies tend to have negative impacts on employment rate across all US regions.

Hypothesis 2: In low and middle income US regions, the magnitudes of negative employment effects from automation technologies are more substantial. While in high income regions, automation technologies are likely to have positive or non-negative effects on employment rate.

Hypothesis 3: The impacts of automation technologies on job destructions are insignificant across regions. In addition, automation technologies could have significantly negative impacts on job creation dynamics in all US regions.

Hypothesis 4: In high income US regions, new job creations induced by productivity effects, could compensate job destructions driven by displacement effects. But in low and

[2]Details about regional variations of technological unemployment across US regions, will be provided in Section 2.3.

[3]Detailed information about the contributions to existing literature will be illustrated in Subsection 2.1.3.

middle income regions, new job creations could not compensate job destructions.

To verify these hypotheses, this thesis leverages comprehensive macro and micro dataset across US states and commuting zones from 2000 to 2019 in Chapter 2, to explore the impacts of automation technologies on employment rate and job creations, from the perspective of advanced economies.

The next subsection will outline the contributions of this chapter, based on identified gaps in the literature.

2.1.3 Contribution

This chapter offers three main contributions, including heterogeneous employment effects from technical changes, regional variation of RBTC (Routine Biased Technical Change), and mechanism analysis through channel of job creations.

For the first main contribution, this chapter explores the heterogeneous employment effects across regions from different income groups within a specific country. Previous studies have employed measures such as TFP (total factor productivity) growth and patent awards as broad indicators of technological updating across occupations (Autor and Salomons, 2018; Autor et al., 2020; Bloom et al., 2015). In contrast, this chapter utilises two complementary indicators, namely robotic density calculated as robotic stocks per thousand labour force, and ICT intensity measured by ICT trade volumes per thousand workers. These specifications offer a more accurate depiction of automation adoptions across US regions, allowing for a clearer distinction between job replacement and productivity growth originating from automated and non-automated sectors.

For the second main contribution, this chapter also complements a sizeable recent literature on RBTC (Routine Biased Technical Change) across regions. Studies exploiting time series or cross sector variation discovered the phenomenon of job polarisation in Western economies (Autor and Dorn, 2013; Goos et al., 2014; Graetz and Michaels, 2017), but found little evidence about regional variations of technological unemployment. For example, Autor et al. (2003); Autor and Dorn (2013) showed how automation could replace labour forces in occupations with high routine intensities, and those occupations are mainly located in the middle of the skill distribution. Compared with those routine occupations, positive employment and wage effects could be observed in other occupations. Unlike previous occupational level analysis, this chapter builds upon these prior insights to show RBTC across regions. Based on data from Autor and Dorn (2013), where the researchers calculated Routine Task Intensity (RTI) index as an algebraic function of manual intensities, routine intensities, and analytical intensities, this chapter points out that compared with low income regions, job replacement is likely to be more harmful in middle income regions, where occupations with higher proportion of routine tasks are mainly concentrated. This finding aligns with the conclusion in Acemoglu and Loebbing (2022) that the negative employment effects from automation technologies are not disproportionately harmful to workers in low income regions, as machines have great comparative advantage in terms of production cost in middle income regions.

For the third main contribution, this chapter sheds light on the fact that net employment effects are primarily attributable to differentials in productivity effects measured by job creations, and job destructions, a good proxy of displacement effects, are widespread across regions. In terms of mechanisms, this chapter complements the work of Acemoglu and Restrepo (2020, 2022); Bonfiglioli et al. (2021); Dauth et al. (2021), and confirms that job creations[4] typically benefits high skilled workers with advanced education, while welfare deteriorations from unemployment primarily influence low skilled workers.

In particular, I attempt to complement literature that studies the role of skill shares and structural changes on net job creation. Prior work by Acemoglu and Restrepo (2021) has

[4]Here "job creation" refers to rising job vacancies in incumbent occupations, rather than creation of new occupations or new tasks, as the latter only applies in the context of artificial intelligence.

examined the relationship between ageing trends and adoption of automation technologies, and documented that growing educational attainment could lead to a shortage of production workers in blue collar jobs. As manufacturing wages rise and participation rates decline, opportunities for automation become increasingly attractive. This chapter also contributes to the growing body of research on educational upgrading and automation adoptions. Rather than focusing on workers with low educational attainment, this chapter shows that the channel for high skilled labour force could be different. With intensive growth of highly educated workers, supply effect appears to generate stronger productivity effects, and act as a main driver of employment growth in advanced economies.

2.2 Data

This section presents data sources in US, consisting labour market outcomes such as employment rate and demographic characteristics, and automation adoptions. Besides, this thesis also leverages comprehensive firm level data in US to discover the mechanisms driving net job creations.

2.2.1 Labour Market Outcomes

To relate automation technologies with employment and job creation across US local labour markets, I follow Autor et al. (2013); Acemoglu and Restrepo (2020, 2021); Bonfiglioli et al. (2021), and identify US local labour markets based on the concept of commuting zones (CZs), which could be regarded as aggregation of several counties. Introduced by Tolbert and Sizer (1996), 722 commuting zones covering the US continental territory[5] could offer a more accurate representation of strong commuting ties within CZs and weak commuting ties among them. This sample selection process for robotic pen-

[5]Usually detailed data from Alaska and Hawaii are not included in the research sample due to low population densities, and estimation results are similar in directions and magnitudes for all US states. Besides, Washington DC, the US capital, became the 51st state of US in 2021. In this thesis, I only use 49 states in continental US to conduct the quantitative analysis.

etration is similar to that of Autor et al. (2013); Acemoglu and Restrepo (2020, 2021); Bonfiglioli et al. (2021), except that the sample period for this thesis is 2000-2019, exceeding the duration covered in previous studies.

In the main analysis, I focus on socio-economic outcomes and collect county-level data about employment rate and other demographic characteristics between 2000 and 2019 from Bureau of Economic Analysis (2021), and aggregate to CZ level[6]. The employment rate is measured as the ratio of employed workers to whole population with the age of 15 and above. This age threshold is motivated by definition of working-age labour force (Acemoglu and Restrepo, 2021). To further investigate the determinants of labour market outcomes, I also leverage data on employment ratios categorised by education and industry groups. Other demographic controls include total population, proportion of age, gender, race, education, and Census Divisions[7].

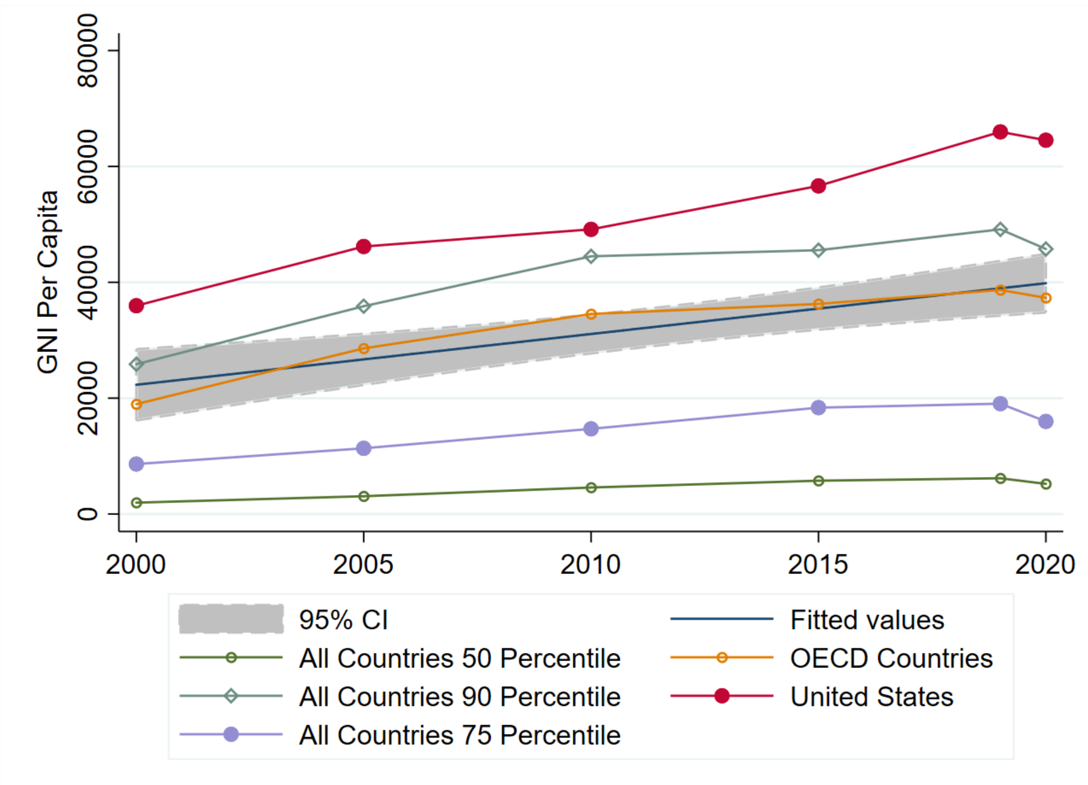
The detailed descriptions of control variables are as follows: I draw upon data from US Bureau of Economic Analysis (2021), to calculate the proportion of labour force with high school education and those who hold university diplomas. This information informs my definition of the share of skilled labour. For comparisons of heterogeneous effects between middle income regions and low income regions, I use the number of high school educated workers to measure middle skilled labour force, and describe the distribution of routine tasks performed by middle skilled workers. Meanwhile, the amount of high skilled workers, who are believed to engage in non-routine tasks or abstract tasks in high paid jobs, can be proxied by the number of university educated workers. Industry groups are based on International Federation of Robotics (2021), and all economic activities are classified into six broad sectors, including manufacturing, agriculture, mining, utility, construction, and R&D activities. To facilitate a more in-depth industry level anal-

[6]Because Bureau of Economic Analysis (2021) provides high quality data across counties over the sample period of 2000-2019, we do not need to take the problem of missing values into accounts.

[7]Based on geographic locations, the US states are grouped into 4 regions (Northeast, Midwest, South, West) and 9 divisions (New England Division, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific).

ysis, I add data about several sub-sectors under manufacturing industry, namely textiles, wood and furniture, paper, pharmaceuticals and cosmetics, other chemical products, rubber and plastic products (non-automotive), glass ceramics stone mineral products (non-automotive), basic metals, metal products (non-automotive), electrical or electronics, industrial machinery, automotive, other vehicles, and all other manufacturing branches. Demographic data, including the proportion of old workers who are above 65 years old, female workers, Hispanic workers, are incorporated to account for other determinants of employment status. For some variables which are only available at US state level, such as proportion of females, share of old people, and percentage of Hispanic individuals, I use state level data to proxy variables in each commuting zone. To avoid potential issues of multi-collinearity, education levels are not taken into accounts when analysing the employment effects of automation technologies across regions with varying skill shares.

Figure 2.2: Income Level Across Countries, 2000-2020



Notes:
The graph presents trends of GNI per capita for countries from different income groups, and advanced economies - using data from World Bank (2021). The sample economies of OECD countries are obtained from OECD (2020).

For baseline regression, classification of regions into high, middle and low income groups is determined by personal income per capita, and is comparable to the income percentile of OECD countries around the world. Figure 2.2 unpacks the overall trend in GNI per capita across countries in different income groups, compared with data from the US and OECD countries. Two main facts emerge from the aggregate trends. First, income growth in advanced economies are substantially higher than that in developing countries, and the gaps in growth rate remain relatively constant, thereby suggesting a lack of convergence. Second, most of the OECD countries are located around the 80 percentile of the overall income distribution across countries. Hence, I define CZs from high income group as those which are above 80 percentile of the whole income distribution, and define low income CZs as the bottom quintile by personal income per capita. The remaining areas constitute the middle income regions.

Besides arbitrary classification of income groups, in a more general model, I also explore the impacts of the interaction between automation technologies and income levels, aiming to identify any gradual shifts in employment effects. This generalised approach serves an additional purpose: to establish a comparative framework including US evidence, cross country analysis, and individual context based on UK data, considering the challenges in directly comparing diverse US commuting zones and different countries[8]. For mechanism analysis, I will only focus on generalised version of econometric model.

To support the hypothesis that the heterogeneous impacts of automation technologies on employment are determined by the channel through net job creations, I construct CZ-level measures of job destruction rates and job creation rates. These measures are derived from the Business Dynamics Statistics (US Census Bureau, 2021), and are employed to compute the evolution of net job creations by mixing data of job destructions and job creations. For each commuting zone, I observe job destructions, job creations[9], number

[8]In other words, it is unclear whether the state with lowest income per capita in US is comparable to the country with lowest GNI per capita all over the world or not, therefore, it tends to become less persuasive to generalise US evidence to countries from low income groups. But using interaction term between automation technologies and income level helps to solve this problem to some extent, as we only pay attention to employment effects of automation technologies with respect to rising income levels, regardless of arbitrary classification of income groups.

[9]Job destruction is defined as number of jobs lost from contracting and closing establishments during the last 12 months;

of firms and employees, and detailed industry codes.

In addition, recognising the US's status as an open economy, trade links with other countries necessitate considerations. Following Bonfiglioli et al. (2021), I utilise trade data from United Nations (2021), and obtain data about import volumes from China and Mexico, as well as export volumes to Germany, Japan, and Korea. This inclusion aims to account for macroeconomic effects arising from international trade.

2.2.2 Automation Technologies

To obtain a comprehensive picture of the relationship between automation technologies and employment, I combine the labour market dataset with several sources of data on automation technologies, namely robotic usage and ICT intensity, during the sample period of 2000-2019.

In this research, I employ two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on dataset from International Federation of Robotics (2021), United Nations (2021) and The Conference Board (2021).

The primary data source on robotic usage is International Federation of Robotics (2021). It contains counts of operational stocks and installations of robots covering six broad industrial sectors in 72 countries between 1993 and 2019, based on yearly surveys of global robot manufacturers[10]. Those six broad sectors include manufacturing, agriculture, mining, utility, construction and R&D activities. To facilitate a detailed industry level anal-

and job creation is defined as number of jobs created from expanding and opening establishments during the last 12 months. It is noticed that job creations contain new jobs within existing occupations, and new vacancies for jobs created by AI. To better disentangle those two components, I also collect data about job creations defined as number of jobs created from expanding and opening establishments during the last 12 months, to better investigate variations of productivity effects. Regression results are consistent with baseline estimates.

[10] According to Dauth et al. (2021), "Single-purpose machines such as elevators or transportation bands are, by contrast, no robots in this definition, as they cannot be re-programmed to perform other tasks, require a human operator, or both." Hence, it is assumed that robotic adoptions across countries which were documented by International Federation of Robotics (2021) share no systematic differences, and all of them could replace routine tasks previous performed by production workers.

ysis, I add data about several sub-sectors under manufacturing industry, namely textiles, wood and furniture, paper, pharmaceuticals and cosmetics, other chemical products, rubber and plastic products (non-automotive), glass ceramics stone mineral products (non-automotive), basic metals, metal products (non-automotive), electrical or electronics, industrial machinery, automotive, other vehicles, and all other manufacturing branches. For empirical analysis, the main explanatory variable is computed using operational stocks of robots per thousand labour force. Robustness checks using installations of robots per thousand labour force are qualitatively similar to the baseline results, suggesting that regression results are insensitive to alternative measures of robotic usage.

Since International Federation of Robotics (IFR) does not report data on industry breakdowns regarding robot stocks until 2004 (Acemoglu and Restrepo, 2020), unclassified components are re-allocated to each industry based on the proportion of robotic stocks. The sample selection process regarding robotic penetration is similar to that of Acemoglu and Restrepo (2020), except that the sample period for this thesis is 2000-2019, extending beyond that of previous studies.

The second measure of automation technologies, namely ICT intensity, is motivated by Acemoglu and Restrepo (2021); Graetz and Michaels (2017, 2018); Michaels et al. (2014); Kim et al. (2021). These studies highlight the substitutability between ICT and low skilled workers. Bearing this motivation in mind, I complement the IFR data with US ICT import and export obtained from bilateral trade statistics of Comtrade database (United Nations, 2021). Trade volumes of re-export are subtracted from final calculations. To ensure the robustness of the findings, results based on overall import and export of automation technologies, as well as net export of ICT products and automation technologies are also presented. Regression results do not exhibit significant differences when only considering bilateral trade with China and Mexico.

Since IFR data on operational stocks of robots, and Comtrade data on trade volumes are only available at the country-by-industry level, this study adopts a shift-share design, following Acemoglu and Restrepo (2020); Bonfiglioli et al. (2021); Dauth et al. (2021). This approach allocates industry level robotic adoptions and ICT trade volumes to each CZ based on their initial employment ratios (adjusted for overall expansions of each industry).

In certain analysis, the adoption of automation technologies is instrumented utilising Bartik IV based on average robotic density in eight European countries with similar industrial compositions and trade structures. Following Acemoglu and Restrepo (2020); Benmelech and Zator (2022); Bonfiglioli et al. (2021), eight European countries are comprised of: Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland. Robustness checks utilising alternative country combinations are also presented[11].

2.3 Stylised Facts

Now I present a number of facts regarding technological changes and labour market outcomes across US commuting zones throughout the study period.

When analysing regional variations of technological unemployment across commuting zones, it is essential to account for measurement errors by time trend. This is because the linear progression of both automation technologies and employment rate may lead to pseudo correlations. Therefore, this study offers evidence about the relationship between residuals of robotic densities, ICT usage, and employment rate, after controlling for macro shocks and geographic specific factors, over the period of analysis. The main measure of employment is obtained by first regressing employment on year dummies, region dummies, and the interaction terms between time fixed effects and geographic fixed effects.

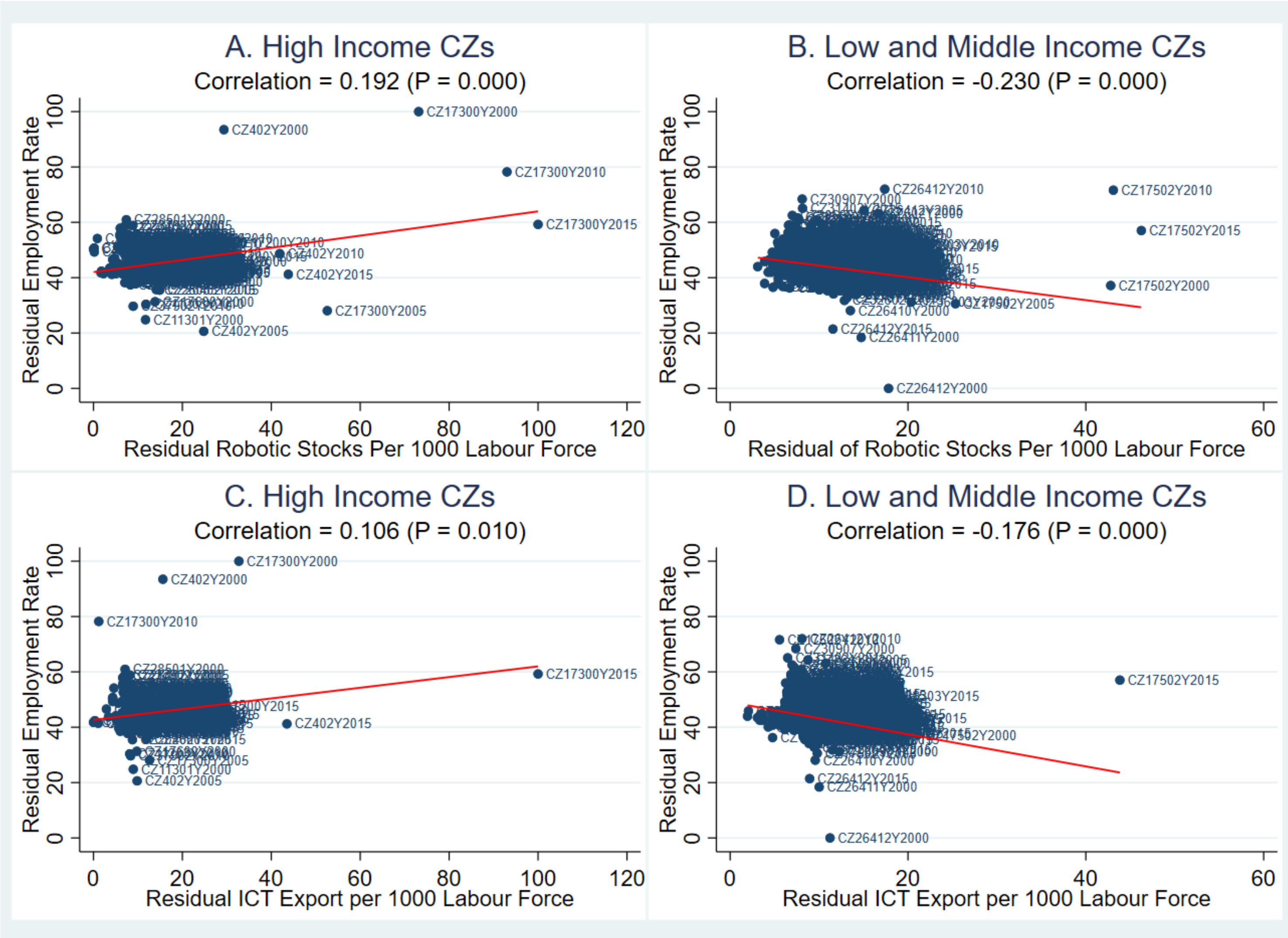
[11] Other country combinations contain various specifications, such as data from all European countries; or data from Denmark, Finland, France, Italy, Sweden; or data from Denmark, Finland, France, Italy, Sweden, Germany, as Germany is know to have great comparative advantage in manufacturing; or data from Spain, Finland, France, Italy, Norway, Sweden, UK; or data from Denmark, Netherlands, Italy, Sweden, UK; or data from Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK.

The residual outcome variables are then normalised to a scale of 0 to 100. The measure of robotic adoptions is obtained through a similar process, first regressing robotic densities on year dummies, region dummies, and the interaction terms between time fixed effects and geographic fixed effects, then normalising residual outcome variables between 0 and 100. The measure of ICT usage is calculated similarly, utilising ICT exports as the base variable.

Figure 2.3 turns to unpack the association for areas across different income groups, and reflect different employment responses after technological shocks. For high income commuting zones, the relationship between robotic density and employment rate after accounting for macro shocks is significantly positive. However, the magnitudes of the slope between variations of ICT intensity and employment rate are slightly lower, suggesting a somewhat weaker complementarity between ICT investments and labour inputs. This indicates that expanding automation adoption might, to a certain degree, complement human labours, and does not necessarily lead to employment reductions.

In contrast, for regions from low and middle income groups exhibited in Panels B and D of Figure 2.3, employment dynamics demonstrate a negative correlation with automation technologies, with statistically significant coefficients. These findings align with the hypothesis that job destructions have outweighed job creations in low and middle income countries.

Figure 2.3: Residual Automation and Employment Dynamics for US Regions, 2000-2019



Notes:
The figure displays the correlation of automation adoptions and employment variations US commuting zones, conditional on year and state dummies. The employment rate, defined as the ratio of employed people and total population who are above 15 years old, is from Bureau of Economic Analysis (2021). Robot density refers to operational stock of robots per 1000 labour force, and data about robotic stocks is from International Federation of Robotics (2021). Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

2.4 Regression Model

In the panel data regression analysis, the main specification relating changes in automation technologies and dynamics of employment rate is constructed as below:

$$\Delta Employment_{it} = \beta_0 + \beta_1 \Delta AutomationExposure_{it} + \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it} \quad (2.1)$$

Following Acemoglu and Restrepo (2020); Bonfiglioli et al. (2021); Dauth et al. (2021), this analysis estimates Equation 2.1 by stacking five-year equivalent first differences across four time periods[12]: 2000-2005, 2005-2010, 2010-2015, and 2015-2019. Here, $\Delta Employment_{it}$ is the changes in employment rate for CZ i over period t, measured by the changes in ratio of employment to working age population. $\Delta AutomationExposure_{it}$ is some proxies of CZ-level exposure to automation technologies, as defined in Equation 2.2. Several specifications include CZ level control variables X_i, which are geographic fixed effects represented by region dummies and Census Divisions, along with demographic characteristics such as total population, and the proportion of age, gender, race, education. The parameter δ are $K \times 1$ vectors, where K is the number of time-varying variables capturing demographic characteristics displayed above. α_i refers to CZ level geographic FE, and α_t measured by year FE captures macro shocks such as business cycles. Finally, ε_{it} is a heteroscedastic error term.

The detailed descriptions of the expected signs of control variables are as follows: I utilise data on the proportion of labour force with high school education and those holding university diplomas from US Bureau of Economic Analysis (2021), to define the share of skilled labour. According to the theory of SBTC (Skill Biased Technical Change) (Au-

[12]One concern which may lead to measurement errors is that the length of period 2015-2019 is different from others. Hence I also conduct sensitivity checks to display results containing different combination of time periods.

tor et al., 2003; Autor and Dorn, 2013), a positive correlation is expected between the estimated coefficients for proportion of high skilled workers and employment rate. Industry groups are based on International Federation of Robotics (2021), and all economic activities are classified into six broad sectors, including manufacturing, agriculture, mining, utility, construction, and R&D activities. Demographic structure variables, including the proportion of old workers who are above 65 years old, female workers, and Hispanic workers, control for other determinants of employment status. Since previous evidence such as Keane and Rogerson (2015) indicated lower labour force participation rates among female, Hispanic, and old individuals, negative correlations are expected for these variables. Moreover, as regions exposed to import competitions from developing countries are likely to experience decreasing employment rate (Autor et al., 2013), the estimated signs for variables of imports from China and Mexico are expected to be negative.

All the estimates reported in this article, unless noted otherwise, are weighted by the amount of total labour force in 2000, the initial year covered in the sample data, to avoid endogenous changes in employment[13].

The parameter of primary interest is β_1, which captures the link between dynamics of automation technologies and employment rate. According to the hypothesis at Section 1.3 of Chapter 1, the correlation between automation technologies and employment rate is expected to be negative in low and middle income regions, and positive or insignificant in high income regions. In other words, β_1 is predicted to be significantly negative for low and middle income CZs, and significantly positive or at least insignificant for CZs in high income group. Overall, the development of automation technologies corresponds to declining employment to population ratio across US regions, with slightly lower magnitudes, as suggested in Figures 3.2 and 2.3.

[13] One of the endogenous factors is population growth, as the overall population could affect employment rate, and automation exposure can also be influenced by population.

2.4.1 Key Variable Construction

The main analysis centres on socio-economic outcomes. I collect county-level data about employment rate and other demographic characteristics for the period 2000-2019 from Bureau of Economic Analysis (2021), and aggregate to CZ level[14]. Employment rate is measured as the ratio of employed workers to whole population with the age of 15 and above. This 15-year-old threshold is motivated by definition of working-age labour force (Acemoglu and Restrepo, 2021). To further investigate the determinants of labour market outcomes, I also leverage data on employment ratio by education and industry groups. Other demographic controls include total population, proportion of age, gender, race, education, and Census Divisions[15].

This research utilises two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on dataset from International Federation of Robotics (2021), United Nations (2021) and The Conference Board (2021).

Since IFR data on operational stocks of robots, and Comtrade data on trade volumes are only available at the country-by-industry level, this research follows the approach of Acemoglu and Restrepo (2020); Bonfiglioli et al. (2021); Dauth et al. (2021), by utilising a shift share design. This approach allocates industry level robotic adoptions and ICT trade volumes to each CZ based on their initial employment ratios (adjusted for overall expansions of each industry). Exposure to automation is then constructed as follows.

$$\Delta AutomationExposure_{it} = \Sigma_j^J \frac{\Delta Automation_{jt}^{US}}{Labour_{jt}^{US}} \times \frac{Employed_{it_0}}{Employed_{t_0}} \tag{2.2}$$

[14]Because Bureau of Economic Analysis (2021) provides high quality data across counties over the sample period of 2000-2019, we do not need to take the problem of missing values into accounts.

[15]Based on geographic locations, the US states are grouped into 4 regions (Northeast, Midwest, South, West) and 9 divisions (New England Division, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific).

The numerator of the term $\frac{\Delta Automation_{jt}^{US}}{Labour_{jt}^{US}}$ is five year equivalent changes in robotic density and ICT trade volume for US industry j over period t, and the denominator of the term $\frac{\Delta Automation_{jt}^{US}}{Labour_{jt}^{US}}$ is five year equivalent changes in total working labour force for US industry j over period t. The second term $\frac{Employed_{it_0}}{Employed_{t_0}}$ is share of industrial employment of commuting zone i at year t_0[16].

In some of the specifications, I instrument the adoption of automation technologies using Bartik IV based on average robotic density in eight European countries with similar industrial compositions and trade structures. Following Acemoglu and Restrepo (2020); Benmelech and Zator (2022); Bonfiglioli et al. (2021), eight European countries are comprised of: Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland. Robustness checks utilising alternative country combinations are also provided[17]. The instrument is computed as follows:

$$\Delta AutomationIV_{it} = \frac{1}{8} \times \Sigma_k^K \Sigma_j^J \frac{\Delta Automation_{jt}^k}{Labour_{jt}^k} \times \frac{Employed_{it_0}^{US}}{Employed_{t_0}^{US}} \tag{2.3}$$

Similarly, the numerator of the term $\frac{\Delta Automation_{jt}^k}{Labour_{jt}^k}$ is five year equivalent changes in robotic density and ICT trade volume for industry j in European country k over period t, and the denominator of the term $\frac{\Delta Automation_{jt}^k}{Labour_{jt}^k}$ is five year equivalent changes in total working labour force for industry j in European country k over period t. Then I allocate summation of predicted robotic usage in the sample European countries based on $\frac{Employed_{it_0}}{Employed_{t_0}^{US}}$, which is the share of industrial employment in CZ i at year t_0. The identification of initial sample year of IV is consistent with that of exposure to automation technologies defined in Equation 2.2.

[16] t_0 refers to initial year of shift share analysis. For US evidence, I perform this shift share allocation based on employment ratio in year 2000. While for cross country analysis, the "initial" year becomes 2019, so as to avoid problems of missing data.

[17] Other country combinations contain various specifications, such as data from all European countries; or data from Denmark, Finland, France, Italy, Sweden; or data from Denmark, Finland, France, Italy, Sweden, Germany, as Germany is know to have great comparative advantage in manufacturing; or data from Spain, Finland, France, Italy, Norway, Sweden, UK; or data from Denmark, Netherlands, Italy, Sweden, UK; or data from Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK.

To support the hypothesis that the heterogeneous impacts of automation technologies on employment are driven by net job creations, this study constructs CZ-level measures of job destruction rates and job creation rates, based on Business Dynamics Statistics (US Census Bureau, 2021), and then calculate evolution of net job creations by mixing data of job destructions and job creations. For each commuting zone, I observe job destructions, job creations[18], number of firms and employees, and detailed industry codes. The change of net job creation rate for CZ i over period t is then computed as follows:

$$\Delta Net\, Job\, Creation\, Rate_{it} = \frac{\Delta Job\, Creation_{it} - \Delta Job\, Destruction_{it}}{N(Employees)_{it}} \tag{2.4}$$

where $N(Employees)_{it}$ is number of employees for a given firm, aggregated to CZ i at year t. Robustness checks based on number of establishments are insensitive to baseline results.

2.4.2 Summary Statistics

This subsection provides summary statistics about variables, which will be exhibited in the following regression model.

Figure 2.1 reports summary statistics on the main variables used in the regressions. All results are calculated across commuting zones and periods of analysis. The first two rows show an increase in automation adoption in our sample between 2000 and 2019. On average, the employment rate increased by 1% for every period, and the variation is similar to the findings of Bonfiglioli et al. (2021). Table 2.1 also confirms an increase of automation adoptions, with a rise of robotic penetration by 17%, and positive average number of ICT

[18]Job destruction is defined as number of jobs lost from contracting and closing establishments during the last 12 months; and job creation is defined as number of jobs created from expanding and opening establishments during the last 12 months. It is noticed that job creations contain new jobs within existing occupations, and new vacancies for jobs created by AI. To better disentangle those two components, I also collect data about job creations defined as number of jobs created from expanding and opening establishments during the last 12 months, to better investigate variations of productivity effects. Regression results are consistent with baseline estimates.

Table 2.1: Summary Statistics for US Evidence, 2000-2019

Variable	Mean	Std.Dev.	Min	Max	Obs
Employment	0.010	0.039	-0.328	0.469	2888
Robot	0.170	0.074	0.052	1.736	2888
ICT Import	0.229	0.464	-0.674	7.321	2888
ICT Export	0.104	0.156	-0.192	2.527	2888
ICT Net	-0.126	0.316	-4.793	0.482	2888
Auto Import	0.560	1.179	-3.041	17.757	2888
Auto Export	0.298	0.535	-1.193	8.336	2888
Auto Net	-0.262	0.728	-9.421	3.106	2888
Population	417.720	1.140	0.911	18700	2888
High School	0.871	0.036	0.795	0.945	2888
Bachelor	0.274	0.048	0.164	0.450	2888
Old	0.223	0.055	0.058	0.456	2888
Female	0.502	0.015	0.325	0.542	2888
Hispanic	0.099	0.146	0.002	0.957	2888
Import	0.160	0.228	0.001	1.422	2888

Notes:
Statistics for variables in changes are computed across 722 commuting zones for four time periods, namely 2000-2005, 2005-2010, 2010-2015, 2015-2019, and those variables include changes in employment rate (Employment), robotic density (Robot), ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net). Other control variables in levels include total population in thousands (Population), proportion of people who achieved high school degree (High School) and bachelor's degree (Bachelor), percentage of old people (Old), female people (Female), Hispanic people (Hispanic), import volumes from China and Mexico (Import). And they are computed across 722 commuting zones and four years: 2000, 2005, 2010, 2015.

import, ICT export, automation import, and automation export. Combined with stylised facts displayed in Section 2.3, Table 2.1 demonstrates that automation technologies can account for employment dynamics. The regression analysis in the following sections confirms these patterns and establishes their robustness.

For other control variables, there are also variations across commuting zones and time periods, as suggested by the standard deviations reported in the table.

2.4.3 Preliminary Results

This subsection presents the preliminary results of the estimation based on Equation 2.1, using state level data spanning US continental territory[19]. One issue requiring attention is

[19]Outcomes including Alaska and Hawaii over the sample period of 2000-2019 are consistent with baseline results.

that, in contrast to commuting zones, the classification of these administrative state areas depends on historical origins instead of worker flows and business activities. Therefore, it ignores commuting ties within detailed geographical units in states.

Table 2.2 presents results for changes in robotic density. Columns 1-4 are regressions of the full sample. Column 1 provides the most parsimonious specification, only including year dummies to account for macro shocks. Column 2 adds baseline demographics X_i. Column 3 also considers geographic dummies as covariates for regional specific characteristics. Column 4 additionally controls the interactions between state FE and year FE, to account for time varying policy changes across states. Columns 5-6 present heterogeneous effects in regions across different income groups. Due to limited data availability, I take both middle income regions and low income regions together into accounts. I define states from high income group as those above 80 percentile of the whole income distribution by personal income per capita, and define low income states as the rest. Baseline results in Section 2.5 will extend to generalised versions, and disentangle the effects from middle income regions and low income regions. Corresponding results for all other measures of automation technologies, namely changes in ICT trade volumes (ICT import, ICT export, and ICT net export), as well as automation trade volumes (automation import, automation export, and automation net export), appear in Table 1 of Appendix.

Across all columns of Table 2.2, robotic adoption exhibits a negative correlation with employment responses. All estimates are statistically significant and sizeable. For the preferred specification in Column 4, the estimated coefficient in robotic density is -0.805, indicating that one additional robot per thousand workers tends to reduce employment rate by 0.81 percentage points. These findings imply that robots are likely to be associated with employment reductions across US states.

In response to extensive adoption of automation technologies, Column 5 shows that employment rate experienced a significant increase in high income states. In these states, one

Table 2.2: Preliminary Results for US State-Level Employment and Robotic Adoption, 2000-2019

	Total				High Income CZs	Low Income CZs
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Employment Rate						
Robot	-0.694***	-0.673***	-0.673***	-0.805***	0.710***	-1.630***
	(0.068)	(0.056)	(0.056)	(0.072)	(0.141)	(0.311)
Population		0.110***	0.110***	0.120***	-0.138	0.031
		(0.018)	(0.018)	(0.025)	(0.343)	(0.065)
Female		-0.212***	-0.212***	-0.235***	0.252	-0.062
		(0.034)	(0.034)	(0.049)	(0.651)	(0.125)
Hispanic		-0.012***	-0.012***	-0.009**	0.006	-0.008
		(0.003)	(0.003)	(0.003)	(0.025)	(0.006)
Old		0.039***	0.039***	0.043***	0.089	0.064*
		(0.013)	(0.013)	(0.012)	(0.052)	(0.033)
Bachelor		1.626***	1.626***	1.833***	0.459	1.626***
		(0.500)	(0.500)	(0.362)	(0.591)	(0.552)
Import		0.133**	0.133**	0.261***	0.103	0.284***
		(0.051)	(0.051)	(0.056)	(0.164)	(0.070)
R^2	0.919	0.934	0.934	0.963	0.993	0.958
Year FE	√	√	√	√	√	√
Geographic×Year FE			√	√	√	√
N of CZs	48	48	48	48	10	38
N of Obs	960	960	960	960	200	760

Notes:
The table presents preliminary results about within group estimates of the effects of exposure of robotic penetration on employment rate, based on US state level data. Explanatory variables are changes in robotic density. Other demographics include total population (Population), proportion of old people (Old), female people (Female), Hispanic people (Hispanic) and high skilled workers who achieved bachelor's degree (Bachelor). Import volume from China and Mexico (Import) are also controlled. Geographic FE refers to Census Divisions. The regressions are weighted by total labour force in 2000. The classification of US states from high income group and low income group are illustrated in Section 2.4.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

robot per thousand labour force could translate to 0.71 percentage increase in employment rate. The evidence implies that new job creations are complementing employment losses, thus lowering the probability of welfare deteriorations. Whereas, the estimates from low income states indicate sizeable and robust negative impacts of robotic density on employment rate. The data demonstrates that 1000 unit increase in robotic stocks per worker will lead to a drop of 1.63 percentage points in employment rate for low income states. These magnitudes suggest that negative employment effects are mainly driven by displacement forces in low income states.

The expected signs of control variables are consistent with Section 2.4. The population is positively correlated with employment rate. Since previous evidence such as Keane and Rogerson (2015) revealed that female people, Hispanic people, and old people are less likely to participate in the workforce, the estimation results exhibit negative correlations for these demographic variables. The proportion of high skilled workers, measured by those with bachelor's degree, shows a positive correlation with employment rate. This finding can be partly attributed to the theory of SBTC (Skill Biased Technical Change) (Autor et al., 2003; Autor and Dorn, 2013), which will be explored further in Section 2.6. Different from Autor et al. (2013), the estimation results for imports from China and Mexico indicate a positive correlation between import competition and employment rate. This difference may arise because state level analysis cannot fully reflect the relationship between trade shocks and employment dynamics.

Corresponding results for all other measures of automation technologies, namely changes in ICT trade volumes (ICT import, ICT export, and ICT net export), as well as automation trade volumes (automation import, automation export, and automation net export), are exhibited in Table 1 of Appendix. They are all consistent with estimation results regarding robotic penetrations.

Drawing on the findings concerning ICT import volumes, Panel A of Table 1 demonstrates a negative correlation between ICT import volumes and employment responses across all columns. All estimates are statistically significant and sizeable. For the preferred specification in Column 4, the estimated coefficient in ICT import volume is -0.162, implying that one thousand more dollars of ICT import per thousand workers tends to reduce employment rate by 0.16 percentage points. These findings suggest that other automation technologies are also associated with employment declines across US states.

Column 5 illustrates that, in widespread automation technology adoption, high-income states experienced a significant increase in employment rates. Specifically, \$1000 ICT import per thousand labour force could translate to 0.22 percentage increase in employment rate. The evidence implies that new job creations are complementing employment losses, thus lowering the probability of welfare deteriorations. The estimates from low income states indicate sizeable and robust negative impacts of ICT import volumes on employment rate. The data indicates that $1000 dollars increase in ICT import volumes per worker will lead to a drop of 0.44 percentage points in employment rate for low income states. These significant estimates suggest that displacement forces in low income states are the primary drivers of negative employment effects.

In summary, automation technologies measured by robotic densities and alternative measures of automation such as ICT trade volumes (ICT import, ICT export, and ICT net export), as well as automation trade volumes (automation import, automation export, and automation net export), are negatively correlated the employment rate across US states. In addition, the heterogeneous employment effects across areas from different income groups are consistent with the hypotheses outlined in Chapter 1. However, these preliminary findings rely on US state level data, which failed in taking commuting ties and labour force flows within administrative areas into account, and may be restricted by insufficient data sample size. In addition, when using ICT trade volumes and automation trade volumes as alternative measures of automation technologies, it is hard to disentangle the impact of automation technologies from the import competitions of China and Mexico. Therefore, the following section will conduct baseline regressions across US commuting zones, and discuss identification issues.

2.5 Empirical Results in US

In this section, I establish the first empirical implication, and present econometric results about heterogeneous effects of automation technologies on employment rate, across US commuting zones from different income groups. Then I describe identification issues and

IV approach, along with results from alternative automation technologies. Building on this evidence, the following section will assess the critical role of net job creations as it relates to displacement effects and productivity effects.

2.5.1 Baseline Results

This subsection presents results for robotic density, based on the estimation of Equation 2.1 in Section 2.4 using commuting zone level data spanning US continental territory. I prefer to use within group estimation method, based on panel data model considering fixed effects, as Durbin-Wu-Hausman test shows that within-group estimator is more efficient[20].

Over the sample period of 2000-2019, Table 2.3 displays regression results based on panel data structure using stacked difference model with fixed effects. Columns 1-4 are regressions of full sample. Column 1 provides the most parsimonious specification, only including year dummies to account for macro shocks. Column 2 adds baseline demographics X_i. Column 3 also considers geographic dummies as covariates for regional specific characteristics. Column 4 additionally controls the interactions between state FE and year FE, to account for time varying policy changes across states. Heterogeneous effects in regions across different income groups are presented in Columns 5-7.

Across all columns of Table 2.3, a negative correlation is observed between robotic adoption and employment responses. All estimates are statistically significant and sizeable, irrespective of various combinations of control variables. For the preferred specification in Column 4, the estimated coefficient in robotic density is -0.673. This suggests that one additional robot per thousand workers tends to reduce employment rate by 0.67 percentage points. This coefficient aligns with estimations of employment reductions about 0.45%

[20] Assuming within-group estimator is consistent, and GLS estimator is inconsistent but efficient, $\chi^2(15) = 27.22$, with p-value of less than 0.00. So, we can reject the null hypothesis that both of them are consistent, implying that explanatory variables can be regarded as correlated with unobserved heterogeneities. In order to obtain unbiased estimates, it would be better to use within group estimator based on fixed effects model.

Table 2.3: Regression of Employment Rate on Robotic Penetration for US, 2000-2019

	Total				High Income CZs	Middle Income CZs	Low Income CZs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Employment Rate							
Robotic Penetration	-0.522***	-0.224**	-0.205**	-0.673***	-0.036	-1.369***	-0.869***
	(0.117)	(0.096)	(0.096)	(0.208)	(0.216)	(0.153)	(0.216)
Population		0.011**	0.012***	0.042***	0.065***	0.034***	0.179***
		(0.005)	(0.004)	(0.009)	(0.008)	(0.011)	(0.050)
High School		0.121	0.125	7.627***	3.045**	7.799***	8.185
		(0.119)	(0.132)	(2.549)	(1.407)	(1.876)	(5.035)
Bachelor		0.055	0.072	2.914	5.052**	2.062***	5.441**
		(0.061)	(0.058)	(2.418)	(2.452)	(0.517)	(2.285)
Old		-0.193	-0.195	-0.310*	-0.114	-0.286	-0.083
		(0.145)	(0.145)	(0.163)	(0.209)	(0.219)	(0.193)
Female		-3.106***	-3.069***	-1.915***	-1.470*	-1.609***	-0.338
		(0.467)	(0.466)	(0.430)	(0.745)	(0.549)	(0.509)
Hispanic		-0.031	-0.044	0.334***	0.477***	0.296**	0.345*
		(0.100)	(0.105)	(0.093)	(0.133)	(0.139)	(0.197)
Import		-0.010	-0.018	-0.019	-0.033	-0.024	-0.387
		(0.007)	(0.014)	(0.052)	(0.063)	(0.090)	(0.305)
Year FE	√	√	√	√	√	√	√
Geographic FE			√	√	√	√	√
State $\times$ Year FE				√	√	√	√
R^2	0.583	0.635	0.635	0.770	0.817	0.796	0.640
N of Commuting Zones	722	722	722	722	143	424	155
N of Observations	2890	2888	2888	2888	572	1696	620

Notes:
The table presents within group estimates of the effects of robotic penetration on employment rate. Explanatory variable is changes in robotic density. Other control variables include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico (Import). Geographic FE refers to Census Divisions. The regressions are weighted by total labour force in 2000. The classification of US states from high income group, middle income group, and low income group are illustrated in Section 2.2.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

by Acemoglu and Restrepo (2020)[21]. and 0.16% decline by Bonfiglioli et al. (2021).

These findings support the evidence presented in Section 2.3, indicating that displace-

[21]The reason why the magnitudes of the coefficient in this thesis is larger than Acemoglu and Restrepo (2020), is because their analysis is based on sample period of 1990-2007. It is uncovered that after the financial crisis in 2008-2009, the rate of technological replacement is accelerating (Sachs and Kotlikoff, 2012; Sachs et al., 2015; Brynjolfsson and Mitchell, 2017). (Because previous articles were published before, the data in those articles is only available before year of publication, and I can also get access to the data after the publication year. That is why the sample period in my thesis is longer.)

ment effects may outweigh productivity effects when considering all CZs. Because the amounts of less developed CZs are substantially larger than those of high income areas, new vacancies induced by rising high skilled labour demand in non-automated sectors in advanced economies, cannot absorb displaced workers and new entrants across US CZs.

Columns 5-7 turn to results across different income groups. Following widespread adoption of automation technologies, my findings indicate that employment rate in high income CZs remained largely stable, implying that new job creations are complementing employment losses, thus lowering the probability of welfare deteriorations. However, the estimates from middle and low income CZs indicate sizeable and robust negative impacts of robotic density on employment rate. Specifically, a 1000 unit increase in robotic stocks per worker will lead to a drop of 1.37 percentage points in employment rate for middle income CZs, and that in low income counterparts could generate a displacement effect of 0.87 percentage points. The substantial magnitudes suggest that negative employment effects are mainly driven by displacement forces in low and middle income CZs.

The control variables align with the expectations. The population is positively correlated with employment rate. Since previous evidence such as Keane and Rogerson (2015) revealed that female people, Hispanic people, and old people are less likely to be employed, the estimation results show negative correlations for these variables. The estimation results for the proportion of high skilled workers, measured by those with bachelor's degree, are positively correlated with employment rate. This finding can be partly attributed to the theory of SBTC (Skill Biased Technical Change) (Autor et al., 2003), which will be explored further in Section 2.6. Different from Autor et al. (2013), the estimation results for imports from China and Mexico did not demonstrate a significant correlation between import competition and employment rate, though the negative coefficients for import competition reveal negative employment effects.

To ensure the robustness of the baseline results, several sensitivity checks were conducted.

Firstly, as noted in Section 1.3, the productivity effects could arise both from automated and non-automated sectors. To isolate the effects of automation from gross economic growth, Table 2.4 exhibits results using adjusted penetration to robots, taking gross economic expansion across all sectors into considerations. Following Acemoglu and Restrepo (2020), the amount of adjusted penetration of robots is computed as

$$\begin{aligned}\Delta AutomationExposure_{it} =& \Sigma_j^J \left(\frac{\Delta Automation_{jt}}{Labour_{jt}} - \eta_{jt} \times \frac{Automation_{jt}}{Labour_{jt}}\right) \\ &\times \frac{Employed_{it_0}}{Employed_{t_0}}\end{aligned} \tag{2.5}$$

The term $\frac{\Delta Automation_{jt}}{Labour_{jt}}$ is five year equivalent changes in robotic density and ICT trade volume for US industry j over period t, and $\frac{Employed_{it_0}}{Employed_{t_0}}$ is share of employment of CZ i at year 2000. η_{it} measures growth rate of overall value added[22] in industry j over period t, accounting for gross economic expansions.

Table 2.4: Regression of Employment Rate on Adjusted Robotic Penetration for US, 2000-2019

	(1)	(2)	(3)	(4)
Dependent Variable: Δ Employment Rate				
Adjusted Robotic Penetration	-0.247***	-0.212***	-0.211***	-0.195***
	(0.018)	(0.018)	(0.019)	(0.017)
Year FE	√	√	√	√
Demographics		√	√	√
Geographic FE			√	√
State × Year FE				√
R^2	0.689	0.689	0.691	0.758
N of Commuting Zones	722	722	722	722
N of Observations	2890	2888	2888	2888

Notes:
The table presents within group estimates of the effects of adjusted robotic penetration on employment rate. Explanatory variable is changes in robotic density calculated as Equation 2.5. Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico (Import) are also controlled. Geographic FE refers to Census Divisions. The regressions are weighted by total labour force in 2000.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[22] For simplicity, here I only present the outcomes where overall value added is measured using GDP constant dollars. Results based on other calculations provides qualitatively same outcomes.

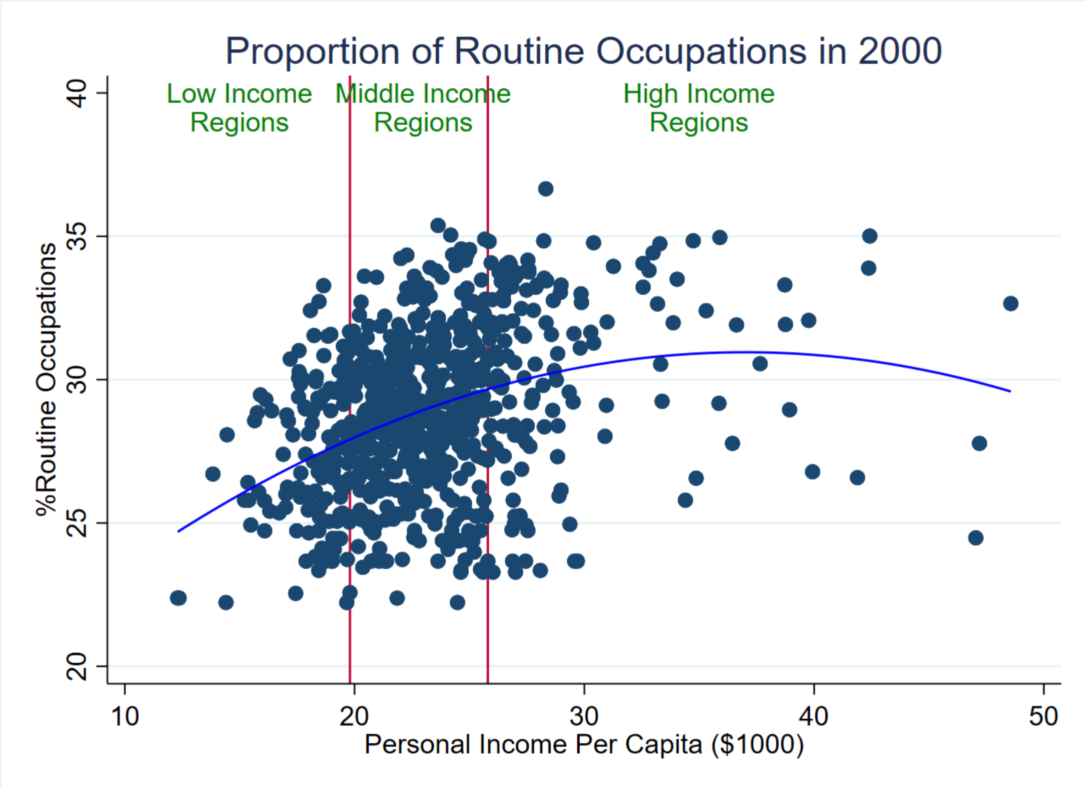
In Table 2.4, I conduct panel data regressions using adjusted robotic penetration over the sample period of 2000-2019. Columns 1-4 suggest significantly negative employment effects from adjusted robotic exposure, irrespective of various combinations of control variables. For the preferred specification in Column 4, one additional robot per thousand labour force raises employment rate by 0.23%. The observed decrease in the magnitude of the coefficients is expected, considering that the majority of job displacement variations occur in sectors susceptible to automation technologies. The qualitative and quantitative results are remarkably similar.

Secondly, the duration of period 2015-2019 is different from others. To accommodate heterogeneous impacts of automation technologies across different stages of economic development, Table 2 in the Appendix displays results containing different combination of time periods. Column 1 shows higher job reductions at the initial period of robotic adoptions, as 1000 unit increase in robotic stocks per worker will lead to a drop of 1.33 percentage points in employment rate. The long-term horizons suggest slightly lower magnitudes. According to the preferred specification in Column 3, the estimated coefficient in robotic density is -0.861, implying that one additional robot per thousand workers tends to reduce employment rate by 0.86 percentage points. The slightly lower magnitudes are also consistent with the previous interpretation that most of the variations of job replacement were driven by productivity effects in automated sectors. Columns 4-6 repeat the specification by using adjusted robotic penetration as independent variable, and again I find similar and significantly negative employment effects.

The employment effects observed in middle income regions are of significant interest[23], and evaluating this difference allows for understanding the mechanisms underpinning the geographical disparities of technological job losses. To address this concern, I present the proportion of routine occupations across US commuting zones from different income

[23]The t statistics of the difference in coefficients of robotic penetration between middle income CZs (-1.369) and low income CZs (-0.869) in Table 2.3 is 1.889, with p value less than 0.000, implying that the employment reductions induced by robotic adoptions in middle income regions are significantly larger than those in low income regions, under the confidence level of 0.000.

Figure 2.4: Routine Occupations Across Income Levels in 2000



Notes:
The proportion of routine occupations is from Autor and Dorn (2013), and income level measured by personal income per capita are from Bureau of Economic Analysis (2021). The classification of regions from high income group, middle income group, low income group is based on Figure 2.2.

groups in Figure 2.4. Based on data from Autor and Dorn (2013), where the researchers calculated Routine Task Intensity (RTI) index as an algebraic combination of manual intensities, routine intensities, and analytical intensities, and defined routine occupations as those whose RTI index are above 66 percentile of skill distribution[24], the Figure depicts a near-linear increase in the share of routine occupations in low and middle income regions, and a declining trend for high income regions. Overall, Figure 2.4 confirms that the routine jobs whose tasks can be easily codified by machines are concentrated in regions with middle income levels, especially at the border of commuting zones from middle income group and high income group. Consistent with other industry level evidence by Autor and Dorn (2013); Goos et al. (2014), the clustering of occupations with a higher degree of routine task intensity in middle-income regions can account for the more significant employment reductions observed in these areas in response to automation.

[24]Autor and Dorn (2013) shows that results are qualitatively similar if we adopt different thresholds of distribution percentiles to define routine occupations.

As alternative measures of degree of routineness, I also investigate the skill distribution across regions in the Appendix. Ranking US commuting zones according to their personal income per capita in 2000, Figure 13 compares the regional variation of skill shares, defined as the ratio of individuals with degrees of advanced education. Proxied by labour force with university education, Figure 13a shows a near-monotonic increase in the proportion of high skilled workers as we move up the income distribution. In contrast, the share of middle skill workers, measured by those with high school education in Figure 13b, is considerably larger in middle income regions, relative to other areas. This illustrates an inverted-U shape of the proportion of middle skilled workers, primarily engaged in routine tasks, against income levels.

Table 2.5: Proportion of Skilled Workers and Income Levels for US in 2000

	(1)	(2)	(3)	(4)
Dep Var	%University Educated Workers		%High School Educated Workers	
$Income$	0.326***	0.579***	0.174***	1.027***
	(0.033)	(0.187)	(0.031)	(0.139)
$Income^2$		-0.005		-0.016***
		(0.004)		(0.003)
R^2	0.162	0.164	0.059	0.106
N of Obs	722	722	722	722

Notes:
The table presents OLS estimates of the effects of quadratic form of income level on proportion of skilled workers in 2000. Explanatory variables are proportion of university educated workers and percentage of high school educated workers collected from Bureau of Economic Analysis (2021), and income level measured by personal income per capita are also obtained from Bureau of Economic Analysis (2021).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Further evidence is provided by Table 2.5, which shows the OLS results for high and middle skilled workers as the dependent variables, and quadratic form of personal income per capita as explanatory variables[25]. Because this is cross sectional data, econometric methods such as fixed effects estimation or random effects estimation are not employed. Autor and Dorn (2013) only provides the proportion of routine occupations across US commuting zones at year 2000. As additional robustness check for Figure 2.4, Table 2.5 only utilise data for 2000. Since this analysis aims to demonstrate correlation rather than

[25] I do not take other US commuting zone level characteristics as control variables, as the goal is to examine the quadratic relationship based on cross sectional data in 2000 rather than causal effects.

causation, it is not necessary to determine whether the Gauss-Markov assumptions are met. In other words, Table 2.5 is presented to show the correlation between quadratic form of income level, and proportion of skilled workers, rather than causal effects of income level on skill shares.

The results at US commuting zone level are clear: income level is positively correlated with proportion of university educated workers, with insignificant role of squared term. This suggests that a $1000 rise of personal income per capita is associated with 0.326% increase of share of university educated workers; while for high school educated labour force, I find a positive and statistically significant coefficient on income levels, with a negative and statistically significant coefficient for the squared term. The results imply that the share of middle skilled workers is expected to reach a maximum when the personal income per capita is $4011.7. This figure roughly corresponds to the boundary, confirming the fact that majority of middle skilled workers performing routine tasks are concentrated in middle income regions. In addition, it confirms that the proportion of routine tasks is comparatively lower in occupations located at the top and bottom of skill percentile.

Overall, robotic densities are negatively correlated with employment rate. It appears that the employment rate is decreasing, alongside the widespread adoption of automation technologies across US. However, this is based on the assumption that all the OLS assumptions are satisfied, which is not feasible in reality. The following section will outline several identification issues.

2.5.2 Identification Issues

The evidence presented so far strongly suggests that the adoption of automation technologies, represented by exposure to robotic usage, is negatively associated with the employment across US commuting zones, even after controlling for geographic variations and macro shocks. Such effects are more pronounced in low and middle income CZs, and are insignificant in high income CZs. Nonetheless, it may not be sufficient to guarantee that the main results are free from contamination by endogenous adjustments of local labour force. In this part, I address identification threats, and then implement a quasi-experimental shift share design to estimate the causal effects of automation technologies on US labour market outcomes.

Several reasons explain why the development of automation technologies could be correlated with error terms in Equation 2.1.

Firstly, a firm's decision to adopt automation may also be driven by other local industry specific changes, which could directly affect the labour demand. For example, consumers' demand shock[26] could motivate firm owners to invest more capital and labour inputs to produce final goods, hence simultaneously rising automation and employment (Aghion et al., 2017; Webb, 2019). In addition, common trade shocks from emerging markets such as China and Mexico may drive the move towards automation (Bloom et al., 2015). Confronted with upward pressure on labour costs in high income countries, firms from labour intensive industries are inclined to use automation, as they are vulnerable to international competition due to comparative advantages in labour inputs for emerging market and developing economies, and finally reduce manufacturing employment (Autor et al., 2013). In other words, enterprises in developed countries prefer to raise the percentage of capital input, as they are not able to compete with countries from emerging markets and developing economies, resulting in extended adoption of automation technologies.

Secondly, any shocks from labour demand and market competition will affect industries' decisions to locate in specific areas (Acemoglu and Restrepo, 2020), and individual workers' adjustments across occupations and regions (Dauth et al., 2021). On the one hand, establishments from affected industries tend to re-allocate their production process. They produce labour intensive goods at the places where labour costs are lower, and perform

[26]Consumer demand shocks sometimes are not endogenously driven by income growth and output expansions, such as dramatic increase of demand for masks during the time period of pandemic induced by COVID 19.

capital intensive activities at the places where they lack comparative advantages in labour costs. On the other hand, affected workers from industries with high exposure of automation technologies tend to switch tasks within original establishments, or move to other firms, especially young workers[27] or those with higher educational attainments (Dauth et al., 2021). Therefore, such spillover effects will lead to downward biased estimation of the quantitative magnitudes of both displacement effects and productivity effects.

Finally, reverse causality presents a concern. Industries with labour saving technologies and fast growing TFP (total factor productivity) tend to invest more on automation technologies, particularly those facing intense competition and having a large number of robotic suppliers (Beaudry et al., 2016; Graetz and Michaels, 2018). Such firms are likely to experience further waves of labour substituting process, and ”ripple effects” could cause displaced labour to replace workers at the lower skill ladder (Acemoglu and Restrepo, 2022; Jackson and Kanik, 2019). Alternatively, characteristics such as ”path dependence” may mean that higher robotic adoption is itself a consequence of lower employment growth (de Vries et al., 2020).

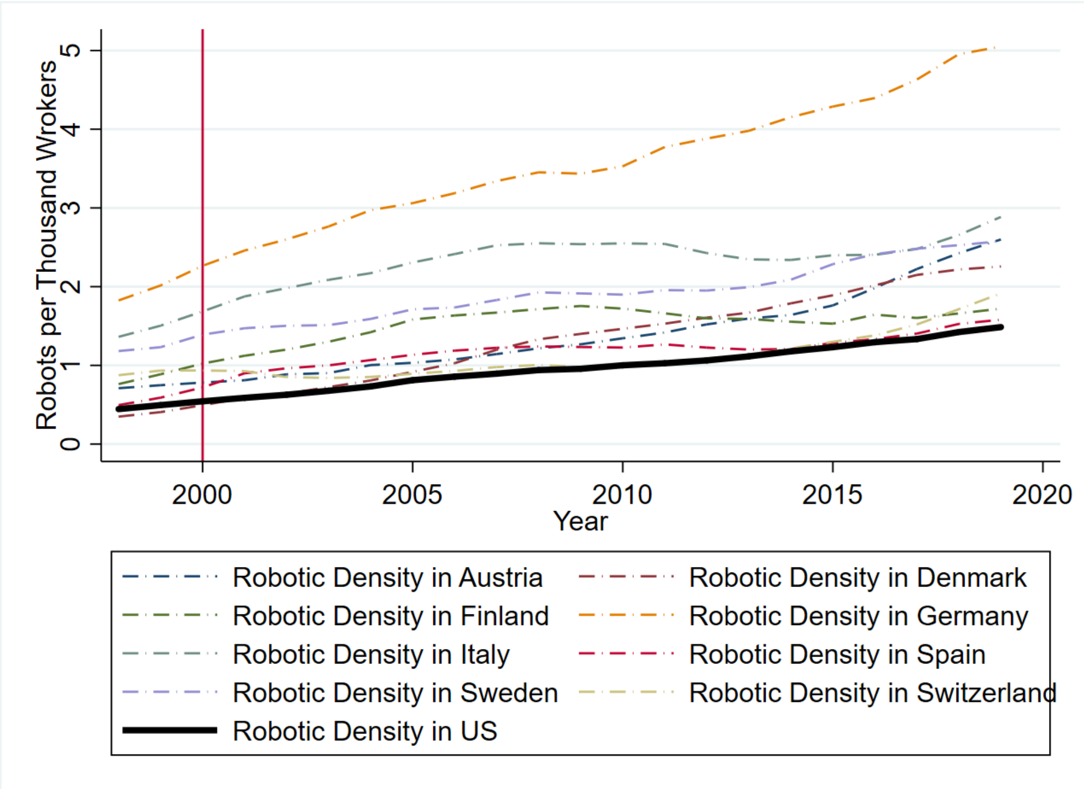
2.5.3 Shift Share IV Research Design

To alleviate potential endogeneity concerns, I undertake a shift share IV research design as instruments for exposure to automation technologies. This leverages two components: predetermined exposure shares and idiosyncratic shocks. This research design is motivated by several important papers from Acemoglu and Restrepo (2020); Aghion et al. (2017); Autor et al. (2013); Bartik (1991); Bonfiglioli et al. (2021); Bound and Holzer (2000); Dauth et al. (2021), based on the fact that local labour markets differ markedly in

[27]There are two hypothesis about heterogeneous response to susceptibilities of automation technologies for old workers and young workers. One is about institutional environment. Because the firing costs are higher for incumbent workers due to institutional factors such as unionisation rate, enterprises prefer to use machine to replace young workers instead of old labour force (Dauth et al., 2021; Rogerson and Wallenius, 2022). The other one is about task specific human capital. For old workers endowed with task specific human capital, the skill bundle will be similar within occupation, so old workers prefer to switch within occupation (skills are portable), while young worker prefer to switch across occupation (Autor and Dorn, 2009; Cortes and Gallipoli, 2017; Gathmann and Schonberg, 2010; Poletaev and Robinson, 2008; Yamaguchi, 2012). In addition, firms prefer to hire people with decision making skills (Deming, 2021), which require experience accumulations.

their industry specialisations and employment concentrations, due to differential endowments and comparative advantages.

Figure 2.5: Robotic Density Across Countries, 1998-2019



Notes:
The graph presents trends of robotic density for European countries and US - using data from International Federation of Robotics (2021) and World Bank (2021). Robot density refers to operational stock of robots per 10000 labour force. The 8 European countries include Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland.

The shifts are obtained from the supply shocks of robotic usage in other European countries. These shocks can be considered as an exogenous driver of automation in US (Autor et al., 2013; Bonfiglioli et al., 2021), as they are unlikely to be intervened by government policies in the short run. As depicted in Figure 2.5, the robotic densities across eight European countries are higher than those in US[28], implying that European countries, particularly those specialising in manufacturing industries like Germany, are technologically more advanced than US in robotics (Acemoglu and Restrepo, 2022). Therefore, European robotic density could only affect US labour market exclusively through robotic adoption

[28] Overall, US is more technologically advanced in robotic usage than European countries, but for the sample countries I chose to perform shift share analysis, they are all specialised in manufacturing industries, hence we can observe higher robotic density in those European countries than that in US. Another possibility would be: there are innovation spillover effects from US to Europe, but the flows of knowledge and technologies from the sample European countries to US, are far more than those from US to the sample European countries.

in US, due to similar industrial structures. Besides, as revealed by the parallel pre-trends before 2000 (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018), the macro shocks confronted by these European countries and US did not share systematic differences during the time period of 2000-2019. The parallel trends also support the plausibility of valid Bartik IV[29]. The shift share design combines these sets of shocks with variations in the CZ level employment shares, and the IV is constructed as Equation 2.3.

Such supply driven components are not liable to reverse casualty (Bound and Holzer, 2000; Graetz and Michaels, 2018). This is because the decisions of firm owners in Europe to adopt robots and other automatic machines, are not largely determined by employment rate in US. In other words, it shuts down unobserved changes in decision making by firms and workers. It implies that the IV can only influence employment rate through a direct channel without spillover effects. To address common trade shocks, I run regressions of constructed IV on trade volumes and other country level demographics such as age, gender and fertility rates, alongside geographic specific factors and year fixed effects. Figure 14 in the Appendix displays the relationship between predicted robotic density and total trade volumes regarding import, export, net import, net export situations[30]. The t-statistics from both two regressions suggest insignificant association between constructed IV and trade shocks. Therefore, this instrumental variable approach offers strong support for the identification strategy.

Compared with other articles adopting shift share IV approach such as Acemoglu and Restrepo (2020); Autor et al. (2013), the IV method of this thesis is a little different. Firstly, the selection of sample European countries for constructing the IV is different. In contrast to Acemoglu and Restrepo (2020), I exclude France, because the robotic density of

[29] It is observed that there is a widening gap between robotic density in US and Germany, and sensitivity checks excluding Germany in Table 2.8 also show consistent results.

[30] Motivated by Autor et al. (2013); Bonfiglioli et al. (2021), I select China and Mexico as countries which have great import competitions with US, and choose Germany, Japan and South Korea as economies which account for large proportion of US export volumes. Regression results using all five countries including China, Mexico, Germany, Japan and South Korea do not qualitatively alter the directions and significance.

France fell below that of US after 2017[31]. Secondly, for the IV results using ICT trade volumes, previous articles used alternative IVs such as ICT patents (Acemoglu and Restrepo, 2021; Bloom et al., 2015). I continue to use ICT usage in European countries to instrument US counterparts. Thirdly, the sample periods are different. The regression analysis of this chapter covering 2000-2019, consists of a different period in the development of automation technology, compared to those studied by Acemoglu and Restrepo (2020); Autor et al. (2013).

Following Acemoglu et al. (2001, 2019); Aghion et al. (2017), I report the results of shift share IV design for seven specifications with the same sets of controls X_i in Table 2.6. The first specification repeats within group estimate for panel data regression with full controls. The second specification constructs reduced form equation to examine the correlation between the instrument and outcome variable. Specifically, it evaluates whether predicted robotic exposure from European countries has any impact on employment rate in US. The third specification verifies if the IV could satisfy the condition for relevance through first stage regression. It also evaluates the explanatory power from European robotic technologies on US automation adoptions, induced by regional and innovation spillover effects. The final specification reports IV structural estimates based on two-stage GMM (Generalised Method of Moments) techniques.

Table 2.6 contains IV results for the impacts of robotic penetration on employment. Column 2 displays reduced form outcomes of the effects of European robotic usage on US employment rate. The significantly negative estimates show a dramatic reduction in US employment status, triggered by spillover effects of European robotic technologies from the supply side, with quantitatively large magnitudes. For each additional adoption of robotic usage in Europe, the employment rate in US would decline by 6.78 percentage points.

[31] Robustness checks including France will be presented in Table 2.8.

Table 2.6: IV Regression of Employment Rate on Robotic Penetration for US, 2000-2019

	(1)	(2)	(3)	(4)
	Within Group	Reduced Form	First Stage	IV Structural Form
Dep Var	ΔEmployment	ΔEmployment	ΔRobot	ΔEmployment
Robotic Penetration	-0.610***			-4.820***
	(0.180)			(1.799)
Robotic Penetration (Europe)		-6.780***	1.407***	
		(1.192)	(0.479)	
Year FE	√	√	√	√
Demographics	√	√	√	√
Geographic FE	√	√	√	√
State × Year FE	√	√	√	√
First Stage F Statistics			126.37	
N of Commuting Zones	722	722	722	722
N of Observations	2888	2888	2888	2888

Notes:
The table presents within group and IV estimates of the relationship between robotic penetration and employment rate in US, where robotic penetration computed using operational stocks of robots from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) is used as the instrument. Dependent variable for Columns 1, 2, and 4 is employment rate, and that for Column 3 is robotic penetration in US. The regressions are weighted by total labour force in 2000. Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Column 3 displays the results for first stage equation of the instrument on robotic density, which reveals substantial explanatory power of predicted automation exposure for robotic density. The coefficient in Column 3 is -1.41, suggesting that 1000 unit increase in operational stocks of robots per worker in those European counties corresponds to 1.41 unit increase in US robotic penetrations, with high F-statistics of 126.37 on the excluded instrument, implying a low probability of occurrence of weak instrument problems. Robustness checks regarding the first stage regressions for all measures of automation technologies are presented in Table 4 of Appendix.

Moreover, I provide results for other diagnostic tests to prove the validity of the instruments. Following Acemoglu and Restrepo (2021), I address this concern in two aspects[32]. Firstly, I conduct under-identification test. The Kleibergen-Paap rk LM statistic is 53.52

[32] As Acemoglu and Restrepo (2021) examined the determinants of automation adoption, rather than employment effects of automation, here I am not able to compare my results with this article.

with p-value less than 0.00, implying that the model can be regarded as identified, and the shift share IV is correlated with US robotic penetration. Secondly, I conduct week identification test. The test reveals that Cragg-Donald Wald F statistic is 101.640 and Kleibergen-Paap rk Wald F statistic is 72.913, and both of them are larger than Stock-Yogo weak ID test critical values (the critical value under 10% maximal IV size is 16.38). Therefore, the null hypothesis must be rejected, indicating no weak identification problem under confidence level of 10%. This signifies that the IV is not only correlated with endogenous variable, but also a strong predictor of US robotic penetration. In addition, I do not conduct over-identification test, as this issue only arises with multiple IVs, whereas this chapter only utilises one.

Finally, Column 4 offers the structural IV estimates of the effects of robotic density on employment. Instrumenting with predicted robotic penetration, the coefficient of -4.82 indicates that 1000 unit exogenous rise in robotic stocks per worker is predicted to reduce overall employment by 4.82 percentage points. The relatively larger absolute magnitude of the IV estimates is consistent with the presence of downward endogeneity bias (Acemoglu and Restrepo, 2020; Dauth et al., 2021), as reallocation forces by both industries and workers in response to robotic usage could hamper the welfare changes of displacement effects to some extent, causing downward biased estimation of previous OLS results.

2.5.4 Robots and Employment by Income Level

To account for smooth changes of the employment effects, this subsection also includes interaction term between automation technologies and income level for IV estimation. The structural form is then estimated as follows:

$$\begin{aligned}\Delta Employment_{it} = \beta_0' &+ \beta_1' \Delta Autom\widehat{ationE}xposure_{it} \\ &+ \beta_2' \Delta Autom\widehat{ationE}xposure_{it} \times Income_{it_0} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{2.6}$$

where $Income_{it_0}$ is average value of personal income per capita in CZ i at year 2000, and explanatory variable $\Delta Autom\widehat{ationE}xposure_{it}$ is predicted based on first stage estimation:

$$\Delta Autom\widehat{ationE}xposure_{it} = \pi_0 + \pi_1 \Delta AutomationIV_{it} + \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it} \tag{2.7}$$

Hence β_1' from Equation 2.6 captures evolution of employment effects along with levels of income. When adopting continuous income levels in the generalised model, the coefficient of automation technologies β_1' is expected to be negative, implying that displacement effects are dominating the process for least developed regions. With growing income levels, the productivity effects become stronger, and could generate greater labour demand to flatten job losses. Therefore, the coefficient for interaction term between automation and income level, namely β_2', is expected to be positive.

Table 2.7 presents within group estimates and IV estimates based on Equations 2.1 and 2.6. Compared with baseline results displayed in Column 1, Column 2 turns to results using interactions between robotic exposure and continuous levels of income. Specifically, the positive coefficient estimate of interaction term reveals that rising income level could slow down negative employment effects of robotic adoption. The coefficient in Column 2 is -1.708, suggesting that 1000 unit increase in operational stocks of robots per worker in US corresponds to 1.71 unit increase in robotic penetrations. Meanwhile, the coefficient estimate of 0.242 for the interaction term between robotic penetration and income level suggests that, a \$1000 increase in personal income per capita will cause a decline of 0.24 percentage points of employment reductions, in response to extensive robotic penetrations.

Table 2.7: Employment Effects of Robots and Income Level for US, 2000-2019

	Within Group		IV Structural Form		
	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Δ Employment Rate					
Robotic Penetration	-0.673***	-1.708***	-5.144**	-8.426***	-9.284***
	(0.208)	(0.338)	(2.524)	(2.499)	(3.483)
Robotic Penetration×Income		0.242***		1.234***	1.556*
		(0.052)		(0.355)	(0.901)
Year FE	√	√	√	√	√
Demographics	√	√	√	√	√
Geographic FE	√	√	√	√	√
State × Year FE	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888

Notes:
The table presents within group and IV estimates of the relationship between robotic penetration and employment rate by income level in US, where robotic penetration from 8 European countries is used as the instrument. Endogenous components in Columns 4-5 only refer to CZ level robotic penetration in US, while Column 6 treats both robotic penetration and the interaction term with income level as endogenous variables. The regressions are weighted by total labour force in 2000. Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Instrumented with the shift share IV, Column 3 repeats the structural IV estimates of the effects of robotic density on employment. The coefficient of -5.144 indicates that 1000 unit exogenous rise in robotic stocks per worker is predicted to reduce overall employment by 5.14 percentage points. Treating both robotic penetration and the interaction term with income levels as endogenous variables, Columns 5 indicates that one extra unit in robotic stocks per thousand workers tends to reduce employment rate by 9.28 percentage points. Moreover, the coefficient estimate for interaction term is 1.56, highlighting the flattening effects of regional economic growth. This reveals that a \$5000 increase in personal income per capita, approximating the gap between the threshold of high income CZs ($30443) and low income CZs ($24868), will cause a decline of 0.78 percentage points of employment reductions in response to extensive robotic penetrations in high income CZs.

Considering that the income level is measured using personal income per capita in 2000, the initial year of US analysis, it could be treated as an exogenous factor in US context. However, utilising both predicted robotic exposure and the interaction term with income level as IV has potential risks of weak instrumental variable problem. Therefore, Column 4 also presents IV results where only robotic penetration can be treated as an endogenous variable. These do not qualitatively alter the results, and 1 extra unit in robotic stocks per thousand workers tends to reduce employment rate by 8.43 percentage points. Further, the coefficient estimate for interaction term is 1.234, again highlighting the moderating effects of regional economic growth. This reveals that a $1000 increase in personal income per capita, will cause a decline of 1.23 percentage points of employment reductions in response to extensive robotic penetrations.

Taking the roles of economic corporations and sectoral compositions among western countries into accounts, Table 2.8 presents sensitivity checks under different constructions[33], including specifications using all European countries, one using five European countries[34] (Acemoglu and Restrepo, 2020), and another incorporating Spain and UK[35] (Bonfiglioli et al., 2021).

Table 2.8 displays the IV results for the impacts of robotic penetration on employment

[33]Column 1 is based on data from country sample of Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland; Column 2 is based on data from country sample of all European countries; Column 3 is based on data from country sample of Denmark, Finland, France, Italy, Sweden; Column 4 is based on data from country sample of Denmark, Finland, France, Italy, Sweden, Germany; Column 5 is based on data from country sample of Spain, Finland, France, Italy, Norway, Sweden, UK; Column 6 is based on data from country sample of Denmark, Netherlands, Italy, Sweden, UK; Column 7 is based on data from country sample of Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK.

[34]The five European countries are Denmark, Finland, France, Italy, Sweden. As robotic density is more pronounced in Germany due to higher concentration of manufacturing industry, which acted as a leading country in manufacturing and robotic usage (Dauth et al., 2021), so I exclude Germany.

[35]Taking trade structures into accounts, I also implement robustness checks based on Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK.

Table 2.8: Employment Effects of Robots and Income Level using Alternative IV, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Employment Rate							
Robotic Penetration	-5.036***	-3.705***	-6.213**	-6.242***	-7.370**	-3.815***	-4.750***
	(1.411)	(1.150)	(2.822)	(2.228)	(3.616)	(1.007)	(1.267)
Robotic Penetration	0.904***	0.630*	1.266**	1.098***	1.233**	0.654**	0.850***
$\times$ Income	(0.303)	(0.356)	(0.546)	(0.372)	(0.484)	(0.272)	(0.300)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√	√
N of CZs	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the relationship between robotic penetration in US and employment rate, where robotic penetration computed using operational stocks of robots from European countries is used as the instrument. Column 1 is based on data from Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland; Column 2 is based on data from all European countries; Column 3 is based on data from Denmark, Finland, France, Italy, Sweden; Column 4 is based on data from Denmark, Finland, France, Italy, Sweden, Germany; Column 5 is based on data from Spain, Finland, France, Italy, Norway, Sweden, UK; Column 6 is based on data from Denmark, Netherlands, Italy, Sweden, UK; Column 7 is based on data from Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK. Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

rate, treating both robotic penetration and interaction term between predicted exposure of robotic adoption and income level as endogenous variables. Utilising various combinations of IV constructions, the IV estimates range from -3.705 to -7.370, revealing that the employment reductions caused by an additional robot per thousand labour force would be below 7.37 percentage points, and above 3.70 percentage points. Accounting for flattening effects of regional economic growth, a $1000 rise of personal income per capita would mitigate employment losses by around 0.63 to 1.27 percentage points, and relatively small robust standard errors reflect quite stable magnitudes.

Moreover, I conduct other robustness checks in Table 3 in the Appendix. In Panel A, I do not consider the variation of income levels across different time periods, and only use robotic penetration as an explanatory variable. In Panel B, I also add an interaction term between predicted robotic exposure and income level, but only treat robotic penetration as an endogenous variable. Both are consistent with the results in Table 2.8.

Therefore, all these different model specifications do not qualitatively alter the results. The IV estimates indicate sizeable and robust negative impacts of robotic exposure on employment rate, and those negative employment reductions will gradually diminish, alongside rising levels of income.

2.5.5 Alternative Automation Technologies

In this subsection, I continue to investigate how exposure to other automation technologies has affected employment rate in CZs from different stages of economic growth. In order to gauge the robustness of the results, I estimate Equation 2.6 with trade volumes of goods containing ICT import, ICT export, and ICT net export. The dependent variables also include overall automation technologies import, overall automation technologies export, and overall automation technologies net export.

I present corresponding IV estimates of the impacts of ICT import and export under the same specifications in Table 2.9, respectively. Detailed information about first stage regressions is presented in Table 4 of Appendix. All the estimates are strong and significant. The implications with regard to interactions between automation and income level do not qualitatively alter the results. Consistent with Subsection 2.5.3, the estimates for interaction terms between alternative measures of automation technologies exposure and personal income per capita are significantly positive, confirming the flattening effects of economic development. The estimated quantitative magnitudes for trade volumes of ICT and the whole automated machines are similar to those exhibited so far.

Table 2.9 displays the IV results for the impacts of alternative automation technologies on employment rate, treating both alternative automation technologies and interaction term between their exposure and income level as endogenous variables. With various choices

Table 2.9: Employment Effects of Other Automation and Income Level in US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Employment Rate						
ICT Import	-0.583***					
	(0.185)					
ICT Export		-0.742***				
		(0.253)				
ICT Net Exp			1.992**			
			(0.839)			
Auto Import				-1.210		
				(0.829)		
Auto Export					-0.231***	
					(0.081)	
Auto Net Exp						-0.433***
						(0.103)
ICT Import × Income	0.102***					
	(0.037)					
ICT Export × Income		0.113**				
		(0.054)				
ICT Net Exp × Income			0.366**			
			(0.165)			
Auto Import × Income				0.225		
				(0.158)		
Auto Export × Income					0.036**	
					(0.017)	
Auto Net Exp × Income						0.088***
						(0.020)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the relationship between ICT and automation trade volumes in US and employment rate, where corresponding other automation computed using ICT and automation trade volumes from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) is used as the instrument. The regressions are weighted by total labour force in 2000. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of automation exposures, the IV estimates range from -0.231 to -1.992, revealing that the employment reductions caused by additional \$1000 ICT import per thousand labour force would become 0.58 percentage points, those caused by additional \$1000 ICT export per thousand labour force would become 0.74 percentage points, those caused by additional

$1000 net ICT export per thousand labour force would become 1.99 percentage points, those caused by additional $1000 automation import per thousand labour force would become 1.21 percentage points, those caused by additional $1000 automation export per thousand labour force would become 0.23 percentage points, those caused by additional $1000 automation net export per thousand labour force would become 0.43 percentage points. Accounting for flattening effects of regional economic growth, a $1000 rise of personal income per capita would mitigate employment losses. This effect is estimated at approximately 0.10 percentage points from ICT import, 0.11 percentage points from ICT export, 0.37 percentage points from ICT net export, 0.04 percentage points from automation export, 0.09 percentage points from automation net export, and relatively small robust standard errors reflect quite stable magnitudes.

For further sensitivity tests, estimations excluding variations in personal income per capita are presented in Panel A of Table 5 in Appendix. Moreover, I also add interaction term between predicted robotic exposure and income level, treating only robotic penetration as endogenous variable in Panel B of Table 5 in Appendix. These findings remain consistent with the main results.

In summary, these findings are broadly consistent with the stylised facts in Section 2.3 of Chapter 2, and support the empirical implications on the relationship between automation technologies and employment status.

2.6 Mechanism

Having studied the heterogeneous effects of automation technologies on local labour market outcomes, this research now turns to investigate the mechanisms behind the net employment effects of technological changes.

As outlined in the conceptual framework of Chapter 1, the phenomenon of job replacement is widespread across regions with different income levels. However, the welfare improvements arising from productivity effects are more pronounced in high income regions, and could complement job losses by displacement effects. Whereas, in low and middle income regions, new job vacancies triggered by productivity effects are not as strong as those in economically more advanced areas. Therefore, new job creations cannot adequately compensate for job losses by displacement effects.

In other words, the hypotheses are as follows: the impacts of automation technologies on job destructions are insignificant across regions, and automation could have negative impacts on dynamics of job creations. Rising income levels could mitigate the slowdown of job creations. These technological shifts are believed to be biased towards high skilled labour force, and are more pronounced in manufacturing sectors.

In this section, I utilise the availability of comprehensive panel data across US commuting zones, to explore the relationship between automation technologies and job creations, job destructions, net job creations. This section also seeks to discover the types of jobs susceptible to creation and replacement. Besides, industry heterogeneities will also be examined in this Section. The following analysis will prioritise IV estimates.

2.6.1 Automation and Reduced Job Creation

As a starting point, this analysis presents evidence linking adoptions of automation technologies, with changes in job destruction rate, job creation creation rate and net job creation rate. This relationship is then evaluated utilising the equation presented below.

$$\begin{aligned}\Delta Job_{it} = \gamma_0 + \gamma_1 \Delta AutomationExposure_{it} \\ + \gamma_2 \Delta AutomationExposure_{it} \times Income_{it_0} + \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{2.8}$$

Contrary to Equation 2.6, the left hand side variable ΔJob_{it} in Equation 2.8 denotes changes in job destruction rate, job creation rate and net job creation rate for CZ i over period t, where the denominator is the overall number of employees in 2000, the initial year of analysis. The remaining variables in this five-year stacked first difference model are defined as outlined in Section 2.5.3. Specifically, I also add controls for interactions between year fixed effects and firm quartiles, to account for evolution of establishments affiliated with different firm sizes.

Table 2.10 reports results based on Equation 2.8, where exposure to automation technologies, represented by US robotic penetrations, is instrumented by their European counterparts. Conceptually, I distinguish between job destructions and job creations in Panel A for all US commuting zones, and those in Panel D for middle income commuting zones, and describe the consequences of both displacement effects and productivity effects. The overall effects regarding net job creations for all US commuting zones are displayed in Columns 5-6 of Panel A, and those for middle income CZs are displayed in Columns 5-6 of Panel B.

As displayed in Columns 1-2 of Panel A, the insignificant estimates for the impacts of robotic density on changes of job destruction rate across US commuting zones reveal that technological job losses are widespread across regions with different income levels. These findings remain consistent across different specifications of control variables displayed in Table 6 of Appendix. The insignificant coefficient estimates of interaction term between robotic penetration and income level confirm that, automation technologies could replace production workers irrespective of stages of economic growth, proxied by personal income per capita.

Columns 3-4 of Panel A in Table 2.10 document the impacts of robotic adoptions on job creations. The preferred point estimate for all CZs is statistically significant at 1 percent with a coefficient of -1.354, after controlling for state specific macro shocks. This implies

Table 2.10: Business Dynamics, Robotic Penetration and Income Level for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Δ Job Destruction Rate		Δ Job Creation Rate		Δ Net Job Creation Rate	
A. All Commuting Zones						
Robot Penetration	0.059	-0.588	-1.354***	-6.176***	-1.413**	-5.588*
	(0.462)	(2.261)	(0.516)	(2.387)	(0.602)	(2.924)
Robot Penetration × Income		0.023		0.170**		0.147*
		(0.064)		(0.068)		(0.084)
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888
B. Middle Income Commuting Zones						
Robot Penetration	0.938	4.844	-1.296*	-7.758*	-2.233*	-12.602*
	(0.795)	(5.008)	(0.749)	(4.413)	(1.178)	(7.139)
Robot Penetration × Income		-0.138		0.229*		0.367*
		(0.149)		(0.131)		(0.212)
N of Commuting Zones	424	424	424	424	424	424
N of Observations	1696	1696	1696	1696	1696	1696
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√

Notes:
The table presents IV estimates of the effects of robotic penetration on changes of job destruction rate, job creation rate and net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Coefficients in Panel A are estimated based on all US commuting zones, and those in Panel B are based on middle income commuting zones. Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

that a rise of robotic stocks per thousand workers could lower job creation rate by 1.35 percentage points. The positive coefficient for interaction with income level, displayed in Column 4, suggests that new vacancies created by productivity effects could gradually complement technological job losses, especially in economically advanced areas. These results are insensitive to various specifications of control variables, displayed in Table 6 of Appendix.

Furthermore, the coefficients for net job creations in Columns 5-6 are substantially larger in absolute magnitude[36]. This evidence supports the interpretation that displacement ef-

[36]The t statistics of the difference in coefficients of robotic penetration between Column 3 (-1.354) and Column 5 (-1.413)

fects of automation technologies in low income CZs could act as key drivers for overall decline of net job creation rate. Meanwhile, stronger productivity effects in high income CZs cause slightly weaker power of job replacement. The preferred point estimate for all CZs is statistically significant at 5 percent with a coefficient of -1.413 after controlling for state specific macro shocks, implying that a rise of robotic stocks per thousand workers could lower job creation rate by 1.41 percentage points. The positive coefficient for interaction with income level, displayed in Column 6, suggests that new vacancies created by productivity effects could gradually complement technological job losses, especially in economically advanced areas. These results hold across various specifications of control variables displayed in Table 6 of Appendix.

To test the factors of routine intensities on business dynamics by automation technologies, I also report results of Equation 2.8 in Panel B of Table 2.10. As displayed in Columns 1-2, the insignificant estimates for the impacts of robotic density on changes of job destruction rate across middle income CZs reveal that, technological job losses are widespread across regions within middle income regions, where the majority of workers are performing routine tasks. These results hold across various specifications of control variables in Table 7 of Appendix. Insignificant coefficient estimates of interaction term between robotic penetration and income level confirm that, automation technologies could replace production workers regardless of stages of economic growth, proxied by personal income per capita. And such effects can be reinforced by Routine Biased Technical Change (RBTC).

Columns 3-4 of Panel B document the impacts of robotic adoptions on job creations. The preferred point estimate in middle income CZs is statistically significant at 10 percent with a coefficient of -1.296, after controlling for state specific macro shocks. This implies that a rise of robotic stocks per thousand workers could lower job creation rate by 1.30 percentage points. The positive coefficient for interaction with income level, displayed

in Panel A of Table 2.10 is 0.074, with p value larger than 0.1, implying that there is an insignificant gap between those two coefficients.

in Column 4, suggests that new vacancies created by productivity effects could sharply complement technological job losses, especially in areas at stages with middle level of economic growth. These results are insensitive to various specifications of control variables in Table 7 of Appendix.

In addition, the coefficients for net job creations in Columns 5-6 are substantially larger in absolute magnitude[37], suggesting that the displacement effects of automation technologies in lower middle income CZs could act as key drivers for overall decline of net job creation rate. Meanwhile, stronger productivity effects in upper middle income CZs cause slightly weaker power of job replacement. The preferred point estimates in middle income CZs are all insignificant, indicating relatively stronger displacement effects in middle income regions. This is likely due to concentration of routine occupations in these areas, which are not able to generate sufficient job vacancies for new entrants and displaced labour force. These results hold across various specifications of control variables in Table 7 of Appendix.

All columns in Table 2.11 turn to only focus on the changes of job destruction rate. This table presents results for ICT import, export, and net export, and automation trade volumes such as import, export, net export as alternative measures of automation technologies. Across all US commuting zones, all the estimates are statistically insignificant, reflecting the fact that technological job losses are pervasive across regions with different income levels, irrespective of their stages of economic growth, proxied by personal income per capita. The outcomes where variations across personal income per capita are not taken into accounts, and the outcomes when treating only robotic penetration as endogenous variable across all US commuting zones, are exhibited in Table 8 of Appendix. In addition, the outcomes are similar when considering only middle income regions with a large proportion of routine tasks. Detailed results are displayed in Table 9 and Table 10

[37]The t statistics of the difference in coefficients of robotic penetration between Column 3 (-1.296) and Column 5 (-2.233) in Panel B of Table 2.10 is 0.671, with p value larger than 0.1, implying that there is an insignificant gap between those two coefficients.

Table 2.11: Job Destructions, Other Automation Technologies and Income Level for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
ICT Import	0.447					
	(0.391)					
ICT Export		0.687				
		(0.600)				
ICT Net Exp			-1.353			
			(1.203)			
Auto Import				0.458		
				(0.446)		
Auto Export					0.216	
					(0.188)	
Auto Net Exp						0.291
						(0.313)
ICT Import$\times$Income	-0.084					
	(0.073)					
ICT Export$\times$Income		-0.133				
		(0.113)				
ICT Net Exp$\times$Income			0.252			
			(0.222)			
Auto Import$\times$Income				-0.083		
				(0.080)		
Auto Export$\times$Income					-0.042	
					(0.036)	
Auto Net Exp$\times$Income						-0.048
						(0.054)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job destruction rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of Appendix. These findings are all consistent with the analysis in Table 2.11.

In contrast with the situation of job destructions displayed in Table 2.11, the results listed in Table 2.12 exhibit regression results regarding job creations.

Table 2.12: Job Creations, Other Automation Technologies and Income Level for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
ICT Import	-0.669***					
	(0.221)					
ICT Export		-0.994***				
		(0.267)				
ICT Net Exp			-2.063*			
			(1.088)			
Auto Import				-0.699		
				(0.445)		
Auto Export					-0.311***	
					(0.085)	
Auto Net Exp						-0.475***
						(0.168)
ICT Import$\times$Income	0.123***					
	(0.042)					
ICT Export$\times$Income		0.183***				
		(0.053)				
ICT Net Exp$\times$Income			0.379*			
			(0.202)			
Auto Import$\times$Income				0.058***		
				(0.017)		
Auto Export$\times$Income					0.042	
					(0.036)	
Auto Net Exp$\times$Income						0.081***
						(0.029)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12 displays the IV results for the impacts of alternative automation technologies on job creation rate across all US commuting zones. I add interaction term between alternative exposure of automation trade volumes and income level, and treat both alternative automation technologies and the interactions as endogenous variables. With various choices of automation trade volumes, the IV estimates range from -0.311 to -2.063, revealing that the reductions of job creations caused by additional \$1000 ICT import per thousand labour force would become 0.67 percentage points, those caused by additional \$1000 ICT export per thousand labour force would become 0.99 percentage points, those caused by additional \$1000 net ICT export per thousand labour force would become 2.06 percentage points, those caused by additional \$1000 automation export per thousand labour force would become 0.31 percentage points, those caused by additional \$1000 automation net export per thousand labour force would become 0.48 percentage points. Accounting for flattening effects of regional economic growth, a \$1000 rise of personal income per capita would results mitigate job creation losses by around 0.12 percentage points from ICT import, 0.18 percentage points from ICT export, 0.37 percentage points from ICT net export, 0.06 percentage points from automation import, 0.08 percentage points from automation net export. These relatively small robust standard errors indicate the stability of these results.

The outcomes where variations across personal income per capita is not taken into accounts, and the outcomes when I only treat robotic penetration as endogenous variable across all US commuting zones, are exhibited in Table 11 in the Appendix. Similar results are obtained when considering only middle income regions with a large proportion of routine tasks, and detailed results are displayed in Table 12 and Table 13 of Appendix. These findings are all consistent with the analysis in Table 2.12.

In addition, I also present regression results listed in Table 2.13, which exhibits estimates regarding net job creations.

Table 2.13 displays the IV results for the impacts of alternative automation technologies on job creation rate across all US commuting zones. I add interaction term between alternative exposure of automation trade volumes and income level, and treat both alternative

Table 2.13: Net Job Creations, Other Automation Technologies and Income Level for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
ICT Import	-1.116***					
	(0.409)					
ICT Export		-1.681***				
		(0.590)				
ICT Net Exp			-3.416**			
			(1.675)			
Auto Import				-1.156		
				(0.714)		
Auto Export					-0.528***	
					(0.186)	
Auto Net Exp						-0.766**
						(0.389)
ICT Import$\times$Income	0.207***					
	(0.077)					
ICT Export$\times$Income		0.316***				
		(0.112)				
ICT Net Exp$\times$Income			0.630**			
			(0.312)			
Auto Import$\times$Income				1.156		
				(0.130)		
Auto Export$\times$Income					0.100***	
					(0.035)	
Auto Net Exp$\times$Income						0.129*
						(0.067)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

automation technologies and the interactions as endogenous variables. The analysis indicates significant insights. The IV estimates range from -0.528 to -3.416, revealing that the reductions of net job creation rate caused by additional \$1000 ICT import per thousand labour force would become 1.12 percentage points, those caused by additional \$1000 ICT export per thousand labour force would become 1.68 percentage points, those caused by additional \$1000 net ICT export per thousand labour force would become 3.42 percentage points, those caused by additional \$1000 automation export per thousand labour force would become 0.53 percentage points, those caused by additional \$1000 automation net export per thousand labour force would become 0.77 percentage points. In addition, accounting for the flattening effects of regional economic growth, a \$1000 rise of personal income per capita appears to mitigate net job creation losses by around 0.21 percentage points from ICT import, 0.32 percentage points from ICT export, 0.63 percentage points from ICT net export, 0.10 percentage points from automation export, 0.13 percentage points from automation net export. The relatively small robust standard errors highlight the stability of these magnitudes.

The outcomes where variations across personal income per capita are not taken into accounts, and the outcomes when I only treat robotic penetration as endogenous variable across all US commuting zones, are exhibited in Table 14 of Appendix. In addition, the outcomes are similar when we only consider middle income regions with a large proportion of routine tasks, and detailed results are displayed in Table 15 and Table 16 of Appendix. These supplementary analysis yield results consistent with the those presented in Table 2.13.

In summary, these findings suggest that the displacement effects due to automation are widespread geographically. Final employment outcomes are determined by differentials in productivity effects, proxied by job creations. The following section provides a detailed investigation of other empirical implications concerning skill composition.

2.6.2 Skill Upgrading and Net Job Creation

This chapter has documented the presence of net job creations behind the employment effects of automation technologies. In this subsection, I present further results, highlighting what kind of jobs could be created (replaced) by automation technologies. This analysis focuses on the impacts from robotic usage, together with regressions adopting alternative measures such as ICT import, ICT export, ICT net export, and automation trade volumes. Table 2.14 to Table 2.16 estimates the following regression model, where I interact exposure of automation technologies with skill shares and personal income per capita:

$$
\begin{aligned}
\Delta Job_{it} = \gamma_0' &+ \gamma_1' \Delta AutomationExposure_{it} \\
&+ \gamma_2' \Delta AutomationExposure_{it} \times SkillShare_{it} \\
&+ \gamma_3' \Delta AutomationExposure_{it} \times SkillShare_{it} \times Income_{it_0} \\
&+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}
\end{aligned}
\tag{2.9}
$$

where $\Delta AutomationExposure_{it}$ is commuting zone level exposure to automation adoption. I use $SkillShare_{it}$, measured by the proportion of workers with university or high school education, to describe geographic disparities of skill upgrading across US CZs. Therefore, γ_2' can be interpreted as the mitigating effects of skill share, on the dynamics of job destructions, job creations, and net job creations induced by exposure to automation technologies. And γ_3' depicts the evolving forces of skill upgrading alongside economic development.

The results regarding job destructions for both university and high school educated workers are reported in Table 2.14. It includes the interaction of robotic usage, skill shares, and income level. Results excluding estimation of income levels are exhibited in Table 17 of Appendix.

Table 2.14: Job Destructions and Robots by Skill Share for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
Robotic Penetration	3.640	1.216	1.055	1.463	-0.170	-0.273
	(5.076)	(1.577)	(1.416)	(2.595)	(6.560)	(25.237)
Robotic Penetration	-0.021		-0.083		0.011	
$\times$ %High School Educated Worker	(0.030)		(0.105)		(0.051)	
Robotic Penetration		-0.020		-0.089		0.145
$\times$ %University Educated Workers		(0.027)		(0.106)		(3.153)
Robotic Penetration $\times$ Income	0.003		0.011		-0.002	
$\times$ %High School Educated Workers	(0.004)		(0.014)		(0.007)	
Robotic Penetration $\times$ Income		0.003		0.014		-0.026
$\times$ %University Educated Workers		(0.004)		(0.016)		(0.542)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on changes of job destruction rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is the instrument. Columns 1 to 2 only treat robotic penetration as endogenous variable; Columns 3 to 4 treat both robotic penetration and the interaction term with education level as endogenous variables; Columns 5 to 6 treat all variables including robotic penetration and the interaction term with education level and income level as endogenous variables. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As exhibited in Table 2.14, the point estimates for interaction with the proportion of both two types of skilled labour are statistically insignificant even at confidence level 10 percentage, implying that the impacts of robotic exposures on job destructions are prevalent across regions with different skill shares. In addition, the job vacancies from both high school and university educated workers could not mitigate decline of net job creation rate. This evidence aligns with the hypothesis before, as productivity effects induced by high skilled labour tend to become more powerful, and could potentially compensate for job losses by displacement effects.

In contrast with the situation of job destructions displayed in Table 2.14, the results listed in Table 2.15 exhibit regression results regarding job creations. Results excluding estimation of income levels are exhibited in Table 18 of Appendix.

Table 2.15: Job Creations and Robots by Skill Share for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
Robotic Penetration	-8.300**	-2.452**	-1.581*	-2.695	-4.560	-1.716
	(3.665)	(1.164)	(0.957)	(2.241)	(5.350)	(9.270)
Robotic Penetration	0.051**		0.118*		0.019	
× %High School Educated Worker	(0.022)		(0.071)		(0.040)	
Robotic Penetration		0.048**		0.115		-0.016
× %University Educated Workers		(0.021)		(0.074)		(1.152)
Robotic Penetration × Income	-0.006**		-0.015*		-0.002	
× %High School Educated Workers	(0.003)		(0.009)		(0.006)	
Robotic Penetration × Income		-0.007**		-0.018		0.005
× %University Educated Workers		(0.003)		(0.011)		(0.198)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on changes of job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1 to 2 only treat robotic penetration as endogenous variable; Columns 3 to 4 treat both robotic penetration and the interaction term with education level as endogenous variables; Columns 5 to 6 treat all variables including robotic penetration and the interaction term with education level and income level as endogenous variables. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Following similar specifications in Table 2.14, and despite variations in endogenous variable combinations, all the estimates are statistically significant. This suggests that skill shares could moderate the employment reduction effects induced by robotic penetrations. As showed in Columns 1-2, a rise of percentage of high school and university educated workers could mitigate decline of job creation rate by 0.05 percentage points. Specifically, the negative coefficients for interactions with both skill share and income level exhibit that the importance of mitigation effects from skill shares are diminishing. This evidence aligns with the earlier hypothesis, as productivity effects induced by high skilled labour tend to become more powerful, and could complement job losses by displacement effects. Such mitigation effects tend to depreciate with growing income level, suggesting that additional $1000 increase of personal income per capita would lower mitigation effects of proportion of high school and university educated workers on technological unemployment by 0.01 percentage points. This pattern is consistent with rule of diminishing marginal returns. In economically more advanced areas, capabilities of learning by doing and labour market experience could play a relatively more substantial role in high-skill tasks, compared with human capital accumulation (Stinebrickner et al., 2019).

The results regarding net job creations for both university and high school educated workers are reported in Table 2.16. Results excluding estimation of income levels are exhibited in Table 19 of Appendix.

In accordance with the specifications in Table 2.14, and despite variations in the combinations of endogenous variables, all the estimates demonstrate statistical significance. This suggests that skill shares could flatten employment reduction effects arising from robotic penetrations. As showed in Columns 1-2, a rise of percentage of high school educated workers could mitigate decline of net job creation rate by 11.94 percentage points. Similarly, a rise of percentage of university educated workers could mitigate decline of net job creation rate by 3.67 percentage points. Specifically, the negative coefficients for interactions with both skill share and income level suggest a reducing influence of skill shares. This finding aligns with the previously stated hypothesis, as productivity effects induced by high skilled labour tend to become more powerful, and could complement job losses by displacement effects. In addition, such mitigation effects appear to weaken as income level grows, reflecting that additional $1000 increase of personal income per capita would lower mitigation effects of proportion of high school and university educated workers on technological unemployment by 0.01 percentage points. This pattern is consistent with principle of diminishing marginal returns, suggesting that in more economically devel-

Table 2.16: Net Job Creations and Robots by Skill Share for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
Robotic Penetration	-1.194*	-3.668*	-2.636	-4.158	-4.390	-1.443
	(0.716)	(2.121)	(2.157)	(4.419)	(11.138)	(34.301)
Robotic Penetration	0.072*		0.200		0.008	
$\times$ %High School Educated Worker	(0.042)		(0.159)		(0.086)	
Robotic Penetration		0.069*		0.204		-0.162
$\times$ %University Educated Workers		(0.037)		(0.157)		(4.287)
Robotic Penetration $\times$ Income	-0.009*		-0.026		0.001	
$\times$ %High School Educated Workers	(0.005)		(0.021)		(0.012)	
Robotic Penetration $\times$ Income		-0.009*		-0.032		0.031
$\times$ %University Educated Workers		(0.005)		(0.024)		(0.738)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is the instrument. Columns 1 to 2 only treat robotic penetration as endogenous variable; Columns 3 to 4 treat both robotic penetration and the interaction term with education level as endogenous variables; Columns 5 to 6 treat all variables including robotic penetration and the interaction term with education level and income level as endogenous variables. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

oped regions, factors such as learning by doing and labour market experience may play a more significant role in high-skill tasks, compared with human capital accumulation (Stinebrickner et al., 2019).

The findings reflect the fact that automation technologies represented by robotic adoptions, are killing low skilled employment for workers without high school qualifications, and bring welfare improvements for high skilled workers with tertiary and university educations. Further examination of the role of income level indicates that the slowdown effects of net job creation reductions are more pronounced in CZs with high percentage of university educated workers. This suggests that new occupations are primarily created for high skilled workers.

Table 2.17: US Job Destructions, ICT Trade and University Education by Income, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Job Destruction Rate			
ICT Import	0.801		
	(0.960)		
ICT Export		1.640	
		(1.966)	
ICT Net Exp			-1.585
			(1.923)
ICT Import	-0.014		
$\times$%University Educated Workers	(0.017)		
ICT Export		-0.028	
$\times$%University Educated Workers		(0.035)	
ICT Net Exp			0.027
$\times$%University Educated Workers			(0.034)
ICT Import$\times$Income	0.002		
$\times$%University Educated Workers	(0.002)		
ICT Export$\times$Income		0.003	
$\times$%University Educated Workers		(0.005)	
ICT Net Exp$\times$Income			-0.003
$\times$%University Educated Workers			(0.004)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job destruction rate, by share of university education workers and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In addition, I also present regression results listed in Tables 2.17 to 2.19, which exhibits estimates regarding changes on job destructions, job creations and net job creations, triggered by ICT import, ICT export, and ICT net export as alternative measures of automation technologies. Interaction terms are included between these alternative measures of automation technologies, proportion of university educated workers, and personal income per capita. Corresponding results regarding automation import, automation export, and automation net export, along with their interactions with proportion of university educated workers, are presented in Table 20 of Appendix. Robustness checks only including the interaction terms between alternative measures of automation technologies and university educated workers are displayed in Table 21 of Appendix. Sensitivity tests concerning ICT import, ICT export, ICT net export, automation import, automation export, and automation net export, and their interactions with proportion of high school educated workers, are presented in Table 22 and Table 23 of Appendix.

All the estimates listed in Table 2.17 are statistically insignificant. This reflects the fact that technological job losses are widespread across regions with different income levels, regardless of their stages of economic growth, proxied by personal income per capita. These patterns remain consistent across alternative measures of automation technologies. Robustness checks in Tables 20 to 23 reveal that the results are insensitive to different specifications.

In contrast with the situation of job destructions displayed in Table 2.17, the results listed in Table 2.18 exhibits regression results regarding job creations.

Table 2.18 displays the IV results for the impacts of alternative automation technologies on job creation rate, and I also add interaction term between ICT trade volumes, skill shares and income level. Across various choices of automation trade volumes, the IV estimates in Panel D range from -2.728 to -3.817. These results reveal that the reductions of job creation rate caused by additional \$1000 ICT import per thousand labour force would become 2.73 percentage points, and those caused by additional \$1000 ICT export per thousand labour force would become 3.82 percentage points. The inclusion of skill shares indicates mitigation effects. One percent rise of proportion of university educated workers would results mitigate job creation losses by around 0.01 percentage points from ICT import, and 0.02 percentage points from ICT export, and relatively small robust stan-

Table 2.18: US Job Creations, ICT Trade and University Education by Income, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Job Creation Rate			
ICT Import	-2.728***		
	(0.980)		
ICT Export		-3.817***	
		(1.192)	
ICT Net Exp			19.083
			(24.713)
ICT Import	0.012***		
$\times$%University Educated Workers	(0.005)		
ICT Export		0.018***	
$\times$%University Educated Workers		(0.006)	
ICT Net Exp			-0.082
$\times$%University Educated Workers			(0.108)
ICT Import$\times$Income	-0.001**		
$\times$%University Educated Workers	(0.000)		
ICT Export$\times$Income		-0.002***	
$\times$%University Educated Workers		(0.001)	
ICT Net Exp$\times$Income			0.008
$\times$%University Educated Workers			(0.010)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job creation rate, by share of university education workers and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

dard errors reflect quite stable magnitudes. Specifically, the diminishing marginal returns of high school education across areas from different income groups are also notable, as the reduction of mitigation effects by proportion of high school educated workers from additional $1000 personal income per capita is 0.001 for ICT import, and 0.002 for ICT export. The magnitudes are quite small compared with coefficients of alternative measures of automation technologies. Similar patterns are observed for automation trade volumes in Table 24 of Appendix, occasions where income levels are not considered in Table 25 of Appendix, and high school educated workers in Table 26 and Table 27 of Appendix.

Finally, I also present the results concerning regression outcomes of how alternative measures of automation technologies affect changes of net job creations in Table 2.19.

Table 2.19: US Net Job Creations, ICT Trade and University Education by Income, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Net Job Creation Rate			
ICT Import	-4.093**		
	(2.080)		
ICT Export		-5.475**	
		(2.511)	
ICT Net Exp			29.543
			(40.247)
ICT Import	0.018*		
$\times$%University Educated Workers	(0.010)		
ICT Export		0.025**	
$\times$%University Educated Workers		(0.012)	
ICT Net Exp			-0.127
$\times$%University Educated Workers			(0.176)
ICT Import$\times$Income	-0.002*		
$\times$%University Educated Workers	(0.001)		
ICT Export$\times$Income		-0.003*	
$\times$%University Educated Workers		(0.001)	
ICT Net Exp$\times$Income			0.012
$\times$%University Educated Workers			(0.017)
Year FE	√	√	√
Demographics	√	√	√
Geographic FE	√	√	√
State $\times$ Year FE	√	√	√
Firm Size $\times$ Year FE	√	√	√
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of net job creation rate, by share of university education workers and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.19 displays the IV results for the impacts of alternative automation technologies on job creation rate, with the addition of an interaction term between ICT trade volumes, skill shares and income level. While the IV estimates vary from -4.093 to -5.475 for different automation trade volumes, they indicate that the reductions of net job creation rate caused by additional \$1000 ICT import per thousand labour force would become 4.09 percentage points, and those caused by additional \$1000 ICT export per thousand labour force would become 3.82 percentage points. Accounting for flattening effects of skill shares, one percent rise of proportion of university educated workers would mitigate net job creation losses by approximately 0.02 percentage points from ICT import, and 0.03 percentage points from ICT export. The relatively small robust standard errors reflect fairly stable magnitudes. The diminishing marginal returns of university education across areas from different income groups are also notable, as the reduction of mitigation effects by proportion of university educated workers from additional \$1000 personal income per capita is 0.002 for ICT import, and 0.003 for ICT export. These magnitudes are relatively small compared with coefficients of alternative measures of automation technologies. Comparable trends are also observed for automation trade volumes in Table 28 of Appendix, in cases where income levels are not considered in Table 29 of Appendix, and high school educated workers in Table 30 and Table 31 of Appendix.

In summary, the results above provide the evidence that technological changes represented by automation technologies are biased towards high skilled labour force.

2.6.3 Structural Change and Net Job Creation

Lastly I go one step further, and discover various patterns of employment effects of automation technologies across 19 IFR sectors, including 6 broad sectors together with 13 manufacturing sub-sectors. In contrast to Equation 2.9, the econometric model is modified as follows:

$$\begin{aligned}\Delta Job_{it} = \gamma_0'' &+ \gamma_1''\Delta AutomationExposure_{it} \\ &+ \gamma_2''\Delta AutomationExposure_{it} \times Industry\,Share_{it} \\ &+ \gamma_3''\Delta AutomationExposure_{it} \times Industry\,Share_{it} \times Income_{it_0} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{2.10}$$

where $Industry\,Share_{it}$ is defined as the ratio of value added for a given sector and overall GDP. Based on IFR classifications (International Federation of Robotics, 2021), these six broad sectors include manufacturing, agriculture, mining, utility, construction, and R&D activities. Following Acemoglu and Restrepo (2020), this study utilises a comprehensive dataset covering 13 sub-sectors within manufacturing industries, namely textiles; wood and furniture; paper; pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Combining six broad IFR sectors with 13 dis-aggregated manufacturing sub-sectors, this section will explore the mechanism through net job creations across 19 sectors. Estimation results regarding the impacts of robotic usage on job destructions, job creations, and net job creations across six broad IFR sectors are displayed in Table 2.20 to Table 2.22, and those regarding the impacts of robotic usage on job destructions, job creations, and net job creations across 13 dis-aggregated sub-sectors within manufacturing industries are displayed in Table 35 to Table 40.

The results regarding evolutionary effects on job destructions across six broad IFR sectors are reported in Table 2.20. This study offers IV estimates of robotic exposure on job destruction rate by different industries, and includes the interaction of robotic usage, GDP share of each industry, and income level. Similarly, the IV results excluding the influence of income level are reported in Table 32 of Appendix, and those regarding evolutionary

Table 2.20: Job Destruction Dynamics and Robotic Penetration by Industry for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
Robot Penetration	0.981	1.582	1.455	1.128	18.509	1.793
	(1.370)	(1.988)	(1.795)	(1.578)	(90.571)	(2.200)
Robot Penetration	0.016					
×%Manufacturing GDP	(0.017)					
Robot Penetration		0.008				
×%Agriculture GDP		(0.006)				
Robot Penetration			-0.004			
×%Mining GDP			(0.003)			
Robot Penetration				0.021		
×%Utility GDP				(0.020)		
Robot Penetration					-0.365	
×%Construction GDP					(1.936)	
Robot Penetration						0.036
×%R&D GDP						(0.048)
Robot Penetration×Income	-0.003					
×%Manufacturing GDP	(0.003)					
Robot Penetration×Income		-0.002				
×%Agriculture GDP		(0.001)				
Robot Penetration×Income			0.000			
×%Mining GDP			(0.001)			
Robot Penetration×Income				-0.004		
×%Utility GDP				(0.004)		
Robot Penetration×Income					0.094	
×%Construction GDP					(0.490)	
Robot Penetration×Income						-0.011
×%R&D GDP						(0.009)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job destruction rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

effects on job destructions across other 13 sub-sectors within manufacturing industries are reported in Table 35 and Table 36 of Appendix.

As exhibited in Table 2.20, the point estimates for the interaction with GDP proportion of all sectors are statistically insignificant even at confidence level of 10 percent[38], implying the impacts of robotic exposures on job destructions are widespread across regions with different industrial comparative advantages. The estimated coefficients for other manufacturing sub-sectors in Table 35 and Table 36 of Appendix are also statistically insignificant, which are consistent with those among the six broad IFR industries.

In contrast with the patterns of job destructions displayed in Table 2.20, the coefficients listed in Table 2.21 exhibit regression results regarding job creations.

Following similar specifications in Table 2.20, Table 2.21 reveals different results. Treating all variables related to robotic penetration as endogenous variables, only the estimates for manufacturing are statistically significant, reflecting the fact that the job creations induced by productivity effects would be pronounced in the manufacturing sector. As showed in Column 1, a rise of percentage of manufacturing GDP could reinforce decline of job creation rate by 0.03 percentage points. Specifically, the positive coefficients for interactions with both GDP share and income level exhibit that the importance of reinforcement effects from skill shares are diminishing. These strengthening effects tend to depreciate with growing income level, suggesting that additional $1000 increase of personal income per capita would lower reinforcement effects of GDP proportion of manufacturing on technological unemployment by 0.006 percentage points. This pattern is consistent with the rule of diminishing marginal returns. Robustness checks excluding influence of income levels are presented in Table 33 of Appendix, and the results are insensitive to different specifications. Regression results in other 13 sub-sectors within manufacturing industries, listed in Table 37 and Table 38 of Appendix, are consistent with the previous evidence.

The results regarding dynamics of net job creations across six broad IFR sectors are re-

[38]The regression results for the interaction term between robotic penetration and percentage of value added in mining over total GDP, listed in Table 32 of Appendix, is statistically significant under confidence interval of 5 percent, but the magnitudes of the estimation coefficient is small, suggesting potentially zero effects.

Table 2.21: Job Creation Dynamics and Robotic Penetration by Industry for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
Robot Penetration	-2.238**	-3.074*	-2.780*	-2.606**	-27.660	-3.640*
	(1.039)	(1.645)	(1.500)	(1.322)	(135.736)	(2.210)
Robot Penetration	-0.028**					
×%Manufacturing GDP	(0.011)					
Robot Penetration		-0.008				
×%Agriculture GDP		(0.010)				
Robot Penetration			0.003			
×%Mining GDP			(0.004)			
Robot Penetration				-0.020		
×%Utility GDP				(0.020)		
Robot Penetration					0.523	
×%Construction GDP					(2.892)	
Robot Penetration						-0.017
×%R&D GDP						(0.089)
Robot Penetration× Income	0.006***					
×%Manufacturing GDP	(0.002)					
Robot Penetration×Income		0.002				
×%Agriculture GDP		(0.002)				
Robot Penetration×Income			-0.001			
×%Mining GDP			(0.001)			
Robot Penetration×Income				0.004		
×%Utility GDP				(0.004)		
Robot Penetration×Income					-0.136	
×%Construction GDP					(0.731)	
Robot Penetration×Income						0.013
×%R&D GDP						(0.017)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ported in Table 2.22.

Table 2.22: Net Job Creation Dynamics and Robotic Penetration by Industry for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
Robot Penetration	-3.218*	-4.655	-4.236*	-3.733*	-46.170	-5.434
	(1.719)	(2.836)	(2.449)	(2.172)	(225.018)	(3.318)
Robot Penetration	-0.044**					
$\times$%Manufacturing GDP	(0.018)					
Robot Penetration		-0.016				
$\times$%Agriculture GDP		(0.012)				
Robot Penetration			0.007			
$\times$%Mining GDP			(0.005)			
Robot Penetration				-0.041		
$\times$%Utility GDP				(0.029)		
Robot Penetration					0.889	
$\times$%Construction GDP					(4.806)	
Robot Penetration						-0.053
$\times$%R&D GDP						(0.124)
Robot Penetration$\times$Income	0.009**					
$\times$%Manufacturing GDP	(0.004)					
Robot Penetration$\times$Income		0.004				
$\times$%Agriculture GDP		(0.003)				
Robot Penetration$\times$Income			-0.001			
$\times$%Mining GDP			(0.001)			
Robot Penetration$\times$Income				0.008		
$\times$%Utility GDP				(0.006)		
Robot Penetration$\times$Income					-0.230	
$\times$%Construction GDP					(1.215)	
Robot Penetration$\times$Income						0.023
$\times$%R&D GDP						(0.021)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of net job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Following similar specifications outlined in Table 2.20, Table 2.22 produces similar results. Treating all variables associated with robotic penetration as endogenous variables, only the estimates for manufacturing are statistically significant, reflecting the fact that the job creations induced by productivity effects are particularly significant in the manufacturing sector. As showed in Column 1, a rise of percentage of manufacturing GDP could reinforce decline of net job creation rate by 3.22 percentage points. Strikingly, the negative coefficients for interactions with both GDP share and income level exhibit that the importance of mitigation effects from skill shares are diminishing. Such mitigation effects tend to depreciate with growing income level, reflecting that additional $1000 increase of personal income per capita would lower reinforcement effects of GDP proportion of manufacturing on technological unemployment by 0.009 percentage points. This evidence indicates that new vacancies created by productivity effects could absorb production workers from manufacturing industries, and high income CZs with growing high skilled task requirements would experience a slowdown of net job creations. Robustness checks excluding influence of income levels are presented in Table 34 of Appendix, and the results remain consistent across different specifications. Regression results in other 13 sub-sectors within manufacturing industries, detailed in Table 39 and Table 40 of Appendix, are consistent with the aforementioned findings.

In addition, I also present regression results listed in Tables 2.23 to 2.25, which exhibit estimates regarding changes in job destructions, job creations and net job creations. These changes are triggered by ICT import, ICT export, and ICT net export, as alternative measures of automation technologies. Since net job creation dynamics are primarily observed in the manufacturing industry, the analysis will centre on the systematic difference between manufacturing sector and non-manufacturing sector, and consider the percentage of manufacturing GDP. I then add interaction term between alternative exposure of automation technologies and proportion of manufacturing in overall GDP, as well as interaction terms among alternative exposure of automation technologies, proportion of manufacturing in overall GDP and personal income per capita. Results concerning automation trade volumes such as import, export, net export are presented in Table 41 to Table 45 of Ap-

Table 2.23: Job Destruction Dynamics and ICT Trade Volumes by Industry for US, 2000-2019

	(1)	(2)	(3)
Dependent Variable: △ Job Destruction Rate			
ICT Import	0.028		
	(0.037)		
ICT Export		0.066	
		(0.086)	
ICT Net Exp			-0.050
			(0.064)
ICT Import	0.002		
×%Manufacturing GDP	(0.002)		
ICT Export		0.004	
×%Manufacturing GDP		(0.004)	
ICT Net Exp			-0.003
×%Manufacturing GDP			(0.004)
ICT Import×Income	-0.000		
×%Manufacturing GDP	(0.000)		
ICT Export×Income		-0.001	
×%Manufacturing GDP		(0.001)	
ICT Net Exp×Income			0.001
×%Manufacturing GDP			(0.001)
Year FE	√	√	√
Demographics	√	√	√
Geographic FE	√	√	√
State × Year FE	√	√	√
Firm Size × Year FE	√	√	√
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on interactions between changes of job destruction rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

pendix. Evidence excluding the impacts of income levels are displayed in Table 42 to Table 46 of Appendix.

All the estimates listed in Table 2.23 lack statistical significance. This reflects the fact that technological job losses are pervasive across regions with different income levels, irrespective of their economic development, proxied by personal income per capita, and industrial specialisations, proxied by percentage manufacturing in overall GDP. These trends remain consistent with alternative measures of automation technologies.

Table 2.24: Job Creation Dynamics and ICT Trade Volumes by Industry for US, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Job Creation Rate			
ICT Import	-0.058***		
	(0.021)		
ICT Export		-0.136***	
		(0.041)	
ICT Net Exp			-0.101**
			(0.042)
ICT Import	-0.003**		
×%Manufacturing GDP	(0.001)		
ICT Export		-0.006***	
×%Manufacturing GDP		(0.002)	
ICT Net Exp			0.006**
×%Manufacturing GDP			(0.003)
ICT Import×Income	0.001**		
×%Manufacturing GDP	(0.000)		
ICT Export×Income		0.001***	
×%Manufacturing GDP		(0.000)	
ICT Net Exp×Income			-0.001**
×%Manufacturing GDP			(0.001)
Year FE	√	√	√
Demographics	√	√	√
Geographic FE	√	√	√
State × Year FE	√	√	√
Firm Size × Year FE	√	√	√
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on interactions between changes of job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In contrast with the situation of job destructions displayed in Table 2.23, the evidence listed in Table 2.24 exhibits regression results regarding job creations.

Table 2.24 introduces interaction terms between alternative exposure of ICT trade volumes and manufacturing GDP shares, and those between ICT trade volumes, manufacturing GDP shares and income level. Depending on the automation trade volume measure utilised, the IV estimates range from -0.058 to -0.136, revealing that the reductions of job creation rate caused by additional \$1000 ICT import per thousand labour force would become 0.06 percentage points, those caused by additional \$1000 ICT export per thousand labour force would become 0.14 percentage points, and those caused by additional \$1000 ICT net export per thousand labour force would become 0.10 percentage points. Accounting for heterogeneous effects of manufacturing GDP shares, one percent rise of proportion of manufacturing in overall GDP would mitigate job creation losses by approximately 0.003 percentage points from ICT import, 0.006 percentage points from ICT export, and 0.006 percentage points from ICT net export. The relatively small robust standard errors reflect quite stable magnitudes. The diminishing marginal returns of manufacturing power across areas from different income groups are not notable. This is evident in the near-zero effects of rising income per capita on job creation losses from ICT import, ICT export, ICT net export across manufacturing sector and non-manufacturing sector.

Robustness checks about automation trade volumes, including automation import, automation export, and automation net export, are exhibited in Table 43. Those excluding influence of income levels are displayed in Table 44. They showed that the results are insensitive to different specifications.

Finally, I also present the results concerning regression outcomes of alternative measures of automation technologies on changes of net job creations in Table 2.25.

Table 2.25 includes interaction terms between alternative exposure of ICT trade volumes and manufacturing GDP shares, as well as those between ICT trade volumes, manufacturing GDP shares and income level. Though with various choices of automation trade volumes, the IV estimates range from -0.086 to -0.202, revealing that the reductions of net job creation rate caused by additional \$1000 ICT import per thousand labour force

Table 2.25: Net Job Creation Dynamics and ICT Trade Volumes by Industry for US, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Net Job Creation Rate			
ICT Import	-0.086**		
	(0.043)		
ICT Export		-0.202**	
		(0.096)	
ICT Net Exp			0.151*
			(0.081)
ICT Import	-0.005**		
$\times$%Manufacturing GDP	(0.002)		
ICT Export		-0.009**	
$\times$%Manufacturing GDP		(0.004)	
ICT Net Exp			0.009**
$\times$%Manufacturing GDP			(0.004)
ICT Import$\times$Income	0.001**		
$\times$%Manufacturing GDP	(0.000)		
ICT Export$\times$Income		0.002**	
$\times$%Manufacturing GDP		(0.001)	
ICT Net Exp$\times$Income			-0.002**
$\times$%Manufacturing GDP			(0.001)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on interactions between changes of net job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographic controls which are not displayed here, include number of firms (Firms), total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

would become 0.09 percentage points, those caused by additional \$1000 ICT export per thousand labour force would become 0.20 percentage points, and those caused by additional \$1000 ICT net export per thousand labour force would become 0.15 percentage points. Accounting for heterogeneous effects of manufacturing GDP shares, one percent rise of proportion of manufacturing in overall GDP would mitigate net job creation losses by approximately 0.005 percentage points from ICT import, 0.009 percentage points from ICT export, and 0.009 percentage points from ICT net export. The relatively small robust standard errors reflect quite stable magnitudes. The diminishing marginal returns of manufacturing power across areas from different income groups are not notable. The results indicate that the rising income per capita would have almost significantly zero effects on job creation losses from ICT import, ICT export, and ICT net export across manufacturing sector and non-manufacturing sector.

Robustness checks about automation trade volumes, including automation import, automation export, and automation net export, are exhibited in Table 45. Those excluding influence of income levels are displayed in Table 46. They showed that the results remain consistent across different specifications.

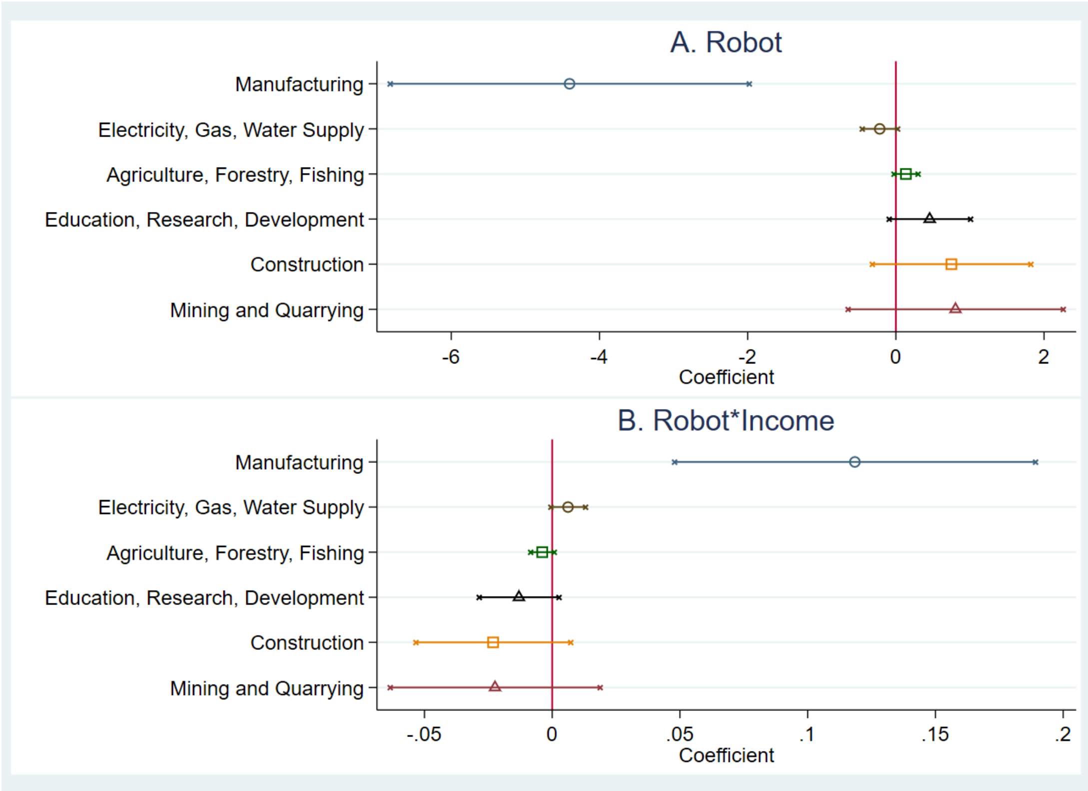
To further support the role of structural change and business dynamics, the econometric model is modified as follows:

$$\begin{aligned}\Delta Job_{ijt} =& \gamma_0'' + \gamma_1'' \Delta RobotExposure_{ijt} + \gamma_3'' \Delta RobotExposure_{ijt} \times Income_{it_0} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it}\end{aligned} \tag{2.11}$$

where j refers to 19 IFR sectors (International Federation of Robotics, 2021), including 6 broad industries and 13 sub-sectors within manufacturing industry.

Figure 2.6 provides a visual representation of IV estimates in Equation 2.11. Following Oberfield and Raval (2021), each panel shows results for six broad industries, where the horizontal bars represent 90% confidence intervals for the coefficient estimates. Panel A documents that robots are slowing down the net job creations most strongly in manufacturing, with limited effects observed in other sectors. Likewise, Panel B also reveals mitigation effects of rising income level across industries. This evidence suggests that new job vacancies created by productivity effects could absorb production workers from

Figure 2.6: Net Job Creation Effects of Robots by Industries, 2000-2019

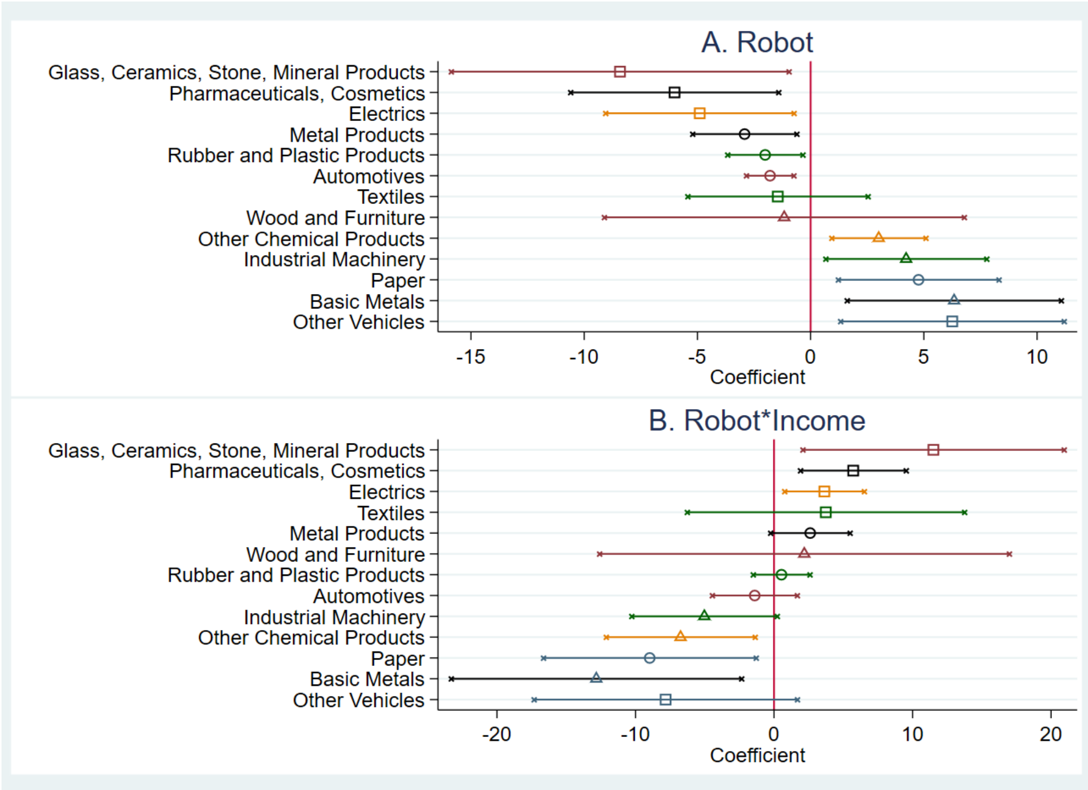


Notes:
The graph presents IV estimates of the effects of robotic penetration on changes of net job creation rate for six broad IFR sectors (International Federation of Robotics, 2021), where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Panel A reports coefficient estimates for γ_1'' in Equation 2.10 and 90% confidence intervals for these estimates, and Panel B exhibits corresponding information for γ_2'' in Equation 2.10. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions.

manufacturing industries, and high income CZs with growing high skilled task requirements would witness a slowdown of net job creations.

Turning to results within manufacturing, Figure 2.7 displays the IV estimates across 13 sub-sectors, where the outcome variable refers to net job creation rate in production sectors. The cross industry variation appears to be substantial, as automation technologies tend to affect employment across manufacturing sub-sectors in quantitatively and qualitatively different extents. Similar patterns in manufacturing net job creations are mainly driven by robotic usage in glass, ceremics, stone, mineral products; and pharmaceuticals, cosmetics, electrics. These findings lend further weight to a growing body of research, suggesting that technological changes could induce shifts in employment composition within sectors (Autor et al., 2015).

Figure 2.7: Net Job Creation Effects of Robots Within Manufacturing, 2000-2019



Notes:
The graph presents IV estimates of the effects of robotic penetration on changes of net job creation rate for 13 IFR sub-sectors within manufacturing (International Federation of Robotics, 2021), where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Panel A reports coefficient estimates for γ_1'' in Equation 2.10 and 90% confidence intervals for these estimates, and Panel B exhibits corresponding information for γ_2'' in Equation 2.10. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions.

In all instances, the results emphasise the crucial role of net job creations in heterogeneous effects of automation technologies on labour market outcomes. Moreover, they highlight that technical updating is biased against unskilled workers and those in manufacturing industries.

2.7 Summary

Automation seems to influence employment differently depending on the income level of a given country or region. Leveraging comprehensive US state level and commuting zone level data between 2000 and 2019, this chapter provides empirical analysis regarding the impacts of automation technologies on employment rate. It further evaluates the mechanisms underpinning these impacts, focusing on the responses of workers with different skill levels and from different industries, under forces of displacement effects and productivity effects.

For baseline empirical results, I find that rising penetration of automation technologies, including industrial robots, ICT trade volumes and automation trade volumes, corresponds to the reductions in employment rate across all commuting zones. The magnitudes of negative employment responses are larger and more significant in low- and middle-income areas, implying that displacement effects are dominant in the process of technological updating. However, higher income levels may mitigate these effects, suggesting that productivity effects can help counteract some of the welfare deteriorations by displacement effects. Overall, the rise of 1 unit robot per thousand labour force could generate job losses by 0.67 percentage points. This coefficient is similar to the estimated employment reductions of approximately 0.45 by Acemoglu and Restrepo (2020)[39]. The results for alternative measures of automation technologies using ICT and automation trade volumes, are also consistent with other evidence using automation patent data (Acemoglu and Restrepo, 2021).

Besides the main hypotheses, this chapter also examines the mechanisms behind such heterogeneous effects, using a simple net job creation channel. Following the adoption of automation technologies, job displacement is observed across all regions. In high income CZs, new vacancies are created in other non-automated sectors, where high skilled labour forces are required in most cases. While relatively lower percentage of skilled workers in low and middle CZs limits opportunities for such job creations, leading to substantial employment losses. On average, a rise of robotic stocks per thousand workers could lower the job creation rate by 1.35 percentage points, and the impacts are also significantly negative for ICT and automation trade volumes. The growing income levels could mitigate job losses by 0.15 percentage points in the net job creation rate. As a consequence, grow-

[39]The reason why the magnitudes of the coefficient in this thesis is larger than Acemoglu and Restrepo (2020), is that their analysis is based on sample period of 1990-2007. It is uncovered that after the financial crisis in 2008-2009, the rate of technological replacement is accelerating (Sachs and Kotlikoff, 2012; Sachs et al., 2015; Brynjolfsson and Mitchell, 2017).

ing income levels could surpress the absolute magnitudes of negative employment effects, and reduce the welfare deterioration to some extent. Interestingly, such technical changes are biased towards high skilled workers, and more prevalent in manufacturing sectors.

In this part, I also point out some challenges and future directions for US analysis.

Firstly, there are still some caveats regarding identification threats presented before. This chapter aligns with the majority of existing literature, and obtains exogenous shocks based on automation adoptions in other European countries. It adopts shift share IV approach, assuming that European automation could only affect US employment exclusively through US automation. Although the robotic densities of sample European countries are all above US counterparts, the technological spillover from US to Europe remains a significant confounding factor. Therefore, the following chapter will explore alternative exogenous shocks, based on advanced econometric methods, to address endogenous issues such as spillover effects.

Secondly, utilising comprehensive datasets to select a suitable indicator of automation technologies is challenging. Early works often focus on general measures of technological updating such as TFP (total factor productivity) growth and patent awards across various countries (Autor and Salomons, 2018; Autor et al., 2020). But they failed to differentiate between productivity growth from automated and non-automated sectors. This chapter follows recent literature such as Acemoglu and Restrepo (2020), which utilised data from International Federation of Robotics (2021) to perform empirical analysis. It contains counts of robotic stocks across 19 industrial sectors in the US from 2000 to 2019, In addition, I adopt data about US ICT import and export from bilateral trade statistics of Comtrade database (United Nations, 2020), to obtain a comprehensive picture of the relationship between automation technologies and employment. However, this approach may encounter difficulties in cross country comparisons, due to potential variations in robot quality across different regions. Relying on novel datasets, patent awards about automation technologies, as discussed by Autor et al. (2020); Bloom et al. (2015), could represent a more reliable indicator for the development of automation technologies in future research.

Overall, empirical analysis based on US contexts only shows that differential employment responses to automation technologies work in developed countries. Considering the status of the US as a leading global economy, it is essential to examine whether these findings can be generalised to other developed countries at similar stages of economic development. Besides, whether the applications in developed countries also work in other economies, especially low income countries, or regions with different institutional settings, is under investigations. Therefore, the following chapter will employ a cross country dataset to perform further analysis.

Chapter 3

Cross Country Analysis

So far, this thesis has examined the employment effects and net job creations related to automation technologies across US regions. In this stage of analysis, this thesis will discuss implications for cross country evidence. Guided by the conceptual framework outlined in Chapter 1, the research question is to explore the impacts of automation technologies on employment rate. In addition, it evaluates the mechanisms behind heterogeneous effects across regions from different income groups.

3.1 Introduction

This section introduces cross country analysis, with a focus on the motivation, hypothesis, and contribution of this chapter.

3.1.1 Motivation

The reasons why I plan to perform cross country analysis are as follows.

Firstly, as established in Chapter 1, understanding the impacts of automation technologies on labour market outcomes at all levels of analysis, including individual workers, skill groups, metropolitan areas, and entire countries, is important. Chapter 2 offered insights based on evidence from US, the most advanced economy all over the world, and focused on state level data and commuting zone level data. This chapter expands the scope by presenting cross country evidence, and performs regression analysis across countries from different income groups. Therefore, cross country analysis will shed light on the heterogeneous effects of automation technologies on employment rate based on macro level evidence.

Secondly, empirical analysis based on US contexts shows that the differential employment responses from automation technologies are relevant to advanced economies. As suggested in Chapter 2, it is essential to examine whether US results can be generalised to other economies, particularly low income countries with lower adoptions of automation technologies, or regions with different institutional settings. Stylised facts in Section 3.3 reveal regional variations about the impacts from automation technologies on labour market outcomes. Therefore, research exploiting technological unemployment across countries at different stages of economic development, is interesting.

Thirdly, evidence of heterogeneous employment effects from automation technologies can be observed in European countries (Acemoglu et al., 2023; Antonczyk et al., 2018; Goos et al., 2009). However, there is only limited empirical works regarding technological unemployment in emerging economies. This chapter aims to address this gap in the literature[1]. In addition, the World Bank (2021) provides subjective classification of economies from different income groups, and offers detailed information about the thresholds between these income groups. This classification system facilitates the analysis of heterogeneous effects of automation technologies on employment across regions from different income groups.

[1]Detailed information about the contributions to existing literature will be illustrated in Subsection 3.1.3.

3.1.2 Hypothesis

The hypotheses are similar to those in Chapter 1.

Hypothesis 1: Across all the countries, the correlation between automation technologies and employment rate tends to become negative.

Hypothesis 2: In high income countries with a large proportion of high skilled workers, automation technologies are likely to have positive impacts on employment rate. While in low and middle income economies with fewer high skilled workers, there is a negative correlation between automation adoptions and employment responses.

Hypothesis 3: A key determinant behind heterogeneous employment effects is the skill proportion. The percentage of high skilled labour force is higher in advanced economies, and lower in low and middle income countries.

Hypothesis 4: Differential employment dynamics from automation technologies, as highlighted in *Hypothesis 2*, are more pronounced in countries at higher stage of economic development such as OECD countries, due to concentration of manufacturing activities.

The following section outlines the contributions of this chapter in relation to existing gaps in the literature.

3.1.3 Contribution

This chapter contributes to three branches of literature on technology, skills, and employment, including heterogeneous employment effects from technical changes, identification strategies based on ageing society, and the regional variations of structural transformations.

For the first main contribution, this chapter connects with the vast literature on the heterogeneous employment effects across countries from different income groups. Several papers have sought to develop general measures of technological updating such as TFP (total factor productivity) growth and patent awards with US regions or firms (Autor and Salomons, 2018; Autor et al., 2020). However, there is only limited evidence on technological unemployment across countries from different income groups, due to lack of unified measure of technical updating. This chapter aims to address this gap by employing two complementary indicators, namely robotic density calculated by robotic stocks per thousand labour force, and ICT intensity measured by ICT expenditure per thousand workers. Therefore, thesis thesis provides novel evidence by analysing the impacts of automation technologies on job replacement and productivity growth originating from automated sectors, based on cross country evidence.

For the second main contribution, this chapter contributes to a contemporary literature about identification issues when exploring how automation technologies substitute for existing work, adding to a developing body of literature. This research aligns with several existing papers that use automation adoptions in other advanced economies as instrumental variables for dynamics of automation technologies in a specific country (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Giuntella et al., 2022), and those utilising event studies based on patent policy shocks (Bloom et al., 2015). In contrast to these studies, this chapter introduces a method to identify automation technologies across countries. I extend the pioneering work by Acemoglu and Restrepo (2021), which estimated the relationship between ageing trends and adoption of automation. On the one hand, evolution of demographic structures can solely be determined by birth and death rates, and cannot be intervened by short-term government policies. On the other hand, rising wages for manufacturing workers in ageing societies, along with decline of participation rate, will finally provide great opportunities for automation. This approach enables us to better identify the role of automation technologies in technological unemployment.

For the third main contribution, analysis on regional variations of technological unemployment also complements a vast body of literature on technological updating and structural changes. Buera et al. (2021); Herrendorf et al. (2014) and others discovered that the value added in manufacturing sectors is higher in advanced economies. Based on heterogeneous analysis for OECD and non-OECD countries, this chapter attributes this phenomenon to different GDP shares of manufacturing sectors.

Overall, following similar structure as Chapter 2, I plan to perform regression analysis based on cross country data.

3.2 Data

This section presents data sources across countries, including labour market outcomes such as employment rate and demographic characteristics, as well as automation adoptions.

3.2.1 Labour Market Outcomes

For cross country analysis, detailed information of macro economic indicators on 216 countries stems from World Bank (2021) for the period 1993-2019. The employment rate is measured as the ratio of employed workers to total population with the age of 15 and above. This age threshold aligns with the definition of working-age labour force (Acemoglu and Restrepo, 2021). To further investigate the determinants of labour market outcomes, for each country, I observe employment rate alongside factors such as gender and industry composition[2], GDP per capita, total population, total labour force, proportion of adults and female workers, and regions[3].

Based on GNI per capita in current USD, the world's main economies are categorised

[2]Since industry classifications vary across different economies, I only obtain employment and GDP based on three broad sectors, namely agriculture, manufacturing, and service.

[3]Based on geographic locations, the sample countries are grouped into 7 groups, including East Asia & Pacific, Europe & Central Asia, Latin America & Carribean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa.

into four income groups, including low income countries, lower middle income countries, upper middle income countries, and high income countries[4]. This subjective classification allows for an exploration of heterogeneous effects behind regions from different income groups.

Besides arbitrary classification of income groups, in a more general model, I also explore the impacts of the interaction between automation technologies and income level, to investigate gradual shifts in employment patterns. This generalised approach aims to connect findings from US evidence, cross country analysis, and individual context based on UK data, as direct comparisons between US commuting zones and different countries are difficult to establish[5].

Other demographic controls include total population, proportion of age, gender, GDP, and regions. The detailed descriptions of control variables are as follows: For demographic structures, I obtained proportion of old workers who are above 65 years old, female workers, and total population, to control for other determinants of employment status. GDP (Gross Domestic Products) is measured in current US dollars, to control for economic growth. Since industry classifications vary across different economies, employment and GDP data are based on three broad sectors, namely agriculture, manufacturing, and service. To identify geographic regions, the sample countries are categorised into 7 groups, including East Asia & Pacific, Europe & Central Asia, Latin America & Carribean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa.

Among all the countries covered by International Federation of robots and the Total Economy Database, I exclude the data about Venezuela, as the employment information is not

[4]The calculation of GNI per capita is based on the World Bank Atlas method (World Bank, 2021). For instance, the GNI per capita threshold for low and lower middle income economies in 2020 is $1,045, and the threshold between lower and upper middle income economies is $4,095; economies with a GNI per capita above $12,696 are defined as high income economies.

[5]In other words, it is unclear whether the state with lowest income per capita in US is comparable to the country with lowest GNI per capita all over the world or not, therefore, it tends to become less persuasive to generalise US evidence to countries from low income groups. But using interaction term between automation technologies and income level helps to solve this problem to some extent, as we only pay attention to employment effects of automation technologies with respect to rising income levels, regardless of arbitrary classification of income groups.

documented in World Bank (World Bank, 2021). In addition, data for countries established after 2000, such as South Sudan and East Timor, were removed, as it is hard to make the comparisons with the regression results in the 1990s.

In addition, I follow Acemoglu and Restrepo (2021), and take other factors into accounts in data cleaning process. Firstly, I exclude the data from Japan and Russia, due to observed adjustments in their classification system of robots[6]. Secondly, other countries such as Belarus, Bosnia and Herzegovina, North Korea, Puerto Rico, and Uzbekistan were removed due to the absence of key covariates. Because most of these countries are classified as low and middle income regions in World Bank, the truncated data structure would lead to biased estimation, and the results primarily reflect the performance of high and middle income countries. Thirdly, oiled-rich economies like Iran, Kuwait, Oman, Saudi Arabia, and United Arab Emirates were excluded. These countries are classified as high income countries because of high capacity of natural resources, rather than advanced technologies. Moreover, their demographic structures are heavily influenced by immigration, as the number of native workers is insufficient to satisfy the labour demand from oil industry. Consequently, most of them do not have high adoption of automation technologies. Finally, the regression analysis is conducted using a sample of 108 economies[7] during the period of 1993-2019.

For this chapter about cross country evidence, I will only focus on generalised version of econometric model, and adopt interaction term between automation technologies and GNI per capita. To facilitate cross country comparisons, all the variables are measured in currency values of current US dollars.

[6] Acemoglu and Restrepo (2021) used the example from Japan to illustrate the problem of reclassification process. Before year 2000, the IFR regarded dedicated machinery as part of operational stocks of robots, but they did not continue to do so after 2000, making the data about robotic adoptions not comparable over time.

[7] For analysis about ICT intensities, the number of economies is 108, while for analysis about robotic adoption, the number of economies is 65, as the data about robotic usage is not recorded for some low income countries.

3.2.2 Automation Technologies

To obtain a comprehensive picture of the relationship between automation technologies and employment, this study integrates the labour market dataset with several sources of data on automation technologies, namely robotic usage and ICT intensity, from 2000 to 2019.

In this research, I employ two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on the datasets from International Federation of Robotics (2021), United Nations (2021) and The Conference Board (2021).

The primary data source on robotic usage is International Federation of Robotics (2021), covering six broad industrial sectors over 72 countries between 1993 and 2019, based on yearly surveys of global robot manufacturers[8]. Those six broad sectors include manufacturing, agriculture, mining, utility, construction, and R&D activities. For detailed industry level analysis, I add data about several sub-sectors under manufacturing industry. These sub-sectors are textiles, wood and furniture, paper, pharmaceuticals and cosmetics, other chemical products, rubber and plastic products (non-automotive), glass ceramics stone mineral products (non-automotive), basic metals, metal products (non-automotive), electrical or electronics, industrial machinery, automotive, other vehicles, and all other manufacturing branches. For empirical analysis, the main explanatory variable is computed using operational stocks of robots per thousand labour force. Robustness checks using installations of robots per thousand labour force yield qualitatively similar results, implying that regression results are insensitive to alternative measures of robotic usage.

Since International Federation of Robotics (IFR) does not report data on industry break-

[8]According to Dauth et al. (2021), "Single-purpose machines such as elevators or transportation bands are, by contrast, no robots in this definition, as they cannot be re-programmed to perform other tasks, require a human operator, or both." Hence, it is assumed that robotic adoptions across countries which were documented by International Federation of Robotics (2021) share no systematic differences, and all of them could replace routine tasks previous performed by production workers.

downs regarding robot stocks until 2004 (Acemoglu and Restrepo, 2020), it is necessary to redistribute unclassified components to each industry according to share of robotic stocks. However, this reallocation was not conducted for the cross country analysis for two primary reasons: First, this procedure would exceed my computational capacities, and the results are expected to be qualitatively comparable, particularly for emerging market and developing economies from low and middle income groups. Second, the majority of the cross country analysis are based on the time period 2004-2019, and the unclassified components have already been categorised into six IFR broad sectors or three industries in World Bank (2021), namely agriculture, manufacturing, and services.

The second measure of automation technologies, namely ICT intensity, is motivated by Acemoglu and Restrepo (2021); Graetz and Michaels (2017, 2018); Michaels et al. (2014); Kim et al. (2021). These previous articles emphasise the substitutability between ICT and low skilled workers. Bearing this motivation in mind, I complement the IFR data with ICT capital data from Total Economy Database by The Conference Board (2021), which could provide the share of ICT capital compensation in GDP over 125 countries between 1993 and 2019. To attain data on actual amount of ICT capital, I multiply percentage of ICT capital compensation by GDP, measured in current US dollars. The ICT intensity is then defined by ICT capital values per thousand total labour force.

Unless otherwise stated, all the estimates reported in this chapter, are weighted by a country's total labour force in 2019, the final year covered in the IFR data. To further investigate the determinants of labour market outcomes, I also leverage data on employment rate by gender and industry groups. In certain specifications, I instrument the adoption of automation technologies using shift share analysis, based on robotic density and ICT intensity by industry, along with the exogenous demographic shocks related to aging trends. The shocks are defined as the ratio of the old workers and middle aged workers from World Bank (2021).

3.3 Stylised Facts

This section presents several facts regarding technological changes and labour market outcomes across countries over the period of analysis[9].

The relationship between adoption of automation technologies and employment for all countries are presented in Figures 1 and 7, separately for robotic usage and ICT investment. It is clear that both robotic density and ICT intensity[10] are economically significant and negatively correlated with employment rate. This suggests that the growth of automation technologies tends to reduce the employment across countries. These results remain consistent even when employing alternative measures of automation technologies, such as operational stocks of robotic usage per ten thousand population, robotic installations per ten thousand labour force, robotic installations per ten thousand population, and ICT investments per ten thousand population. All these measures support the hypothesis of technological unemployment across economies.

However, evidence from the sample of OECD countries displayed in Figures 2 and 8a reveal positive correlation between automation technologies and employment rate. This highlights the fact that the replacement of the labour force by automation technologies does not appear to hold true in developed countries[11], and those developing countries located in upper middle income group. It seems that productivity effects are likely the dominating factor in these wealthier countries.

[9] Since there are too many graphs in this section, I only put the most important two graphs (Figure 3.1 and Figure 3.2) at the end of this section, and the rest can be found in the Appendix.

[10] Due to large magnitudes for country level robotic data, here the denominator of robotic density is ten thousand total labour force, while for US evidence in Chapter 2, the denominator becomes one thousand working population. ICT intensity is computed following the same procedure.

[11] According to polarisation evidence in the context of EU and US (Michaels et al., 2014), countries and industries with fast ICT growth are likely to witness demand shifts from workers with intermediate education level to college educated workers, and have no clear effects on the least educated groups, causing less job displacement. Moreover, ICT's overall contribution to productivity growth is higher relative to robots (Graetz and Michaels, 2018), implying less labour inputs required for the same amount of output. In other words, adoption of conventional ICT appears to boost economy through rising TFP instead of job creations. Driven by low levels of substitutability and complementarity, the graph for OECD countries reveals a less significant relationship between ICT intensity and employment rate.

These patterns observed in both the full sample of countries and economically advanced economies, raise the interests about the potential for heterogeneous effects of automation technologies on employment rate, across countries from different income groups.

Therefore, I switch my attention to examine the relationship between automation technologies and employment rate in economically advanced countries. Similarly, the pattern of negative employment responses does not seem to hold true in countries from high income group. As exhibited in Figures 3 and 8b, the relationship between robotic density and employment rate in advanced economies are significantly positive. However, the magnitudes of the slope between ICT intensity and employment rate are slightly lower, implying less complementarity between ICT investments and labour inputs. Therefore, expanding adoption of automation technologies may complement human labours to some extent, and does not necessarily lead to employment reductions.

Figures 4 and 9a turn to unpack the association for low and lower middle income countries[12]. I find that the employment rate is negatively associated with automation technologies measured by robotic density and ICT intensity, and the coefficients are statistically significant. These findings remain robust even under alternative measures of automation technologies, such as operational stocks of robotic usage per ten thousand population, robotic installations per ten thousand labour force, robotic installations per ten thousand population, and ICT investments per ten thousand population. These all support the hypothesis that technological unemployment is prevalent across countries from low and middle income groups, with more substantial magnitudes of job losses induced by displacement effects.

Negative and similar results are also observed in countries from upper middle income group presented in Figures 5 and 9b, and those from middle income group presented in Figures 6 and 10. These results are consistent with the hypothesis that job destructions

[12] I do not look at results only for low income countries, due to limited observations available for robotic usage and ICT investments.

driven by displacement effects have outweighed job creations from productivity effects. This suggests that new job vacancies are not able to complement job losses in low and middle income countries.

One concern which may lead to measurement errors is the presence of time trends. The linear progression of automation technologies and employment rate may cause pseudo correlations. Therefore, I also provide evidence about the relationship between the residuals of robotic densities, ICT intensities, and employment rate, after controlling for macro shocks and geographic specific factors, over the period of analysis. The main measure of employment is derived through a two-step process. First, employment is regressed on year dummies, region dummies, and the interaction terms between time fixed effects and geographic fixed effects. Then, the resulting residual outcome variables are normalised between 0 and 100. The measure of robotic adoptions is obtained through a similar procedure. Robotic densities are regressed on year dummies, region dummies, and the interaction terms between time fixed effects and geographic fixed effects. The residuals from this regression are then normalised to a scale of 0 to 100. The measure of ICT usage follows a similar approach. ICT intensities are regressed on year dummies, region dummies, and the interaction terms between time fixed effects and geographic fixed effects, with the residuals normalised to a scale of 0 to 100.

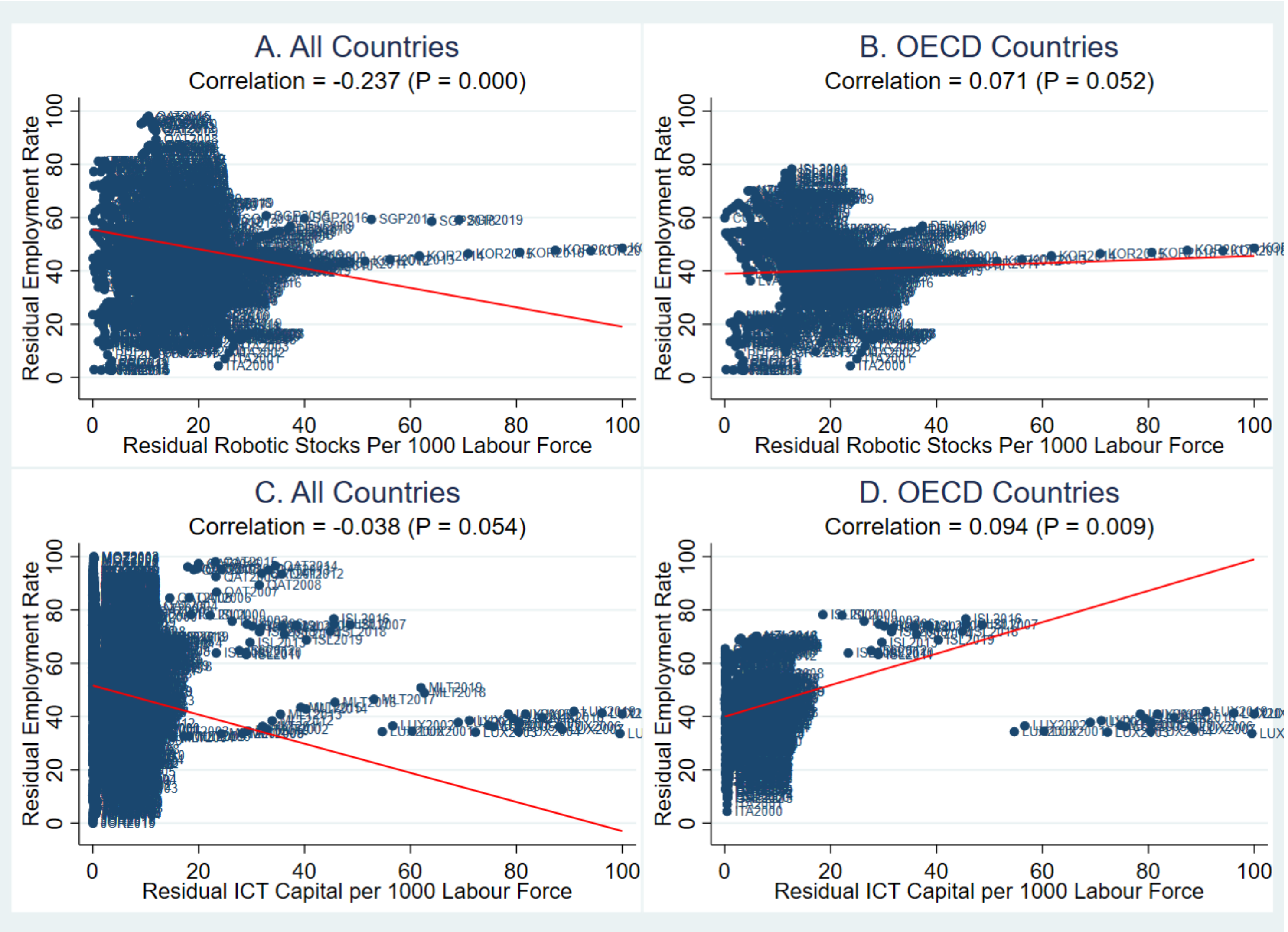
The relationship between adoption of automation technologies and employment across all countries is presented in Figure 3.1. It is clear that the developments of both robotic density and ICT intensity are economically significant and negatively correlated with employment dynamics. This suggests that the growth of automation technologies may be associated with declining employment across countries. However, evidence from the sample of OECD countries displayed in Panel B and Panel D reveals positive correlation between variations of automation technologies and residual employment. This finding suggests that, the notion of automation technologies displacing the labour force, may not hold true in developed countries[13], and productivity effects appear to be the dominant effects in these wealthier countries.

Shifting focus to different income groups, Figure 3.2 evaluates the association between automation and employment across various economic contexts. In advanced economies, the relationship between robotic density and employment rate after accounting for macro shocks is significantly positive. Whereas, the magnitudes of the slope between variations of ICT intensity and employment rate are slightly lower, implying a weaker complementary relationship between ICT investments and labour inputs. Therefore, expanding automation adoption may complement human labours to some extent, and does not necessarily lead to employment reductions.

While for countries from low and middle income groups exhibited in Panels B and D of Figure 3.2, I find that the employment dynamics is negatively associated with automation technologies, and the coefficients are statistically significant. These results are consistent with the hypothesis that job destructions have outweighed job creations in low and middle income countries.

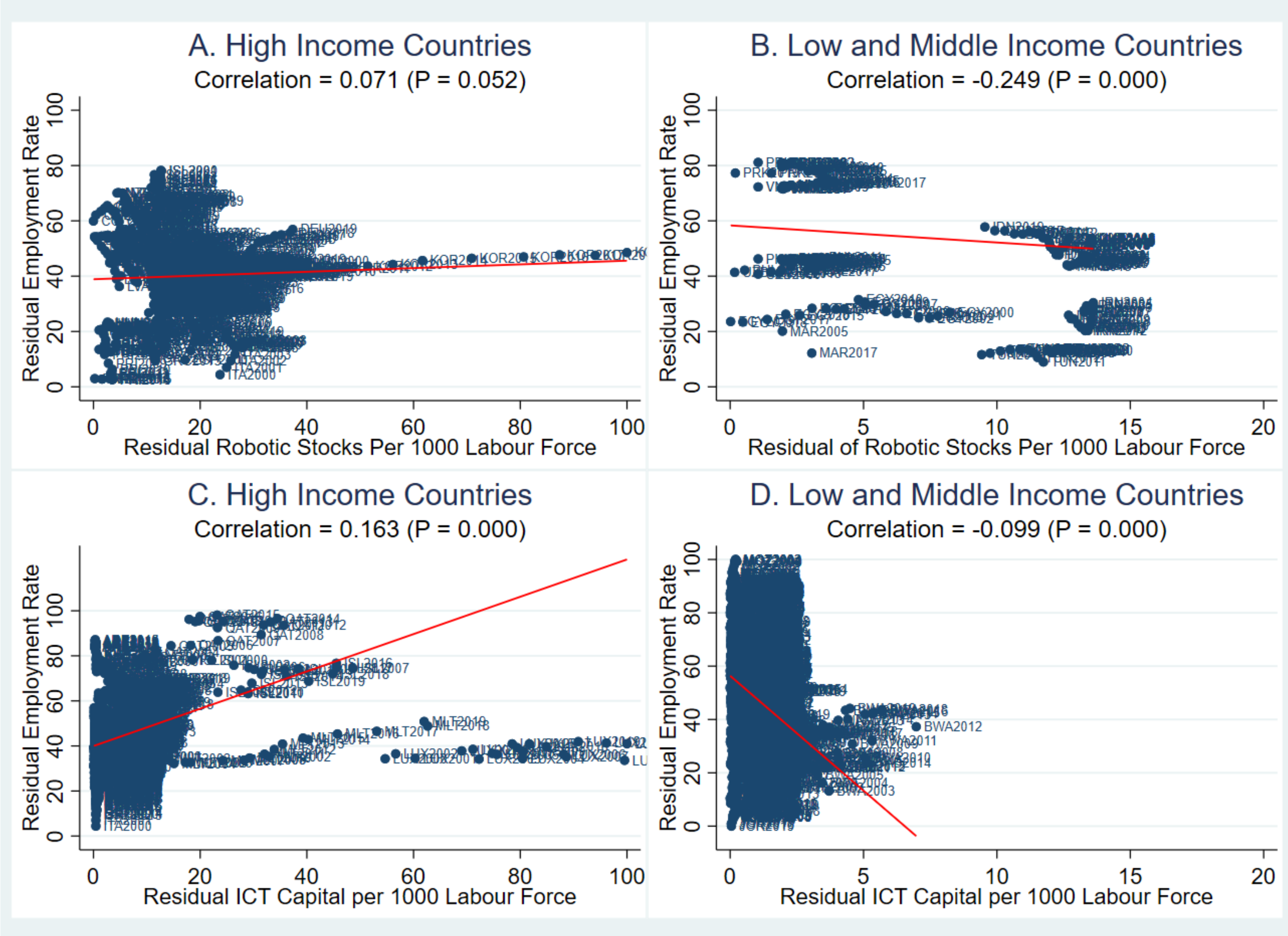
[13]According to polarisation evidence in the context of EU and US (Michaels et al., 2014), countries and industries with fast ICT growth are likely to witness demand shifts from workers with intermediate education level to college educated workers, and have no clear effects on the least educated groups, causing less job displacement. Moreover, ICT's overall contribution to productivity growth is higher relative to robots (Graetz and Michaels, 2018), implying less labour inputs required for the same amount of output. In other words, adoption of conventional ICT appears to boost economy through rising TFP instead of job creations. Driven by low levels of substitutability and complementarity, the graph for OECD countries reveals a less significant relationship between ICT intensity and employment rate.

Figure 3.1: Residual Automation and Employment Dynamics for All Countries and OECD Countries, 2000-2019



Notes:
The figure displays the correlation of automation adoptions and employment variations for all countries, conditional on year and region dummies. The employment rate, defined as the ratio of employed people and total population who are above 15 years old, is from World Bank (2021). Robot density refers to operational stock of robots per 1000 labour force, and data about robotic stocks is from International Federation of Robotics (2021). ICT intensity, defined as ICT capital per 1000 labour force, is from The Conference Board (2021). ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

Figure 3.2: Residual Automation and Employment Dynamics for High and Low Income Economies, 2000-2019



Notes:

The figure displays the correlation of automation adoptions and employment variations for hig and low income countries, conditional on year and region dummies. The employment rate, defined as the ratio of employed people and total population who are above 15 years old, is from World Bank (2021). Robot density refers to operational stock of robots per 1000 labour force, and data about robotic stocks is from International Federation of Robotics (2021). ICT intensity, defined as ICT capital per 1000 labour force, is from The Conference Board (2021). ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

Informal employment, particularly in low and middle income countries, is another factor that may contribute to measurement errors. As suggested by Elgin et al. (2021), workers in informal sectors constitute about 70 percent of total employment in emerging market and developing economies. This is in stark contrast to developed countries, where advanced measurement tools and precise statistical methods result in a considerably smaller informal employment sector. Therefore, I also present employment outcomes for formal and informal sectors in Figures 11 through 12. The results demonstrate a slightly positive relationship with respect to employment in formal sectors, which specialise in more capital intensive tasks. This suggests that the overall negative relationship in emerging market and developing economies, is primarily driven by employment forces from informal sectors, as the majority of labour force in countries from low and middle income group are performing routine tasks associated with labour intensive products.

3.4 Econometric Model

In this Section, I establish the empirical implication using cross country data, and investigate heterogeneous effects based on countries from different income groups. The specification relating automation technologies and employment rate is constructed as follows:

$$\begin{aligned} Employment_{it} = \eta_0 &+ \eta_1 AutomationExposure_{it} \\ &+ \eta_2 AutomationExposure_{it} \times Income_{it} \\ &+ \delta X_i + \alpha_i + \alpha_t + \varepsilon_{it} \end{aligned} \tag{3.1}$$

In this study, $Employment_{it}$ is employment rate for country i in year t, measured by the ratio of employment to population who are above 15 years old. $AutomationExposure_{it}$ is some proxies of exposures to automation technologies, including robotic density calculated by operational stocks of robots per thousand workforce, and ICT intensity calculated by ICT capital values per thousands of full time workers. $Income_{it}$ refers to GNI per capita in country i at year 2019[14]. Regressions are weighted by the amount of the total labour force in 1993, the initial year of IFR dataset, to account for endogenous shifts in employment[15]. Certain specifications include other covariates X_i, which capture geographic fixed effects represented by region dummies, and demographic characteristics such as population and GDP. The parameter δ are $K \times 1$ vectors, where K is the number of time-varying variables capturing the aforementioned demographic characteristics. Finally, ε_{it} is a heteroscedastic error term.

Other demographic controls include total population, proportion of age, gender, GDP, and regions. The detailed descriptions of control variables are as follows: For demographic structures, I obtained proportion of old workers who are above 65 years old, female workers, and total population, to control for other determinants of employment status. GDP (Gross Domestic Products) is measured in current US dollars, to control for economic growth. Since industry classifications vary across different economies, employment and GDP data are based on three broad sectors, namely agriculture, manufacturing, and service. To identify geographic regions, the sample countries are categorised into 7 groups, including East Asia & Pacific, Europe & Central Asia, Latin America & Carribean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa.

The parameter of primary interest is the coefficient η_1, which captures the relationship between automation technologies and employment rate. It is expected that η_1 could be significantly negative, implying strong displacement effects in low and middle income countries. Whereas, η_2 is expected to be significantly positive, reflecting positive employment effects in countries from high income group, as growing income level could

[14] I use GNI per capita in 2019 as there are missing values in previous years. Regression results based on income level in 1993 and other years are also consistent with Table 3.3. The reason why I fix GNI per capita in 2019 is to avoid interruptions of gross economic expansions.

[15] One of the endogenous factors is population growth, as the overall population could affect employment rate, and automation exposure can also be influenced by population.

reinforce productivity effects and complement job losses with new job vacancies. Overall, the automation technologies are associated with declining employment to population ratio, with slightly lower magnitudes, as suggested in Figure 1 and 7.

3.4.1 Key Variable Construction

In the main analysis, I focus on socio-economic outcomes, and collect country-level data about employment rate and other demographic characteristics for the period 1993-2019 from World Bank (2021). The employment rate is measured as the ratio of employed workers to whole population with the age of 15 and above. This cutoff age of 15 years aligns with the definition of working-age labour force (Acemoglu and Restrepo, 2021). To further investigate the determinants of labour market outcomes, for each country, I observe employment rate along with gender and industry composition[16].

This research utilises two complementary measures of automation technologies, namely robotic density and ICT (Information and Communication Technologies) intensity, based on dataset from International Federation of Robotics (2021), United Nations (2021) and The Conference Board (2021).

For empirical analysis, the main explanatory variable is computed using operational stocks of robots per thousand labour force. Robustness checks using installations of robots per thousand labour force yield qualitatively similar results, implying that the regression results are insensitive to alternative measures of robotic usage.

The second measure of automation technologies, namely ICT intensity, is motivated by Acemoglu and Restrepo (2021); Graetz and Michaels (2017, 2018); Michaels et al. (2014); Kim et al. (2021). These previous articles emphasise the substitutability between ICT and low skilled workers. To attain data on actual amount of ICT capital, I multiply

[16]Since industry classifications vary across different economies, I only obtain employment and GDP based on three broad sectors, namely agriculture, manufacturing, and service.

percentage of ICT capital compensation by GDP, measured in current US dollars. The ICT intensity is defined by ICT capital values per thousand total labour force.

3.4.2 Summary Statistics

This subsection provides summary statistics (sample means, standard deviations, ranges, and number of observations) for the variables employed in the following regression model.

Table 3.1: Summary Statistics for Cross Country Evidence, 1993-2019

Variable	Mean	Std.Dev.	Min	Max	Obs
Employment	57.551	11.875	26.330	88.740	2866
Robot	0.491	1.061	0	11.353	1686
ICT	28.321	0.118	0.007	1588.173	2866
Population	30400	123	9.194	1400000	2866
GDP	13.076	21.374	0.054	190.513	2866
Old	7.462	5.188	0.686	28.002	2866
Female	50.063	2.830	23.289	54.565	2866

Notes:
Statistics for variables in changes are computed across 108 countries and regions for time periods 1993-2019, and those variables include changes in employment rate (Employment), robotic density (Robot), and ICT intensity (ICT). Other control variables in levels include total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). And they are computed across 108 countries and regions for time periods 1993-2019.

Figure 3.1 reports descriptive statistics for the main variables, in the baseline cross-country sample. All results are calculated across countries and periods of analysis. The first two rows show an increase in employment rate and automation adoptions in our sample between 1993 and 2019. On average, the employment rate has increased by 1% for every period, a finding consistent with Bonfiglioli et al. (2021). Table 3.1 further corroborates this upward trend, indicating a rise of robotic penetration by 0.04%, and positive average number of ICT intensities. For other control variables, there are also variations across countries and time periods, as suggested by the standard deviations reported in the table.

In conjunction with Section 3.3 in this chapter, Table 3.1 further shows that the rising employment rate can be attributed, in part, to the growth in robotic density and ICT intensity. The following regression analysis will confirm these patterns and establish their robustness.

3.5 Regression Results

Table 3.2 presents main results for robotic density of full sample during the time period of 1993-2019, under various specifications across different countries[17]. Columns 1 and 2 provide the most parsimonious specification without any covariates. Columns 3 and 4 only include year FE as covariates to account for macro shocks. Columns 5 and 6 add geographic dummies and interactions with time trends, to capture regional economic dynamics. While Columns 7 and 8 additionally control baseline country characteristics X_i to account for initial demographic characteristics. Robustness checks for the period 2004-2019 are presented in Table 47 of Appendix, and those for 2010-2019 are presented in Table 48 of Appendix.

Across all eight columns of Table 3.2, it is observed that robotic density is negatively correlated with employment rate. All estimates are statistically significant and sizeable. Column 1 indicates this negative correlation: as one unit rise in robotic density could lead to employment reduction by 0.90 percentage points. The coefficient estimate of robotic density in Column 2 is -1.176, implying that one more robot per thousand workers tends to reduce employment rate by 1.18 percentage points. While the coefficient for interaction term with income level suggests that 1 extra dollar in GNI per capita could flatten employment decrease by 0.04 percentage points, indicating that the negative employment responses induced by robotic adoptions are often more pronounced in low income countries. With growing GNI per capita, employment rate in high income countries rises

[17]The information of robotic stocks are missing for 33 countries, so there are only 65 countries in the regression about employment rate and robotic densities across countries.

Table 3.2: Employment Rate and Robotic Densities Across Countries, 1993-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Employment Rate								
Robotic Density	-0.897***	-1.176***	-0.718***	-0.968***	-1.514***	-1.654***	-0.454**	-1.423***
	(0.266)	(0.348)	(0.226)	(0.290)	(0.195)	(0.268)	(0.210)	(0.189)
Robotic Density ×Income		0.036***		0.033***		0.030***		0.068***
		(0.008)		(0.007)		(0.009)		(0.007)
Population							0.013***	0.014***
							(0.001)	(0.000)
GDP							0.104***	0.168***
							(0.014)	(0.013)
Female							0.773***	0.570***
							(0.156)	(0.140)
Old							-0.532***	-0.525***
							(0.064)	(0.061)
Year FE			√	√	√	√	√	√
Geographic FE					√	√	√	√
Location×Year FE					√	√	√	√
Demographics							√	√
N of Obs	1686	1686	1686	1686	1686	1686	1686	1686
N of Countries	65	65	65	65	65	65	65	65
R^2	0.011	0.015	0.023	0.030	0.453	0.520	0.673	0.789

Notes:
The table presents within group estimates of the effects of robotic penetration on employment rate. Explanatory variable is changes in robotic density. The regressions are weighted by total labour force in 1993. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE or location FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

sharply in response to extensive adoption of automation technologies. Accounting for geographic controls and macro shocks does not change the results qualitatively. For the preferred specification in Column 8, one more robot per thousand workers tends to reduce employment rate by 1.42 percentage points. While growing GNI per capita could lead to complementary effects of 0.07 percentage points, and mitigate such job destructions.

One concern which may lead to measurement errors is truncated data structure, particularly for emerging market and developing economies. As most of low and middle income countries are in early stages of adoption of automation technologies, low penetration of robotic usage in the first few years of IFR report made it hard for survey conductors to document the actual number of operational stock of robots. In other words, IFR data on robotic usage in earlier periods may partially reflect situations in developed countries, and robotic exposures in developing countries are difficult to observe. Therefore, I present the regression results for the period 2004-2019 in Table 47 of Appendix. In addition, to avoid the negative influence of global recession in 2008 and 2009, I also provide results for the period 2010-2019 in Table 48 of Appendix.

The reason why I use year 2004 as a discontinuity in Panel B has already been illustrated in Section 3.2. Since IFR does not report data on industry breakdowns regarding total stock of industrial robots until 2004 (Acemoglu and Restrepo, 2020), I plan to examine whether systematic changes are apparent when only using data after 2004. All estimates in Table 47 of Appendix are statistically significant and sizeable, particularly after accounting for geographic factors and demographic controls. According to preferred specifications in Columns 7 and 8, robotic density is negatively correlated with employment rate, as one unit rise in robotic density could lead to employment reduction by 0.44 percentage points. The coefficient estimate of robotic density in Column 8 is -1.623, implying that one more robot per thousand workers tends to reduce employment rate by 1.62 percentage points, while growing GNI per capita could generate productivity effects and slow down job destructions by 0.06 percentage points.

Concerning the employment effects from robotic adoption, I also conduct panel data regressions for ten years from 2010 onwards, to take shocks from global recessions in 2008-2009 into accounts. As displayed in Table 48 of Appendix, all estimates are statistically significant and sizeable, especially after accounting for geographic factors and demographic controls. According to preferred specifications in Columns 7 and 8, robotic density is negatively correlated with employment rate, as one unit rise in robotic density could lead to employment reduction by 0.30 percentage points. The coefficient estimate of robotic density in Column 8 is -1.622, suggesting that one more robot per thousand workers tends to reduce employment rate by 1.62 percentage points, while growing GNI per capita could generate productivity effects and slow down job destructions by 0.06 percentage points. The quantitative results are similar, reflecting stable dynamics of heterogeneous employment effects from automation technologies.

The expected signs of control variables are consistent with Section 3.4. The population is positively correlated with employment rate. Since previous evidence such as Keane and Rogerson (2015) revealed that female people, Hispanic people, and old people are less likely to participate in jobs, the estimation results demonstrate negative correlations for these variables. The estimation results for the proportion of high skilled workers, measured by those with bachelor's degrees, are positively correlated with employment rate. This can be partly explained by the theory of SBTC (Skill Biased Technical Change) (Autor et al., 2003), as examined in Section 2.6 of Chapter 2.

Regression results for ICT counterparts are also consistent with interpretations for robotic densities. The estimates for ICT intensities displayed in Table 3.3 are similar to those for robotic densities. Columns 1 and 2 provide the most parsimonious specification without covariates. Columns 3 and 4 only include year FE as covariates to account for macro shocks. Columns 5 and 6 add geographic dummies and interactions with time trends, to capture regional economic dynamics. Meanwhile, Columns 7 and 8 additionally control for baseline country characteristics X_i to account for initial demographic characteristics. Robustness checks for period 2004-2019 are presented in Table 49 of Appendix, and those for the period 2010-2019 are presented in Table 50 of Appendix.

Across all eight columns of Table 3.3, it is clear that ICT intensity is negatively correlated with employment rate. All estimates are statistically significant and sizeable[18]. Column

[18]The reason of insignificant employment effects from ICT intensities are stated in footnotes of Section 3.3. According to polarisation evidence in the context of EU and US (Michaels et al., 2014), countries and industries with fast ICT growth are likely to witness demand shifts from workers with intermediate education level to college educated workers, and have no clear effects on the least educated groups, causing less job displacement. Moreover, ICT's overall contribution to productivity growth is higher relative to robots (Graetz and Michaels, 2018), implying less labour inputs required for the same amount of output. In other words, adoption of conventional ICT appears to boost economy through rising TFP instead of job creations. Driven by low levels of substitutability and complementarity, the graph for OECD countries reveals a less significant relationship between ICT

Table 3.3: Employment Rate and ICT Intensities Across Countries, 1993-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Employment Rate								
ICT Intensity	-0.036***	-0.042***	-0.033***	-0.038***	-0.036***	-0.036***	-0.007**	0.000
	(0.008)	(0.009)	(0.007)	(0.008)	(0.005)	(0.005)	(0.003)	(0.003)
ICT Intensity $\times$Income		0.001		-0.003		-0.004		0.030***
		(0.010)		(0.011)		(0.008)		(0.005)
Population							0.012***	0.013***
							(0.000)	(0.000)
GDP							0.127***	0.166***
							(0.013)	(0.012)
Female							1.689***	1.434***
							(0.163)	(0.155)
Old							-0.920***	-0.946***
							(0.057)	(0.053)
Year FE			√	√	√	√	√	√
Geographic FE					√	√	√	√
Location$\times$Year FE					√	√	√	√
Demographics							√	√
N of Obs	2866	2866	2866	2866	2866	2866	2866	2866
N of Countries	108	108	108	108	108	108	108	108
R^2	0.002	0.003	0.017	0.021	0.332	0.380	0.487	0.575

Notes:
The table presents within group estimates of the effects of ICT adoption on employment rate. Explanatory variable is changes in ICT intensity. The regressions are weighted by total labour force in 1993. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE or location FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1 indicates that ICT intensity is negatively correlated with employment rate, as one unit rise in ICT intensity could lead to employment reduction by 0.04 percentage points. The coefficient estimate of ICT intensity in Column 2 is -0.04, implying that one more dollars investment in ICT per thousand workers tends to reduce employment rate by 0.04 percentage points. Accounting for geographic controls and macro shocks does not change the results qualitatively. For the preferred specification in Column 8, one additional dollars investment in ICT per thousand workers tends to reduce employment rate by 0.01 percentage points. Growing GNI per capita could lead to complementary effects of 0.03

intensity and employment rate.

percentage points, and mitigates such job destructions. This suggests that the negative employment responses induced by ICT investments tend to be more pronounced in low income countries. With growing GNI per capita, employment rate in high income countries rises sharply in response to extensive adoption of automation technologies.

In contrary to the results based on time period 1993-2019, Table 49 and Table 50 in Appendix show a similar relationship between automation technologies and employment using ICT investment[19]. These tables share the structure of those presented previously. The OLS estimate in Column 7 of Table 49 in Appendix implies that, 1 unit increase in ICT capital per thousand labour force leads to 0.007 percentage decline in employment rate, which is comparable to the coefficient estimates for robotic densities.

To take shocks from global recessions in 2008-2009 into accounts, I also conduct panel data regressions from 2010 onwards. Focusing on this shorter timeframe, Table 50 of Appendix suggests that ICT capital has insignificant impacts on employment rate. Moreover, the mitigating effects of income level remain prominent, as growing GNI per capita could lead to complementary effects of 0.03 percentage points. The larger magnitude of coefficient in the period 2010-2019 indicates stronger productivity effects.

In summary, the fact that automation technologies are negatively correlated with the employment rate, persists in cross country analysis. Productivity effects are more pronounced in developed countries with high income levels. In contrast, negative employment effects are much stronger in low and middle income countries, as rising demand of high skilled labour in other non-automated sectors cannot compensate for job losses induced by automation technologies.

[19]The reason why I use year 2004 as discontinuity in Table 49 is to ensure the consistency with analysis regarding robotic adoptions, which has already been illustrated in Section 3.2 of Chapter 3. Since IFR does not report data on industry breakdowns regarding total stock of industrial robots until 2004 (Acemoglu and Restrepo, 2020), I plan to examine whether there are systematic changes when only using data after 2004.

3.6 Shift Share IV Research Design

The evidence presented so far strongly suggests that the expansion of automation adoptions is negatively associated with the employment across countries, even after controlling for geographic variations and macro shocks. Rising GNI per capita could flatten such technological unemployment. Nonetheless, it may not be sufficient to guarantee that the main results can avoid contamination by endogenous adjustment of local labour force. In this part, I address identification threats, and then implement a quasi-experimental shift share design, to estimate the causal effects of automation technologies on labour market outcomes across countries.

Several reasons explain why the development of automation technologies could be correlated with error terms in Equation 3.1.

Firstly, a firm's decision to adopt automation may also be driven by other local industry specific changes, which could directly affect their labour demand. For example, consumers' demand shock[20] could motivate firm owners to invest more capital and labour inputs to produce final goods, hence simultaneously rising automation and employment (Aghion et al., 2017; Webb, 2019). In addition, common trade shocks from emerging markets such as China and Mexico may drive the move towards automation (Bloom et al., 2015). Confronting with upward pressure of labour costs in high income countries, firms in labour intensive industries are inclined to use automation, as they are vulnerable to international competition due to comparative advantages in labour inputs for emerging market and developing economies, and finally reduce manufacturing employment (Autor et al., 2013). In other words, enterprises in developed countries prefer to raise the percentage of capital input, as they are not able to compete with countries from emerging market and developing economies, resulting in extended adoption of automation technologies.

[20]Consumer demand shocks sometimes are not endogenously driven by income growth and output expansions, such as dramatic increase of demand for masks during the time period of pandemic induced by COVID 19.

Secondly, any shocks from labour demand and market competition will affect industries' decisions to locate in specific areas (Acemoglu and Restrepo, 2020), and individual workers' adjustments across occupations and regions (Dauth et al., 2021). On the one hand, establishments from affected industries tend to re-allocate their production process. They are likely to produce labour intensive goods at the places where labour costs are lower, and perform capital intensive activities at the places where they lack comparative advantages in labour costs. On the other hand, affected workers from industries with high exposure of automation technologies tend to switch tasks within original establishments, or move to other firms, This is especially true for young workers[21] or those with higher education attainments (Dauth et al., 2021). Therefore, such spillover effects will lead to downward bias in the estimation of the quantitative magnitudes of both displacement effects and productivity effects.

Finally, reverse causality presents a concern. Firms in industries with labour saving technologies and fast growing total factor productivity tend to invest more on automation technologies, particularly those facing intense competition and substantial amounts of robotic suppliers (Beaudry et al., 2016; Graetz and Michaels, 2018). Such firms are likely to experience further waves of labour substitution, and "ripple effects" could cause displaced labour to replace workers at the lower skill ladder (Acemoglu and Restrepo, 2022; Jackson and Kanik, 2019). In other words, following such characteristics like "path dependence", higher robotic adoption is itself a consequence of lower employment growth (de Vries et al., 2020).

To alleviate potential endogeneity concerns, I adopt an alternative shift share design as instruments for robotic density and ICT intensities, which leverages two components:

[21]There are two hypothesis about heterogeneous response to susceptibilities of automation technologies for old workers and young workers. One is about institutional environment. Because the firing costs are higher for incumbent workers due to institutional factors such as unionisation rate, enterprises prefer to use machine to replace young workers instead of old labour force (Dauth et al., 2021; Rogerson and Wallenius, 2022). The other one is about task specific human capital. For old workers endowed with task specific human capital, the skill bundle will be similar within occupation, so old workers prefer to switch within occupation (skills are portable), while young worker prefer to switch across occupation (Autor and Dorn, 2009; Cortes and Gallipoli, 2017; Gathmann and Schonberg, 2010; Poletaev and Robinson, 2008; Yamaguchi, 2012). In addition, firms prefer to hire people with decision making skills (Deming, 2021), which require experience accumulations.

predetermined exposure shares and idiosyncratic shocks. This research design is motivated by several important papers from Aghion et al. (2017); Autor et al. (2013); Bartik (1991); Bound and Holzer (2000); Dauth et al. (2021), based on the fact that local labour market differ markedly in their industrial compositions, due to differential employment concentrations and industrial specialisations.

In contrast to the shift share IV in Chapter 2, which uses European automation adoption to instrument US automation density, I utilise another unique shock as the exogenous "shift". The shocks are derived from the growth of ageing societies, which can be regarded as an exogenous driver of automation (Acemoglu and Restrepo, 2022). This is because the evolution of demographic structures is solely determined by birth rate and death rate, and cannot be intervened by government policies in the short-run. In rapidly ageing countries, it is observed that the number of middle aged workers specialising in manual production tasks are declining as a result of falling fertility rate. The shortage in middle aged workers will lower the opportunity cost of developing automation technologies, and this effect is more pronounced in industries with higher fractions of routine tasks. Therefore, in such industries, firm owners tend to favour machines over production workers. The ageing shocks can be computed as follows:

$$\Delta Ageing_{it} = \frac{Ageing_{it} - Ageing_{i,t_0}}{Ageing_{i,t_0}} \times \frac{1}{t - t_0} \tag{3.2}$$

In this expression, the term $Ageing_{it}$ measures the degree of demographic changes[22], defined by the ratio of old workers ageing 55 to 65, and adults ageing between 20 to 55. Following Equation (3.2), the shocks are calculated as average annual growth rate of ageing in country i from the start of the period t_0.

[22]Since World Bank (2021) does not provide number of labour force for corresponding ages, instead, I use the ratio of overall population ageing 55 to 65 and those with age of 22 to 55, to approximate the ageing trend. As reflected in Figure 15 in the Appendix, the trends of percentage of labour force with respect to overall population were stable over time, both globally and for countries from different income groups, with differences around 0.1 percent.

The shift share design combines this set of shocks with variation in the initial level of automation technologies. For robotic usage, the exposure share is measured as operational stocks of robots in each sector[23]. Due to measurement errors arising from various industrial classifications across countries, only agriculture, manufacturing, and service are utilised here to identify industry level variations. Since IFR does not report data on industry breakdowns regarding total stock of industrial robots until 2004 (Acemoglu and Restrepo, 2020), Section 3.5 suggests that systematic variations for regression results could not be observed when only using data after 2004. Therefore, this analysis will only present shift share IV results based on the time period 2004-2019, and regression results based on the time period 2010-2019 are qualitatively the same.

Ideally, we would observe actual numbers of old workers and adults in each industry of each country. However, the comprehensive World Bank data on population of different age groups are available only at country level. Therefore, I follow Acemoglu and Restrepo (2020); Dauth et al. (2021), and approximate the exposure of ageing trends based on shares of employment in each sector. The predicted shift share IV is constructed as follows:

$$\widehat{AutomationExposure}_{it} = \frac{\Sigma_j^J [\frac{Employment_{jt}}{Employment_t} \times (1 + \Delta Ageing_t)^{t-t_0} \times Automation_{j,t_0}]}{Labour_{it}} \tag{3.3}$$

The index is a weighted average of ageing trends, where weights represent the different distributions of automation adoptions across sectors in each country. Such supply driven components are not liable to reverse causality (Bound and Holzer, 2000; Graetz and Michaels, 2018), as the ageing index is assumed to be determined only by birth rate and death rate in recent years. Further, this ageing trend shuts down unobserved changes

[23]For robustness checks, I also construct alternative IV for ICT investment, and allocate country level exposure to sectors according to shares of GDP value added. The regression results are insensitive to main IV estimates.

in decision making by firms and workers, implying that it can only influence employment rate through the channel of automation adoptions, without interventions of spillover effects. Therefore, this IV approach makes this identification highly plausible.

3.7 IV Estimates

This section presents IV estimates of the effects of automation technologies on employment rate across countries.

Following Acemoglu et al. (2001, 2019); Aghion et al. (2017); Autor et al. (2013), this section reports the results of shift share IV design for four specifications, with the same sets of controls X_i in Table 3.4. The first specification repeats OLS regression with full controls, which performs within group estimation based on panel data structure. The second specification constructs reduced form equation to examine exclusion restriction, where instruments are directly treated as control variables. The third specification is to check whether the instrumental variable satisfies the relevance condition through first stage regression. Estimation results for predicted exposure of robotic density, and F statistics for single instrument are displayed. The final specification reports IV estimates utilising two-stage GMM procedure.

Panel A reports employment effects of robotic penetration on employment, instrumented by predicted exposure of robots. Column 2 displays reduced form outcomes of the effect of Bartik IV on employment. The significantly negative estimates show a dramatic reduction in employment, driven by evolution of demographic composition from the supply side in an ageing society, with quantitatively large magnitudes.

Column 3 displays the results, based on the first stage equation of the instrument on robotic density, which reveals substantial explanatory power of predicted automation exposure for robotic density. The coefficient in Column 3 suggests that 1000 unit increase in

Table 3.4: IV Regression of Employment on Automation Across Countries, 2004-2019

	(1)	(2)	(3)	(4)
Dep Var	Within Group Employment	Reduced Form Employment	First Stage Robot	IV Structural Form Employment
A. Robotic Density				
Robotic Penetration	-0.444*			-1.492***
	(0.228)			(0.280)
Predicted Robotic Exposure		-2.526***	1.692***	
		(0.559)	(0.159)	
First Stage F Statistics			113.38	
N of Observations	1136	1136	1136	1136
B. ICT Intensity				
ICT Intensity	-0.017***			-0.479***
	(0.005)			(0.106)
Predicted ICT Intensity		-2.526***	5.482***	
		(0.559)	(0.910)	
First Stage F Statistics			36.28	
N of Observations	1088	1088	1088	1088
Year FE	√	√	√	√
Geographic FE	√	√	√	√
Geographic FE × Year FE	√	√	√	√
Demographics	√	√	√	√

Notes:
The table presents within group and IV estimates of the relationship between automation adoption and employment rate across countries, where robotic penetration predicted using aging trend is used as the instrument. Independent variables include robotic penetration and ICT intensities. The regressions are weighted by total labour force in 2004. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

operational stocks of robots per worker induced by aging trends corresponds to 2.53 unit increase in US robotic penetrations. This finding, coupled with high F-statistics on the excluded instrument, implies the absence of weak instrument issues. Robustness checks for detailed information about first stage regressions are presented in Table 51 of Appendix.

To further verify the instruments, I conduct additional diagnostic tests. Following Acemoglu and Restrepo (2021), I address potential concerns in two aspects[24]. Firstly, I conduct under-identification test. For robotic usage, the Kleibergen-Paap rk LM statistic is

[24] As Acemoglu and Restrepo (2021) examined the determinants of automation adoption, rather than employment effects of automation, here I am not able to compare my results with this article

57.29 with p-value less than 0.00, while for ICT adoption, it is 40.33 with p-value less than 0.00, implying that the model can be regarded as identified, and the shift share IV is correlated with US robotic penetration. Secondly, I conduct week identification test. The Cragg-Donald Wald F statistic is 868.26 and Kleibergen-Paap rk Wald F statistic is 113.38. Both values exceed the Stock-Yogo weak ID test critical values. So we need to reject the null hypothesis, and it is believed that there is no weak identification problem under confidence level of 10%. Therefore, the IV is not only correlated with endogenous variable, but also a strong predictor of US automation penetration. In addition, I do not conduct over-identification test, as this issue only arises with multiple IVs, whereas this chapter utilises only one.

Further, Column 4 offers the IV estimates of the effects of robotic density on employment. The coefficient of -1.49 indicates that 1000 unit exogenous rise in robotic stocks per worker is predicted to reduce overall employment by 1.49 percentage points. The relatively larger absolute magnitude of IV estimates is consistent with the downward endogeneity bias for US evidence.

On the contrary, the results for ICT intensities are displayed in Panel B of Table 3.4. Similarly, reduced form estimation from Column 2 suggests that exclusion restriction can be satisfied. Taking relevance condition into considerations, the first stage estimation from Column 3 with high F-statistics on the excluded instrument, suggests no weak instrument problems.

Lastly, Column 4 of Panel B in Table 3.4 presents the IV estimates of the effects of ICT intensities on employment. The coefficient of -0.48 indicates that 1000 dollars exogenous rise in ICT investments per worker is predicted to reduce overall employment by 0.48 percentage points. The relatively larger absolute magnitude on IV estimates is consistent with downward endogeneity bias for US evidence and robotic usage counterparts, suggesting potential generalisability of the US to other countries.

Table 3.5: Employment Effects of Automation and Income Level Across Countries, 2004-2019

	Within Group		IV Structural Form	
	(1)	(2)	(3)	(4)
Dependent Variable: Employment Rate				
A. Robotic Density				
Robotic Penetration	-0.444*	-1.623***	-1.492***	-1.790***
	(0.228)	(0.265)	(0.280)	(0.268)
Robotic Penetration × Income		0.062***		0.067***
		(0.008)		(0.015)
N of Observations	1024	1024	1024	1024
B. ICT Intensity				
ICT Intensity	-0.017***	-0.015***	-0.479***	-0.507***
	(0.005)	(0.005)	(0.106)	(0.103)
ICT Intensity × Income		0.027***		0.007
		(0.007)		(0.012)
N of Observations	976	976	976	976
Year FE	√	√	√	√
Geographic FE	√	√	√	√
Geographic FE × Year FE	√	√	√	√
Demographics	√	√	√	√

Notes:
The table presents within group and IV estimates of the relationship between automation adoption and employment rate across countries, where robotic penetration predicted using aging trend is used as the instrument. Independent variables include robotic penetration and ICT intensities. The regressions are weighted by total labour force in 2004. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE refers to region dummies. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Following the logic established in Chapter 2, Table 3.5 combine the variations of GNI per capita, augmenting with interaction term between exposure of automation technologies and income level. Table 3.5 presents both within group and IV estimates for robotic usage in Panel A. In contrast with baseline results displayed Column 1, Columns 2 turns to consider interactions between robotic exposure and continuous income levels. Specifically, the positive coefficient estimate of interaction term reveals that rising income level could slow down employment destructions of robotic adoption. Instrumented with the shift share IV, Columns 4 indicates that 1 extra unit of robotic stocks per thousand workers tends to reduce employment rate by 1.79 percentage points. Further, the coefficient estimate for interaction term is 0.07, highlighting the flattening effects of regional economic growth.

Similarly, Panel B displays ICT counterparts augmenting with GNI per capita. ICT investments appear to have negative impacts on employments, and the magnitudes are more substantial when instrumented with ageing trends. Specifically, 1 extra dollar in ICT expenditure per thousand workers tends to reduce employment rate by 0.48 percentage points. The mitigating effects of income level lose significance, suggesting that the evolution of demographic structure might not be the primary factor influencing firms' decisions regarding automation technologies.

Broadly speaking, these findings align with US evidence. Nonetheless, the absence of robust identification strategies is potentially puzzling, making it challenging to isolate spillover effects and other endogenous factors. While ageing trends offer a potential avenue for addressing some of these endogeneity concerns, doubts remain about the intuitions of plausibly exogenous conditions, because the labour force participation rate is found to be higher among young workers, and lower among old workers, particularly in developed countries[25]. As revealed by Ahituv and Zeira (2010), old workers are less likely to adopt new technologies and acquire technology specific human capital, due to shorter career horizons compared with their younger counterparts. These erosion effects push old workers to retire earlier, especially if we make comparisons across workers in a fixed timeframe, leading to decreasing labour participation rate across age profiles. Therefore, the effectiveness of employing IV estimation using demographic changes requires further investigations. A more in-depth research uncovering exogenous variations of penetration to automation technologies across countries, is a promising direction for future empirical implications.

[25]That is also the reason why I did not use ageing trend as instrumental variable for US evidence.

3.8 Heterogeneous Analysis

This section turns to investigate heterogeneous effects across regions at different stages of economic development. Since missing values of robotic usage and ICT adoption mainly concentrate in low and middle income countries, this analysis focuses solely on employment dynamics of automation technologies in OECD countries and non-OECD countries.

This question bears particular importance for several reasons. Firstly, as an organisation comprising mostly developed countries, companies in OECD member countries benefit from policy recommendations and evaluations conducted by experts in the organisation (OECD, 2020), thereby cultivating trade and investment among these member countries. Secondly, as noted in Section 3.2, this chapter explores the impacts of automation technologies on employment rate across countries from different income groups. Besides arbitrary classification of income groups, in a more general model, I also explore the impacts of the interaction between automation technologies and income level, to investigate the gradual changes of the employment effects. However, the mitigation effects from income levels may vary across countries. Therefore, following He et al. (2023), I investigate this possibility by separating the sample into OECD countries and non-OECD countries, to conduct heterogeneous analysis. The regression results are estimated based on Equation 3.1, and IV estimates using shift share IV are based on Equation 3.3.

Table 3.6 shows OLS estimation[26] and IV estimation results, regarding the heterogeneous effects of robotic adoption on employment rate, across OECD countries and non-OECD countries. For OECD countries, Column 1 reveals that one robot per thousand labour force is associated with 2.03 percentage decline of employment rate. Utilising shift share IV, Column 2 reveals that adopting one additional robot per thousand workers reduces the employment rate by 1.99 percentage point, and rising income level could mitigate

[26] For this section, I still utilise within group estimation to estimate fixed effects model, based on panel data structure. From the perspective of econometric theory, we need to first do within group transformation based on panel data structure, and then use OLS to estimate the coefficient, therefore, here I can also call them ”OLS results”.

Table 3.6: Employment Effects of Robot and Income Across OECD and Non-OECD Countries, 2004-2019

	OECD Countries		Non-OECD Countries	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Dependent Variable: Employment Rate				
Robotic Penetration	-2.029***	-1.989***	-1.005	1.373
	(0.178)	(0.171)	(1.622)	(2.415)
Robotic Penetration $\times$ Income	0.080***	0.125***	7.030***	-5.725
	(0.007)	(0.012)	(0.785)	(4.556)
Year FE	√	√	√	√
Geographic FE	√	√	√	√
Geographic FE $\times$ Year FE	√	√	√	√
Demographics	√	√	√	√
N of Economies	35	35	30	30
N of Observations	560	560	464	464

Notes:
The table presents within group and IV estimates of the relationship between robotic usage and employment rate across OECD countries and non-OECD countries, where robotic penetration predicted using aging trend is used as the instrument. The regressions are weighted by total labour force in 2004. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE refers to region dummies. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

such employment decline by 0.13 percent. While for non-OECD countries, both OLS estimation and IV approach produce insignificant results, implying that technological unemployment induced by robotic usage and mitigation effects of income level are only observed in high income economies. This phenomenon may be attributed to variations in the GDP share of manufacturing, as Section 2.6 of Chapter 2 discovered that heterogeneous employment effects of robots are prevalent in manufacturing sectors. According to Buera et al. (2021); Herrendorf et al. (2014), the value added for manufacturing sectors is higher in advanced economies, potentially explaining the insignificant employment responses of robotic adoptions in non-OECD countries.

For the employment effects from ICT intensities, I also find evidence that the heterogeneous effects of ICT adoptions on employment dynamics are indeed prevalent in OECD

Table 3.7: Employment Effects of ICT and Income Across OECD and Non-OECD Countries, 2004-2019

	OECD Countries		Non-OECD Countries	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Dependent Variable: Employment Rate				
ICT Intensity	-0.021***	-0.447***	-0.001	-0.618
	(0.007)	(0.060)	(0.012)	(5.585)
ICT Intensity × Income	0.055***	0.049***	0.009	0.172
	(0.007)	(0.011)	(0.032)	(0.160)
Year FE	√	√	√	√
Geographic FE	√	√	√	√
Geographic FE × Year FE	√	√	√	√
Demographics	√	√	√	√
N of Economies	36	36	72	72
N of Observations	325	325	651	651

Notes:
The table presents within group and IV estimates of the relationship between ICT usage and employment rate across OECD countries and non-OECD countries, where ICT intensity predicted using aging trend is used as the instrument. The regressions are weighted by total labour force in 2004. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE refers to region dummies. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

countries. Table 3.7 shows OLS estimation[27] and IV estimation results, regarding the heterogeneous effects of ICT intensity on employment rate, across OECD countries and non-OECD countries. Columns 1 and 2 indicate that statistically significant negative effects of ICT intensities on employment rate are only observable in OECD countries. For the preferred specification using ageing trends as shift share IV in Column 2, an increase of 1000 US dollars in ICT investment per thousand labour force tends to reduce employment rate by 0.45 percentage points, and rising income level could flatten such employment declines. The results share qualitative similarities with their robotic counterparts, and indicate that such technological unemployment may primarily affect high income economies.

[27]For this section, I still utilise within group estimation to estimate fixed effects model, based on panel data structure. From the perspective of econometric theory, we need to first do within group transformation based on panel data structure, and then use OLS to estimate the coefficient, therefore, here I can also call them ”OLS results”.

Overall, this section examines heterogeneity across various economic development stages of different countries. This research indicates that technological unemployment driven by robotic adoptions and ICT intensities, and mitigation effects from rising income levels, are observable in OECD countries, with limited evidence in non-OECD countries. These results are consistent with evidence from Machin and Reenen (1998).

3.9 Summary

It appears that automation's influence on employment varies depending on a given country or region's income level. Utilising country level data from 1993 to 2019, this chapter provides empirical analysis regarding the impacts of automation technologies on employment rate across different economies, and investigates heterogeneous effects based on the responses of regions at various economic development stages.

Regression results from cross country analysis point out the potential to generalise US evidence in Chapter 2, to the implications for global economic growth. This study finds that the rising penetration of automation technologies, including industrial robots and ICT investments, corresponds to reductions in employment rate across all countries. Adopting novel shift share IV based on differential ageing trends, rising income levels could mitigate such technological unemployment. It is discovered that one additional robot per thousand workers tends to reduce employment rate by 1.42 percentage points, and growing GNI per capita could lead to complementary effects of 0.07 percentage points. These findings are consistent with results from US evidence in Chapter 2, as rising income levels suggest that productivity effects may flatten welfare deteriorations by displacement effects.

Moreover, heterogeneous effects based on OECD countries and non-OECD countries reveal that differential employment dynamics induced by automation technologies, alongside mitigation effects from income levels, are observable solely in advanced economies.

This phenomenon may be attributed to variations in the GDP share of manufacturing, as Section 2.6 of Chapter 2 discovered that heterogeneous employment effects of automation technologies are particularly apparent in manufacturing sectors. According to Buera et al. (2021); Herrendorf et al. (2014), the value added for manufacturing sectors is comparatively higher in advanced economies, and that could explain the insignificant employment responses to automation adoptions in non-OECD countries.

In this section, I also point out some challenges and future directions for cross country analysis.

Firstly, research about employment effects of automation technologies is frequently complicated by endogenous factors, such as spillover effects and reverse causalities, which are addressed in Section 3.6 of Chapter 3. Shift share IV approach based on ageing trends offers a partial solution to such endogeneity concerns, but reservations remain regarding the plausibility of exogenous conditions. According to Section 3.7 of Chapter 3, the labour force participation rate is higher among young workers, and lower among old workers, particularly in developed countries[28]. Therefore, the effectiveness of employing IV estimation based on demographic changes requires further investigations. With novel datasets and robust identification strategies, I believe empirical studies exploring heterogeneous effects under different institutional settings, would therefore be a promising direction for future research.

Secondly, an additional challenge is represented by obtaining comprehensive datasets, to select an appropriate indicator of automation technologies. Previous studies, often centred around broad measures of technological updating such as TFP (total factor productivity) growth and patent awards across different countries (Autor and Salomons, 2018; Autor et al., 2020). This chapter follows recent literature, such as Acemoglu and Restrepo (2020), which utilised data from International Federation of Robotics (2021) to perform

[28]That is also the reason why I did not use ageing trend as instrumental variable for US evidence.

empirical analysis. It contains counts of robotic stocks across 19 industrial sectors over 72 countries between 1993 and 2019. In addition, I adopt ICT capital data from Total Economy Database of The Conference Board (2021), to obtain a comprehensive picture of the relationship between automation technologies and employment. However, this method presents challenges when generalising to cross country analysis, due to potential variations in robot quality. Also, as noted in Section 3.8, missing values of robotic usage and ICT adoption mainly concentrate in low and middle income countries. Therefore, it is hard to identify such technological unemployment in emerging economies. Relying on novel datasets, other indicators of ICT adoptions and patent awards about automation technologies such as Autor et al. (2020); Bloom et al. (2015); Kim et al. (2021), may represent a more reliable indicator for the development of automation technologies in future research.

In summary, empirical analysis based on cross country evidence demonstrates that differential employment responses to automation technologies are evident across various regions. However, the specific means in which individual workers respond to technological changes remain under investigation. Therefore, in the following chapter, I plan to adopt worker level dataset based UK context to perform further analysis.

Chapter 4

Individual Level Analysis

For further discussions, this thesis will perform micro econometric analysis to complement US and cross country results. My focus lies in empirical evidence from the UK, due to similar institutional background and economic environments to the US.

4.1 Introduction

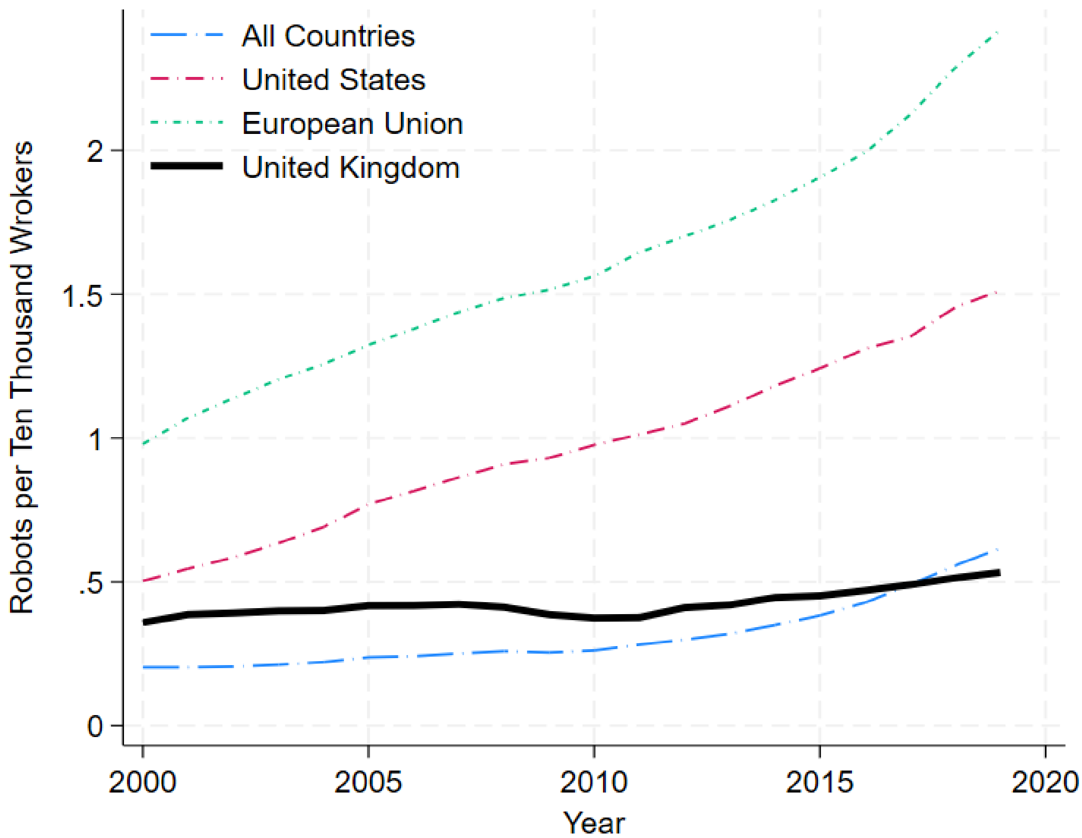
This section presents introduction of individual level analysis based on UK context. It focuses on motivation, hypothesis, and contribution of this chapter.

4.1.1 Motivation

The reasons for the selection of the UK to perform individual level analysis are as follows.

Firstly, as outlined in Chapter 1, understanding the impacts of automation technologies on labour market outcomes at all levels of analysis, including individual workers, skill groups, metropolitan areas, and countries, is important. In Chapter 2, I provide empirical analysis based US evidence, and focus on state level data and commuting zone level data. Then in Chapter 3, I provide cross country evidence to see whether the US results could be generalised to other countries globally. This involves regression analysis across countries from different income groups. Up to now, this thesis has already covered the macro level evidence. However, the specific means in which individual workers respond to technological changes remain under investigations. In this Chapter, I plan to go one step further, to investigate the micro level analysis. Therefore, individual level results are now the focus.

Figure 4.1: Robot Adoption in UK, EU and US, 2000-2019



Notes:
The data about operational stocks of robots are based on International Federation of Robotics (2021). Robot density refers to refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020), and the data is from World Bank (2021). EU countries in 2004 include Austria, Belgium, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain and Sweden (European Union, 2023).

Secondly, the United Kingdom, as one of the most developed countries[1], shares similar institutional background and economic environments to the US (Goos and Manning, 2007; Goos et al., 2009). However, the development of machines and other automation

[1]According to World Bank (2021), the UK GDP per capita in 2019, measured in current US dollars, is approximately $42663, and the United Kingdom is one of the most developed countries. To avoid the influence of COVID 19 on economic growth, here I use the data in 2019.

technologies in the UK, is not as advanced as that in the US or some western countries. As revealed in Figure 4.1, the robotic density in UK is around 0.4 between 2000 and 2019, which is lower than the average level of US and European Union countries. Therefore, further analysis in the UK is interesting, and it proves valuable in understanding the mechanisms behind regions with high economic growth and slow technological updating.

Thirdly, previous analysis by Dolton and Makepeace (2004); Machin and Reenen (1998) uncovered significant association between skill upgrading and technical change, causing growing demand of high skilled labour force. However, there is only limited evidence on individual heterogeneities within one specific advanced economy. This chapter aims to address this gap in the literature[2]. I will provide empirical analysis on individual behaviours in response to automation technologies, and explore the heterogeneous effects across different UK regions, and among workers with different education attainments. In addition, the choice of UK as the sample country, is also supported by the data availability of the information about computerised and automated equipments. This information is accessible through the Skills and Employment Survey conducted in 2006, 2012 and 2017. The degree of automated equipment use refers to answers of ”whether job involves use of computerised or automated equipment”. While for computerisation, the respondent had to answer ”complexity of computer use in job”. As the University of Glasgow is located in the third largest city of UK, it would be convenient to get access to detailed worker level data.

4.1.2 Hypothesis

The hypotheses in this chapter are similar to those in Chapter 1.

Hypothesis 1: For all UK workers, the correlation between exposure to automation technologies and individual working hours tends to become negative.

[2]Detailed information about the contributions to existing literature will be illustrated in Subsection 4.1.3.

Hypothesis 2: For high income workers with affluent human capital accumulations, exposures to automation technologies are likely to have positive impacts on individual working hours. While for low and middle income workers with fewer years of education, there is a negative correlation between automation adoptions and labour supply.

Hypothesis 3: The heterogeneous employment effects from automation technologies, as highlighted in *Hypothesis 2*, can only be observed for college educated workers, as technological updating are biased against low skilled workers.

Hypothesis 4: The differential employment responses from automation technologies, as highlighted in *Hypothesis 2*, are expected to be more pronounced for workers living within London, due to concentration of manufacturing activities.

In the next subsection, this thesis will describe the contributions of this chapter based on existing literature gaps.

4.1.3 Contribution

This chapter synthesises various lines of research, including individual level analysis about heterogeneous employment effects from technical changes, identification issues based on advanced panel data econometric techniques, and regional variations of structural changes.

For the first main contribution, this chapter explores the heterogeneous employment effects from automation technologies across workers with different income levels within one developed country. Numerous studies have examined the role of automation technologies as the determinant of employment dynamics, based on general measures of technological updating such as TFP (total factor productivity) growth and patent awards across different countries (Autor and Salomons, 2018; Autor et al., 2020). However, there is limited evidence at the individual worker level (Autor, 2014), particularly in areas with high economic growth and slow technological updating. To address this gap, I introduce two complementary indicators, namely degree of automated equipments and computerisation complexities at the individual level. Therefore, this chapter provides novel evidence by analysing the impact of exposure to machines on individual working hours, and examines how workers respond to labour market shocks caused by automation technologies.

For the second main contribution, this chapter complements a handful of studies on identification issues when exploring how automation technologies replace existing jobs. This work is closely related to several existing studies that use automation adoptions in other advanced economies as instrumental variables for the dynamics of automation technologies in a specific country (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Giuntella et al., 2022), or those that conduct event studies based on patent policy shocks (Bloom et al., 2015). Distinct from this literature, this thesis develops a method to address endogenous issues from time varying components of intrinsic abilities. This chapter extends the pioneering work by Arellano and Bond (1991), which adopted lagged differenced variables or lagged level variables to instrument the endogenous variables based on two-step variants of system GMM. This approach helps to rule out spurious or coincidental effects that might affect labour supply trends. The results highlight the fact that automation technologies have negative impacts on individual working hours, conditional on task intensities.

For the third main contribution, this chapter also contributes to emerging literature on technological updating and structural changes. Buera et al. (2021); Herrendorf et al. (2014) adopted the theory of SBTC (Skill Biased Structural Change), and discovered growing value added for manufacturing sectors in advanced economies. Based on heterogeneous analysis for workers living within London and outside London, this chapter attribute this phenomenon to variations in the GDP shares of manufacturing sectors.

In line with the structure of Chapter 2 and Chapter 3, I plan to perform empirical analysis based on UK individual level data.

4.2 Data

As noted before, a key reason for selecting the UK as a case study to assess individual behavioural responses to automation technologies, is the accessibility of data on the information about computerised and automated equipment. The data is offered by the Skills and Employment Survey on 2006, 2012 and 2017. The degree of automated equipment use is derived from responses to the survey question: ”whether job involves use of computerised or automated equipment”. The annual average value of this job characteristics reflects the likelihood of automated equipment use across different industries and occupations. While for the degree of computerisation, the respondent had to answer ”complexity of computer use in job”, and ranked the frequencies of computer use on a scale of 1 to 4, with 0 indicating no computer use.

To account for occupation-specific or industry-specific task intensities, this article will calculate skill distribution according to job characteristics and working conditions, utilising data from UK Skills and Employment Survey (Office for National Statistics, 2018). To ensure a representative sample of labour market outcomes, the sample is restricted to adults in full-time and permanent employment, excluding retirees, unemployed individuals, and self-employed individuals. The analysis centres around survey questions about the types and importance of job activities, which respondents ranked on a scale of 1 to 4. The average value of these scores every year represents a measure of job characteristics.

Following Bisello (2013), skill measures are categorised into three groups based on task intensities, namely analytical skills, interpersonal skills, and manual skills. Detailed descriptions of these categories are presented at Section .1 in the Appendix. Although this survey relies on subjective evaluations, it offers valuable insights into the degree of repetition and task intensities across different industries and occupations (Bisello, 2013; Goos and Manning, 2007). Missing data points in specific years, were linearly interpolated to maintain consistent records[3]. Though the noise introduced by such aggregation would lead to biased estimates, Acemoglu and Restrepo (2020) revealed that such measurement errors can be considered uncorrelated with error terms. I matched the measures of task intensities with individual characteristics from APS dataset (Annual Population Survey), based on the four job classifications detailed later in this work.

All the data related to individual characteristics are from APS dataset (Annual Population Survey), covering the period from 2011 to 2018 in the UK. The APS dataset comprises key variables from the Labour Force Survey (LFS), offering comprehensive information on employment and wage conditions for individuals across all regions within the United Kingdom (Office for National Statistics, 2018). Variables such as working hours, gross earning, and highest educational degree received by individuals and job classification, are available in this dataset. Considering the focus on labour market outcomes, the analysis centres around main jobs, with the sample limited to adults engaged in full-time and permanent employment, excluding retirees, unemployed individuals, and self-employed individuals. Finally the regression analysis is conducted based on 142852 individual observations.

To match individual characteristics with industry-level and occupation-level job task information, this survey also collected data on various job classifications. This research utilises 1-digit level SIC2007 (Standard Industrial Classification)[4], 1-digit SOC2010 (Standard Occupational Classification), 3-digit SOC2010 (Standard Occupational Classification)[5], and NS-SEC category (National Statistics Socio-Economic Classification based on SOC2010).

[3]For example, if the score of one specific skill in 2012 is 1.1, and that in 2017 is 1.3, I can assign the scores in 2013-2016 to be 1.14, 1.18, 1.22, 1.26. Fortunately, the variation of scores is not large across years.

[4]For those with missing value of SIC2007, I use SIC1992 as alternative measures, because these two kinds of classification system have the some coding system

[5]For those with missing value of SOC2010, I use SOC2000 as alternative measures, because these two kinds of classification system have the some coding system

4.3 Stylised Facts

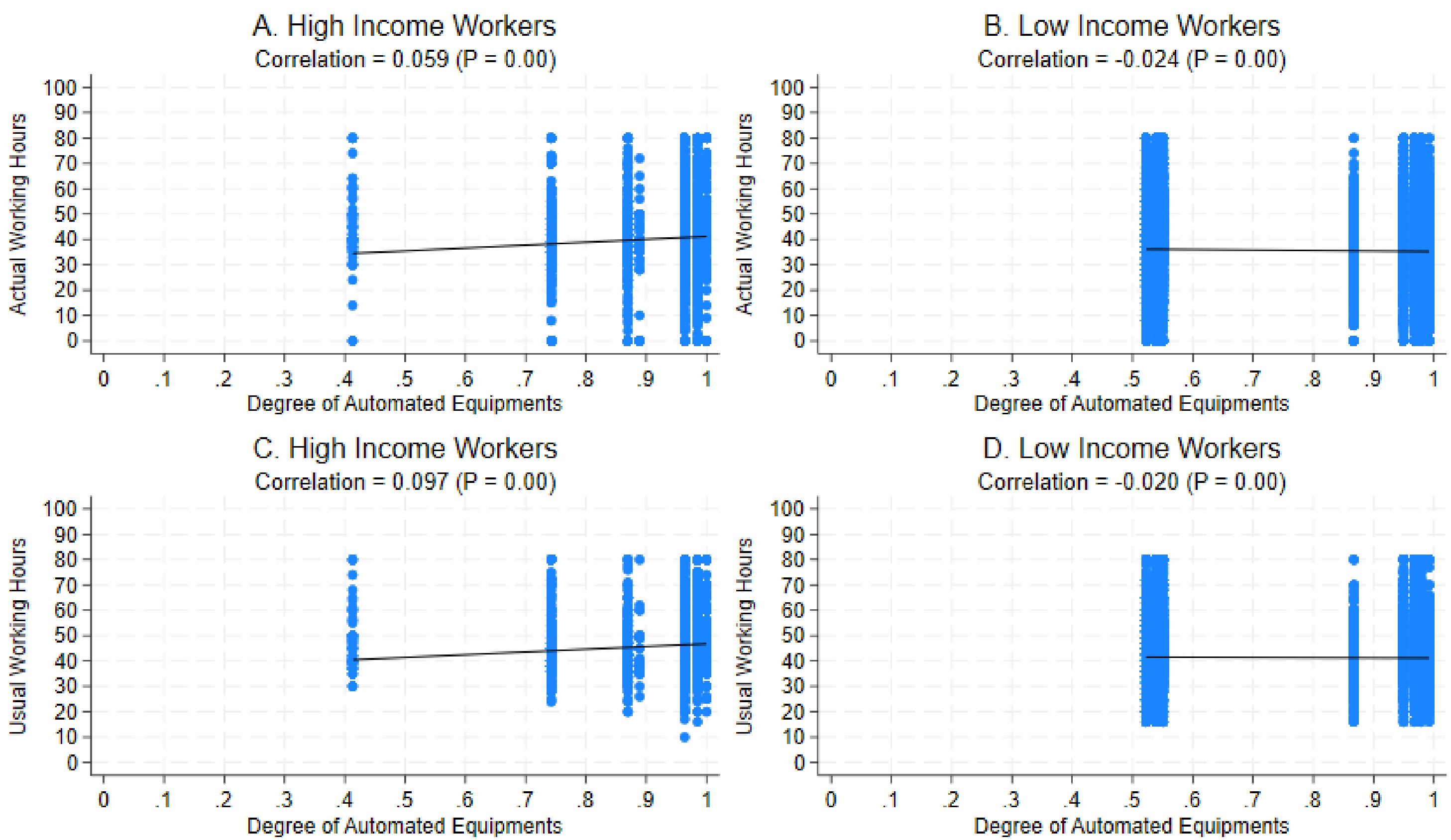
This section presents several key findings concerning technological changes and labour market outcomes, among UK workers over the period of analysis.

Figure 4.2 discovers the association for workers across different income groups, highlighting differential labour supply responses following technological shocks. For high income workers displayed in Panels A and C, the relationship between degree of automated equipments and working hours is significantly positive, suggesting a degree of complementarity between exposure of automation and labour inputs. Therefore, growing exposure of automation adoption may, to some extent, complement human labours.

Conversely, for low income workers exhibited in Panels B and D of Figure 4.2, labour supply, as measured by individual working hours, demonstrates a negative correlation with automation exposure, with statistically significant coefficients. These results are consistent with the hypothesis that low income workers are more susceptible to displacement due to technological changes.

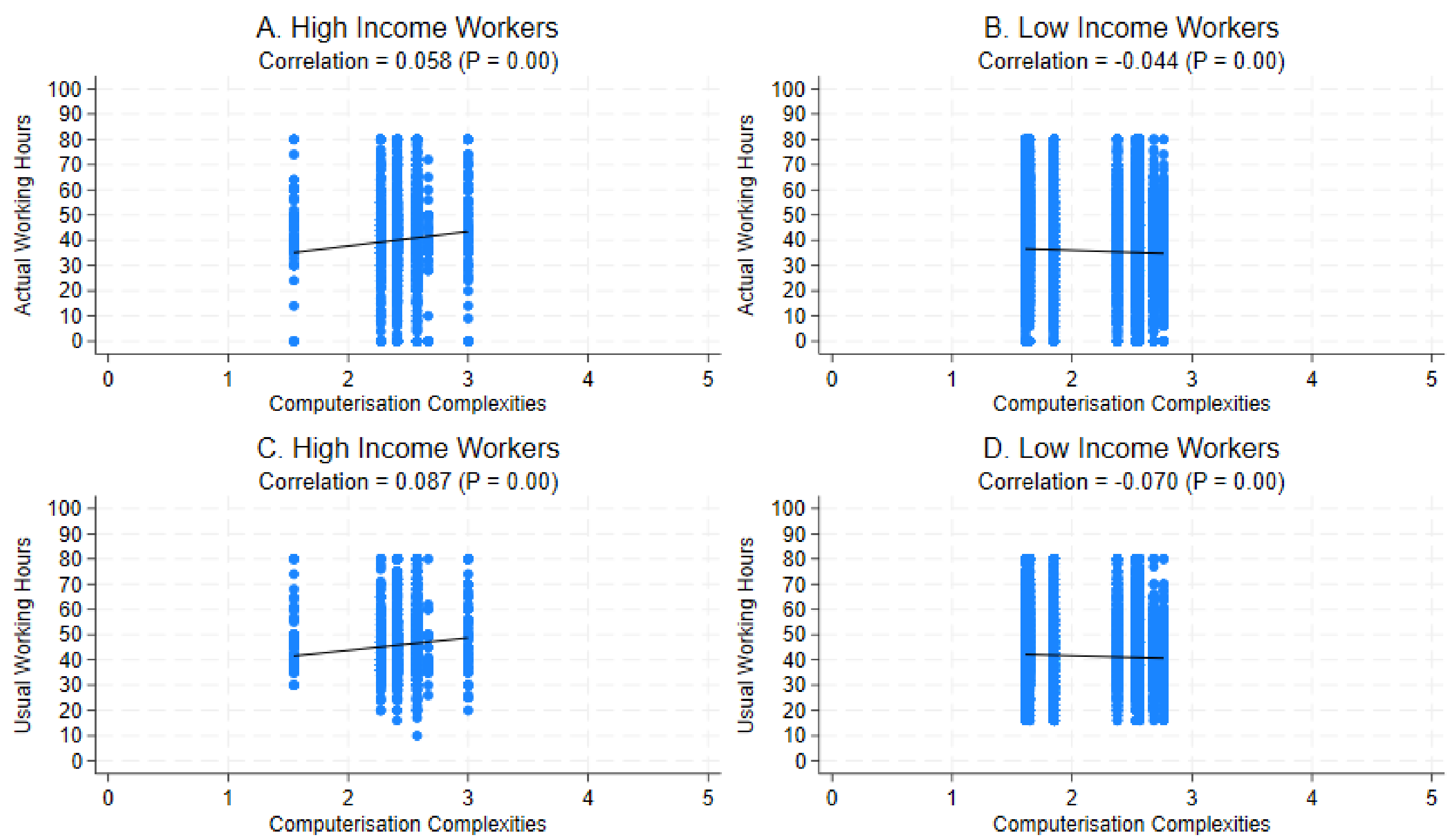
In addition, Figure 4.3 offers evidence of the relationship between computerisation complexities and individual working hours. As an alternative measure of individual automation exposure, the magnitudes of negative employment responses by low income workers are slightly larger than those for the degree of automated equipments, indicating strong displacement effects. The results are consistent with analysis presented in Figure 4.2.

Figure 4.2: Automated Equipments and Weekly Working Hours for UK Workers, 2011



Notes:
The actual working hours and usual working hours are from Office for National Statistics (2018), and the degree of automated equipments is based on Bisello (2013) defined in Section .1 of Appendix. Vertical axis in Graphs A and B are actual weekly working hours, which measures individual's working time during survey reference week, and vertical axis in Graphs C and D are usual weekly working hours reflecting individual habits on work schedule. High income workers in Graphs A and C refer to those who are above 80 percentile of income distribution, and low income workers in Graphs B and D refer to those who are below 80 percentile of income distribution.

Figure 4.3: Computerisation Complexities and Weekly Working Hours for UK Workers, 2011



Notes:
The actual working hours and usual working hours are from Office for National Statistics (2018), and the computerisation complexities is based on Bisello (2013) defined in Section .1 of Appendix. Vertical axis in Graphs A and B are actual weekly working hours, which measures individual's working time during survey reference week, and vertical axis in Graphs C and D are usual weekly working hours reflecting individual habits on work schedule. High income workers in Graphs A and C refer to those who are above 80 percentile of income distribution, and low income workers in Graphs B and D refer to those who are below 80 percentile of income distribution.

4.4 Empirical Analysis

This section evaluates the overall UK sample, and investigates the labour market outcomes facing technical change, conditional on task intensities and other demographic controls. It also explores heterogeneous effects based on workers endowed with different income levels.

The basic idea is as follows: All things equal, an increase in exposure of automation technologies will decrease the actual and usual working hours. However, rising gross earnings could mitigate such negative effects. Therefore, the main evidence supporting this assumption lies in the expected negative coefficients of automation technologies, and the expected positive coefficients of interactions between automation technologies and gross earnings.

4.4.1 Summary Statistics

This subsection provides summary statistics about variables, which will be exhibited in the following regression model.

Table 4.1 reports summary statistics for the main variables employed in the regressions. All results are calculated for UK workers across all periods of analysis. On average, the labour market outcome, measured by individual actual weekly total working hours, is approximately 37.2 hours for every period. Whereas, the labour market performance measured by individual usual weekly total working hours, is 42.7 hours. Table 4.1 further confirms a high degree of automation adoptions, with an average rise in the degree of automated equipments by 0.9, alongside a high level of computerisation complexities. As indicated by the standard deviations reported in the table, other control variables also exhibit variations across individual workers and time periods.

Table 4.1: Summary Statistics for UK Evidence, 2011-2018

Variable	Mean	Std.Dev.	Min	Max	Obs
Actual Hours	37.224	15.845	0	80	142582
Usual Hours	42.733	9.011	0	80	141910
Auto Equip	0.921	0.116	0.413	1	142582
Computer	2.487	0.201	1.548	5	142582
Income	9.100	1.644	0	10.621	142582
Male	0.514	0.500	0	1	142582
Age	52.123	18.449	16	99	142582
Marry	1.356	0.479	1	2	142582
Task Intensity:					
Repeat	3.336	0.408	2.632	4	142582
Analytical	2.927	0.224	1.498	3.196	142582
Interpersonal	3.062	0.262	1.062	3.310	142582
Manual	1.715	0.648	0.659	3.288	142582
Education:					
School (Full)	0.001	0.025	0	1	1250127
Sandwich	0.001	0.017	0	1	1250127
College (Full)	0.032	0.176	0	1	1250127
School (Part)	0.001	0.006	0	1	1250127
Nursing	0.001	0.031	0	1	1250127
College (Part)	0.015	0.122	0	1	1250127

Notes:
Statistics for variables in levels are computed across 142582 UK workers for time periods, namely 2011-2018, and those variables include changes in actual working hours (Actual Hours), usual working hours (Usual Hours), degree of automated equipments (Auto Equip), and computerised complexities (Computer). Other control variables regarding task intensities in levels include degree of repetitiveness (Repeat), analytical skill score (Analytical), interpersonal skill score (Interpersonal), and manual skill score (Manual). Those regarding education level include full time at school (School Full), sandwich course (Sandwich), full time at university or college (College Full), part time at school (School Part), training in nursing (Nursing), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry).

Among all the control variables, the statistics of task intensities are similar to the US evidence documented by Autor (2013). The degree of repetitiveness is around 3.3, with standard deviation of 0.4, implying that the task routineness has a large variation across different occupations. While for the scores of analytical skill, interpersonal skill, and manual skill, the distribution of these three dimensions is similar to those found in the UK (Bisello, 2013).

4.4.2 Baseline Results for Static Model

Drawing upon the worker level analysis from Dauth et al. (2021), this paper will employ a static linear panel data model for individual hours worked, conditional on quadratic form of different task intensities. Below is the specification of static panel data model based on direct task measures.

$$\begin{aligned} Hour_{ijt} = \eta_0' + \eta_1' Automation_{jt} + \eta_2' Automation_{jt} \times Income_{ijt} \\ + \eta_3' Task_{jt} + \eta_4' Task_{jt}^2 + \delta_i X_i + \mu_i + \mu_j + \varepsilon_{ijt} \end{aligned} \tag{4.1}$$

The explained variable $Hour_{ijt}$ refers to the total actual working hours in main job by individual i in industry j at year t. Total usual hours in main job will also be utilised to conduct robustness checks. Actual hours measure an individual's working time during survey reference week, while usual hours reflect an individual's typical work schedule (Office for National Statistics, 2018; Borowczyk-Martins and Lale, 2019). Since skill upgrading within industries contributes significantly to the variation of working hours (Berman et al., 1994), the initial focus will be on people with full-time and permanent jobs.

The main explanatory variables $AutoEquip_{jt}$ and $Computer_{jt}$ refer to automation technologies in a given industry or occupation. These include the importance of automated equipment use ($AutoEquip_{jt}$), and complexity of computer use in job ($Computer_{jt}$). I use these two proxies to measure $Automation_{jt}$. Currently, a linear relationship is assumed between automation technologies and individual working time, and lagged variables of $AutoEquip_{jt}$ and $Computer_{jt}$ would be taken into considerations in the following subsection.

$Task_{jt}$ refers to task intensities, including analytical skill, interpersonal skill, and manual skill, as detailed in Appendix .1. Occupation-level task intensities are based on 3-digit SOC 2010 classification. For time-invariant variables, X_i denotes the individual's personal characteristics, including age, sex, and marital status. The parameter δ are $K \times 1$ vectors, where K is the number of time-varying variables capturing demographic characteristics outlined above. Nation dummies[6] are also included to control for systematic variations across different regions (Dauth et al., 2021). To capture evolution of occupational demands (Beaudry et al., 2014), year dummies, industry dummies, and occupation dummies could also be taken into considerations. This is because PwC (2018) has discovered heterogeneities across countries, industry sectors, as well as individual genders, ages, and education groups.

Among those factors concerning occupational structures, the proportion of women in the labour force could account for small predicted rise in employment changes of lousy jobs (Goos and Manning, 2007). Besides, educational attainment, along with age cohort effects, could explain variations in lovely jobs (Acemoglu et al., 2004; Autor and Dorn, 2009; Bluestone and Harrison, 1988; Goos and Manning, 2007; Sachs and Kotlikoff, 2012). Since Autor and Dorn (2009) has pointed out causal link between routine task intensity and education-age profile, these heterogeneous effects will be tested as robustness checks. Individual specific effects μ_i and idiosyncratic error ε_{it} constitute the unobserved error term in this equation. Unless otherwise noted, all standard errors are robust against heteroscedasticity.

[6]Nations inside UK in this article refer to England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland.

Table 4.2: Actual Weekly Working Time and Automation Technologies for UK Workers based on NS-SEC 2010, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Actual Working Hours								
Auto Equip	-3.039***	-3.456***	-2.293***	-1.482***				
	(2.588)	(2.670)	(2.821)	(3.631)				
Computer					-0.166	-0.311	-0.721	-0.748
					(0.561)	(0.574)	(0.635)	(0.751)
Auto Equip				0.362***				
$\times$Income				(0.035)				
Computer								0.130***
$\times$Income								(0.013)
$Repeat$	-50.648***	-39.220***	-5.081	33.501***	-26.313***	-14.861***	8.091	44.447***
	(4.782)	(5.642)	(5.858)	(8.223)	(4.450)	(5.640)	(5.820)	(7.480)
$Analytical$	69.124***	90.379***	80.213***	34.287***	106.361***	120.965***	99.391***	33.422***
	(7.184)	(9.051)	(9.089)	(11.190)	(7.891)	(9.649)	(9.644)	(11.775)
$Interpersonal$	-26.644***	-24.372***	1.054	-1.281	-56.432***	-56.290***	-18.493***	-10.286***
	(3.236)	(3.263)	(3.650)	(4.116)	(2.800)	(2.807)	(3.210)	(3.640)
$Manual$	-10.392***	-16.672***	-11.147***	-8.056***	-17.440***	-22.557***	-13.891***	-8.269***
	(1.554)	(2.111)	(2.112)	(2.375)	(1.511)	(2.151)	(2.163)	(2.457)
Male			4.601***	4.419***			4.601***	4.419***
			(0.098)	(0.109)			(0.098)	(0.109)
Age			-0.025***	-0.027***			-0.025***	-0.027***
			(0.004)	(0.004)			(0.004)	(0.004)
Marry			0.662***	0.815***			0.662***	0.817***
			(0.099)	(0.110)			(0.099)	(0.110)
School (Full)			-36.049***	-34.742***			-35.835***	-34.501***
			(1.980)	(2.170)			(1.998)	(2.179)
College (Full)			-31.196***	-29.545***			-31.060***	-29.309***
			(1.855)	(2.148)			(1.866)	(2.153)
School (Part)			-36.995***	-36.479***			-36.812***	-36.247***
			(0.948)	(1.083)			(0.971)	(1.096)
College (Part)			-37.960***	-36.980***			-37.800***	-36.778***
			(1.944)	(2.169)			(1.953)	(2.175)
Year FE		√	√	√		√	√	√
Nation FE			√	√			√	√
Occupation FE			√	√			√	√
R^2	0.014	0.015	0.051	0.050	0.013	0.014	0.051	0.050
N of Obs	142582	142582	142582	142582	142582	142582	142582	142582

Notes:

The table presents within group estimates of the effects of automation technologies on individual working hours. Dependent variable is actual weekly working hours. Explanatory variable are degree of automated equipments, and computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time. The classification of occupation dummies are 3-digit level SOC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2 provides estimation results of the effects on labour supply, measured by total working hours in main job conditional on task intensities. These estimations are derived from Equation 4.1 using static linear panel data model. I prefer to use GLS estimator, as Durbin-Wu-Hausman test shows that both within-group estimator and GLS estimator are consistent[7].

Based on the classification of NS-SEC 2010 in Table 4.2, the degree of automated equipments has significantly negative impacts on individual actual working hours, particularly when accounting for occupation specific effects, geographic disparities, and macro shocks. The preferred specification in Column 3, demonstrates that 1 unit increase of importance of automated equipment is associated with 2.29 hours increase of actual working time. Taking income level into accounts, there is less support for the roles played by automation technologies. This implies that, with 1 additional pound of gross earnings, the impacts of the degree of automated equipments on actual working time will be flattened by 0.36 hours, and the effects on usual working time will be flattened by 0.38 hours. The

[7]Assuming within-group estimator is consistent, and GLS estimator is inconsistent but efficient, for degree of automated equipments on total actual hours $\chi^2(9) = 5.19$, with p-value of 0.8178; for degree of automated equipments on total usual hours $\chi^2(9) = 8.56$, with p-value of 0.4784; for computerisation complexities on total actual hours $\chi^2(9) = 2.28$, with p-value of 0.9862; and for computerisation complexities on total usual hours $\chi^2(9) = 7.39$, with p-value of 0.5968. So, we cannot reject the null hypothesis that both of them are consistent, implying that explanatory variables can be regarded as uncorrelated with unobserved heterogeneities. In order to observe time invariant components, it would be better to use GLS estimator.

estimates for computerisation complexities counterparts are almost statistically insignificant. Evidence regarding the impacts on usual individual working hours are displayed in Table 52 of Appendix, and it reveals that the results remain consistent across different proxies of labour supply.

Based on the classification of 1 digit SIC 2007 in Panels A and B of Table 53 in Appendix, the degree of automated equipments has significantly negative impacts on individual actual working hours and individual usual working hours, especially when occupation specific effects, geographic disparities, and macro shocks are taken into considerations. From the preferred specification in Column 3, Panel A shows that 1 unit increase in the importance of automated equipments is associated with 4.70 hours increase of actual working time. Whereas, Panel B indicates 1.54 hours decrease of usual working time. When income is factored in, the effects of automation technologies appear to reduce. Specifically, for every additional pound of gross earnings, the impacts of degree of automated equipments on actual working time will be flattened by 0.42 hours, and the effects on usual working time will be flattened by 0.39 hours. Similarly, the estimates for computerisation complexities counterparts also display statistical significance at the confidence level of 1 percentage point. These findings suggest that the degree of computerisation complexities have significantly negative impacts on both actual and usual individual working hours, especially when occupation specific effects, geographic disparities, and macro shocks are taken into considerations.

Based on the classification of 1 digit SOC 2010 in Panels A and B of Table 54 in Appendix, this analysis finds that the degree of automated equipments has significantly negative impacts on individual actual working hours and individual usual working hours, particularly after controlling for occupation specific effects, geographic disparities, and macro shocks. From the preferred specification in Column 3, Panel A shows that 1 unit increase in the importance of automated equipment is associated with 1.74 hours increase of actual working time, and Panel B exhibits 1.50 hours decrease of usual working time.

When income level is factored in, the analysis suggests a reduced role for automation technologies in influencing working hours. Specifically, for every additional pound of gross earnings, the impacts of degree of automated equipments on actual working time will be flattened by 0.41 hours decline, and the effects on usual working time will be flattened by 0.39 hours decline. Similarly, the estimates for computerisation complexities counterparts are also statistically significant at the confidence level of 5 percentage point. The findings indicate that the degree of computerisation complexities has significantly negative impacts on both actual and usual individual working hours, particularly after controlling for occupation specific effects, geographic disparities, and macro shocks.

Therefore, conditional on task intensities, the individual labour supply, measured by actual weekly working time and usual weekly working time, would respond negatively facing susceptibilities of automation technologies. This negative response could be flattened be rising income levels. This finding aligns with US analysis and cross country analysis.

4.4.3 Further Analysis for Dynamic Model

In a dynamic setting, labour supply responses vary across time (Keane and Rogerson, 2015). This section presents regression results based on dynamic panel data approach. Considering the U-shape changes of individual working hours over skill percentile, I plan to use lagged dependent variable $Hour_{ij,t-1}$, to account for pre-trend of individual working hours. Occupation-level task intensities are based on SOC 2010 classification. Below is the specification of autoregressive dynamic panel data model of order one, based on direct task measures.

$$
\begin{aligned}
Hour_{ijt} = \eta_0'' + \eta_1'' Hour_{ij,t-1} + \eta_2'' Automation_{jt} + \eta_3'' Automation_{jt} \times Income_{ijt} \\
+ \eta_4'' Task_{jt} + \eta_5'' Task_{jt}^2 + \delta_i X_i + \mu_i + \mu_j + \varepsilon_{ijt}
\end{aligned}
\tag{4.2}
$$

All the regressors are assumed to be weakly exogenous, implying that the idiosyncratic error term ε_{ijt} should be uncorrelated with individual specific effects μ_i, occupation specific effects μ_j, and all the current and past values of explanatory variables[8], including $Hour_{ij,t-1}$. This suggests that workers, when adjusting their working hours, solely consider working time at the last term, which satisfies the true state dependence assumption. This is consistent with macro level analysis by Borowczyk-Martins and Lale (2019) and household-level analysis by Chang et al. (2011). For comparative purposes across different estimation methods, the impacts from demographic controls and geographic dummies are disregarded here. Only macro shocks are considered, as Table 4.2 reveals that the panel data regression results remain consistent across different combinations of control variables.

For estimation methods, I prefer to use within-group estimator, as Durbin-Wu-Hausman test shows that within-group estimator is unbiased and consistent compared with GLS estimator[9].

Table 4.3 provides dynamic analysis of the impacts from automation technologies on individual total working hours in main job, conditional on task intensities. Columns 1 and 2 present regression results about the impacts from the degree of automated equipments

[8]Now ε_{ijt} is assumed to be serially uncorrelated, and later this assumption will be relaxed.

[9]Assuming within-group estimator is consistent, and GLS estimator is inconsistent but efficient, for degree of automated equipments on total actual hours $\chi^2(10) = 370.69$, with p-value less than 0.0000; for degree of automated equipments on total usual hours $\chi^2(10) = 267.86$, with p-value less than 0.0000; for computerisation complexities on total actual hours $\chi^2(10) = 370.30$, with p-value less than 0.0000; and for computerisation complexities on total usual hours $\chi^2(10) = 264.71$, with p-value less than 0.0000. So, we can reject the null hypothesis that both of them are consistent, implying that explanatory variables cannot be regarded as uncorrelated with unobserved heterogeneities. In order to get more consistent and efficient estimators, it would be better to use within-group estimation methods.

Table 4.3: Dynamics about Actual Working Time and Automation based on NS-SEC 2010, 2011-2018

	(1)	(2)	(3)	(4)
Dependent Variable: Actual Working Hours				
$Hour_{t-1}$	-0.311***	-0.305***	-0.311***	-0.305***
	(0.019)	(0.023)	(0.019)	(0.023)
$Auto\,Equip_t$	-3.446*	-5.208*		
	(1.876)	(2.659)		
$Auto\,Equip_t \times Income_t$		0.407*		
		(0.239)		
$Computer_t$			-5.604	-9.696
			(5.391)	(7.378)
$Computer_t \times Income_t$				0.167*
				(0.087)
N of Observations	38718	38718	38718	38718
R^2	0.014	0.015	0.028	0.028
Task Intensities	√	√	√	√
Year FE	√	√	√	√

Notes:
Based on NS-SEC 2010 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Coefficients are estimated based on Equation 4.2 with dependent variable of individual hours worked. Dependent variables include actual weekly working hours measures individual's working time during survey reference week. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

on total actual working hours. Specifically, the role of the degree of automated equipments becomes significantly negative, indicating that 1 unit increase of the importance of automated equipments is associated with 3.45 hours increase of actual working time. Simultaneously, the negative responses of automated equipments on total actual working hours are mitigated by gross earnings, implying that with 1 pound increase of personal income, the impacts from the degree of automated equipments on actual working time will be flattened by 0.41 hours.

For Columns 3 and 4 in Table 4.3, I continue to examine the impacts from computerisation complexities. The estimation results suggest that neither computerisation complexities, nor their interaction with individual gross earnings, are statistically significant.

Overall, taking lagged effects into accounts, automation technologies have negative impacts on individual actual total working hours conditional on task intensities. Besides, rising individual income level could weaken the negative effects of automation technologies. These results are determined by various forces related to task intensities. However, a series of previous literature reveals that regression results of static and dynamic progress may be influenced by potential endogeneity issues. Therefore, I intend to address this endogeneity problem by employing a panel data IV approach.

4.4.4 IV Results

Up to now, this chapter provides empirical analysis about the correlation between automation technologies and individual actual working hours, utilising both static and dynamic panel data settings. However, previous research suggests that regression results of static and dynamic models may be influenced by potential endogeneity issues.

Although within-group transformation could make the estimation free of unobserved individual heterogeneities such as intrinsic abilities, the time-varying attributes of skills and abilities, which people acquired through on-the-job training and working experience, could also affect $Hour_{ij,t-1}$ via mean deviation[10]. Put simply, the time-varying components of intrinsic abilities could not only affect people's decisions to adjust their working time directly, but also interact with automation technologies through displacement ef-

[10]When conducting within-group transformation, we have to estimate this model by taking mean deviations of explained and explanatory variables

$$(Hour_{ijt} - \overline{Hour}_{ij}) = \beta_1'(Hour_{ij,t-1} - \overline{Hour}_{ij}) + \kappa + (\varepsilon_{ijt} - \overline{\varepsilon}_{ij}) \tag{4.3}$$

And we can also write

$$(Hour_{ij,t-1} - \overline{Hour}_{ij}) = \beta_1'(Hour_{ij,t-2} - \overline{Hour}_{ij}) + \kappa + (\varepsilon_{ij,t-1} - \overline{\varepsilon}_{ij}) \tag{4.4}$$

Therefore, $(\varepsilon_{ijt} - \overline{\varepsilon}_{ij})$ becomes an MA(1) process by construction. Then we can identify endogeneities in Equation 4.3 by fects and productivity effects. Therefore, I try to implement two-step variants of system GMM, to address these endogeneities under small-sample correction procedure (Windmeijer, 2005), which utilises lagged differenced variables or lagged level variables to instrument the endogenous variables.

Columns 1 and 2 of Panel A in Table 4.4 describe dynamic process of the impacts on total working hours in main job, conditional on task intensities. Utilising lagged level variables as instruments, the Arellano-Bond estimation presents inconsistencies compared to the previous analysis. Considering these ambiguous findings, further robust econometric analysis is necessary.

Technically, only on the occasion with the absence of overidentification and serial correlation, can we assure the validity of system GMM estimations (Arellano and Bond, 1991). However, autocorrelation analysis of working time based on Arellano-Bond test shows that, the variation of individual working hours exhibits an AR(1) process[11]. This temporal characteristic gives rise to the issue of weak instruments, which, as highlighted by Chao and Swanson (2005), constitutes a primary factor contributing to inconsistent estimations, particularly when the number of instruments is limited. To address this, I also implement Blundell-Bond method (also known as Arellano-Bover method) in Columns 3 and 4 of Table 4.4. This approach utilises lagged differenced variables to instrument

calculating

$$\begin{aligned} covariance &= cov[(Hour_{ij,t-1} - \overline{Hour}_{ij}), (\varepsilon_{ijt} - \overline{\varepsilon}_{ij})] \\ &= cov\{[\beta_1'(Hour_{ij,t-2} - \overline{Hour}_{ij}) + \kappa + (\varepsilon_{ij,t-1} - \overline{\varepsilon}_{ij})], (\varepsilon_{ijt} - \overline{\varepsilon}_{ij})\} \\ &= \sigma_{\overline{\varepsilon}_{ij}} + others \end{aligned} \tag{4.5}$$

Therefore, mean deviation of lagged dependent variable and mean deviation of idiosyncratic error are still correlated, which violates the weak exogeneity assumption and will finally lead to inconsistent estimation of β_1'.

[11]For the impacts of degree of automated equipments on total actual working hours, the correlation coefficient between $Hour_{ijt}$ and $Hour_{ij,t-1}$ is -0.914 with p-value of 0.36, and the second order correlation is 0.220 with p-value of 0.0448; for the impacts of computerisation complexities on total actual working hours, the correlation coefficient between $Hour_{ijt}$ and $Hour_{ij,t-1}$ is -0.934 with p-value of 0.350, and the second order correlation is 0.214 with p-value of 0.831; for the impacts of the degree of automated equipments on total usual working hours, the correlation coefficient between $Hour_{ijt}$ and $Hour_{ij,t-1}$ is -2.224 with p-value of 0.026, and the second order correlation is -0.693 with p-value of 0.488; for the impacts of computerisation complexities on total usual working hours, the correlation coefficient between $Hour_{ijt}$ and $Hour_{ij,t-1}$ is -2.379 with p-value of 0.017, and the second order correlation is -0.621 with p-value of 0.535. In other words, $(Hour_{ijt} - Hour_{ij,t-1})$ is not likely to be close to be a random walk, and weakly correlated with instrumental variable $Hour_{ij,t-2}$, which associated with weak instrument problem. To ensure the robustness of estimation results under dynamic panel data model, I continue to perform this regression.

Table 4.4: IV Estimates about Actual Working Time and Automation based on NS-SEC 2010, 2011-2018

	(1)	(2)	(3)	(4)
A. Total Actual Hours in Main Job and Automated Equipments				
$Hour_{t-1}$	-0.014	0.022	0.049	0.049
	(0.092)	(0.123)	(0.049)	(0.049)
$Auto\,Equip_t$	-4.498	-1.471	-1.351	-1.351
	(13.547)	(22.515)	(22.069)	(22.069)
$Auto\,Equip_t \times Income_t$		1.125	1.021	1.021
		(0.835)	(0.799)	(0.799)
N of Observations	38718	38718	38718	38718
R^2	0.051	0.050	0.051	0.050
B. Total Actual Hours in Main Job and Computerisation Complexities				
$Hour_{t-1}$	-0.023	-0.026	-0.038	-0.038
	(0.091)	(0.125)	(0.048)	(0.048)
$Computer_t$	-3.243	-2.032	-5.833	-5.833
	(2.655)	(1.496)	(5.269)	(5.269)
$Computer_t \times Income_t$		0.469	0.392	0.392
		(0.290)	(0.279)	(0.279)
N of Observations	38718	38718	38718	38718
R^2	0.118	0.117	0.117	0.117
Task Intensities	√	√	√	√
Year FE	√	√	√	√

Notes:
Based on NS-SEC 2010 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Based on Equation 4.2 with dependent variable of individual hours worked, Columns 1 and 2 describe the results of system GMM using Arellano–Bond method, and Columns 3 and 4 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include actual weekly working hours measures individual's working time during survey reference week. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

explanatory variables (Arellano and Bond, 1991; Blundell and Bond, 1998). To circumvent potential overfitting issues arising from instrument proliferation, the estimations of Columns 3 and 4 in Panel A of Table 4.4 are conducted using only first order lagged explanatory variables, and collapse the instrument set (Roodman, 2009).

Columns 3 and 4 of Panel A in Table 4.4 further study the dynamic process of the impacts on individual total actual working hours using Blundell-Bond method. The estimation results are insignificant, implying little space for improvements using dynamic panel data regressions.

For Panel B in Table 4.4, I continue to examine the impacts from computerisation complexities. The estimation results suggest that neither computerisation complexities nor their interaction with individual gross earnings are statistically significant.

For Panels A and B in Table 55 in Appendix, I further explore these impacts on total usual working hours. Columns 1 and 2 of Panel A present regression results about the impacts from the degree of automated equipments on total usual working hours. Specifically, the insignificant negative responses of automated equipments on total usual working hours are mitigated by gross earnings. This suggests that for every pound increase of personal income, the impacts about the impacts from the automated equipments on usual working time will be flattened by 0.59 hours. Turning to Panel B regarding the effects from computerisation complexities, similarly, only mitigating effects of gross earnings are statistically significant. This implies that, with 1 pound increase of personal income, the impacts of computerisation complexities on usual working time will be flattened by 0.23 hours.

In summary, adopting advanced panel data econometric methods, it is observed that automation technologies have negative impacts on individual actual total working hours and usual total working hours, conditional on task intensities. Besides, rising individual income level appears to weaken the negative effects of automation technologies. The next subsection will appraise the sensitivity of these results to alternative measures of task intensities.

4.4.5 Robustness Checks

Up to now, my analysis of individual level data from UK demonstrates that automation technologies are reducing individual total working hours. With growing income levels, such negative employment responses are likely to be mitigated. In this subsection, I introduce robustness checks based on various specifications.

Adopting alternative measures of industry level task intensities, Table 4.5 provides dynamic analysis based on SIC 2007. This analysis explores the impacts from automation technologies on individual total working hours in main job, conditional on task intensities. Columns 1 and 2 of Panel A present regression results about the impacts from the degree of automated equipments on total actual working hours. Specifically, the role played by degree of automated equipments turns to become significantly negative, indicating that 1 unit increase of the importance of automated equipments is associated with 5.41 hours decrease of actual working time. Simultaneously, the negative responses are mitigated by gross earnings, implying that with 1 pound increase of personal income, the impacts of automated equipments on actual working time will be flattened by 0.75 hours.

Considering intrinsic endogeneities within dynamic panel data model, Columns 3 and 4 of Panel A in Table 4.5 describe dynamic process of the impacts on total working hours in main job, conditional on task intensities. After Arellano-Bond estimation using lagged level variables as instruments, consistent results emerge compared with the previous analysis. The results show that 1 unit increase of the importance of automated equipments is associated with 6.07 hours decrease of actual working time, and rising personal income would mitigate the declining tendency by 0.85 hours. However, the estimation coefficient appears insignificant when the interaction terms with individual gross earnings are taking into accounts. These mixed results suggest the need for more robust econometric analysis.

Columns 5 and 6 of Panel A in Table 4.5 continue to examine the dynamic process of

Table 4.5: Dynamics about Actual Working Time and Automation based on SIC 2007, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Actual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.303***	-0.290***	-0.006	0.007	0.001	0.001
	(0.004)	(0.006)	(0.007)	(0.010)	(0.007)	(0.007)
$Auto\,Equip_t$	-5.413***	-2.268	-6.074***	-1.894	-2.001	-2.001
	(1.106)	(1.580)	(1.419)	(2.090)	(2.084)	(2.084)
$Auto\,Equip_t \times Income_t$		0.753***		0.851***	0.850***	0.850***
		(0.063)		(0.083)	(0.083)	(0.083)
N of Observations	187916	187916	187916	187916	187916	187916
R^2	0.034	0.037	0.146	0.159	0.145	0.163
B. Total Actual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.302***	-0.291***	-0.006	0.008	0.002	0.002
	(0.004)	(0.006)	(0.007)	(0.010)	(0.007)	(0.007)
$Computer_t$	-1.474***	-4.306***	-1.777***	-4.920***	-4.938***	-4.938***
	(0.330)	(0.487)	(0.418)	(0.647)	(0.646)	(0.646)
$Computer_t \times Income_t$		0.264***		0.297***	0.297***	0.297***
		(0.022)		(0.029)	(0.029)	(0.029)
N of Observations	188166	188166	188166	188166	188166	188166
R^2	0.021	0.022	0.057	0.051	0.056	0.056
Task Intensities	√	√	√	√	√	√
Year FE	√	√		√	√	√

Notes:

Based on SIC 2007 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 2 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 3 and 4 describe the results of system GMM using Arellano–Bond method, and Columns 5 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include actual weekly working hours measures individual's working time during survey reference week. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on SIC 2007. Other control variables regarding task intensities in levels are based on SIC 2007, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

impacts on individual total actual working hours, using Blundell-Bond method. The estimation results are significant only for interaction term between degree of automated equipments and individual gross earnings. This suggests that, with 1 pound increase of personal income, the impacts from the degree of automated equipments on actual working time will be flattened by 0.85 hours.

For Panel B in Table 4.5, the analysis shifts to the impacts from computerisation complexities, based on industry classification of SIC 2007. Columns 1 and 2 present regression results about the impacts from computerisation complexities on total actual working hours. The role played by computerisation complexities becomes significantly negative, indicating that 1 unit increase of computerisation complexities is associated with 1.47 hours decrease of actual working time. Simultaneously, the negative responses of computerisation complexities on total actual working hours are mitigated by gross earnings. This implies that, with 1 pound increase of personal income, the impacts of computerisation complexities on actual working time will be flattened by 0.26 hours.

Considering intrinsic endogeneities within dynamic panel data model, Columns 3 and 4 of Panel B in Table 4.5 describe dynamic process of the impacts on total working hours in main job, conditional on task intensities. Applying Arellano-Bond estimation method using lagged level variables as instruments, it exhibits consistent results compared with the previous analysis. The results show that, 1 unit increase of computerisation complexities is associated with 1.78 hours decrease of actual working time, and rising personal income would mitigate the declining tendency by 0.30 hours. Columns 5 and 6 of Panel B continue to examine dynamic process of impacts on individual total actual working hours, using Blundell-Bond method. Utilising lagged level variables as instruments, it produces consistent results compared with the prior analysis. We observe that 1 unit increase of computerisation complexities is associated with 4.94 hours decrease of actual working time, and rising personal income would mitigate the declining tendency by 0.30 hours.

For Panel A of Table 56 in Appendix, I continue to examine the impacts from degree of automated equipments on individual total usual working hours, based on industry classification of SIC 2007. Columns 1 and 2 indicate a significant, negative correlation between these variables. Specifically, 1 unit increase of the importance of automated equipments is associated with 4.62 hours drop of usual working time. At the same time, the negative responses are mitigated by gross earnings, implying that with 1 pound increase of personal income, the impacts from the importance of automated equipments on usual working time will be flattened by 0.71 hours.

Recognising the characteristics of dynamic panel data model, Columns 3 and 4 of Panel A in Table 56 in Appendix describe the dynamic process of the impacts on total usual working hours, conditional on task intensities. Applying Arellano-Bond estimation method using lagged level variables as instruments, it produces consistent results with the previous analysis. The results show that 1 unit increase of the importance of automated equipments is associated with 5.48 hours decrease of usual working time, and rising personal income continues to mitigate the declining tendency by 0.77 hours. Columns 5 and 6 further appraise this dynamic process utilising Blundell-Bond method. Again employing lagged level variables as instruments, the results remain consistent: 1 unit increase of the importance of automated equipments is associated with 2.16 hours decrease of usual working time, and rising personal income would mitigate the declining tendency by 0.77 hours.

Last, for Panel B in Table 56 of Appendix, I focus on the impacts from computerisation complexities on individual total usual working hours, based on industry classification of SIC 2007. Columns 1 and 2 present regression results about the impacts from computerisation complexities on total usual working hours. The results exhibit that computerisation complexities have significant negative effects on total usual working hours: 1 unit increase of computerisation complexities is associated with 1.58 hours drop of usual working time. However, the negative responses are mitigated by gross earnings, implying that with 1 pound increase of personal income, the impacts of computerisation complexities on usual working time will be flattened by 0.25 hours.

Table 4.6: Dynamics about Actual Working Time and Automation based on S0C 2010, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Actual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.302***	-0.288***	-0.005	0.010	0.003	0.003
	(0.004)	(0.005)	(0.007)	(0.009)	(0.007)	(0.007)
$Auto\,Equip_t$	-4.208***	-2.741	-5.740***	-4.141	-4.112	-4.112
	(1.451)	(2.049)	(1.844)	(2.682)	(2.675)	(2.675)
$Auto\,Equip_t \times Income_t$		0.515***		0.593***	0.592***	0.592***
		(0.066)		(0.086)	(0.086)	(0.086)
N of Observations	192555	192555	192555	192555	192555	192555
R^2	0.064	0.065	0.129	0.150	0.129	0.150
B. Total Actual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.302***	-0.288***	-0.005	0.010	0.003	0.003
	(0.004)	(0.005)	(0.007)	(0.009)	(0.007)	(0.007)
$Computer\_t$	-2.383***	-1.616*	-3.111***	-2.441**	-2.440**	-2.440**
	(0.664)	(0.915)	(0.851)	(1.216)	(1.213)	(1.213)
$Computer_t \times Income_t$		0.180***		0.211***	0.210***	0.210***
		(0.023)		(0.030)	(0.030)	(0.030)
N of Observations	192555	192555	192555	192555	192555	192555
R^2	0.021	0.021	0.050	0.048	0.050	0.048
Task Intensities	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Year FE	$\surd$	$\surd$		$\surd$	$\surd$	$\surd$

Notes:
Based on SOC 2010 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 2 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 3 and 4 describe the results of system GMM using Arellano–Bond method, and Columns 5 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include actual weekly working hours measures individual's working time during survey reference week. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on SOC 2010. Other control variables regarding task intensities in levels are based on SOC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Considering the endogeneities within dynamic panel data model, Columns 3 and 4 of Panel B in Table 56 describe the dynamic process of the impacts on total usual working hours in main job, conditional on task intensities. Adopting Arellano-Bond estimation method using lagged level variables as instruments, the results are consistent with the analysis above, as 1 unit increase of computerisation complexities is associated with 1.87 hours drop of usual working time, and rising personal income would mitigate the declining tendency by 0.27 hours. Columns 5 and 6 of Panel B continue to examine the dynamic process of impacts on individual total usual working hours using Blundell-Bond method. After utilising lagged level variables as instruments, the results are again consistent with the previous analysis: 1 unit increase of computerisation complexities is associated with 3.66 hours decrease of usual working time, and rising personal income would mitigate the declining tendency by 0.27 hours.

Finally, I also implement alternative measures of occupation level task intensities, and provide dynamic analysis based on SOC 2010 in Table 4.6 to explore the impacts from automation technologies on individual total working hours in main job, conditional on task intensities. In Table 57 of Appendix, I continue to examine the impacts on total usual working hours. The estimation results are insensitive to findings with alternative industry classification systems.

Up to this point, my analysis suggests that the automation technologies has negative impacts on individual total working hours conditional on task intensities, particularly when considering lagged effects[12]. Besides, rising individual income level could weaken the negative effects of automation technologies, which is consistent with the evidence from US analysis and cross country analysis. These findings are determined by various forces of task intensities.

However, it is important to acknowledge that even the use of advanced econometric techniques in dynamic panel data settings cannot fully address the biases in estimation. Therefore, future empirical research would benefit from a more profound exploration of exogenous variations, in the penetration to automation technologies at the individual level.

[12] Such hypothesis as human capital accumulation, precautionary saving motives and adjustment costs could give explanations regarding lagged effects of intertemporal working hour changes (Keane and Rogerson, 2015).

4.5 Heterogeneous Analysis

This section turns to investigate heterogeneous effects across UK individual workers, based on education status and living regions. Such a comprehensive micro level dataset has the potential to yield valuable insights into the employment patterns across various demographic groups.

4.5.1 By Education Groups

In this subsection, I examine this heterogeneity in great detail by dividing UK workers into two mutually exclusive groups, namely those with college education[13] and those without college education. The analysis will employ a dynamic panel data model based on Equation 4.2, which takes lagged effects into accounts, and present results derived from both Arellano-Bond method and Blundell-Bond method.

Table 4.7 shows regression results of the impacts from automation technologies on individual total actual working hours, by education status. Panel A points to the coefficient estimation regarding the degree of automated equipments. For within group estimation results of college educated workers presented in Column 1, it is discovered that 1 unit decrease of the importance of automated equipments is associated with 5.21 hours increase of actual working time. To address potential endogeneity bias introduced by time varying components of intrinsic abilities, I then implement Arellano-Bond method in Column 2, and adopt Blundell-Bond method in Column 3. Both of them yield qualitatively similar results to Column 1. For the preferred specification in Column 3, 1 unit increase of the importance of automated equipments is associated with 1.35 hours drop of actual working time. This suggests a downward bias in within group estimation, aligning with the analysis in the previous section.

[13] In this section, "college education" refers to both university education, college education, and other college equivalent education.

Table 4.7: Actual Working Time, Automation and Education based on NS-SEC, 2011-2018

	College Educated Workers			Non-College Educated Workers		
	Within Group	IV		Within Group	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Actual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.305***	0.022	0.049	-0.298***	0.034	0.043
	(0.023)	(0.123)	(0.049)	(0.024)	(0.122)	(0.048)
$Auto\,Equip_t$	-5.208*	-1.471***	-1.351***	-5.095*	-1.428	-1.384
	(2.659)	(0.225)	(0.221)	(2.715)	(2.317)	(2.235)
$Auto\,Equip_t \times Income_t$	0.407*	1.125*	1.021*	0.510**	1.145	0.997
	(0.239)	(0.835)	(0.799)	(0.245)	(0.820)	(0.788)
N of Observations	72716	72716	72716	69865	69865	69865
R^2	0.051	0.050	0.013	0.014	0.051	0.050
B. Total Actual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.305***	0.026	0.038	-0.298***	0.038	0.034
	(0.023)	(0.125)	(0.048)	(0.024)	(0.122)	(0.048)
$Computer\_t$	-9.696*	-2.032*	-5.833***	-6.676*	-1.952	-6.418
	(7.378)	(1.496)	(0.527)	(7.619)	(1.531)	(5.705)
$Computer_t \times Income_t$	0.167*	0.469*	0.392***	0.207**	0.478*	0.397
	(0.087)	(0.290)	(0.279)	(0.089)	(0.284)	(0.276)
N of Observations	72716	72716	72716	69865	69865	69865
R^2	0.014	0.015	0.051	0.050	0.051	0.050
Task Intensities	√	√	√	√	√	√
Year FE	√	√	√	√	√	√

Notes:
Based on NS-SEC 2010 job classification system, the table presents within group and IV estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 4 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 2 and 5 describe the results of system GMM using Arellano–Bond method, and Columns 3 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include actual weekly working hours measures individual's working time during survey reference week. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Turning to coefficient estimations for non-college educated workers, the results in Columns 4 to 6 reveal insignificant impacts from the degree of automated equipments on individual total actual working hours. This lack of significance may be attributed to the lower exposure of automation technologies, leading to insignificant employment responses.

In Panel B of Table 4.7, I report the regression results regarding computerisation complexities. For the preferred specification adopting Blundell-Bond method, Column 3 reveals that rising computerisation complexities are reducing individual total actual working hours. With 1 unit increase of computerisation complexities, the individual total actual working hours tend to decline by 5.83 hours. The positive coefficients for the interaction term between computerisation complexities and personal gross earning, indicate mitigating impacts from income levels. Furthermore, the results in Columns 4 to 6 reveal insignificant impacts from computerisation complexities on individual total actual working hours. These findings are consistent with Panel A, implying that such technical changes are more pronounced among high skilled workers.

For Panels A and B in Table 58 of Appendix, I continue to examine the impacts on total usual working hours. All the estimation results remain consistent across various specifications. Therefore, by examining heterogeneous effects of automation technologies on individual total working hours, it is discovered that technical changes are more pronounced for high skilled workers, characterised by their affluent human capital accumulations.

4.5.2 By Regions

In this subsection, I further explore this heterogeneity in another dimension, by dividing UK workers into two mutually exclusive groups, namely those living in London and those residing outside London. This distinction is particularly relevant, given that empirical analysis based on both US evidence in Chapter 2 and cross country evidence in Chapter 3, highlight regional variations of employment responses to automation technologies.

The following analysis employs a dynamic panel data model based on Equation 4.2, which takes lagged effects into accounts, alongside results adopting Arellano-Bond method.

Table 4.8: Actual Working Time, Automation by Regions based on NS-SEC, 2011-2018

	Within London		Outside London	
	(1)	(2)	(3)	(4)
Dependent Variable: Actual Working Hours				
$Hour_{t-1}$	-0.212**	-0.227**	-0.317***	-0.317***
	(0.102)	(0.098)	(0.024)	(0.024)
$Auto\,Equip_t$	-5.452***		-4.093*	
	(0.948)		(2.916)	
$Computer\_t$		-1.380***		-8.813
		(0.249)		(8.343)
$Auto\,Equip_t \times Income_t$	1.603***		0.369*	
	(0.109)		(0.255)	
$Computer_t \times Income_t$		0.645*		0.151*
		(0.405)		(0.092)
N of Observations	2866	2866	28578	28578
R^2	0.154	0.153	0.147	0.147
Task Intensities	√	√	√	√
Year FE	√	√	√	√

Notes:
Based on NS-SEC 2010 job classification system, the table presents IV estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Based on Equation 4.2 with dependent variable of individual hours worked, this table describe the results of system GMM using Arellano–Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include actual weekly working hours measures individual's working time during survey reference week. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8 shows the regression results of the impacts from automation technologies on individual total actual working hours by regions. It is expected that the dynamics of labour supply would be more pronounced within London, due to concentration of manufacturing sectors in the area, as suggested in Section 2.6 of Chapter 2.

Columns 1 and 2 present the coefficient estimations regarding degree of automated equipments. For panel data regression results of workers living within London, it is discovered that 1 unit increase of the importance of automated equipments is associated with 5.45 hours decline of actual working time, and those driven by computerisation complexities are reduced by 1.38 hours. In addition, the positive coefficients for gross earnings indicate mitigating effects from rising income levels.

Shifting our attention to estimations for people living outside London, Columns 3 and 4 reveal relatively less significant impacts from automation exposure in other areas[14]. This is consistent with the analysis in Section 2.6 of Chapter 2. Because the impacts of automation technologies on labour market outcomes are more prominent in regions with high GDP share attributed to manufacturing sectors. Therefore, people in London, the largest city with intensive manufacturing establishments in the UK, tend to become more susceptible to the effects of automation adoptions.

For Table 59 in Appendix, I continue to examine the impacts on total usual working hours. The findings remain consistent across various specifications. Therefore, by examining heterogeneous effects of automation technologies on individual total working hours, it is discovered that technical changes are more pronounced in regions with a high concentration of manufacturing sectors such as London.

4.6 Summary

This chapter also offers insights into the impacts of automation technologies on labour market outcomes. In contrast with US evidence in Chapter 2 and cross country analysis in Chapter 3, this chapter turns to focus on UK context, to conduct individual level analysis.

[14] Although some of the coefficients are significant at confidence level of 10%, they are sensitive to different measures of automation technologies. For example, the coefficient for computerisation complexities in Column 4 is insignificant.

Utilising comprehensive worker level data from 2011 to 2018, this study indicates that growing exposure of automation technologies, measured by degree of automated equipments and computerisation complexities, translates to declines of individual total working hours. Moreover, the rise of income levels could mitigate such negative employment responses. On average, 1 unit increase of the importance of automated equipment is associated with 2.29 hours increase of actual working time. For each additional pound of gross earnings, the impacts of degree of automated equipments on actual working time will be flattened by 0.36 hours. This result is consistent with the EU evidence by Graetz and Michaels (2018), which showed that one additional robot per thousand labour force could reduce working time by 1.22 hours for high skilled workers, and 8.59 hours for low skilled workers[15].

In addition, this study employs advanced panel data econometric methods to address endogeneity concerns. Utilising both Arellano-Bond method and Blundell-Bond method, along with robustness checks regarding various occupation systems, the results demonstrate consistency across different specifications.

Drawing on the findings presented in Section 2.6 of Chapter 2, this heterogeneous analysis incorporates educational attainments and geographical locations as key factors. The results indicate that negative employment responses to automation technologies, and mitigating effects from income levels, are more pronounced among college educated workers. This is consistent with findings in Chapter 2, implying that such technological change is biased towards high skilled workers (Graetz and Michaels, 2018).

Furthermore, by dividing UK workers into people living within London and those living outside London, it is uncovered that such heterogeneous effects are more pronounced among London-based workers. Taking structural change into accounts, these evidence support the notion that production workers in manufacturing industries could benefit from

[15] As suggested in Figure 4.1, the development of automation technologies in UK is lower than average value of automation adoptions in Europe, that is why the results of displacement effects for UK are slightly lower than those for European Union.

productivity effects, and thus more exposed to technological changes.

This section also points out some challenges and future directions for individual level analysis.

Firstly, as noted in Section 4.4.4, the regression results of both static and dynamic models may be influenced by potential endogeneity issues. For example, the time-varying components of skills and abilities, which people acquired through on-the-job training and working experience, may directly affect individual working hours. Besides, the ability to use machines is considered to be correlated with automation exposures. This chapter builds on advanced panel data models, and utilises Arellano-Bond method and Blundell-Bond method to obtain relatively consistent estimation results. However, these two approaches cannot fully address the endogenous concerns arising from time invariant individual abilities. Therefore, further analysis with appropriate identification strategies would be more valuable.

Secondly, utilising comprehensive datasets and selecting a suitable indicator of automation technologies to perform individual level analysis is challenging. This chapter draws on data from Skills and Employment Survey in 2006, 2012 and 2017, to obtain information about individual responses to automated equipments and computerisation. Averaging these scores across occupations or industries, presents a measure of job characteristics each year. However, this approach ignores individual heterogeneities within occupations and industries, making it hard to identify heterogeneous employment effects from automation technologies across UK workers. Relying on novel datasets, more in-depth research on exogenous variations in individual responses, such as through event studies based on specific policies, might be a promising direction for future empirical implications.

Thirdly, the heterogeneous labour market impacts from automation technologies, can also be influenced by institutional settings. In European countries where union plays an important role in the determinations of employment and wage, the introduction of automation technologies may not have significantly negative impacts on individual total working hours (Dauth et al., 2021). Furthermore, in other economies with high trade openness, the offshoring policies by developed countries could also affect individual responses to automation technologies (Kugler et al., 2020). Therefore, research accounting for institutional factors and international trade would be another potential avenue for explorations.

Overall, these findings produce several policy implications.

Firstly, as technical changes are biased against low skilled workers, encouraging individuals to enhance their human capital is crucial. This can be achieved through increased access to education, or participation in on-the-job training programs. Therefore, it would enable them to remain competitive in the face of automation, or facilitate the transition to new roles driven by productivity effects. Addressing this skill gap represents a potential avenue for policies aiming to deal with high unemployment rate.

Secondly, as the productivity effects from automation technologies are beneficial for workers in manufacturing sectors, a continued emphasis on boosting manufacturing industries is necessary. This approach could offer employment opportunities for individuals displaced from other automated sectors, while simultaneously enhancing overall productivity, thereby contributing to sustainable economic growth.

Chapter 5

Conclusion

Automation seems to influence employment differently depending on the income level of each country, region, and worker. This thesis leverages comprehensive US commuting zone level data, cross country data, and UK worker level data, to provide a unified analysis regarding the impacts of automation technologies on labour market outcomes. In addition, it evaluates mechanisms based on responses of workers with different skill levels and industries, under forces of displacement effects and productivity effects. The results remain consistent under the IV approach and across different specifications.

5.1 Key Findings

The thesis focuses primarily on US evidence. Chapter 2 reveals that rising penetration of automation technologies, including industrial robots and ICT (Information and Communication Technologies) trade volumes, corresponds to reductions in employment rate across all commuting zones. The rise of 1 unit robot per thousand labour force could generate job losses by 0.67 percentage points. The magnitudes of these negative employment responses are more sizeable and significant in low- and middle-income areas. For instance, 1000 unit increase in robotic stocks per worker will lead to a drop of 0.87 percentage points in employment rate over the period 2000-2019. The evidence implies that displacement effects are the prevailing force in the process of technology updating, particularly for those with rising proportion of routine occupations. While mitigating effects of income levels suggest that productivity effects may flatten some of the welfare deteriorations, caused by displacement effects. Specifically, the job losses are more substantial in areas from middle income group, as the concentration of routine occupations would make production workers more susceptible to automation adoptions.

Motivated by the task-based conceptual framework, these patterns can be explained by a simple net job creation channel. After adopting automation technologies, job displacement occurs across all regions. In high income CZs, new vacancies arise in other non-automated sectors, where high skilled labour forces are required in most cases. A larger proportion of university educated workers raises the possibility of successful matches in these regions. Nonetheless, relatively lower percentage of skilled workers in low and middle income CZs limits opportunities for such job creations, leading to substantial employment losses. As a consequence, growing income levels could suppress the absolute magnitudes of negative employment effects, and partially alleviate the welfare deterioration. Encouragingly, the analysis reveals that such technological change is biased towards high skilled workers (Graetz and Michaels, 2018), and causes welfare improvement for them, as new roles primarily emerge for university graduates. Factoring in structural change, production workers in manufacturing industries could benefit from productivity effects, with significant differential effects across sub-sectors within manufacturing.

Moreover, regression results from cross country analysis indicate the potential to generalise the implications for global economic growth. The findings of Chapter 3 demonstrate that rising penetration of automation technologies, including industrial robots and ICT investments, corresponds to reductions in employment rate across all countries. Adopting novel shift share IV approach based on differential ageing trends, this study also discovers that rising income levels could mitigate such technological unemployment. Interestingly, heterogeneous analysis based on OECD countries and non-OECD countries reveals that differential employment dynamics induced by automation technologies, along with mitigation effects from income levels, are only observable in advanced economies. The evidence confirms that heterogeneous employment effects of automation technologies are prevalent in regions with intensive manufacturing activities.

This study also leverages a comprehensive UK dataset, and finds consistent results when focusing on individual behaviours. In contrast to US evidence and cross country evidence, Chapter 4 adopts advanced panel data econometric techniques, such as Arellano-Bond method and Blundell-Bond method, to address endogeneity issues arising from unobserved intrinsic abilities. The findings indicate that growing exposure to automation technologies, measured by degree of automated equipments and computerisation complexities, translates to declines of individual total working hours. Moreover, rising income levels could mitigate such negative employment responses. Encouragingly, the analysis reveals that negative employment responses from automation technologies, and mitigating effects from income levels, are more pronounced among college educated workers. The evidence confirms that such technological change is biased towards high skilled workers. Moreover, the study uncovers that such heterogeneous effects are more pronounced for workers in London, which is also consistent with the analysis about technology updating and structural changes.

In the existing literature, this research connects with several empirical studies on the effects of technological adoption on labour market outcomes, and makes three strands of contributions.

The first main contribution is to explore the heterogeneous effects of technological adoptions across regions from different income groups. While previous research has focused on general measures of technological updating such as TFP (total factor productivity) growth and patent awards across different countries (Autor and Salomons, 2018; Autor et al., 2020), this study employs two complementary indicators, namely robotic density and ICT intensity. These specifications allow for a differentiation between productivity growth originating from automated and non-automated sectors.

In addition, the analysis on regional variations of technological unemployment also complements a vast body of literature on RBTC (Routine Biased Technical Change). (Autor and Dorn, 2013; Goos et al., 2014; Graetz and Michaels, 2017). Others have identified the phenomenon of job polarisation in western developed countries, and showed how automation could replace labour forces in occupations located at the middle of skill percentiles with routine tasks, and cause positive employment and wage effects in other occupations. Departing from previous occupational level analysis, this thesis yields novel insights on RBTC across regions. It emphasises that job displacement due to automation is likely to be more pronounced in middle income regions, compared with low income regions. This difference is attributed to the concentration of routine occupations in middle income regions.

For the second main contribution, this thesis builds upon research exploring the effects of skill shares and industrial structures on net job creation, causing heterogeneous employment effects from automation technologies. Recent work by Acemoglu and Restrepo (2021) has evaluated how educational upgrading affects automation adoption, reflecting the fact that growing educational attainment could result in scarcity of production workers in blue collar jobs. The resulting wage increases for manufacturing workers, coupled with decline of participation rate, will finally provide great opportunities for automation. This thesis departs from previous studies, by shifting the focus from low skilled workers to high skilled labour force, to demonstrate a unique channel. With intensive growth of highly educated workers, supply effect appears to generate stronger productivity effects, and act as the primary driver of rising employment in advanced economies. In addition, such effects are more pronounced in manufacturing industries.

For the third main contribution, this thesis sheds light on the fact that net employment effects primarily result from differentials in productivity effects, as measured by job creations. In contrast, job destructions, a suitable proxy of displacement effects, are widespread across regions. In terms of mechanisms, this study complements the work of Acemoglu and Restrepo (2020, 2022); Bonfiglioli et al. (2021); Dauth et al. (2021), and confirms that job creations[1] typically benefits high skilled workers with advanced education, while welfare deteriorations from unemployment are concentrated among labour force from low skilled groups.

5.2 Limitations and Future Works

As noted in Section 1.2 of Chapter 1, research concerning the effects of technological changes on labour market outcomes often encounters significant challenges, including methods to deal with identification issues, data quality and measurement errors, as well as future works to deal with influence from institutional settings and international trade.

Firstly, research about employment effects of automation technologies is often threatened by endogenous factors, such as spillover effects and reverse causalities, which are addressed in Section 2.5 of Chapter 2. For US evidence, this study follows most existing literature, and adopts shift share IV approach, assuming that European automation could only affect US employment exclusively through US automation. Although the robotic densities of sample European countries in Chapter 2 are higher than their US counterparts, the technological spillover from US to Europe cannot be neglected. Therefore, studies containing detailed information of robots (Graetz and Michaels, 2018), or adopting other policy shocks to address these concerns (Bloom et al., 2015), may provide directions for future research.

In addition, Chapter 3 extends the shift share IV approach, based on the ageing trends

[1] Here "job creation" refers to rising job vacancies in incumbent occupations, rather than creation of new occupations or new tasks, as the latter only applies in the context of artificial intelligence.

in different countries. Nonetheless, there are concerns about the intuitions of plausibly exogenous conditions, as the labour force participation rate tends to be higher among young workers, and lower among old workers, especially in developed countries. As a consequence, whether or not people could implement IV estimation using demographic changes remains unexplored. A more in-depth research uncovering exogenous variations in penetration to automation technologies across countries is a promising direction for future empirical implications.

For individual level analysis, Chapter 4 provides analysis about endogeneity issues arising from time varying intrinsic abilities. It builds on advanced panel data models, and utilises Arellano-Bond method and Blundell-Bond method, to obtain relatively consistent estimation results. However, these two approaches are not able to deal with endogenous concerns arising from time invariant individual abilities. Therefore, a more comprehensive analysis with appropriate identification strategies would be more valuable.

Secondly, obtaining comprehensive datasets and selecting a suitable indicator of automation technologies, is challenging. Early work has focused on general measures of technological updating such as TFP (total factor productivity) growth and patent awards across different countries (Autor and Salomons, 2018; Autor et al., 2020). Yet they fail to distinguish between productivity growth originating from automated and non-automated sectors. Chapter 2 and Chapter 3 follow recent literature, such as Acemoglu and Restrepo (2020), which utilised International Federation of Robotics (2021) to perform empirical analysis, In addition, I adopt data about US ICT import and export from bilateral trade statistics of Comtrade database (United Nations, 2020), and ICT capital data from Total Economy Database of The Conference Board (2021), to obtain a comprehensive picture of the relationship between automation technologies and employment. However, the adoptions of these datasets may face challenges when generalising to cross country analysis, as the quality of robots may vary across regions. Relying on novel datasets, other ICT indicators, or patent awards about automation technologies, such as those in Autor et al.

(2020); Bloom et al. (2015), might be a good indicator for the development of automation technologies in future research.

Furthermore, it is also necessary to identify individual level exposures to automation technologies. Chapter 4 draws on information about average scores of automation exposures from industry level or occupation level. However, this approach ignores individual heterogeneities within occupations and industries, making it hard to identify heterogeneous employment effects from automation technologies across UK workers. A more in-depth research based on individual responses to automation technologies is more interesting.

Thirdly, whether automation technologies have positive or negative impacts on employment rate, can also be influenced by institutional settings. Due to unions, old workers in Germany are not easily replaced by robots (Dauth et al., 2021), even though some are low skilled workers. In other economies with trade openness, firms may tend to relocate production activities to developing countries, thus affecting the adoption of automation technologies.

In addition, the wave of AI (artificial intelligence) may also promote employment through reinstatement effects. In contrast to conventional automation technologies, the adoption of artificial intelligence could have positive impacts on employment rate through job creations in both existing and emerging occupations. Therefore, identifying these new jobs would be a valuable contribution to future research. Previous work by Acemoglu et al. (2022a); Webb (2019) used data from the Burning Glass to identify the AI requirements from job descriptions. However, this approach only allows us to observe ”new” jobs, but does not capture changes in existing jobs (if they are different from ”new” jobs) or disappeared jobs in the job ads data. Therefore, a more comprehensive analysis into the impacts of AI on labour market outcomes would be more interesting.

Another potential avenue for exploration is the role of international trade, as automation reshapes the relative labour costs, which is the determinant of international competitiveness (Rodrik, 2018). At the same time, facing international trade, even with cost effective labour, the firm owner may still choose to use machine. According to the task based framework in Section 2.5 of Chapter 2, when the wage of low skilled workers exceeds the price of machines, the firm owners may favour machines over labour. Whereas, when low skilled wages are below the price of machines, the firms may still choose to employ workers. However, the dynamics change when we introduce international trade. For instance, confronting with comparative advantage of lower labour costs of China, US firms in labour intensive industries may find themselves unable to compete without adopting automation, even when low skilled wages are below the price of machines.

Considering offshoring activities, declining production costs and rising productivity would motivate firm owners to expand output demand for other inputs, including automation (Hummels et al., 2014). Differentiating between the effects of import competition and offshoring would be a valuable contribution. Event studies based on the removal of product-specific quotas following China's entry into WTO (the World Trade Organisation) in 2001 could be employed to address endogeneity concerns (Bloom et al., 2015).

In conclusion, with novel datasets and appropriate identification strategies, both empirical studies exploring heterogeneous effects under diverse institutional settings, and theoretical models incorporating roles of skill upgrading, hold significant promise as directions for future research.

5.3 Policy Implications

Regional variations in employment responses to technological advancements have significant policy implications, particularly in reducing technological unemployment and enhancing labour market conditions. For workers in high income regions, policies can be implemented to encourage on-the-job training, enabling high skilled workers to remain abreast of currently advanced technological development. Therefore, they can become less likely to be replaced by machines. For workers in middle income regions, the acquisition of non-routine skills could prove invaluable. Meanwhile, for workers in low income regions, human capital accumulation remains an effective strategy, and policies could prioritise investments in manual skills development.

In recent years, the UK government has implemented several policies to raise the employment rate and boost the economy. One such instance is the government's plan to raise the minimum wage level in 2023 (GOV.UK, 2023). Similar to the outcomes observed after the last minimum wage reform in 1999, it is expected to see an increase of wage of low skilled workers, potentially protecting the livelihoods of production workers. However, with the adoption of automation technologies in the 21th century, presents a significant risk of labour displacement, as machines become increasingly capable of replacing human workers. Therefore, policy evaluations are crucial in the future.

The analysis of this thesis also offers insights for government policies in the post-pandemic era. For instance, confronting with labour shortages exacerbated by Brexit and COVID 19 pandemic, the UK government launched the policy about Post-Study Work (PSW) visa in 2021 (GOV.UK, 2023). This policy sought to attract high skilled workers, particularly those with postgraduate qualifications. This policy could promote productivity effects from automation technologies to some extent, as it provides a sufficient pool of high skilled workers for non-automated sectors. However, with growing penetration of other technologies like ChatGPT and other forms of AI, it becomes important to consider how to offer on-the-job training, to reduce the possibility to be replaced by other technologies.

Therefore, it is essential to consider policies aiming to raise human capital. For school education and college education, protecting students from any disruptions such as COVID 19 pandemic, is paramount. Moreover, policies about investment in education expenditures are also important. While for those already in the workforce, offering on the job training could help reduce the risks of job displacement, due to automation technologies.

This analysis offers several policy implications.

Firstly, as technical changes are biased against low skilled workers, encouraging people to accumulate more human capital is essential. This can be achieved through further education or participation in on-the-job training. Therefore, such measures would help workers remain competitive in the face of automation technologies, and facilitate their transition to new roles driven by productivity effects. This approach represents a potential avenue for policies that aim to address high unemployment rates.

Secondly, as the productivity effects from automation technologies are beneficial for the workers in manufacturing sectors, a continued focus on boosting manufacturing industries is necessary. It could not only accommodate displaced workers from other automated sectors, but also raise the overall productivity, which would be helpful for sustainable economic growth.

Thirdly, when formulating policies for the adoption of new technologies, the local governments should consider the stages of economic development for given areas. As the employment responses to automation vary across regions with different income levels, automation adoptions in high income regions would be beneficial for productivity improvement, while the introduction of automation technologies in low and middle income regions would lead to substantial job losses. Therefore, it is important to consider the specific development stages and status quo of each region during policy implementations.

Bibliography

Acemoglu, D. (2024). The Simple Macroeconomics of AI. Working Paper 32487, National Bureau of Economic Research. 7

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier. 3, 5, 6, 12, 17

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022a). Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics*, 40(S1):S293–S340. 16, 17, 191

Acemoglu, D., Autor, D. H., and Lyle, D. (2004). Women, War, and Wages: The Effect of Female Labor Supply on the Wage Structure at Midcentury. *Journal of Political Economy*, 112(3):497–551. 160

Acemoglu, D., De Feo, G., and De Luca, G. D. (2019). Weak States: Causes and Consequences of the Sicilian Mafia. *Review of Economic Studies*, 87(2):537–581. 61, 136

Acemoglu, D., Johnson, S., and Robinson, J. A. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation. *American Economic Review*, 91(5):1369–1401. 7, 61, 136

Acemoglu, D., Koster, H. R. A., and Ozgen, C. (2023). Robots and Workers: Evidence from the Netherlands. Working Paper 31009, National Bureau of Economic Research. 11, 13, 108

Acemoglu, D. and Loebbing, J. (2022). Automation and Polarization. Working Paper 30528, National Bureau of Economic Research. 15, 29

Acemoglu, D., Mühlbach, N. S., and Scott, A. J. (2022b). The Rise of Age-Friendly Jobs. *Journal of the Economics of Ageing*, 23:100416. 12

Acemoglu, D. and Restrepo, P. (2018a). Artificial Intelligence, Automation and Work. Working Paper 24196, National Bureau of Economic Research. 6, 16, 17

Acemoglu, D. and Restrepo, P. (2018b). Modeling Automation. *AEA Papers and Proceedings*, 108:48–53. 3, 8, 12

Acemoglu, D. and Restrepo, P. (2018c). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108(6):1488–1542. 6

Acemoglu, D. and Restrepo, P. (2019a). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2):3–30. 3, 4, 5, 6, 7, 8, 10

Acemoglu, D. and Restrepo, P. (2019b). The Wrong Kind of AI? Artificial Intelligence and the Future of Labour Demand. *Cambridge Journal of Regions, Economy and Society*, 13(1):25–35. 6, 7, 17

Acemoglu, D. and Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244. 2, 4, 11, 13, 15, 16, 21, 22, 27, 29, 30, 31, 35, 36, 39, 41, 42, 50, 52, 57, 58, 60, 61, 63, 66, 91, 104, 105, 110, 115, 128, 131, 133, 135, 145, 151, 153, 189, 190

Acemoglu, D. and Restrepo, P. (2021). Demographics and Automation. *Review of Economic Studies*, 89(1):1–44. 16, 17, 20, 22, 27, 29, 30, 31, 35, 41, 61, 62, 104, 110, 111, 113, 115, 124, 137, 188

Acemoglu, D. and Restrepo, P. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica*, 90(5):1973–2016. 2, 4, 7, 13, 15, 16, 21, 27, 29, 58, 59, 133, 134, 189

Adachi, D. (2021). Robots and Wage Polarization: The Effects of Robot Capital by Occupations. Technical report, mimeo. 4

Aghion, P., Jones, B. F., and Jones, C. I. (2017). Artificial Intelligence and Economic Growth. Working Paper 23928, National Bureau of Economic Research. 1, 6, 57, 58, 61, 132, 134, 136

Agrawal, A., Gans, J. S., and Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, 33(2):31–50. 7, 10, 16

Ahituv, A. and Zeira, J. (2010). Technical Progress and Early Retirement. *Economic Journal*, 121(551):171–193. 140

Akerman, A., Gaarder, I., and Mogstad, M. (2015). The Skill Complementarity of Broadband Internet. *Quarterly Journal of Economics*, 130(4):1781–1824. 17

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2018). Polarization and Rising Wage Inequality: Comparing the US and Germany. *Econometrics*, 6(2):20. 12, 13, 108

Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58(2):277–297. 151, 168, 169

Autor, D. and Dorn, D. (2009). This Job is "Getting Old": Measuring Changes in Job Opportunities Using Occupational Age Structure. *American Economic Review*, 99(2):45–51. 12, 16, 58, 133, 160

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., and Shu, P. (2020). Foreign Competition and Domestic Innovation: Evidence from US Patents. *American Economic Review: Insights*, 2(3):357–74. 20, 28, 105, 106, 110, 145, 146, 150, 187, 190

Autor, D. and Salomons, A. (2018). Is Automation Labor Share–Displacing? Productivity Growth, Employment, and the Labor Share. *Brookings Papers on Economic Activity*, pages 1–63. 1, 20, 28, 105, 110, 145, 150, 187, 190

Autor, D. H. (2013). The "Task Approach" to Labor Markets: An Overview. *Journal for Labour Market Research*, 46(3):185–199. 4, 14, 15, 17, 158

Autor, D. H. (2014). Skills, Education, and the Rise of Earnings Inequality among the "Other 99 Percent". *Science*, 344(6186):843–851. 1, 150

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3):3–30. 1, 4, 6, 15, 17

Autor, D. H. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5):1553–1597. 12, 14, 20, 22, 27, 29, 40, 47, 54, 55, 188

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–2168. 30, 31, 40, 47, 51, 57, 58, 59, 60, 61, 132, 134, 136, 224

Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling Trade and Technology: Evidence from Local Labour Markets. *Economic Journal*, 125(584):621–646. 102

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics*, 90(2):300–323. 9

Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing Inequality: Have Computers Changed the Labor Market? *Quarterly Journal of Economics*, 113(4):1169–1213. 15

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4):1279–1333. 3, 12, 29, 39, 47, 51, 129

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute. 58, 134

Beaudry, P., Green, D. A., and Sand, B. (2014). The Declining Fortunes of the Young since 2000. *American Economic Review*, 104(5):381–386. 160

Beaudry, P., Green, D. A., and Sand, B. M. (2016). The Great Reversal in the Demand for Skill and Cognitive Tasks. *Journal of Labor Economics*, 34(S1):199–247. 9, 58, 133

Benmelech, E. and Zator, M. (2022). Robots and Firm Investment. Working Paper 29676, National Bureau of Economic Research. 36, 42

Berman, E., Bound, J., and Griliches, Z. (1994). Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers. *Quarterly Journal of Economics*, 109(2):367–397. 12, 14, 159

Bisello, M. (2013). Job Polarization in Britain from a Task-Based Perspective: Evidence from the UK Skills Surveys. Working Paper 160, Department of Economics and Management, University of Pisa. 152, 155, 156, 158

Bloom, N., Draca, M., and Van Reenen, J. (2015). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *Review of Economic Studies*, 83(1):87–117. 28, 57, 61, 106, 110, 132, 146, 151, 189, 191, 192

Bluestone, B. and Harrison, B. (1988). The Growth of Low-Wage Employment: 1963-86. *American Economic Review*, 78(2):124–128. 12, 160

Blundell, R. and Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, 87(1):115–143. 169

Bonfiglioli, A., Crino, R., Gancia, G., and Papadakis, I. (2021). Robots, Offshoring and Welfare. Working Paper No. DP16363, CEPR Discussion Paper. 21, 29, 30, 31, 34, 36, 39, 41, 42, 43, 50, 58, 59, 60, 66, 125, 189, 224

Borowczyk-Martins, D. and Lale, E. (2019). Employment Adjustment and Part-Time Work: Lessons from the United States and the United Kingdom. *American Economic Journal: Macroeconomics*, 11(1):389–435. 159, 165

Borusyak, K., Hull, P., and Jaravel, X. (2021). Quasi-Experimental Shift-Share Research Designs. *Review of Economic Studies*, 89(1):181–213. 60

Bound, J. and Holzer, H. J. (2000). Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s. *Journal of Labor Economics*, 18(1):20–54. 58, 60, 134, 135

Braxton, J. C. and Taska, B. (2023). Technological Change and the Consequences of Job Loss. *American Economic Review*, 113(2):279–316. 16

Brynjolfsson, E., Hui, X., and Liu, M. (2019). Does Machine Translation Affect International Trade? Evidence from a Large Digital Platform. *Management Science*, 65(12):5449–5460. 7

Brynjolfsson, E. and Mitchell, T. (2017). What can Machine Learning Do? Workforce Implications. *Science*, 358(6370):1530–1534. 1, 4, 15, 22, 50, 104

Buera, F. J., Kaboski, J. P., Rogerson, R., and Vizcaino, J. I. (2021). Skill-Biased Structural Change. *Review of Economic Studies*, 89(2):592–625. 111, 142, 145, 151

Bureau of Economic Analysis, . (2021). BEA Data. 31, 38, 39, 41, 54, 55, 223

Card, D. and DiNardo, J. E. (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labor Economics*, 20(4):733–783. 9

Carneiro, P. and Lee, S. (2011). Trends in Quality-Adjusted Skill Premia in the United States, 1960-2000. *American Economic Review*, 101(6):2309–49. 9

Chang, Y., Kim, S.-B., Kwon, K., and Rogerson, R. (2011). Interpreting Labor Supply Regressions in a Model of Full- and Part-Time Work. *American Economic Review*, 101(3):476–481. 165

Chao, J. C. and Swanson, N. R. (2005). Consistent Estimation with a Large Number of Weak Instruments. *Econometrica*, 73(5):1673–1692. 168

Cortes, G. M. and Gallipoli, G. (2017). The Costs of Occupational Mobility: An Aggregate Analysis. *Journal of the European Economic Association*, 16(2):275–315. 16, 58, 133

Cortes, G. M., Jaimovich, N., Nekarda, C. J., and Siu, H. E. (2020). The Dynamics of Disappearing Routine Jobs: A Flows Approach. *Labour Economics*, 65:101823. 16

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153. 1, 7, 11, 13, 21, 29, 34, 36, 39, 41, 57, 58, 63, 66, 110, 114, 133, 134, 135, 151, 159, 160, 184, 189, 191

de Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The Rise of Robots and the Fall of Routine Jobs. *Labour Economics*, 66:101885. 58, 133

Deming, D. J. (2021). The Growing Importance of Decision-Making on the Job. Working Paper 28733, National Bureau of Economic Research. 58, 133

DiNardo, J. E. and Pischke, J.-S. (1997). The Returns to Computer Use Revisited:

Have Pencils Changed the Wage Structure Too? *Quarterly Journal of Economics*, 112(1):291–303. 10

Dolton, P. and Makepeace, G. (2004). Computer Use and Earnings in Britain. *Economic Journal*, 114(494):C117–C129. 10, 14, 149

Elgin, C., Kose, M. A., Ohnsorge, F., and Yu, S. (2021). Understanding informality. Working paper, CAMA Working Paper. 122, 221, 222

European Union, . (2023). Country Profiles. 148

Felten, E. W., Raj, M., and Seamans, R. (2018). A Method to Link Advances in Artificial Intelligence to Occupational Abilities. *AEA Papers and Proceedings*, 108:54–57. 11

Frey, C. B. and Osborne, M. A. (2017). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114(January):254–280. 10, 11

Gathmann, C. and Schonberg, U. (2010). How General Is Human Capital? A Task-Based Approach. *Journal of Labor Economics*, 28(1):1–49. 16, 58, 133

Giuntella, O., Lu, Y., and Wang, T. (2022). How do Workers and Households Adjust to Robots? Evidence from China. Working Paper 30707, National Bureau of Economic Research. 110, 151

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624. 60

Goos, M. and Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Review of Economics and Statistics*, 89(1):118–133. 14, 22, 148, 152, 160

Goos, M., Manning, A., and Salomons, A. (2009). Job Polarization in Europe. *American Economic Review*, 99(2):58–63. 13, 14, 108, 148

Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104(8):2509–2526. 20, 22, 29, 54, 188

GOV.UK, . (2023). UK Government Website. 193

Graetz, G. and Michaels, G. (2017). Is Modern Technology Responsible for Jobless Recoveries? *American Economic Review*, 107(5):168–73. 1, 14, 15, 16, 20, 29, 35, 115, 124, 188

Graetz, G. and Michaels, G. (2018). Robots at Work. *Review of Economics and Statistics*, 100(5):753–768. 14, 15, 22, 35, 58, 60, 115, 116, 119, 124, 129, 133, 135, 182, 186, 189

Grossman, G. M. and Oberfield, E. (2022). The Elusive Explanation for the Declining Labor Share. *Annual Review of Economics*, 14(Volume 14, 2022):93–124. 3

He, H., Li, S. X., and Han, Y. (2023). Labor Market Discrimination against Family Responsibilities: A Correspondence Study with Policy Change in China. *Journal of Labor Economics*, 41(2):361–387. 141

Herrendorf, B., Rogerson, R., and Valentinyi, A. (2014). Chapter 6 - Growth and Structural Transformation. In Aghion, P. and Durlauf, S. N., editors, *Handbook of Economic Growth*, volume 2 of *Handbook of Economic Growth*, pages 855–941. Elsevier. 111, 142, 145, 151

Hubmer, J. (2023). The Race Between Preferences and Technology. *Econometrica*, 91(1):227–261. 13

Hummels, D., Jørgensen, R., Munch, J., and Xiang, C. (2014). The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data. *American Economic Review*, 104(6):1597–1629. 192

International Federation of Robotics, . (2021). Executive Summary World Robotics 2021. Report, International Federation of Robotics. 2, 11, 26, 31, 34, 38, 40, 41, 59, 91, 101, 102, 103, 105, 114, 120, 121, 124, 145, 148, 190, 211, 212, 213, 214, 215, 216, 221, 222, 224

Jackson, M. O. and Kanik, Z. (2019). How Automation that Substitutes for Labor Affects Production Networks, Growth, and Income Inequality. *Growth, and Income Inequality (September 19, 2019)*. 7, 8, 16, 58, 133

Jaeger, D. A., Ruist, J., and Stuhler, J. (2018). Shift-Share Instruments and the Impact of Immigration. Working Paper 24285, National Bureau of Economic Research. 60

Jones, C. I. and Kim, J. (2018). A Schumpeterian Model of Top Income Inequality. *Journal of Political Economy*, 126(5):1785–1826. 9

Jones, J. B. and Yang, F. (2016). Skill-Biased Technical Change and the Cost of Higher Education. *Journal of Labor Economics*, 34(3):621–662. 9

Kaplan, S. N. and Rauh, J. D. (2013). Family, Education, and Sources of Wealth among the Richest Americans, 1982-2012. *American Economic Review*, 103(3):158–62. 9

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963–1987: Supply and Demand Factors. *Quarterly Journal of Economics*, 107(1):35–78. 9

Keane, M. and Rogerson, R. (2015). Reconciling Micro and Macro Labor Supply Elasticities: A Structural Perspective. *Annual Review of Economics*, 7(1):89–117. 40, 47, 51, 129, 164, 176

Kim, J., Park, J. C., and Komarek, T. (2021). The Impact of Mobile ICT on National Productivity in Developed and Developing Countries. *Information & Management*, 58(3):103442. 35, 115, 124, 146

Kogan, L., Papanikolaou, D., Schmidt, L. D., and Seegmiller, B. (2023). Technology and

Labor Displacement: Evidence from Linking Patents with Worker-Level Data. Working Paper 31846, National Bureau of Economic Research. 3, 11

Kogan, L., Papanikolaou, D., Schmidt, L. D. W., and Seegmiller, B. (2021). Technology, Vintage-Specific Human Capital, and Labor Displacement: Evidence from Linking Patents with Occupations. Working Paper 29552, National Bureau of Economic Research. 13

Krueger, A. B. (1993). How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989. *Quarterly Journal of Economics*, 108(1):33–60. 10

Kugler, A. D., Kugler, M., Ripani, L., and Rodrigo, R. (2020). U.S. Robots and their Impacts in the Tropics: Evidence from Colombian Labor Markets. Working Paper 28034, National Bureau of Economic Research. 184

Machin, S. and Reenen, J. V. (1998). Technology and Changes in Skill Structure: Evidence from Seven OECD Countries. *Quarterly Journal of Economics*, 113(4):1215–1244. 1, 14, 144, 149

Michaels, G., Natraj, A., and Reenen, J. V. (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. *Review of Economics and Statistics*, 96(1):60–77. 35, 115, 116, 119, 124, 129

Mitchell, T. and Brynjolfsson, E. (2017). Track How Technology is Transforming Work. *Nature*, 544(7650):290–292. 1, 4, 15

Mohnen, P. (2024). The Impact of the Retirement Slowdown on the U.S. Youth Labor Market. *Journal of Labor Economics*, 0(ja):null. 12

Montobbio, F., Staccioli, J., Virgillito, M. E., and Vivarelli, M. (2024). Labour-Saving Automation: A Direct Measure of Occupational Exposure. *World Economy*, 47(1):332–361. 10, 11

Moreno-Galbis, E. and Wolff, F.-C. (2011). Evidence on New Technologies and Wage Inequality in France. *Applied Economics*, 43(7):855–872. 10

Murphy, K. M. and Welch, F. (1993). Occupational Change and the Demand for Skill, 1940-1990. *American Economic Review*, 83(2):122–136. 12, 14

Oberfield, E. and Raval, D. (2021). Micro Data and Macro Technology. *Econometrica*, 89(2):703–732. 14, 101

OECD, . (2020). OECD Database. 2, 18, 32, 141, 212, 218

Office for National Statistics, . (2018). The Annual Population Survey. 152, 153, 155, 156, 159

Poletaev, M. and Robinson, C. (2008). Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics*, 26(3):387–420. 16, 58, 133

PwC (2018). Will Robots Really Steal our Jobs? An International Analysis of the Potential Long Term Impact of Automation. 1, 160

Restrepo, P. (2024). Automation: Theory, Evidence, and Outlook. *Annual Review of Economics*. 4, 5

Rodrik, D. (2018). New Technologies, Global Value Chains, and Developing Economies. Working Paper 25164, National Bureau of Economic Research. 15, 192

Rogerson, R. and Wallenius, J. (2022). Shocks, Institutions, and Secular Changes in Employment of Older Individuals. *NBER Macroeconomics Annual*, 36:177–216. 58, 133

Roodman, D. (2009). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics*, 71(1):135–158. 170

Sachs, J. D., Benzell, S. G., and LaGarda, G. (2015). Robots: Curse or Blessing? A Basic Framework. Working Paper 21091, National Bureau of Economic Research. 4, 15, 22, 50, 104

Sachs, J. D. and Kotlikoff, L. J. (2012). Smart Machines and Long-Term Misery. Working Paper 18629, National Bureau of Economic Research. 1, 6, 17, 22, 50, 104, 160

Stinebrickner, R., Stinebrickner, T., and Sullivan, P. (2019). Job Tasks, Time Allocation, and Wages. *Journal of Labor Economics*, 37(2):399–433. 84, 85

The Conference Board, . (2021). The Conference Board Total Economy Database. 2, 11, 34, 41, 114, 115, 120, 121, 124, 146, 190, 217, 218, 219, 220, 221, 222

Tolbert, C. M. and Sizer, M. (1996). U.S. Commuting Zones and Labor Market Areas: A 1990 Update. Staff Reports 278812, United States Department of Agriculture, Economic Research Service. 30

United Nations, . (2020). United Nation Database. 26, 38, 105, 120, 121, 148, 190, 211, 212, 213, 214, 215, 216, 221, 222

United Nations, . (2021). UN Comtrade Database. 2, 11, 34, 35, 41, 114, 124, 224

US Census Bureau, . (2021). Business Dynamics Statistics. 33, 43

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. *Available at SSRN 3482150*. 11, 17, 57, 132, 191

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step gmm estimators. *Journal of Econometrics*, 126(1):25–51. 168

World Bank, . (2021). World Bank Open Data. 18, 26, 32, 59, 108, 111, 112, 113, 115, 120, 121, 124, 134, 148, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 224, 225

Yamaguchi, S. (2012). Tasks and Heterogeneous Human Capital. *Journal of Labor Economics*, 30(1):1–53. 16, 58, 133

Zeira, J. (1998). Workers, Machines, and Economic Growth. *Quarterly Journal of Economics*, 113(4):1091–1117. 3

Zimmerman, S. D. (2019). Elite Colleges and Upward Mobility to Top Jobs and Top Incomes. *American Economic Review*, 109(1):1–47. 9

.1 Job characteristics and Working Conditions

.1.1 Task Intensities

1. Analytical
   - Paying close attention to detail
   - Teaching people (individuals or groups)
   - Making speeches/ presentations
   - Working with a team of people
   - Specialist knowledge or understanding
   - Knowledge of how organisation works
   - Spotting problems or faults
   - Working out cause of problems/faults
   - Thinking of solutions to problems
   - Analysing complex problems in depth
   - Checking things to ensure no errors
   - Noticing when there is a mistake
   - Planning own activities
   - Planning the activities of others
   - Organising own time
   - Thinking ahead
   - Reading written information (e.g. forms, notices and signs)
   - Reading short documents (e.g. reports, letters or memos)
   - Reading long documents (e.g. manuals, articles or books)
   - Writing materials (e.g. forms, notices and signs)
   - Writing short documents (e.g. reports, letters or memos)
   - Writing long documents with correct spelling and grammar
   - Adding, subtracting, multiplying and dividing numbers
   - Calculations using decimals, percentages or fractions
   - Calculations using advanced statistical procedures
2. Interpersonal
   - Dealing with people

- Persuading or influencing others
- Selling a product or service
- Counselling, advising or caring for customers or clients
- Listening carefully to colleagues
- Knowledge of particular products or services

3. Manual
   - Physical strength (e.g. to carry, push or pull heavy objects)
   - Physical stamina (e.g. to work on physical activities)
   - Skill or accuracy in using hands/fingers (e.g. to assemble)
   - Knowledge of use or operation of tools/equipment machinery

.1.2 Degree of Repetition

In the Skills and Employment Survey, the respondent had to answer ”how often work involves short repetitive tasks”, and rank the frequencies by giving score from 1 to 5. I calculate the average value of task repetitiveness every year as a kind of job characteristics measures.

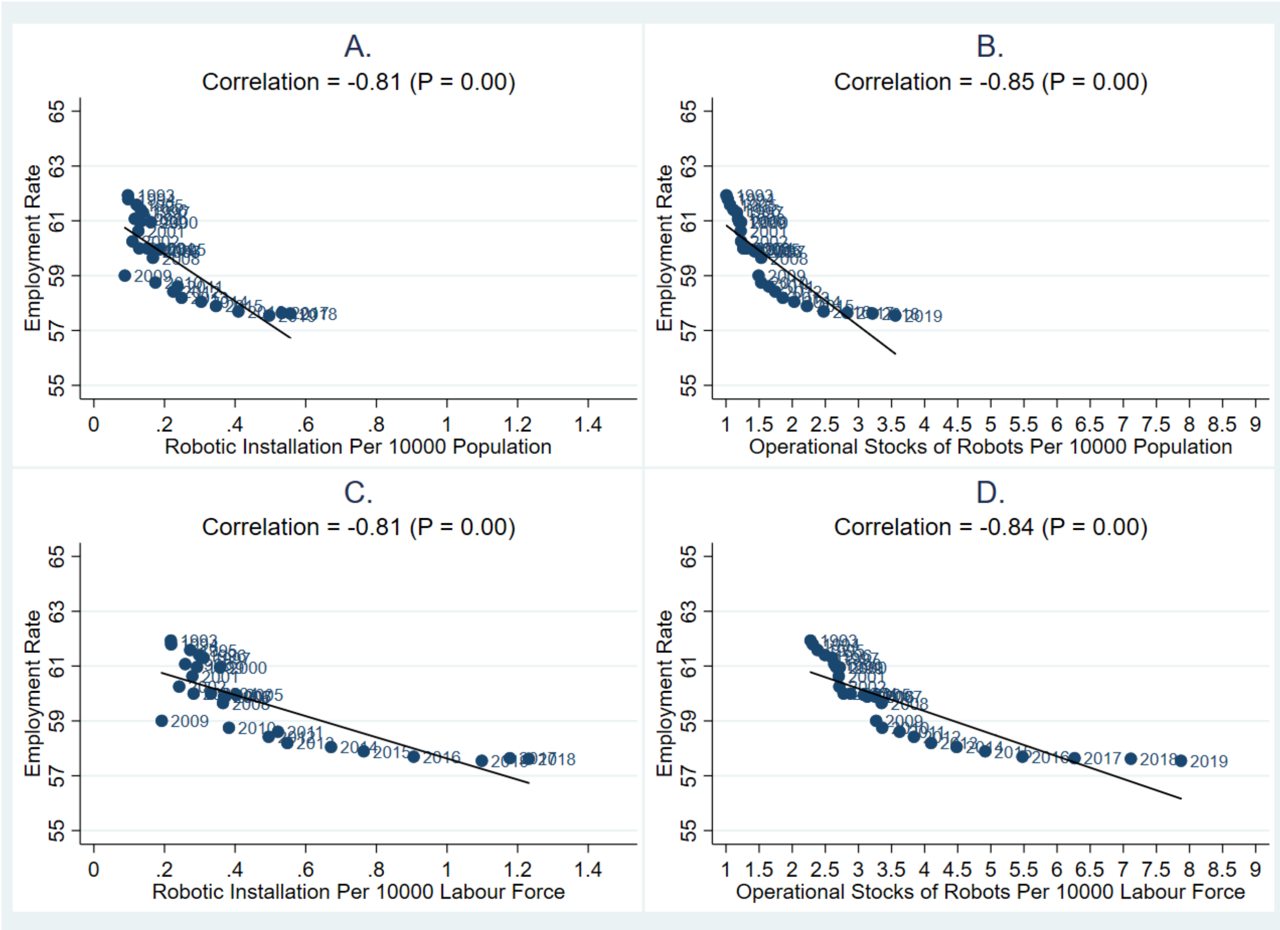
.1.3 Computerised or Automated Equipment

In the Skills and Employment Survey, the respondent had to answer ”whether job involves use of computerised or automated equipment”, and recorded 1 if they used automated equipment, and 0 if not. I calculate the average value every year as the probability of automated equipment use.

For computerisation, the respondent had to answer ”complexity of computer use in job”, and rank the frequencies by giving score from 1 to 4, and 0 if they did not contain any requirements of computerised equipment. I calculate the average value of computer complexity every year as a kind of job characteristics measures.

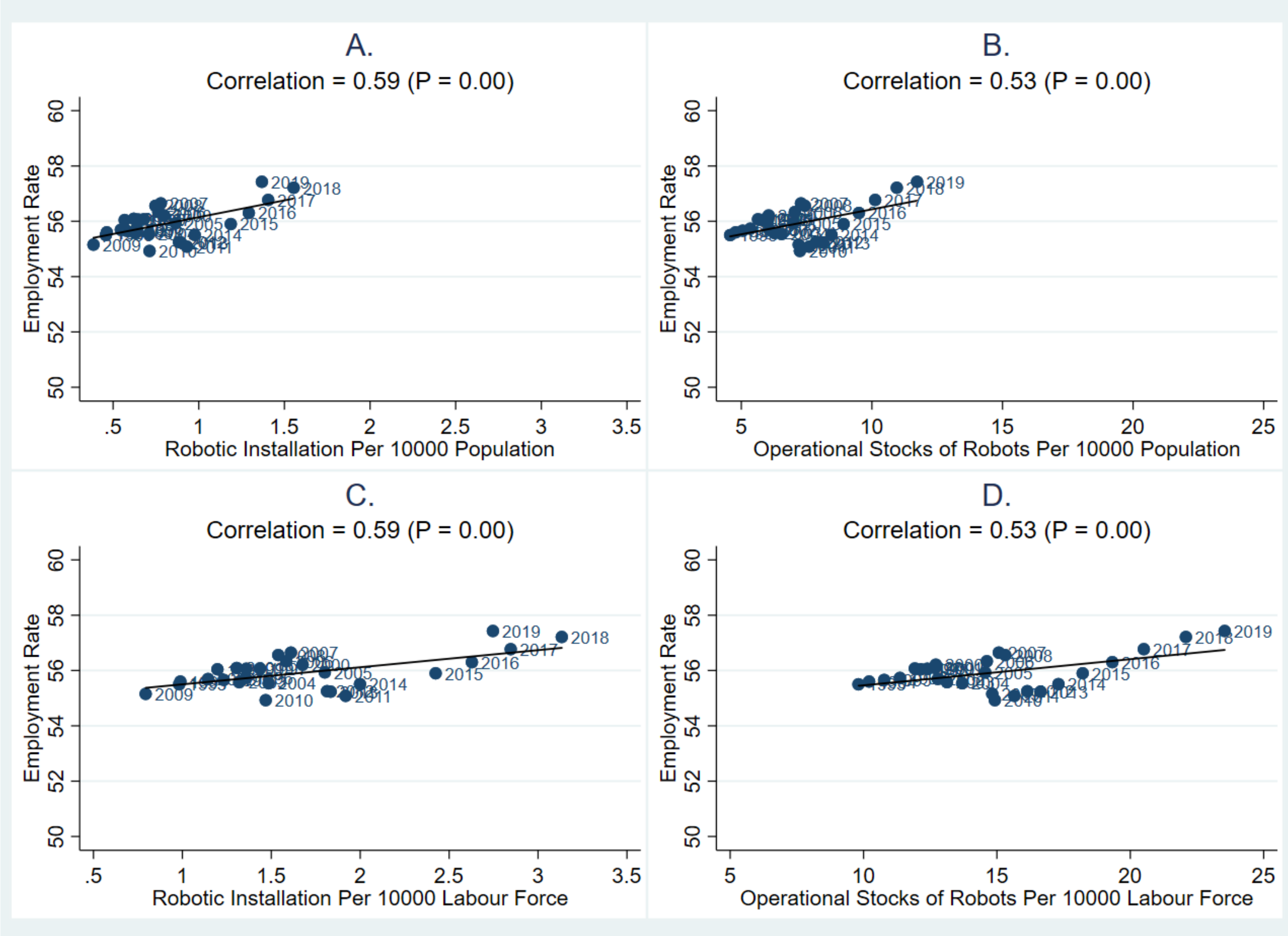
.2 Graphs

Figure 1: Robotic Density and Employment Rate for All Countries, 1993-2019



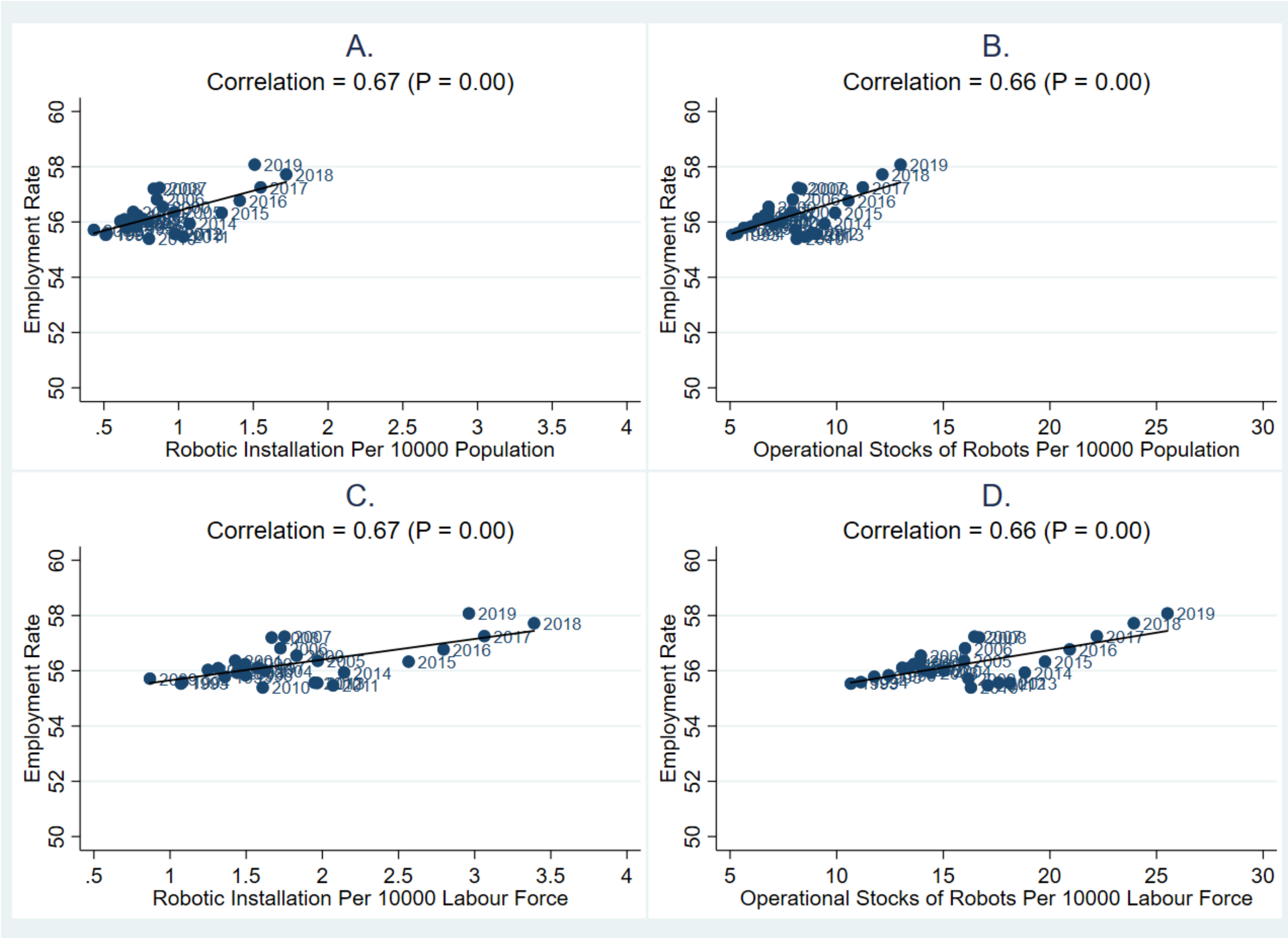
Notes:
The employment rate is from World Bank (2021), and the operational stock and installation of robots are based on International Federation of Robotics (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. Robot density in Graph A refers to robotic installation per 10000 population, that in Graph B refers to operational stock of robots per 10000 population, that in Graph C refers to robotic installation per 10000 labour force, and that in Graph D refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020).

Figure 2: Robotic Density and Employment Rate for OECD Countries, 1993-2019



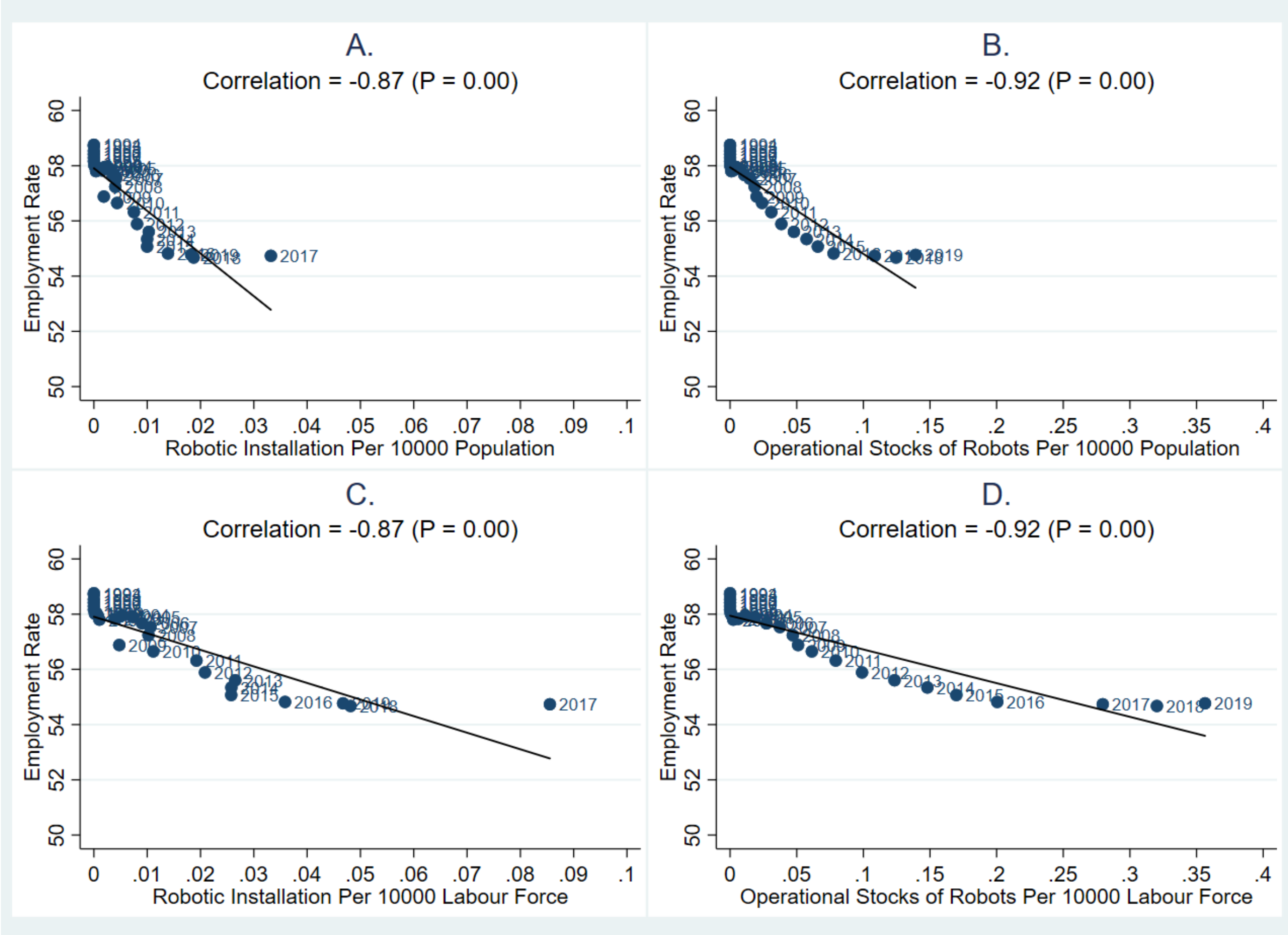
Notes:
The employment rate is from World Bank (2021), and the operational stock and installation of robots are based on International Federation of Robotics (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. Robot density in Graph A refers to robotic installation per 10000 population, that in Graph B refers to operational stock of robots per 10000 population, that in Graph C refers to robotic installation per 10000 labour force, and that in Graph D refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). The sample economies of OECD countries are obtained from OECD (2020).

Figure 3: Robotic Density and Employment Rate for High Income Group, 1993-2019



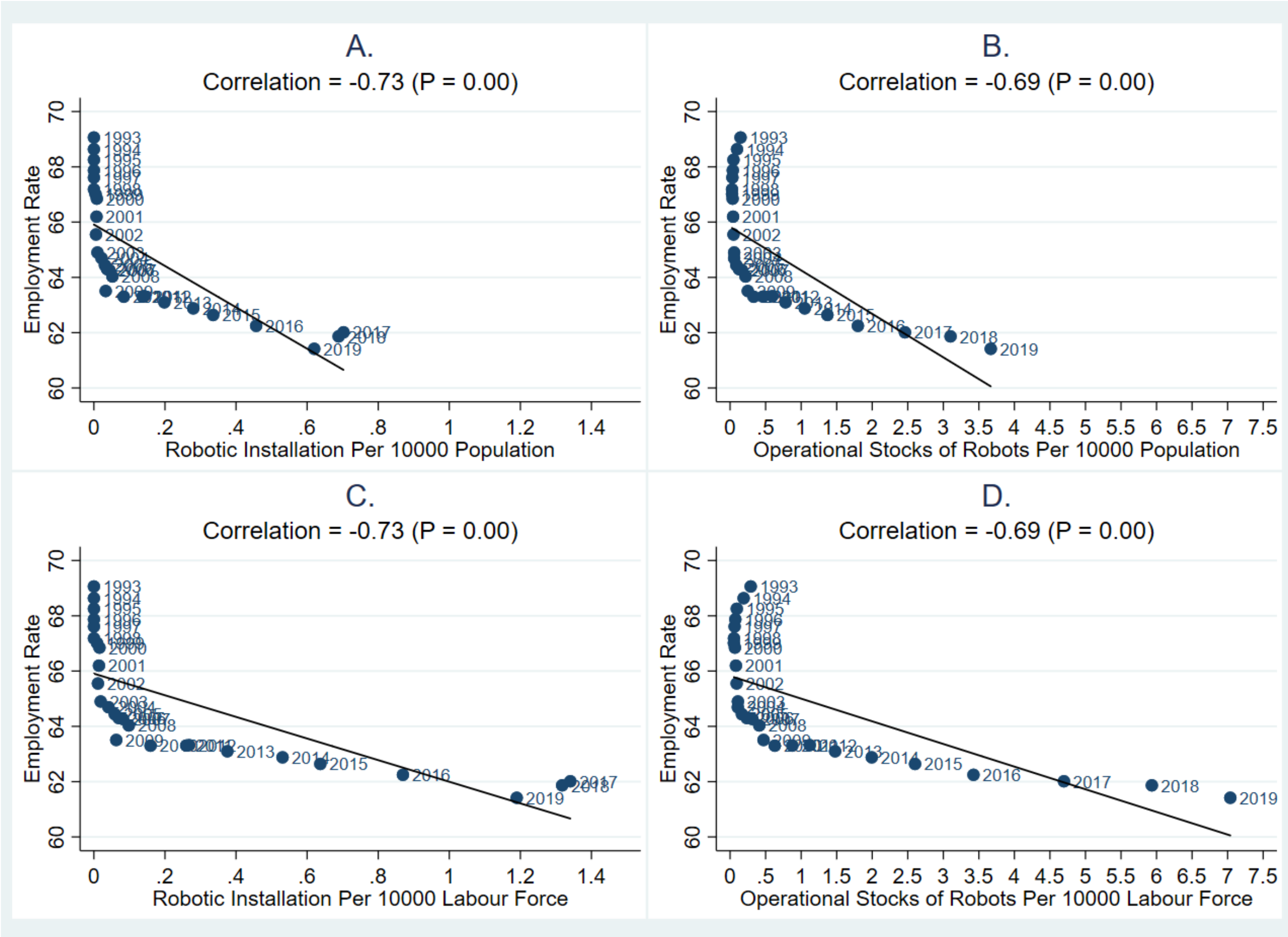
Notes:
The employment rate is from World Bank (2021), and the operational stock and installation of robots are based on International Federation of Robotics (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. Robot density in Graph A refers to robotic installation per 10000 population, that in Graph B refers to operational stock of robots per 10000 population, that in Graph C refers to robotic installation per 10000 labour force, and that in Graph D refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). Countries with a GNI per capita above $12,696 in 2020 are defined as economies from high income group, based on GNI per capita using the World Bank Atlas method World Bank (2021).

Figure 4: Robotic Density and Employment Rate for Low and Lower Middle Income Group, 1993-2019



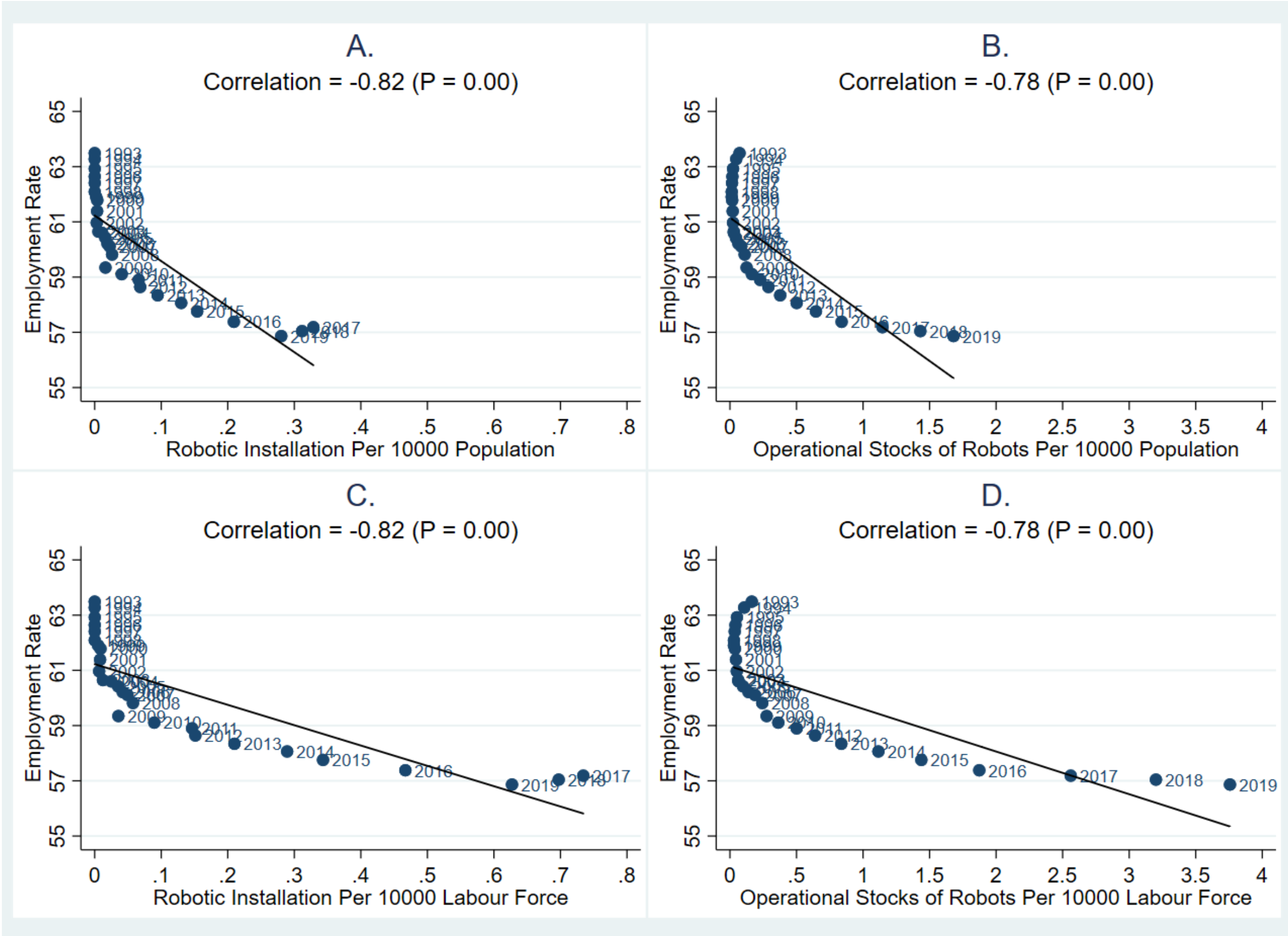
Notes:
The employment rate is from World Bank (2021), and the operational stock and installation of robots are based on International Federation of Robotics (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. Robot density in Graph A refers to robotic installation per 10000 population, that in Graph B refers to operational stock of robots per 10000 population, that in Graph C refers to robotic installation per 10000 labour force, and that in Graph D refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from low income group and lower middle income group in 2020 is $1,045, and the GNI per capita threshold between economies from lower middle income group and upper middle income group in 2020 is $4,095.

Figure 5: Robotic Density and Employment Rate for Upper Middle Income Group, 1993-2019



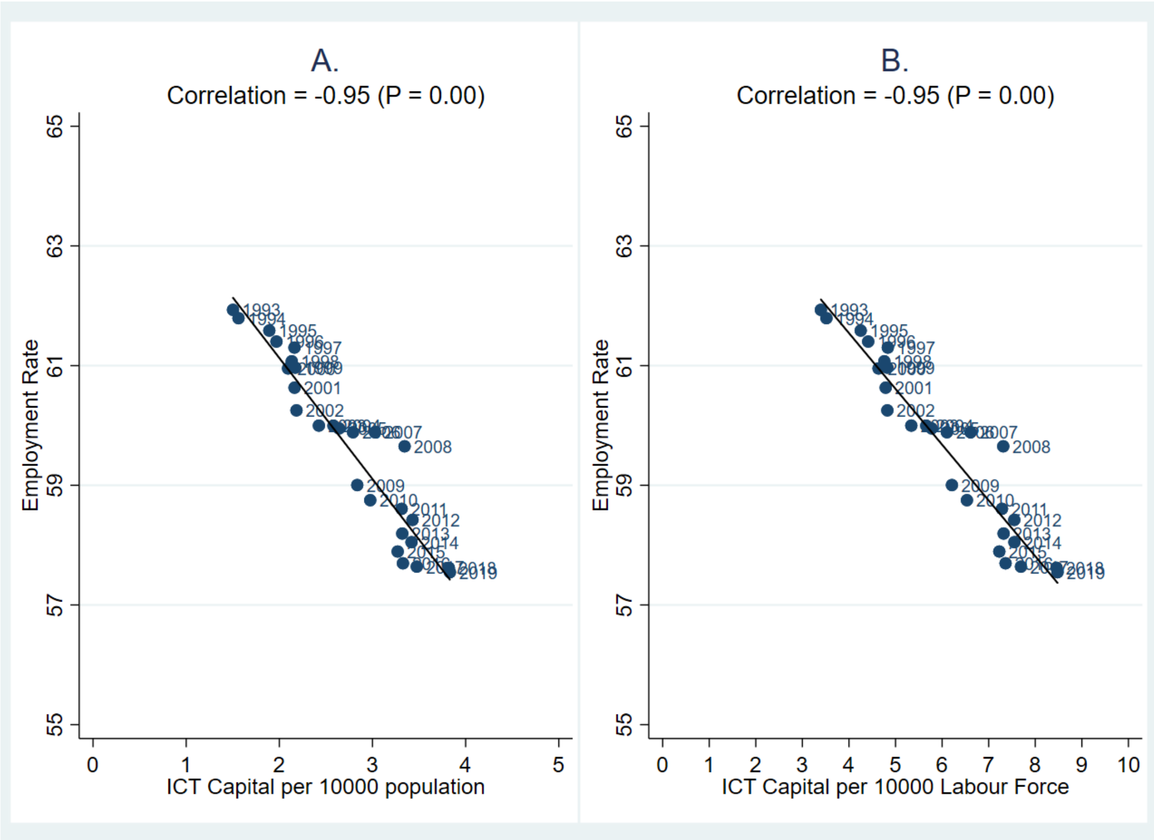
Notes:
The employment rate is from World Bank (2021), and the operational stock and installation of robots are based on International Federation of Robotics (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. Robot density in Graph A refers to robotic installation per 10000 population, that in Graph B refers to operational stock of robots per 10000 population, that in Graph C refers to robotic installation per 10000 labour force, and that in Graph D refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from high income group and upper middle income group in 2020 is \$12,696, and the GNI per capita threshold between economies from lower middle income group and upper middle income group in 2020 is \$4,095.

Figure 6: Robotic Density and Employment Rate for Middle Income Group, 1993-2019



Notes:
The employment rate is from World Bank (2021), and the operational stock and installation of robots are based on International Federation of Robotics (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. Robot density in Graph A refers to robotic installation per 10000 population, that in Graph B refers to operational stock of robots per 10000 population, that in Graph C refers to robotic installation per 10000 labour force, and that in Graph D refers to operational stock of robots per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from low income group and lower middle income group in 2020 is $1,045, and the GNI per capita threshold between economies from high income group and upper middle income group in 2020 is $12,696.

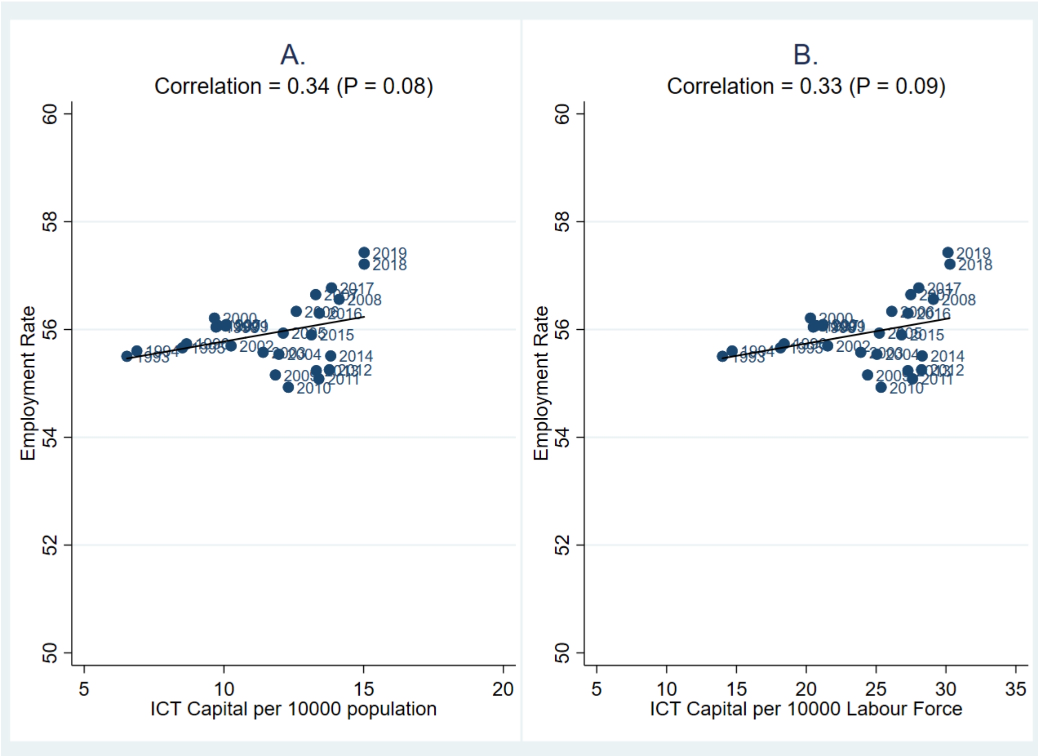
Figure 7: ICT Intensity and Employment Rate for All Countries, 1993-2019



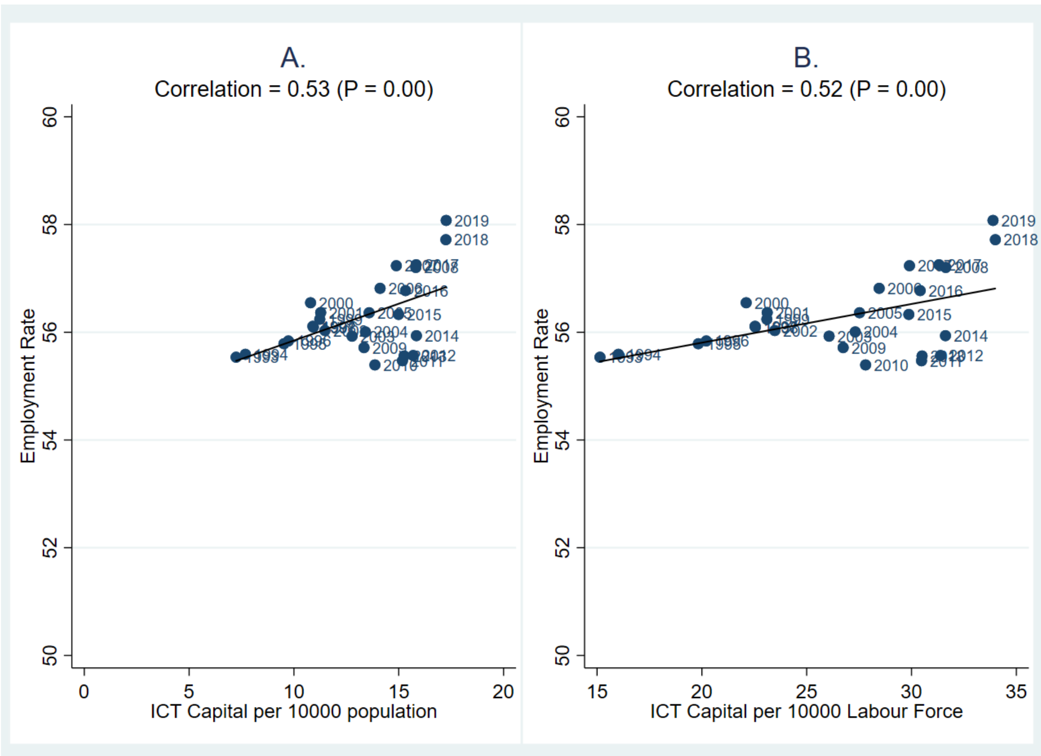
Notes:
The ICT intensity is from The Conference Board (2021), and employment rate is from World Bank (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. ICT intensity in Graph A refers to ICT capital per 10000 population, that in Graph B refers to ICT capital per 10000 labour force. ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars.

Figure 8: ICT Intensity and Employment Rate for Rich Countries, 1993-2019

(a) OECD Countries



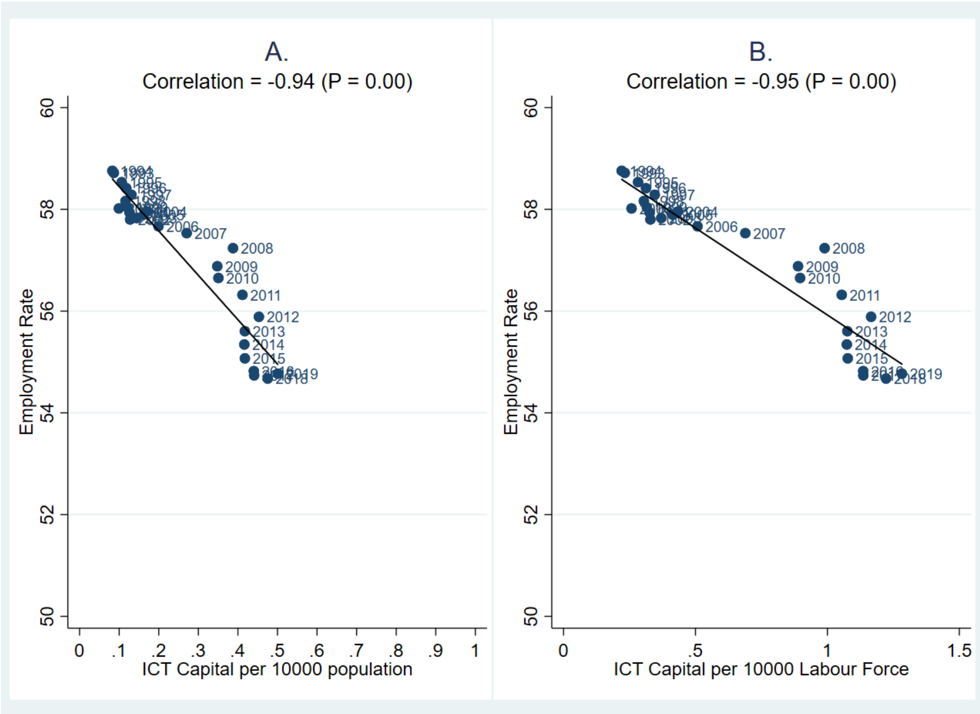
(b) High Income Group



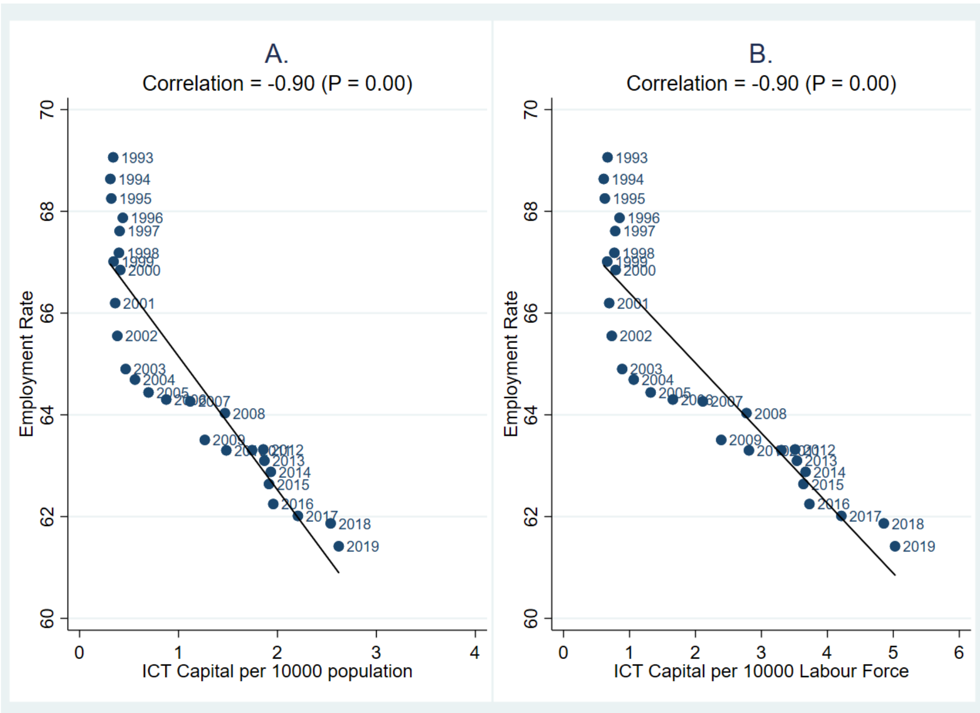
Notes:
The ICT intensity is from The Conference Board (2021), and employment rate is from World Bank (2021). Employment rate is the ratio of employed people and total population who are above 15 years old. ICT intensity in Graph A refers to ICT capital per 10000 population, that in Graph B refers to ICT capital per 10000 labour force. ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. The sample economies of OECD countries are obtained from OECD (2020). Countries with a GNI per capita above \$12,696 in 2020 are defined as economies from high income group, based on GNI per capita using the World Bank Atlas method World Bank (2021).

Figure 9: ICT Intensity and Employment Rate for Poor Countries, 1993-2019

(a) Low and Lower Middle Income Group

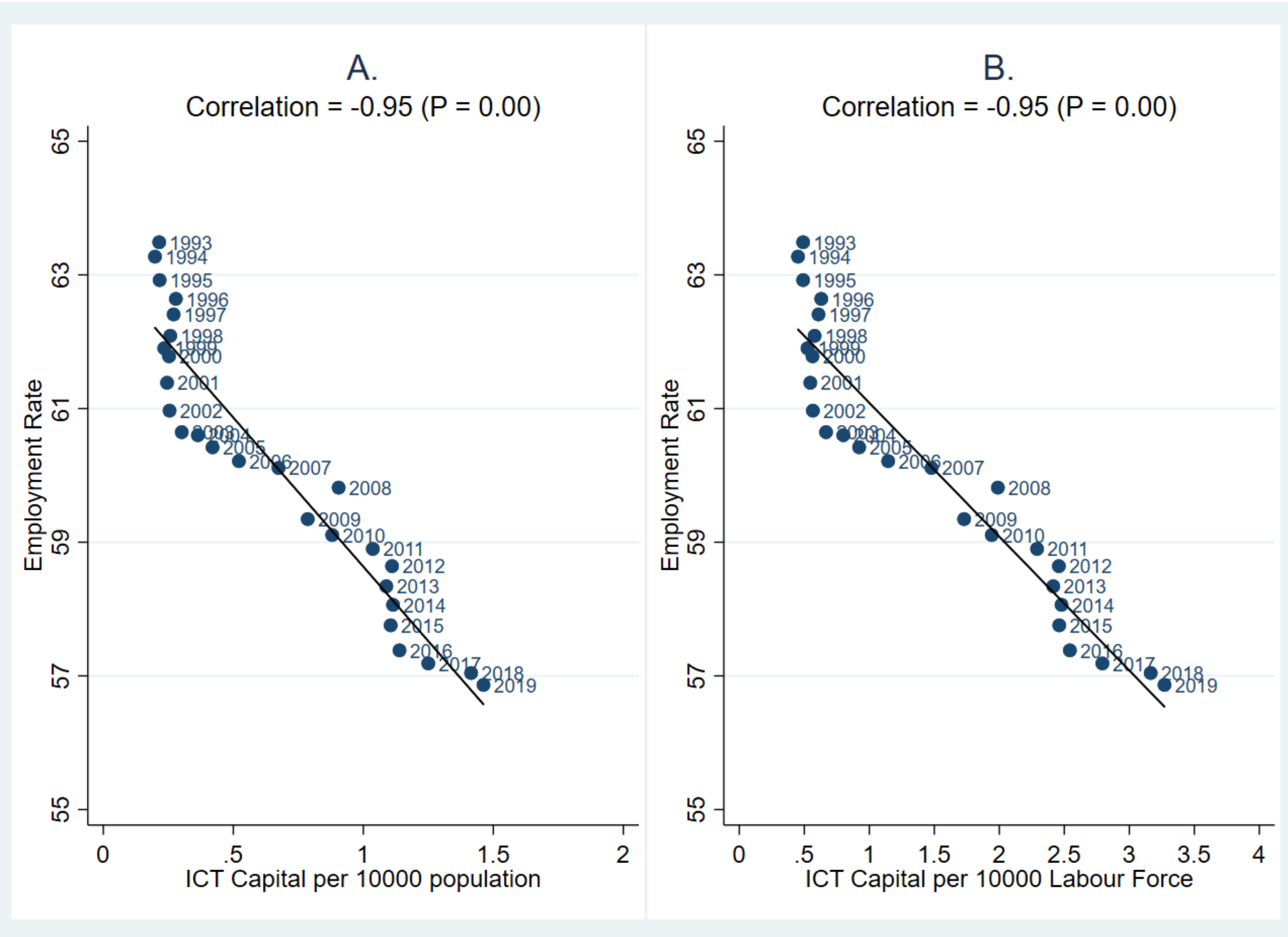


(b) Upper Middle Income Group



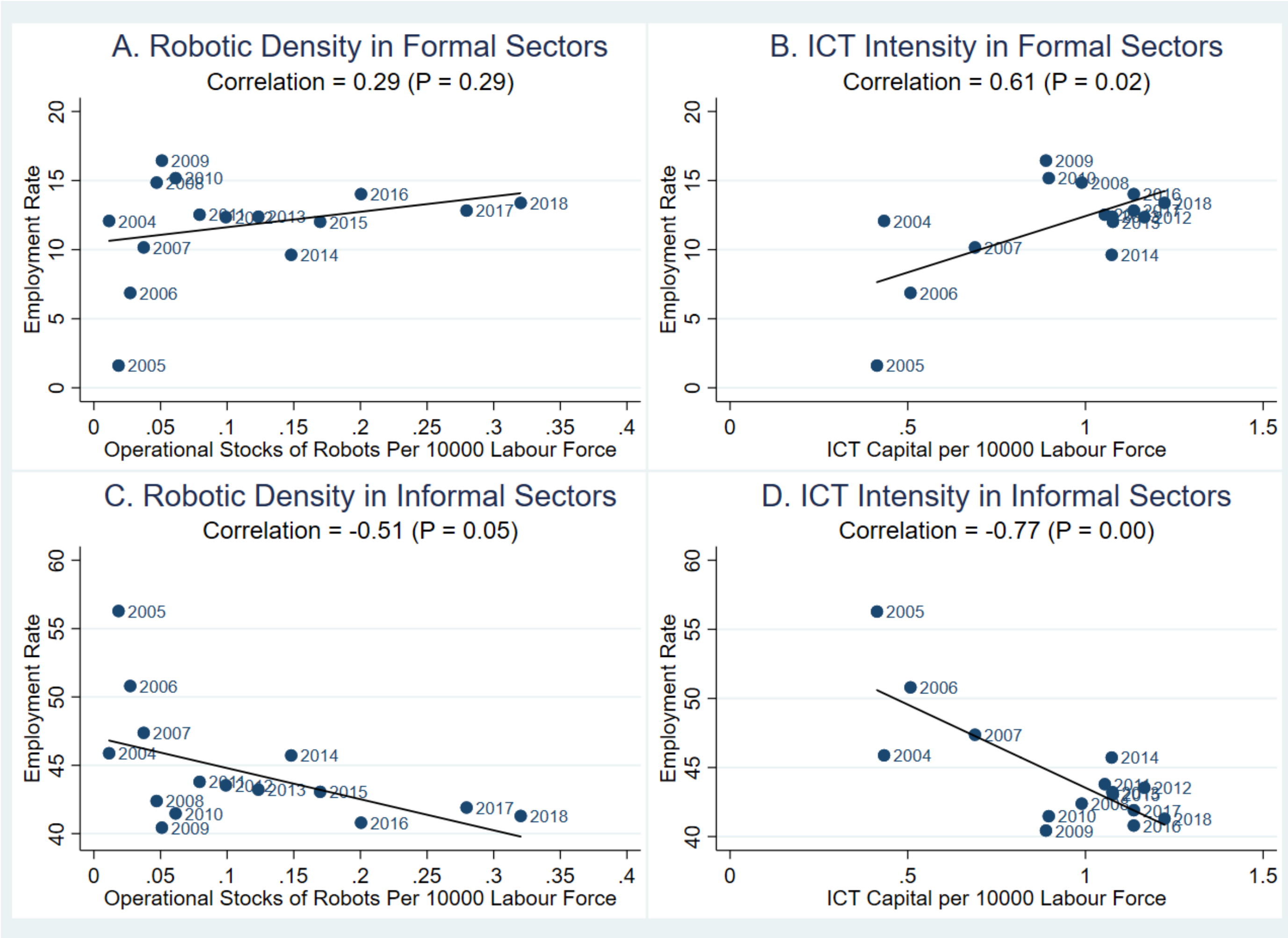
Notes:
The ICT intensity is from The Conference Board (2021), and employment rate is from World Bank (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. ICT intensity in Graph A refers to ICT capital per 10000 population, that in Graph B refers to ICT capital per 10000 labour force. ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from low income group and lower middle income group in 2020 is $1,045, and the GNI per capita threshold between economies from lower middle income group and upper middle income group in 2020 is $4,095, and the GNI per capita threshold between economies from high income group and upper middle income group in 2020 is $12,696.

Figure 10: ICT Intensity and Employment Rate for for Middle Income Group, 1993-2019



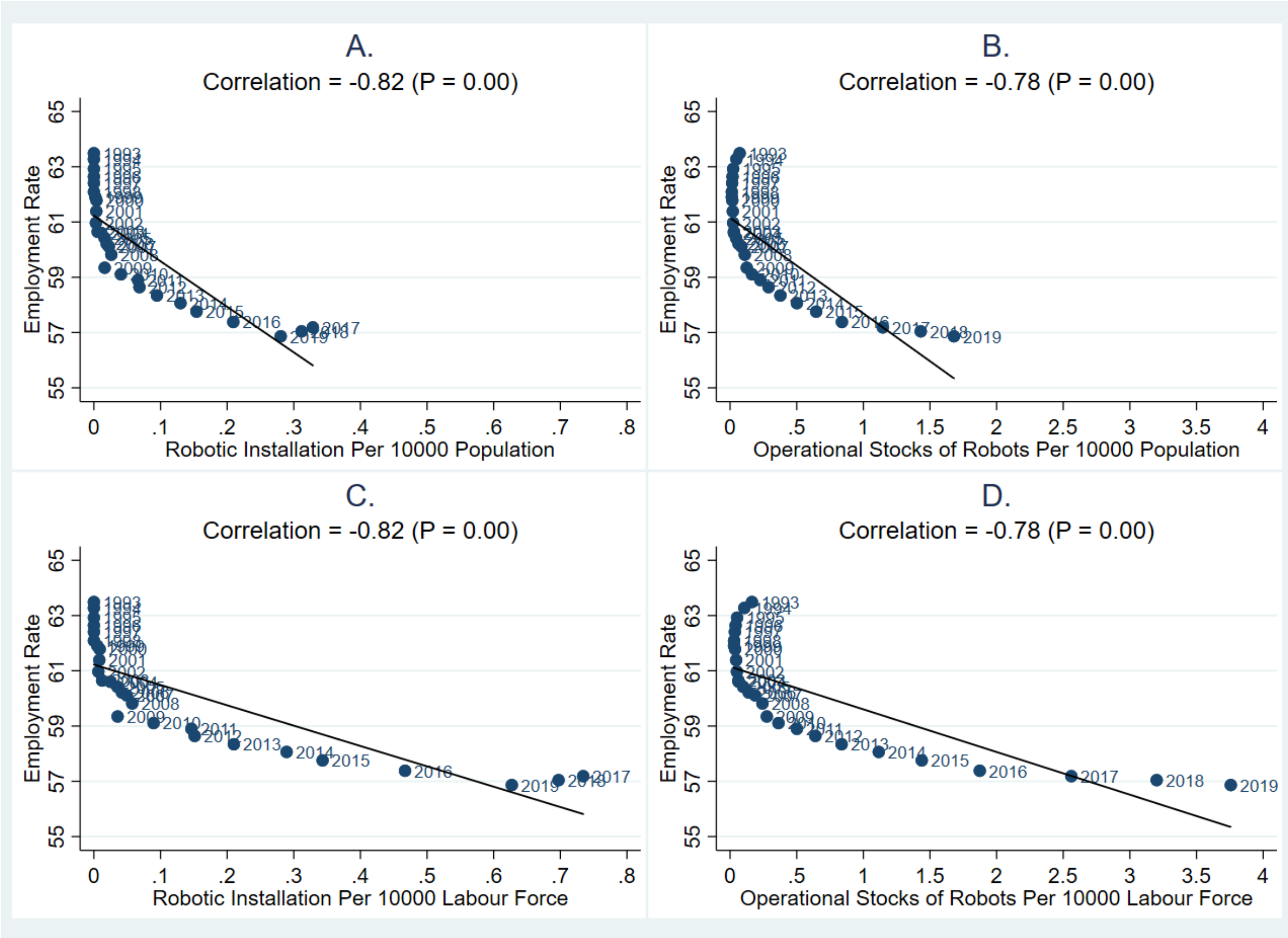
Notes:
The ICT intensity is from The Conference Board (2021), and employment rate is from World Bank (2021). Employment rate is defined as the ratio of employed people and total population who are above 15 years old. ICT intensity in Graph A refers to ICT capital per 10000 population, that in Graph B refers to ICT capital per 10000 labour force. ICT capital is calculated based on ICT capital share and GDP measured by constant US dollars. Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from low income group and lower middle income group in 2020 is $1,045, and the GNI per capita threshold between economies from high income group and upper middle income group in 2020 is $12,696.

Figure 11: Automation Technologies and Informal Employment for Low and Lower Middle Income Group, 1993-2019



Notes:
The employment rate for formal and informal sectors are from Elgin et al. (2021). The operational stock of robots is based on International Federation of Robotics (2021), and ICT intensity is from The Conference Board (2021). Employment rate is the ratio of employed people and total population who are above 15 years old. Robot density refers to operational stock of robots per 10000 labour force. ICT intensity refers to ICT capital per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from low income group and lower middle income group in 2020 is $1,045, and the GNI per capita threshold between economies from lower middle income group and upper middle income group in 2020 is $4,095.

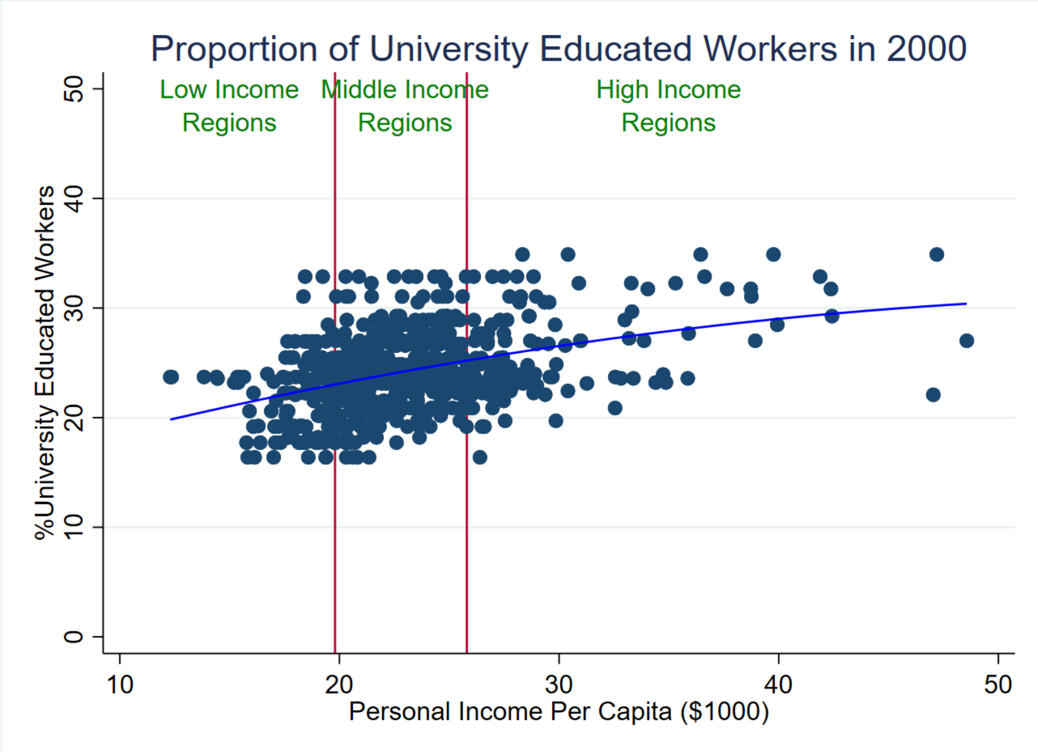
Figure 12: Automation Technologies and Informal Employment for Middle Income Group, 1993-2019



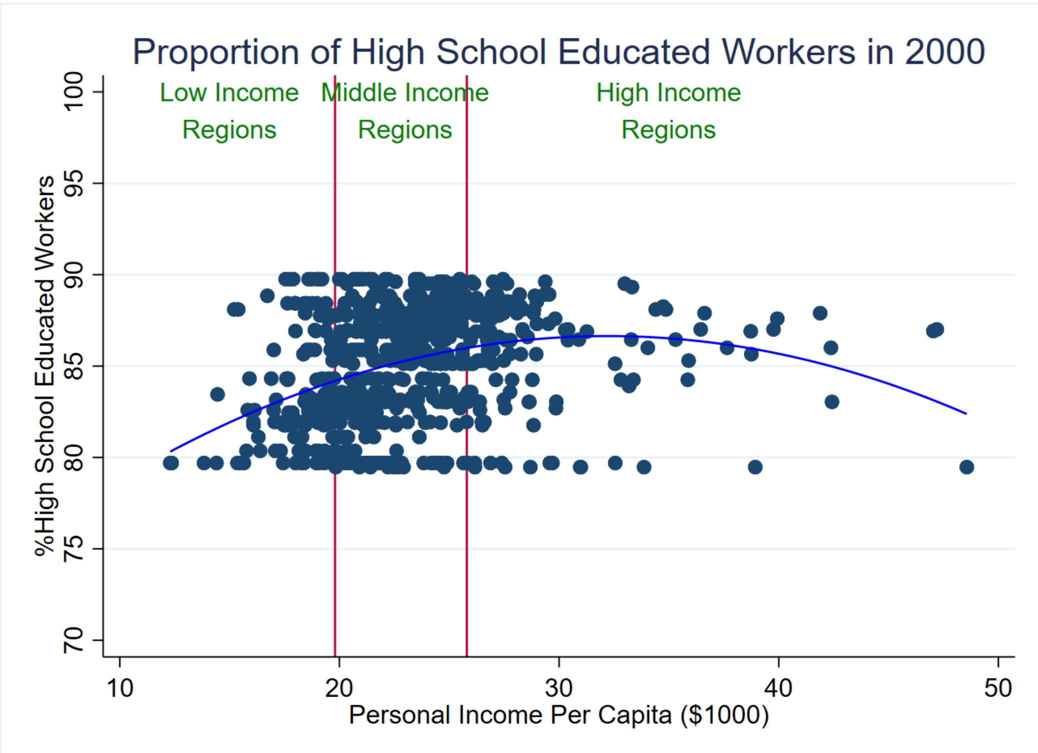
Notes:
The employment rate for formal and informal sectors are from Elgin et al. (2021). The operational stock of robots is based on International Federation of Robotics (2021), and ICT intensity is from The Conference Board (2021). Employment rate is the ratio of employed people and total population who are above 15 years old. Robot density refers to operational stock of robots per 10000 labour force. ICT intensity refers to ICT capital per 10000 labour force. Labour force comprises people ages above 15 who supply labour for the production of goods and services during a specified period (United Nations, 2020). Based on GNI per capita using the World Bank Atlas method World Bank (2021), the GNI per capita threshold for economies from low income group and lower middle income group in 2020 is $1,045, and the GNI per capita threshold between economies from high income group and upper middle income group in 2020 is $12,696.

Figure 13: Skill Distribution Across Income Levels in 2000

(a) High Skilled Labour

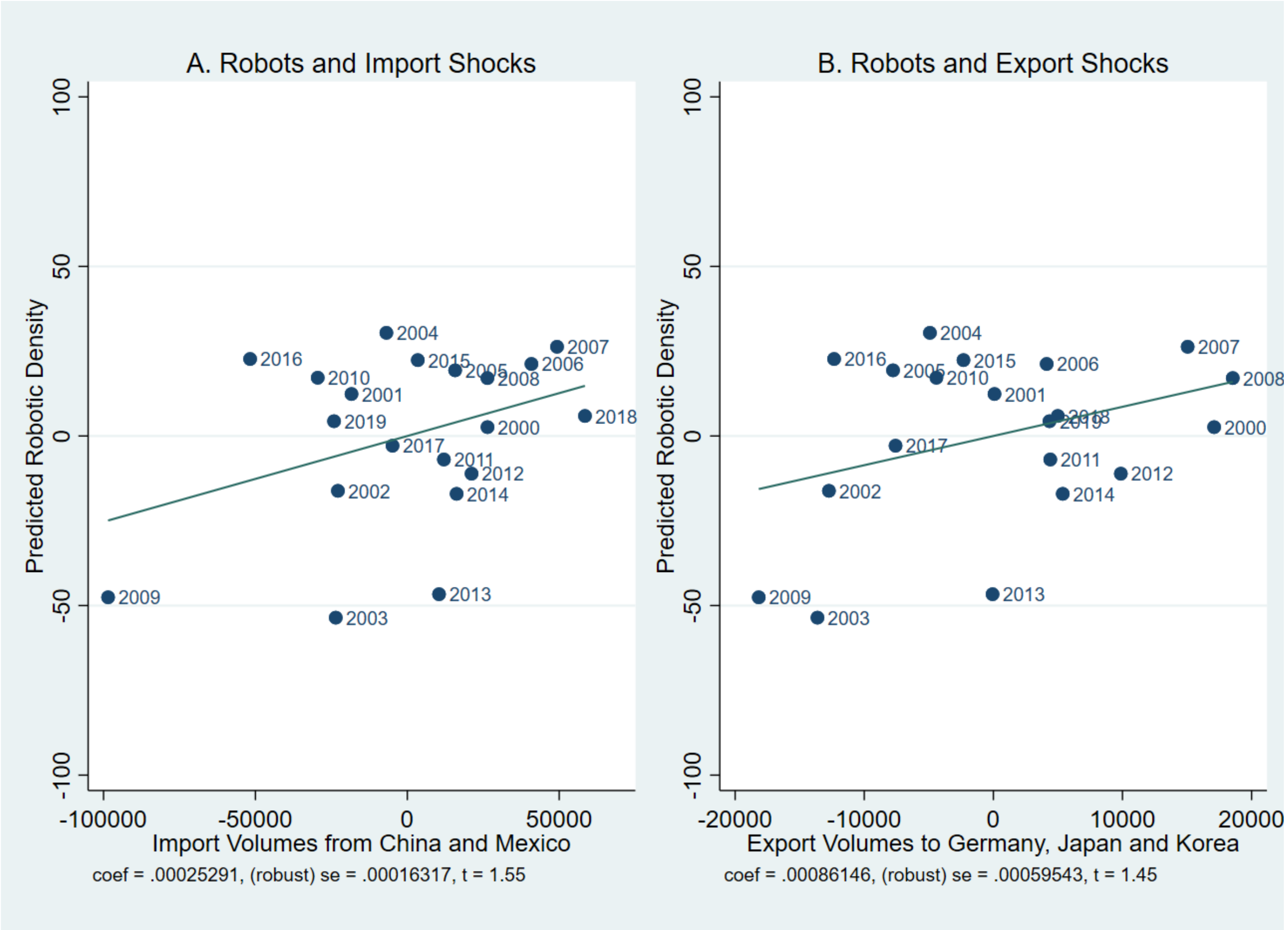


(b) Middle Skilled Labour



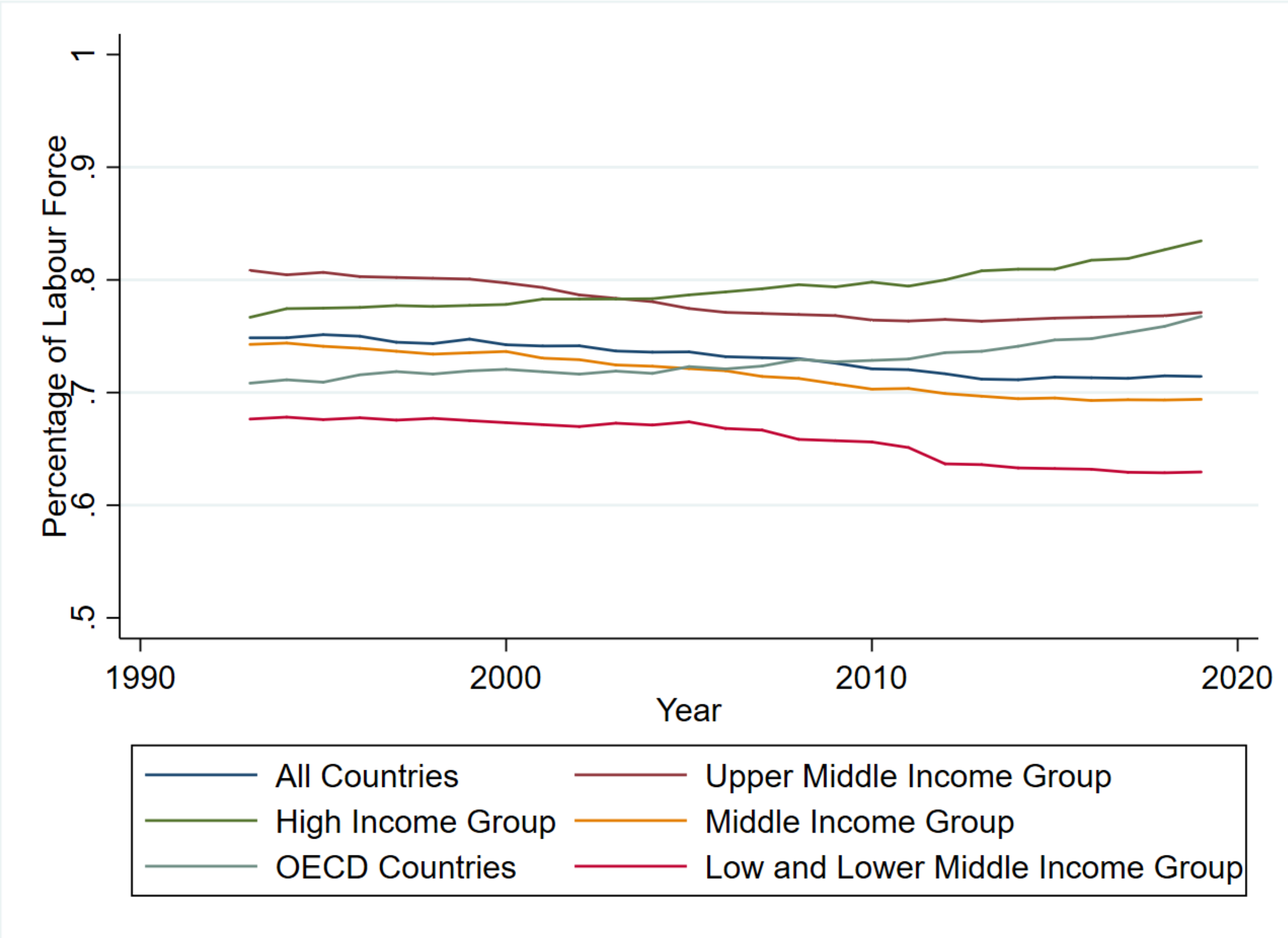
Notes:
The proportion of university educated workers is from Bureau of Economic Analysis (2021), percentage of high school educated workers is from Bureau of Economic Analysis (2021), and income level measured by personal income per capita are from Bureau of Economic Analysis (2021). The classification of regions from high income group, middle income group, low income group is based on Figure 2.2.

Figure 14: Predicted Robotic Density and Trade volumes, 2000-2019



Notes:
The graph presents relationship between predicted robotic density and trade volumes - using data from International Federation of Robotics (2021), World Bank (2021) and United Nations (2021). The predicted robotic density is obtained based on regression of European robotic adoption on trade volumes and country level demographics. European robotic adoption is computed using ratio operational stocks of robots from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) and total labour force. Import volumes from China and Mexico, and export volumes to Germany, Japan and South Korea are measured in million USD. Motivated by Autor et al. (2013); Bonfiglioli et al. (2021), I select China and Mexico as countries which have great import competitions with US, and choose Germany, Japan and South Korea as economies which accounting for large proportion of US export volumes. Regression results using all five countries including China, Mexico, Germany, Japan and South Korea do not qualitatively alter the directions and significance.

Figure 15: Ratio of Labour Force and Population, 1993-2019



Notes:
The graph presents trends in the ratio of total labour force and overall population aging 15-65 - using data from World Bank (2021).

.3 Tables

Table 1: Preliminary Results for US State-Level Employment and Other Automation, 2000-2019

	Total				High Income CZs	Low Income CZs
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Employment Rate						
A. ICT Import Volumes						
ICT Import	-0.184***	-0.153***	-0.196***	-0.162***	0.216***	-0.442***
	(0.024)	(0.032)	(0.018)	(0.020)	(0.026)	(0.048)
R^2	0.380	0.480	0.698	0.725	0.991	0.742
B. ICT Export Volumes						
ICT Export	-0.470***	-0.312***	-0.472***	-0.413***	0.541***	-0.732***
	(0.051)	(0.072)	(0.045)	(0.044)	(0.058)	(0.173)
R^2	0.383	0.476	0.697	0.726	0.982	0.743
C. ICT Net Export Volumes						
ICT Net	-0.283***	-0.263***	-0.303***	0.245***	0.331***	-0.733***
	(0.043)	(0.053)	(0.031)	(0.034)	(0.045)	(0.070)
R^2	0.375	0.482	0.697	0.724	0.991	0.740
D. Automation Import Volumes						
Auto Import	-0.077***	-0.065***	-0.083***	-0.068***	0.091***	-0.183***
	(0.011)	(0.014)	(0.008)	(0.009)	(0.011)	(0.021)
R^2	0.378	0.480	0.698	0.725	0.990	0.742
E. Automation Export Volumes						
Auto Export	-0.152***	-0.113***	-0.156***	-0.133***	0.176***	-0.279***
	(0.018)	(0.024)	(0.014)	(0.015)	(0.019)	(0.049)
R^2	0.382	0.478	0.698	0.726	0.985	0.743
F. Automation Net Export Volumes						
Auto Net	-0.144***	-0.134***	-0.154***	-0.124***	0.171***	-0.324***
	(0.024)	(0.030)	(0.018)	(0.019)	(0.025)	(0.048)
R^2	0.372	0.481	0.696	0.722	0.987	0.739
Year FE	√	√	√	√	√	√
Demographics		√	√	√	√	√
Geographic × Year FE			√	√	√	√
N of Commuting Zones	48	48	48	48	10	38
N of Observations	960	960	960	960	200	760

Notes:
The table presents preliminary results about within group estimates of the effects of exposure of automation technologies on employment rate, based on US state level data. Explanatory variables are changes in ICT trade volumes (ICT import, ICT export, and ICT net export), as well as automation trade volumes (automation import, automation export, and automation net export). Other demographics include population, age (Old People), gender (Female People), race (Hispanic People) and education (Bachelor Degree). Import volume from China and Mexico (Import), and export volume to Germany, Japan, and Korea, are also controlled. Geographic FE refers to Census Divisions. Small magnitudes of the coefficients of control variables are due to different magnitudes of the variables. The regressions are weighted by total labour force in 2000. The classification of US states from high income group and low income group are illustrated in Section 2.4.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Robustness Checks of Employment Effects from Robots Across Different Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Employment Rate						
Robotic Penetration	-1.293***	-0.637***	-0.673***			
	(0.396)	(0.240)	(0.208)			
Robotic Penetration (Adjusted)				-0.289***	-0.218***	-0.195***
				(0.027)	(0.020)	(0.017)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Time Periods	2000-2005	2000-2010	2000-2015	2000-2005	2000-2010	2000-2015
R^2	0.588	0.720	0.714	0.601	0.777	0.758
N of CZs	722	722	722	722	722	722
N of Obs	2890	2888	2888	2888	2888	2888

Notes:
The table presents within group estimates of the effects of robotic penetration on employment rate. Explanatory variable for Columns 4-6 are changes in robotic density calculated as Equation 2.5. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions. The regressions are weighted by total labour force in 2000. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Robustness Checks for Employment, Robot and Income using Alternative IV, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Employment Rate							
A. Without Income Level							
Robotic Penetration	-4.820***	-1.904***	6.369	139.582	13.209	-2.296***	-3.686***
	(1.799)	(0.447)	(4.224)	(1544.896)	(16.272)	(0.532)	(1.130)
B. Only Robot is Endogenous							
Robotic Penetration	-4.994***	-3.281***	-14.160	-7.583***	-9.189**	-3.485***	-4.514***
	(1.145)	(0.579)	(9.015)	(2.603)	(3.919)	(0.642)	(0.954)
Robotic Penetration × Income	0.731***	0.482***	2.066	1.108***	1.342**	0.512***	0.661***
	(0.169)	(0.087)	(1.308)	(0.378)	(0.568)	(0.096)	(0.141)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the relationship between robotic penetration in US and employment rate, where robotic penetration computed using operational stocks of robots from European countries is used as the instrument. Column 1 is based on data from Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland; Column 2 is based on data from all European countries; Column 3 is based on data from Denmark, Finland, France, Italy, Sweden; Column 4 is based on data from Denmark, Finland, France, Italy, Sweden, Germany; Column 5 is based on data from Spain, Finland, France, Italy, Norway, Sweden, UK; Column 6 is based on data from Denmark, Netherlands, Italy, Sweden, UK; Column 7 is based on data from Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: First Stage Regression of Employment and Automation for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Var	Robot	ICT Imp	ICT Exp	ICT Net Exp	Auto Imp	Auto Exp	Auto Net Exp
Robot IV	1.407***						
	(0.001)						
ICT Imp IV		1.008***					
		(0.001)					
ICT Exp IV			1.003***				
			(0.001)				
ICT Net Exp IV				1.005***			
				(0.001)			
Auto Imp IV					1.020***		
					(0.003)		
Auto Exp IV						1.010***	
						(0.001)	
Auto Net Exp IV							1.011***
							(0.002)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√	√
First Stage F Statistics	126.37	132.92	140.13	129.19	140.84	142.78	135.32
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents first stage estimates of the relationship between robotic penetration and employment rate in US, where predicted automation computed using operational stocks of robots from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) is used as the instrument. Dependent variable for Column 1 is robotic penetration (Robot), that for Column 2 is ICT import (ICT Imp), that for Column 3 is ICT export (ICT Exp), that for Column 4 is ICT net export (ICT Net Exp), that for Column 5 is automation import (Auto Imp), that for Column 6 is automation export (Auto Exp), that for Column 7 is automation net export (Auto Net Exp), and all of them are based on US data. The regressions are weighted by total labour force in 2000. Other demographic controls which are not displayed here, include total population (Population), proportion of old people (Old), female workers (Female), Hispanic people (Hispanic), high skilled workers measured by people who received high school degree (High School) and bachelor's degree (Bachelor), and import volumes from China and Mexico are also controlled. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Robustness Checks for Employment, Other Automation and Income in US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Employment Rate						
A. Without Income Level						
ICT Import	-0.100***					
	(0.019)					
ICT Export		-0.242***				
		(0.043)				
ICT Net Exp			-0.171***			
			(0.034)			
Auto Import				-0.052***		
				(0.010)		
Auto Export					-0.070***	
					(0.013)	
Auto Net Exp						-0.200***
						(0.057)
B. Only Robot is Endogenous						
ICT Import	-1.755					
	(0.430)					
ICT Export		-1.682***				
		(0.593)				
ICT Net Exp			-2.016			
			(11.473)			
Auto Import				0.940		
				(0.985)		
Auto Export					-0.559**	
					(0.220)	
Auto Net Exp						-0.330***
						(0.085)
ICT Import × Income	0.349					
	(0.288)					
ICT Export × Income		0.326***				
		(0.120)				
ICT Net Exp × Income			4.091			
			(23.243)			
Auto Import × Income				-0.192		
				(0.200)		
Auto Export × Income					0.110**	
					(0.045)	
Auto Net Exp × Income						0.074***
						(0.018)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes: The table presents IV estimates of the relationship between ICT and automation trade volumes in US and employment rate, where corresponding other automation computed using ICT and automation trade volumes from 8 European countries (Austria, Denmark, Finland, Germany, Italy, Spain, Sweden, Switzerland) is used as the instrument. The regressions are weighted by total labour force in 2000. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). The regressions are weighted by total labour force in 2000. Other demographics include population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Robustness Checks for Business Dynamics, Robot, Income in US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dependent Variable: Δ Job Destruction Rate								
Robot	2.473	3.553	3.001**	9.033	2.573	2.584*	1.374	1.495
	(49.129)	(20.420)	(1.250)	(6.686)	(1.683)	(1.502)	(1.765)	(1.869)
Robot $\times$ Income		-4.306		-1.108		-0.355		-0.192
		(24.881)		(0.850)		(0.219)		(0.267)
R^2	0.002	0.001	0.000	0.001	0.002	0.044	0.045	0.158
B. Dependent Variable: Δ Job Creation Rate								
Robot	-1.945	-2.776	-2.435***	-7.764	-3.690**	-3.707***	-2.864*	-3.170**
	(38.624)	(16.571)	(0.834)	(6.799)	(1.512)	(0.962)	(1.533)	(1.232)
Robot $\times$ Income		3.390		0.979		0.567***		0.484***
		(20.191)		(0.858)		(0.142)		(0.182)
R^2	0.010	0.012	0.020	0.033	0.014	0.015	0.011	0.015
C. Dependent Variable: Δ Net Job Creation Rate								
Robot	-4.418	-6.329	-5.436***	-1.680	-6.262**	-6.291***	-4.238*	-4.665**
	(87.748)	(36.971)	(1.719)	(1.299)	(2.602)	(1.739)	(2.449)	(2.108)
Robot $\times$ Income		7.695		2.086		0.922***		0.676**
		(45.048)		(1.646)		(0.254)		(0.306)
R^2	0.015	0.015	0.011	0.013	0.008	0.006	0.009	0.009
Year FE	√	√	√	√	√	√	√	√
Demographics			√	√	√	√	√	√
Geographic FE					√	√	√	√
State $\times$ Year FE					√	√	√	√
Firm Size $\times$ Year FE							√	√
N of CZs	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetrations on business dynamics, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Dependent variable in Panel A refers to changes in job destruction rate for all US commuting zones, that in Panel B refers to changes in job creation rate for all US commuting zones, and that in Panel C refers to changes in net job creation rate for all US commuting zones. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Robustness Checks for US Business Dynamics, Robot, Income in Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dependent Variable: Δ Job Destruction Rate								
Robot	-1.512	8.060***	4.539***	3.850***	1.583	3.333	-0.478	-2.073
	(1.565)	(2.664)	(1.493)	(1.310)	(1.219)	(2.831)	(1.331)	(3.974)
Robot $\times$ Income		-0.949***		-0.433***		-0.601		0.435
		(0.325)		(0.161)		(0.550)		(0.726)
R^2	0.002	0.001	0.000	0.001	0.002	0.044	0.045	0.158
B. Dependent Variable: Δ Job Creation Rate								
Robot	3.997	-2.297	-1.718	-1.437	-2.142***	-5.473***	-2.489***	-8.618**
	(4.821)	(2.148)	(1.137)	(0.942)	(0.713)	(1.911)	(0.738)	(3.363)
Robot $\times$ Income		0.258		0.177		1.144***		1.672***
		(0.260)		(0.115)		(0.384)		(0.639)
R^2	0.010	0.012	0.020	0.033	0.014	0.015	0.011	0.015
C. Dependent Variable: Δ Net Job Creation Rate								
Robot	1.912	-10.356***	-6.257***	-5.287***	-3.725***	-8.807***	-2.011	-6.545
	(1.895)	(3.808)	(1.784)	(1.534)	(1.228)	(3.182)	(1.355)	(4.539)
Robot $\times$ Income		1.206***		0.609***		1.745***		1.237
		(0.467)		(0.192)		(0.627)		(0.834)
R^2	0.015	0.015	0.011	0.013	0.008	0.006	0.009	0.009
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics			$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE					$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE					$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE							$\surd$	$\surd$
N of CZs	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetrations on business dynamics, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Dependent variable in Panel A refers to changes in job destruction rate for middle income commuting zones in US, that in Panel B refers to changes in job creation rate for middle income commuting zones in US, and that in Panel C refers to changes in net job creation rate for middle income commuting zones in US. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Robustness Checks for Job Destructions, Other Automation and Income for US CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
A. Without Income Level						
ICT Import	0.027					
	(0.035)					
ICT Export		0.066				
		(0.085)				
ICT Net Exp			-0.045			
			(0.058)			
Auto Import				0.014		
				(0.018)		
Auto Export					0.019	
					(0.025)	
Auto Net Exp						-0.048
						(0.062)
B. Only Other Automation is Endogenous						
ICT Import	6.784					
	(53.469)					
ICT Export		1.314				
		(1.271)				
ICT Net Exp			1.040			
			(1.514)			
Auto Import				-0.176		
				(0.224)		
Auto Export					0.500	
					(0.518)	
Auto Net Exp						0.090
						(0.117)
ICT Import$\times$Income	-1.355					
	(10.675)					
ICT Export$\times$Income		-0.267				
		(0.254)				
ICT Net Exp$\times$Income			-0.209			
			(0.306)			
Auto Import$\times$Income				0.035		
				(0.046)		
Auto Export$\times$Income					-0.102	
					(0.105)	
Auto Net Exp$\times$Income						-0.019
						(0.026)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job destruction rate, where robotic penetration computed using operational stocks of robots from 8 European countries is the instrumental variable. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Job Destructions, ICT Trade Volumes, Income for US Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Δ Job Destruction Rate									
ICT Import	-0.017			0.491			0.031		
	(0.046)			(1.246)			(0.455)		
ICT Export		-0.041			0.609			0.185	
		(0.113)			(1.221)			(0.745)	
ICT Net Exp			0.028			4.221			0.025
			(0.077)			(50.304)			(1.387)
ICT Import				-0.119			-0.011		
$\times$Income				(0.283)			(0.097)		
ICT Export					-0.161			-0.056	
$\times$Income					(0.279)			(0.158)	
ICT Net Exp						-9.573			0.001
$\times$Income						(114.215)		(0.298)	
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job destruction rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results without income levels, Columns 4-6 present regression results when ICT trade volumes and interaction terms are endogenous, and Columns 7-9 present regression results when only ICT trade volumes are endogenous. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Job Destructions, Automation Trade Volumes, Income for US Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Δ Job Destruction Rate									
Auto Import	-0.009			-0.211			-0.143		
	(0.024)			(0.694)			(2.715)		
Auto Export		-0.012			0.197			0.061	
		(0.033)			(0.392)			(0.234)	
Auto Net Exp			0.032			0.023			-0.053
			(0.090)			(0.236)			(0.209)
Auto Import $\times$Income				0.044			0.029		
				(0.156)			(0.586)		
Auto Export $\times$Income					-0.052			-0.018	
					(0.090)			(0.050)	
Auto Net Exp $\times$Income						0.002			0.014
						(0.053)			(0.048)
Year FE	√	√	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√	√	√	√
N of CZs	722	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job destruction rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results without income levels, Columns 4-6 present regression results when automation trade volumes and interaction terms are endogenous, and Columns 7-9 present regression results when only automation trade volumes are endogenous. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Robustness Checks for Job Creations, Other Automation and Income for US CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
A. Without Income Level						
ICT Import	-0.056***					
	(0.015)					
ICT Export		-0.137***				
		(0.036)				
ICT Net Exp			-0.094***			
			(0.026)			
Auto Import				-0.028***		
				(0.008)		
Auto Export					-0.040***	
					(0.010)	
Auto Net Exp						-0.100***
						(0.034)
B. Only Other Automation is Endogenous						
ICT Import	-10.395					
	(82.729)					
ICT Export		-1.696*				
		(0.973)				
ICT Net Exp			-1.729			
			(1.520)			
Auto Import				0.278		
				(0.177)		
Auto Export					-0.624	
					(0.438)	
Auto Net Exp						-0.171***
						(0.059)
ICT Import$\times$Income	2.073					
	(16.515)					
ICT Export$\times$Income		0.333*				
		(0.195)				
ICT Net Exp$\times$Income			0.351			
			(0.306)			
Auto Import$\times$Income				-0.057		
				(0.036)		
Auto Export$\times$Income					0.124	
					(0.089)	
Auto Net Exp$\times$Income						0.038***
						(0.013)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Job Creations, ICT Trade Volumes, Income for US Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Δ Job Creation Rate									
ICT Import	-0.087***			-1.954**			-0.774**		
	(0.030)			(0.913)			(0.360)		
ICT Export		-0.214***			-1.864**			-1.168**	
		(0.071)			(0.907)			(0.561)	
ICT Net Exp			0.146***			-1.964			-2.437*
			(0.052)			(24.454)			(1.324)
ICT Import				0.439**			0.162**		
×Income				(0.209)			(0.078)		
ICT Export					0.410*			0.237*	
×Income					(0.216)			(0.125)	
ICT Net Exp						0.446			0.520*
×Income						(5.552)			(0.286)
Year FE	√	√	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√	√	√	√
N of CZs	722	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results without income levels, Columns 4-6 present regression results when ICT trade volumes and interaction terms are endogenous, and Columns 7-9 present regression results when only ICT trade volumes are endogenous. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Job Creations, Automation Trade Volumes, Income for US Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Δ Job Creation Rate									
Auto Import	-0.045***			-1.174**			-4.588		
	(0.017)			(0.561)			(12.293)		
Auto Export		-0.062***			-0.597**			-0.361**	
		(0.021)			(0.288)			(0.178)	
Auto Net Exp			0.168*			-0.416***			-0.380***
			(0.090)			(0.141)			(0.134)
Auto Import $\times$Income				0.265**			0.988		
				(0.124)			(2.651)		
Auto Export $\times$Income					0.133*			0.074*	
					(0.069)			(0.040)	
Auto Net Exp $\times$Income						0.095***			0.089***
						(0.030)			(0.030)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results without income levels, Columns 4-6 present regression results when automation trade volumes and interaction terms are endogenous, and Columns 7-9 present regression results when only automation trade volumes are endogenous. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Robustness Checks for Net Job Creations, Other Automation and Income for US CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
A. Without Income Level						
ICT Import	-0.083**					
	(0.036)					
ICT Export		-0.203**				
		(0.089)				
ICT Net Exp			-0.139**			
			(0.062)			
Auto Import				-0.042**		
				(0.019)		
Auto Export					-0.059**	
					(0.026)	
Auto Net Exp						-0.148**
						(0.071)
B. Only Other Automation is Endogenous						
ICT Import	-17.178					
	(135.908)					
ICT Export		-3.010				
		(1.837)				
ICT Net Exp			-2.769			
			(2.743)			
Auto Import				-0.454		
				(0.341)		
Auto Export					-1.124	
					(0.819)	
Auto Net Exp						-0.261*
						(0.136)
ICT Import$\times$Income	3.428					
	(27.131)					
ICT Export$\times$Income		0.600				
		(0.369)				
ICT Net Exp$\times$Income			0.559			
			(0.554)			
Auto Import$\times$Income				0.092		
				(0.069)		
Auto Export$\times$Income					0.226	
					(0.166)	
Auto Net Exp$\times$Income						0.058*
						(0.030)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is the instrumental variable. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Net Job Creations, ICT Trade Volumes, Income for US Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Δ Net Job Creation Rate									
ICT Import	-0.070			-2.446			-0.805		
	(0.051)			(1.627)			(0.552)		
ICT Export		-0.173			-2.472			-1.352	
		(0.126)			(1.541)			(0.885)	
ICT Net Exp			0.118			-0.239			2.412
			(0.087)			(2.937)			(1.813)
ICT Import				0.559			0.173		
$\times$Income				(0.372)			(0.118)		
ICT Export					0.571			0.293	
$\times$Income					(0.360)			(0.190)	
ICT Net Exp						0.542			-0.521
$\times$Income						(6.669)			(0.390)
Year FE	√	√	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√	√	√	√
N of CZs	722	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results without income levels, Columns 4-6 present regression results when ICT trade volumes and interaction terms are endogenous, and Columns 7-9 present regression results when only ICT trade volumes are endogenous. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Net Job Creations, Automation Trade Volumes, Income for US Middle Income CZs, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Δ Net Job Creation Rate									
Auto Import	-0.037			-1.386*			-4.445		
	(0.027)			(0.834)			(12.173)		
Auto Export		-0.050			-0.794			-0.422	
		(0.037)			(0.494)			(0.279)	
Auto Net Exp			0.135			-0.438*			-0.327
			(0.111)			(0.263)			(0.237)
Auto Import $\times$Income				0.309*			0.959		
				(0.186)			(2.625)		
Auto Export $\times$Income					0.185			0.092	
					(0.116)			(0.061)	
Auto Net Exp $\times$Income						0.094			0.075
						(0.058)			(0.054)
Year FE	√	√	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√	√	√	√
N of CZs	722	722	722	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of other automation technologies on changes of net job creation rate, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results without income levels, Columns 4-6 present regression results when automation trade volumes and interaction terms are endogenous, and Columns 7-9 present regression results when only automation trade volumes are endogenous. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Robustness Checks for Job Destructions, Robots, Skill Share in US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
Robotic Penetration	0.106	1.374	1.480	1.135	1.579	0.859
	(0.071)	(1.765)	(1.860)	(1.375)	(2.094)	(1.373)
Robotic Penetration			-0.002		-0.004	
$\times$ %High School Educated Worker			(0.003)		(0.005)	
Robotic Penetration				-0.003		-0.007
$\times$ %University Educated Workers				(0.005)		(0.009)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes: The table presents IV estimates of the effects of robotic penetration on changes of job destruction rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Column 1 presents within group estimation of robotic penetration on on changes of job destruction rate; Columns 2 to 4 only treat robotic penetration as endogenous variable; Columns 5 to 6 treat both robotic penetration and the interaction term with income level as endogenous variable. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Robustness Checks for Job Creations, Robots, Skill Share in US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
Robotic Penetration	0.256***	-2.864*	-3.134***	-2.264***	-3.260*	-1.936
	(0.088)	(1.533)	(1.211)	(0.872)	(1.742)	(1.273)
Robotic Penetration			0.005***		0.008**	
$\times$ %High School Educated Worker			(0.002)		(0.004)	
Robotic Penetration				0.008***		0.013**
$\times$ %University Educated Workers				(0.003)		(0.007)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes: The table presents IV estimates of the effects of robotic penetration on changes of job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Column 1 presents within group estimation of robotic penetration on on changes of job destruction rate; Columns 2 to 4 only treat robotic penetration as endogenous variable; Columns 5 to 6 treat both robotic penetration and the interaction term with income level as endogenous variable. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Robustness Checks for Net Job Creations, Robots, Skill Share in US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
Robotic Penetration	0.149**	-4.238*	-4.614**	-3.398**	-4.838	-2.795
	(0.067)	(2.449)	(2.114)	(1.543)	(2.976)	(2.208)
Robotic Penetration			0.007**		0.012*	
$\times$ %High School Educated Worker			(0.003)		(0.006)	
Robotic Penetration				0.012**		0.020*
$\times$ %University Educated Workers				(0.005)		(0.012)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Column 1 presents within group estimation of robotic penetration on on changes of job destruction rate; Columns 2 to 4 only treat robotic penetration as endogenous variable; Columns 5 to 6 treat both robotic penetration and the interaction term with income level as endogenous variable. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: US Job Destructions, Automation Trade, and University Education by Income, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Job Destruction Rate			
Auto Import	1.234		
	(5.103)		
Auto Export		0.515	
		(0.618)	
Auto Net Exp			-0.750
			(1.120)
Auto Import	-0.025		
$\times$%University Educated Workers	(0.112)		
Auto Export		-0.009	
$\times$%University Educated Workers		(0.011)	
Auto Net Exp			-0.010
$\times$%University Educated Workers			(0.017)
Auto Import$\times$Income	0.003		
$\times$%University Educated Workers	(0.015)		
Auto Export$\times$Income		0.001	
$\times$%University Educated Workers		(0.001)	
Auto Net Exp$\times$Income			0.001
$\times$%University Educated Workers			(0.002)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job destruction rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Robustness Checks for US Job Destructions, Other Automation, University Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
ICT Import	0.272					
	(0.254)					
ICT Export		0.460				
		(0.421)				
ICT Net Exp			-0.691			
			(0.660)			
Auto Import				0.186		
				(0.180)		
Auto Export					0.143	
					(0.131)	
Auto Net Exp						0.395
						(0.468)
ICT Import	-0.002					
$\times$%University Educated Worker	(0.001)					
ICT Export		-0.003				
$\times$%University Educated Worker		(0.002)				
ICT Net Exp			0.004			
$\times$%University Educated Worker			(0.004)			
Auto Import				-0.001		
$\times$%University Educated Worker				(0.001)		
Auto Export					-0.001	
$\times$%University Educated Worker					(0.001)	
Auto Net Exp						-0.002
$\times$%University Educated Worker						(0.002)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job destruction rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22: US Job Destructions, ICT Trade Volumes, and High School Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
ICT Import	0.525			1.365		
	(0.504)			(1.519)		
ICT Export		0.674			1.658	
		(0.636)			(1.897)	
ICT Net Exp			-2.578			-1.046
			(3.095)			(1.772)
ICT Import	-0.001			-0.006		
$\times$%High School	(0.001)			(0.007)		
ICT Export		-0.001			-0.007	
$\times$%High School		(0.001)			(0.009)	
ICT Net Exp			0.006			0.045
$\times$%High School			(0.007)			(0.077)
ICT Import$\times$Income				0.001		
$\times$%High School				(0.001)		
ICT Export$\times$Income					0.001	
$\times$%High School					(0.001)	
ICT Net Exp$\times$Income						-0.004
$\times$%High School						(0.007)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of CZs	722	722	722	722	722	722
N of Obs	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job destruction rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results by high school education, and Columns 4-6 present regression results by high school education and income level. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23: US Job Destructions, Automation Trade Volumes, and High School Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
Auto Import	0.452			0.655		
	(0.497)			(0.868)		
Auto Export		0.216			0.550	
		(0.203)			(0.624)	
Auto Net Exp			0.303			-0.711
			(0.333)			(1.848)
Auto Import	-0.001			-0.002		
$\times$%High School	(0.001)			(0.003)		
Auto Export		-0.000			-0.002	
$\times$%High School		(0.000)			(0.003)	
Auto Net Exp			-0.001			0.006
$\times$%High School			(0.001)			(0.014)
Auto Import$\times$Income				0.000		
$\times$%High School				(0.000)		
Auto Export$\times$Income					0.000	
$\times$%High School					(0.000)	
Auto Net Exp$\times$Income						-0.001
$\times$%High School						(0.002)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job destruction rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results by high school education, and Columns 4-6 present regression results by high school education and income level. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: US Job Creations, Automation Trade, and University Education by Income, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Job Creation Rate			
Auto Import	-1.360		
	(1.044)		
Auto Export		-1.246***	
		(0.398)	
Auto Net Exp			1.785
			(3.112)
Auto Import	0.005		
×%University Educated Workers	(0.004)		
Auto Export		0.006***	
×%University Educated Workers		(0.002)	
Auto Net Exp			-0.015
×%University Educated Workers			(0.023)
Auto Import×Income	-0.000		
×%University Educated Workers	(0.000)		
Auto Export×Income		-0.001***	
×%University Educated Workers		(0.000)	
Auto Net Exp×Income			0.002
×%University Educated Workers			(0.003)
Year FE	√	√	√
Demographics	√	√	√
Geographic FE	√	√	√
State × Year FE	√	√	√
Firm Size × Year FE	√	√	√
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Robustness Checks for US Job Creations, Other Automation, University Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
ICT Import	-0.396***					
	(0.147)					
ICT Export		-0.645***				
		(0.193)				
ICT Net Exp			-1.025*			
			(0.524)			
Auto Import				-0.272**		
				(0.127)		
Auto Export					-0.200***	
					(0.061)	
Auto Net Exp						-0.609*
						(0.343)
ICT Import	0.002***					
$\times$%University Educated Workers	(0.001)					
ICT Export		0.003***				
$\times$%University Educated Workers		(0.001)				
ICT Net Exp			0.005*			
$\times$%University Educated Workers			(0.003)			
Auto Import				0.001**		
$\times$%University Educated Workers				(0.001)		
Auto Export					0.001***	
$\times$%University Educated Workers					(0.000)	
Auto Net Exp						0.003*
$\times$%University Educated Workers						(0.002)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 26: US Job Creations, ICT Trade Volumes, and High School Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
ICT Import	-0.880**			-1.151		
	(0.344)			(0.751)		
ICT Export		-1.103***			-2.283	
		(0.299)			(1.556)	
ICT Net Exp			4.380			2.329
			(4.428)			(1.535)
ICT Import	0.002***			0.019		
$\times$%High School	(0.001)			(0.014)		
ICT Export		0.002***			0.038	
$\times$%High School		(0.001)			(0.029)	
ICT Net Exp			-0.009			-0.039
$\times$%High School			(0.009)			(0.029)
ICT Import$\times$Income				-0.002		
$\times$%High School				(0.002)		
ICT Export$\times$Income					-0.005	
$\times$%High School					(0.004)	
ICT Net Exp$\times$Income						0.005
$\times$%High School						(0.004)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results by high school education, and Columns 4-6 present regression results by high school education and income level. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 27: US Job Creations, Automation Trade Volumes, and High School Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
Auto Import	-0.757			-1.676		
	(0.521)			(6.199)		
Auto Export		-0.352***			-0.709	
		(0.098)			(0.486)	
Auto Net Exp			-0.526**			-1.121
			(0.211)			(1.362)
Auto Import	0.002			0.034		
×%High School	(0.001)			(0.136)		
Auto Export		0.001***			0.012	
×%High School		(0.000)			(0.009)	
Auto Net Exp			0.001**			0.012
×%High School			(0.000)			(0.023)
Auto Import×Income				-0.005		
×%High School				(0.019)		
Auto Export×Income					-0.001	
×%High School					(0.001)	
Auto Net Exp×Income						-0.001
×%High School						(0.003)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Columns 1-3 present regression results by high school education, and Columns 4-6 present regression results by high school education and income level. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 28: US Net Job Creations, Automation Trade, and University Education by Income, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Net Job Creation Rate			
Auto Import	-2.015		
	(1.724)		
Auto Export		-1.797**	
		(0.833)	
Auto Net Exp			2.496
			(4.839)
Auto Import	0.006		
$\times$%University Educated Workers	(0.006)		
Auto Export		0.008**	
$\times$%University Educated Workers		(0.004)	
Auto Net Exp			-0.021
$\times$%University Educated Workers			(0.036)
Auto Import$\times$Income	-0.000		
$\times$%University Educated Workers	(0.001)		
Auto Export$\times$Income		-0.001*	
$\times$%University Educated Workers		(0.000)	
Auto Net Exp$\times$Income			0.003
$\times$%University Educated Workers			(0.005)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:

The table presents IV estimates of the effects of alternative automation technologies on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 29: Robustness Checks for US Job Net Creations, Other Automation, University Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
ICT Import	-0.669**					
	(0.282)					
ICT Export		-1.105**				
		(0.432)				
ICT Net Exp			-1.716*			
			(0.879)			
Auto Import				-0.458**		
				(0.230)		
Auto Export					-0.343**	
					(0.135)	
Auto Net Exp						-1.003
						(0.693)
ICT Import	0.004**					
$\times$%University Educated Workers	(0.002)					
ICT Export		0.006**				
$\times$%University Educated Workers		(0.002)				
ICT Net Exp			0.009**			
$\times$%University Educated Workers			(0.005)			
Auto Import				0.002**		
$\times$%University Educated Workers				(0.001)		
Auto Export					0.002**	
$\times$%University Educated Workers					(0.001)	
Auto Net Exp						0.005
$\times$%University Educated Workers						(0.003)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:

The table presents IV estimates of the effects of alternative automation technologies on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 30: US Net Job Creations, ICT Trade Volumes, and High School Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
ICT Import	-1.405**			-1.951		
	(0.608)			(1.528)		
ICT Export		-1.776***			-3.922	
		(0.662)			(3.156)	
ICT Net Exp			6.959			3.914
			(6.669)			(3.069)
ICT Import $\times$%High School	0.003**			0.033		
	(0.001)			(0.029)		
ICT Export $\times$%High School		0.004***			0.065	
		(0.001)			(0.059)	
ICT Net Exp $\times$%High School			-0.015			-0.066
			(0.014)			(0.058)
ICT Import$\times$Income $\times$%High School				-0.004		
				(0.004)		
ICT Export$\times$Income $\times$%High School					-0.008	
					(0.008)	
ICT Net Exp$\times$Income $\times$%High School						0.008
						(0.008)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is the instrument. Columns 1-3 present regression results by high school education, and Columns 4-6 present regression results by high school education and income level. Explanatory variables include ICT import (ICT Import), ICT export (ICT Export), and ICT net export (ICT Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 31: US Net Job Creations, Automation Trade Volumes, and High School Education, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
Auto Import	-1.209			-2.910		
	(0.852)			(11.233)		
Auto Export		-0.568***			-1.224	
		(0.213)			(0.991)	
Auto Net Exp			-0.829*			-1.971
			(0.435)			(2.319)
Auto Import	0.002			0.059		
$\times$%High School	(0.002)			(0.247)		
Auto Export		0.001***			0.020	
$\times$%High School		(0.000)			(0.018)	
Auto Net Exp			0.002*			0.021
$\times$%High School			(0.001)			(0.039)
Auto Import$\times$Income				-0.008		
$\times$%High School				(0.034)		
Auto Export$\times$Income					-0.003	
$\times$%High School					(0.002)	
Auto Net Exp$\times$Income						-0.002
$\times$%High School						(0.005)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on changes of net job creation rate, by skills share and income level, where robotic penetration computed using operational stocks of robots from 8 European countries is the instrument. Columns 1-3 present regression results by high school education, and Columns 4-6 present regression results by high school education and income level. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 32: Robustness Checks for US Job Destructions, Robot, Industry, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Destruction Rate						
Robot Penetration	0.763	1.453	1.444	1.370	1.380	1.736
	(1.156)	(1.840)	(1.777)	(1.751)	(1.759)	(2.184)
Robot Penetration	-0.002					
$\times$ %Manufacturing GDP	(0.002)					
Robot Penetration		-0.002				
$\times$ %Agriculture GDP		(0.001)				
Robot Penetration			-0.002**			
$\times$ %Mining GDP			(0.001)			
Robot Penetration				-0.000		
$\times$ %Utility GDP				(0.002)		
Robot Penetration					-0.002	
$\times$ %Construction GDP					(0.005)	
Robot Penetration						-0.032
$\times$ %R&D GDP						(0.036)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job destruction rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 33: Robustness Checks for US Job Creations, Robot, Industry, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
Robot Penetration	-1.844**	-2.944*	-2.755*	-2.846*	-2.852*	-3.573*
	(0.742)	(1.596)	(1.473)	(1.525)	(1.548)	(2.060)
Robot Penetration	0.004***					
$\times$ %Manufacturing GDP	(0.001)					
Robot Penetration		0.002				
$\times$ %Agriculture GDP		(0.001)				
Robot Penetration			-0.003**			
$\times$ %Mining GDP			(0.001)			
Robot Penetration				0.001		
$\times$ %Utility GDP				(0.002)		
Robot Penetration					-0.003	
$\times$ %Construction GDP					(0.009)	
Robot Penetration						0.063*
$\times$ %R&D GDP						(0.033)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 34: Robustness Checks for US Net Job Creations, Robot, Industry, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
Robot Penetration	-2.606*	-4.397*	-4.199*	-4.215*	-4.232*	-5.309*
	(1.335)	(2.606)	(2.404)	(2.440)	(2.445)	(3.174)
Robot Penetration	0.006**					
$\times$ %Manufacturing GDP	(0.003)					
Robot Penetration		0.003*				
$\times$ %Agriculture GDP		(0.002)				
Robot Penetration			-0.001			
$\times$ %Mining GDP			(0.002)			
Robot Penetration				0.002		
$\times$ %Utility GDP				(0.003)		
Robot Penetration					-0.002	
$\times$ %Construction GDP					(0.012)	
Robot Penetration						0.094*
$\times$ %R&D GDP						(0.049)
Year FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Demographics	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Geographic FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
State $\times$ Year FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Firm Size $\times$ Year FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 35: Job Destruction Dynamics and Robotic Penetration by Manufacturing Sectors (Group 1) for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Job Destruction Rate							
Robot Penetration	0.049	0.007	-0.019	0.189	0.259	0.280	0.416
	(1.083)	(1.580)	(0.956)	(1.107)	(1.141)	(1.034)	(1.397)
Robot Penetration	-0.075						
$\times$%Textile GDP	(0.231)						
Robot Penetration		-0.019					
$\times$%Wood GDP		(0.301)					
Robot Penetration			0.045				
$\times$%Paper GDP			(0.105)				
Robot Penetration				0.029			
$\times$%Pharmaceutical GDP				(0.054)			
Robot Penetration					0.027		
$\times$%Chemical GDP					(0.034)		
Robot Penetration						0.211	
$\times$%Plastic GDP						(0.294)	
Robot Penetration							0.303
$\times$%Glass GDP							(0.564)
Robot Penetration$\times$Income	0.007						
$\times$%Textile GDP	(0.084)						
Robot Penetration$\times$Income		-0.002					
$\times$%Wood GDP		(0.058)					
Robot Penetration$\times$Income			-0.015				
$\times$%Paper GDP			(0.032)				
Robot Penetration$\times$Income				-0.006			
$\times$%Pharmaceutical GDP				(0.011)			
Robot Penetration$\times$Income					-0.005		
$\times$%Chemical GDP					(0.008)		
Robot Penetration$\times$Income						-0.041	
$\times$%Plastic GDP						(0.062)	
Robot Penetration$\times$Income							-0.057
$\times$%Glass GDP							(0.113)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job destruction rate and proportion of GDP by manufacturing sectors, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Manufacturing sectors include textiles; wood and furniture; paper; Pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 36: Job Destruction Dynamics and Robotic Penetration by Manufacturing Sectors (Group 2) for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Job Destruction Rate							
Robot Penetration	0.049	1.059	0.591	0.056	-0.177	0.252	0.880
	(1.083)	(2.116)	(1.744)	(1.001)	(1.439)	(1.491)	(1.716)
Robot Penetration		0.301					
$\times$%BasicMetal GDP		(0.330)					
Robot Penetration			0.205				
$\times$%MetalProduct GDP			(0.393)				
Robot Penetration				0.131			
$\times$%Electric GDP				(0.239)			
Robot Penetration					-0.013		
$\times$%Machine GDP					(0.236)		
Robot Penetration						0.051	
$\times$%Automotive GDP						(0.085)	
Robot Penetration							0.108
$\times$%Other GDP							(0.093)
Robot Penetration$\times$Income		-0.058					
$\times$%BasicMetal GDP		(0.070)					
Robot Penetration$\times$Income			-0.038				
$\times$%MetalProduct GDP			(0.076)				
Robot Penetration$\times$Income				-0.030			
$\times$%Electric GDP				(0.057)			
Robot Penetration$\times$Income					-0.000		
$\times$%Machine GDP					(0.047)		
Robot Penetration$\times$Income						-0.010	
$\times$%Automotive GDP						(0.017)	
Robot Penetration$\times$Income							-0.019
$\times$%Other GDP							(0.016)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job destruction rate and proportion of GDP by manufacturing sectors, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Manufacturing sectors include textiles; wood and furniture; paper; Pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 37: Job Creation Dynamics and Robotic Penetration by Manufacturing Sectors (Group 1) for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Job Creation Rate							
Robot Penetration	-2.426**	-3.898*	-2.301**	-1.992***	-1.994**	-2.462**	-3.055**
	(1.186)	(2.064)	(0.901)	(0.625)	(0.946)	(1.255)	(1.529)
Robot Penetration ×%Textile GDP	-0.523*						
	(0.293)						
Robot Penetration ×%Wood GDP		-0.963**					
		(0.423)					
Robot Penetration ×%Paper GDP			-0.288**				
			(0.133)				
Robot Penetration ×%Pharmaceutical GDP				-0.054			
				(0.051)			
Robot Penetration ×%Chemical GDP					-0.020		
					(0.037)		
Robot Penetration ×%Plastic GDP						-0.735***	
						(0.274)	
Robot Penetration ×%Glass GDP							-1.325**
							(0.600)
Robot Penetration×Income ×%Textile GDP	0.164*						
	(0.094)						
Robot Penetration×Income ×%Wood GDP		0.173**					
		(0.075)					
Robot Penetration×Income ×%Paper GDP			0.079***				
			(0.030)				
Robot Penetration×Income ×%Pharmaceutical GDP				0.013			
				(0.010)			
Robot Penetration×Income ×%Chemical GDP					0.009		
					(0.007)		
Robot Penetration×Income ×%Plastic GDP						0.153***	
						(0.055)	
Robot Penetration×Income ×%Glass GDP							0.264**
							(0.115)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job creation rate and proportion of GDP by manufacturing sectors, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Manufacturing sectors include textiles; wood and furniture; paper; Pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 38: Job Creation Dynamics and Robotic Penetration by Manufacturing Sectors (Group 2) for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Job Creation Rate							
Robot Penetration	-2.426**	-3.824	-3.867*	-2.107**	-3.230	-3.320*	-2.787**
	(1.186)	(2.830)	(2.245)	(1.000)	(2.566)	(1.740)	(1.397)
Robot Penetration		-0.626					
×%BasicMetal GDP		(0.469)					
Robot Penetration			-0.867				
×%MetalProduct GDP			(0.589)				
Robot Penetration				-0.517**			
×%Electric GDP				(0.208)			
Robot Penetration					-0.593**		
×%Machine GDP					(0.241)		
Robot Penetration						-0.244**	
×%Automotive GDP						(0.113)	
Robot Penetration							0.034
×%Other GDP							(0.063)
Robot Penetration×Income		0.133					
×%BasicMetal GDP		(0.099)					
Robot Penetration×Income			0.168				
×%MetalProduct GDP			(0.110)				
Robot Penetration×Income				0.125***			
×%Electric GDP				(0.045)			
Robot Penetration×Income					0.116**		
×%Machine GDP					(0.047)		
Robot Penetration×Income						0.046**	
×%Automotive GDP						(0.023)	
Robot Penetration×Income							-0.001
×%Other GDP							(0.010)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of job creation rate and proportion of GDP by manufacturing sectors, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Manufacturing sectors include textiles; wood and furniture; paper; Pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 39: Net Job Creation Dynamics and Robotic Penetration by Manufacturing Sectors (Group 1) for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Net Job Creation Rate							
Robot Penetration	-2.475	-3.905	-2.282*	-2.181*	-2.253	-2.742	-3.472
	(1.765)	(2.518)	(1.375)	(1.261)	(1.518)	(1.841)	(2.289)
Robot Penetration $\times$%Textile GDP	-0.448						
	(0.351)						
Robot Penetration $\times$%Wood GDP		-0.944*					
		(0.520)					
Robot Penetration $\times$%Paper GDP			-0.333**				
			(0.169)				
Robot Penetration $\times$%Pharmaceutical GDP				-0.083			
				(0.077)			
Robot Penetration $\times$%Chemical GDP					-0.047		
					(0.050)		
Robot Penetration $\times$%Plastic GDP						-0.946**	
						(0.406)	
Robot Penetration $\times$%Glass GDP							-1.628*
							(0.894)
Robot Penetration$\times$Income $\times$%Textile GDP	0.157						
	(0.118)						
Robot Penetration$\times$Income $\times$%Wood GDP		0.175*					
		(0.094)					
Robot Penetration$\times$Income $\times$%Paper GDP			0.094**				
			(0.043)				
Robot Penetration$\times$Income $\times$%Pharmaceutical GDP				0.019			
				(0.015)			
Robot Penetration$\times$Income $\times$%Chemical GDP					0.014		
					(0.010)		
Robot Penetration$\times$Income $\times$%Plastic GDP						0.194**	
						(0.083)	
Robot Penetration$\times$Income $\times$%Glass GDP							0.321*
							(0.173)
Year FE	√	√	√	√	√	√	√
Demographics	√	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of net job creation rate and proportion of GDP by manufacturing sectors, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Manufacturing sectors include textiles; wood and furniture; paper; Pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 40: Net Job Creation Dynamics and Robotic Penetration by Manufacturing Sectors (Group 2) for US, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Δ Net Job Creation Rate							
Robot Penetration	-2.475	-4.882	-4.458	-2.163	-3.052	-3.572	-3.667
	(1.765)	(4.260)	(3.060)	(1.549)	(3.179)	(2.303)	(2.393)
Robot Penetration		-0.927					
$\times$%BasicMetal GDP		(0.685)					
Robot Penetration			-1.072				
$\times$%MetalProduct GDP			(0.773)				
Robot Penetration				-0.648**			
$\times$%Electric GDP				(0.323)			
Robot Penetration					-0.580*		
$\times$%Machine GDP					(0.305)		
Robot Penetration						-0.295**	
$\times$%Automotive GDP						(0.149)	
Robot Penetration							-0.075
$\times$%Other GDP							(0.131)
Robot Penetration$\times$Income		0.191					
$\times$%BasicMetal GDP		(0.144)					
Robot Penetration$\times$Income			0.206				
$\times$%MetalProduct GDP			(0.145)				
Robot Penetration$\times$Income				0.155**			
$\times$%Electric GDP				(0.073)			
Robot Penetration$\times$Income					0.116*		
$\times$%Machine GDP					(0.059)		
Robot Penetration$\times$Income						0.056*	
$\times$%Automotive GDP						(0.030)	
Robot Penetration$\times$Income							0.019
$\times$%Other GDP							(0.022)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of robotic penetration on interactions between changes of net job creation rate and proportion of GDP by manufacturing sectors, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Manufacturing sectors include textiles; wood and furniture; paper; Pharmaceuticals and cosmetics; other chemical products; rubber and plastic products (non-automotive); glass, ceramics, stone, mineral products (non-automotive); basic metals; metal products (non-automotive); electrical or electronics; industrial machinery; automotive; and other vehicles. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 41: Job Destruction Dynamics and Automation Trade Volumes by Industry for US, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Job Destruction Rate			
Auto Import	0.015		
	(0.020)		
Auto Export		0.019	
		(0.025)	
Auto Net Exp			-0.095
			(0.180)
Auto Import	0.001		
$\times$%Manufacturing GDP	(0.001)		
Auto Export		0.001	
$\times$%Manufacturing GDP		(0.001)	
Auto Net Exp			-0.009
$\times$%Manufacturing GDP			(0.012)
Auto Import$\times$Income	-0.000		
$\times$%Manufacturing GDP	(0.000)		
Auto Export$\times$Income		-0.000	
$\times$%Manufacturing GDP		(0.000)	
Auto Net Exp$\times$Income			0.002
$\times$%Manufacturing GDP			(0.002)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of automation trade volumes on interactions between changes of job destruction rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 42: Robustness Checks for US Job Destruction Dynamics, Other Automation, Industry, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Destruction Rate						
ICT Import	0.028					
	(0.037)					
ICT Export		0.070				
		(0.090)				
ICT Net Exp			-0.048			
			(0.062)			
Auto Import				0.014		
				(0.019)		
Auto Export					0.020	
					(0.026)	
Auto Net Exp						-0.049
						(0.065)
ICT Import×%Manufacturing GDP	-0.000					
	(0.000)					
ICT Export×%Manufacturing GDP		-0.000				
		(0.000)				
ICT Net Exp×%Manufacturing GDP			0.000			
			(0.000)			
Auto Import×%Manufacturing GDP				-0.000		
				(0.000)		
Auto Export×%Manufacturing GDP					-0.000	
					(0.000)	
Auto Net Exp×%Manufacturing GDP						0.000
						(0.000)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State × Year FE	√	√	√	√	√	√
Firm Size × Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on interactions between changes of job destruction rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Alternative measures of automation technologies include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), automation net export (Auto Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 43: Job Creation Dynamics and Automation Trade Volumes by Industry for US, 2000-2019

	(1)	(2)	(3)
Dependent Variable: △ Job Creation Rate			
Auto Import	-0.031**		
	(0.014)		
Auto Export		-0.040***	
		(0.012)	
Auto Net Exp			0.186
			(0.300)
Auto Import	-0.002**		
×%Manufacturing GDP	(0.001)		
Auto Export		-0.002**	
×%Manufacturing GDP		(0.001)	
Auto Net Exp			0.016
×%Manufacturing GDP			(0.020)
Auto Import×Income	0.000**		
×%Manufacturing GDP	(0.000)		
Auto Export×Income		0.000***	
×%Manufacturing GDP		(0.000)	
Auto Net Exp×Income			-0.003
×%Manufacturing GDP			(0.004)
Year FE	√	√	√
Demographics	√	√	√
Geographic FE	√	√	√
State × Year FE	√	√	√
Firm Size × Year FE	√	√	√
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of automation trade volumes on interactions between changes of job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 44: Robustness Checks for US Job Creation Dynamics, Other Automation, Industry, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Job Creation Rate						
ICT Import	-0.058***					
	(0.016)					
ICT Export		-0.142***				
		(0.038)				
ICT Net Exp			-0.098***			
			(0.028)			
Auto Import				-0.029***		
				(0.008)		
Auto Export					-0.041***	
					(0.011)	
Auto Net Exp						-0.102***
						(0.035)
ICT Import	0.000***					
$\times$%Manufacturing GDP	(0.000)					
ICT Net Exp		0.001***				
$\times$%Manufacturing GDP		(0.000)				
ICT Net Exp			-0.000***			
$\times$%Manufacturing GDP			(0.000)			
Auto Import				0.000***		
$\times$%Manufacturing GDP				(0.000)		
Auto Export					0.000***	
$\times$%Manufacturing GDP					(0.000)	
Auto Net Exp						-0.000***
$\times$%Manufacturing GDP						(0.000)
Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on interactions between changes of job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Alternative measures of automation technologies include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), automation net export (Auto Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 45: Net Job Creation Dynamics and Automation Trade Volumes by Industry for US, 2000-2019

	(1)	(2)	(3)
Dependent Variable: Δ Net Job Creation Rate			
Auto Import	-0.046*		
	(0.026)		
Auto Export		-0.059**	
		(0.028)	
Auto Net Exp			0.281
			(0.453)
Auto Import	-0.003**		
$\times$%Manufacturing GDP	(0.001)		
Auto Export		-0.003**	
$\times$%Manufacturing GDP		(0.001)	
Auto Net Exp			0.025
$\times$%Manufacturing GDP			(0.029)
Auto Import$\times$Income	0.001**		
$\times$%Manufacturing GDP	(0.000)		
Auto Export$\times$Income		0.001**	
$\times$%Manufacturing GDP		(0.000)	
Auto Net Exp$\times$Income $\times$			-0.005
$\times$%Manufacturing GDP			(0.006)
Year FE	$\surd$	$\surd$	$\surd$
Demographics	$\surd$	$\surd$	$\surd$
Geographic FE	$\surd$	$\surd$	$\surd$
State $\times$ Year FE	$\surd$	$\surd$	$\surd$
Firm Size $\times$ Year FE	$\surd$	$\surd$	$\surd$
N of Commuting Zones	722	722	722
N of Observations	2888	2888	2888

Notes:
The table presents IV estimates of the effects of automation trade volumes on interactions between changes of net job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Explanatory variables include automation import (Auto Import), automation export (Auto Export), and automation net export (Auto Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 46: Robustness Checks for US Net Job Creation Dynamics, Other Automation, Industry, 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δ Net Job Creation Rate						
ICT Import	-0.086**					
	(0.040)					
ICT Export		-0.211**				
		(0.097)				
ICT Net Exp			-0.145**			
			(0.067)			
Auto Import				-0.044**		
				(0.020)		
Auto Export					-0.062**	
					(0.028)	
Auto Net Exp						-0.151**
						(0.076)
ICT Import	0.000**					
$\times$%Manufacturing GDP	(0.000)					
ICT Export		0.001**				
$\times$%Manufacturing GDP		(0.000)				
ICT Net Exp			-0.001**			
$\times$%Manufacturing GDP			(0.000)			
Auto Import				0.000**		
$\times$%Manufacturing GDP				(0.000)		
Auto Export					0.000**	
$\times$%Manufacturing GDP					(0.000)	
Auto Net Exp						-0.001**
$\times$%Manufacturing GDP						(0.000)
Year FE	√	√	√	√	√	√
Demographics	√	√	√	√	√	√
Geographic FE	√	√	√	√	√	√
State $\times$ Year FE	√	√	√	√	√	√
Firm Size $\times$ Year FE	√	√	√	√	√	√
N of Commuting Zones	722	722	722	722	722	722
N of Observations	2888	2888	2888	2888	2888	2888

Notes:
The table presents IV estimates of the effects of alternative automation technologies on interactions between changes of net job creation rate and proportion of GDP by industry, where robotic penetration computed using operational stocks of robots from 8 European countries is used as the instrument. Alternative measures of automation technologies include ICT import (ICT Import), ICT export (ICT Export), ICT net export (ICT Net Exp), automation import (Auto Import), automation export (Auto Export), automation net export (Auto Net Exp). Since net job creation dynamics are only pronounced for manufacturing industry, I will focus on the percentage of manufacturing GDP. Other demographics include number of firms, population, age, gender, race and education. Geographic FE refers to Census Divisions. Income level is measured using personal income per capita in 2000, the initial year of US analysis.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 47: Robustness Checks for Employment, Robot Across Countries, 2004-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Δ Employment Rate								
Robotic Density	-0.396	-0.603	-0.300	-0.481	-1.442***	-1.791***	-0.444*	-1.623***
	(0.286)	(0.404)	(0.272)	(0.374)	(0.231)	(0.335)	(0.228)	(0.265)
Robotic Density×Income		0.021**		0.019**		0.035***		0.062***
		(0.009)		(0.009)		(0.010)		(0.008)
Year FE			√	√	√	√	√	√
Geographic FE					√	√	√	√
Location×Year FE					√	√	√	√
Demographics							√	√
N of Observations	1026	1026	1026	1026	1026	1026	1026	1026
N of Countries	65	65	65	65	65	65	65	65
R^2	0.002	0.003	0.001	0.002	0.457	0.543	0.606	0.743

Notes:
The table presents within group estimates of the effects of robotic penetration on employment rate. Explanatory variable is changes in robotic density. The regressions are weighted by total labour force in 2004. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE or location FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 48: Robustness Checks for Employment, Robot Across Countries, 2010-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Δ Employment Rate								
Robotic Density	0.091	0.095	0.138	0.165	-1.171***	-1.594***	-0.295	-1.622***
	(0.330)	(0.518)	(0.318)	(0.490)	(0.260)	(0.434)	(0.248)	(0.368)
Robotic Density × Income		0.003		0.002		0.032***		0.060***
		(0.012)		(0.011)		(0.012)		(0.010)
Year FE			√	√	√	√	√	√
Geographic FE					√	√	√	√
Location×Year FE					√	√	√	√
Demographics							√	√
N of Observations	641	641	641	641	641	641	641	641
N of Countries	65	65	65	65	65	65	65	65
R^2	0.001	0.003	0.012	0.014	0.438	0.508	0.569	0.691

Notes:
The table presents within group estimates of the effects of robotic penetration on employment rate. Explanatory variable is changes in robotic density. The regressions are weighted by total labour force in 2010. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE or location FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 49: Robustness Checks for Employment, ICT Across Countries, 2004-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Δ Employment Rate								
ICT Intensity	-0.018**	-0.022***	-0.018**	-0.022***	-0.027***	-0.028***	-0.007**	-0.002
	(0.007)	(0.008)	(0.007)	(0.008)	(0.005)	(0.005)	(0.003)	(0.004)
ICT Intensity $\times$ Income		0.021		0.019		-0.004		0.030***
		(0.013)		(0.014)		(0.009)		(0.007)
Year FE			$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE					$\surd$	$\surd$	$\surd$	$\surd$
Location$\times$Year FE					$\surd$	$\surd$	$\surd$	$\surd$
Demographics							$\surd$	$\surd$
N of Observations	1728	1728	1728	1728	1728	1728	1728	1728
N of Countries	108	108	108	108	108	108	108	108
R^2	0.000	0.001	0.002	0.005	0.312	0.358	0.408	0.487

Notes:
The table presents within group estimates of the effects of ICT adoption on employment rate. Explanatory variable is changes in ICT intensity. The regressions are weighted by total labour force in 2004. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE or location FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 50: Robustness Checks for Employment, ICT Across Countries, 2010-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Δ Employment Rate								
ICT Intensity	-0.008	-0.012	-0.008	-0.012	-0.022***	-0.023***	-0.004	0.001
	(0.009)	(0.010)	(0.009)	(0.010)	(0.006)	(0.007)	(0.005)	(0.005)
ICT Intensity $\times$ Income		0.049**		0.049**		0.012		0.047***
		(0.020)		(0.020)		(0.014)		(0.010)
Year FE			$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Geographic FE					$\surd$	$\surd$	$\surd$	$\surd$
Location$\times$Year FE					$\surd$	$\surd$	$\surd$	$\surd$
Demographics							$\surd$	$\surd$
N of Observations	1080	1080	1080	1080	1080	1080	1080	1080
N of Countries	108	108	108	108	108	108	108	108
R^2	0.001	0.004	0.006	0.002	0.316	0.352	0.393	0.460

Notes:
The table presents within group estimates of the effects of ICT adoption on employment rate. Explanatory variable is changes in ICT intensity. The regressions are weighted by total labour force in 2010. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE or location FE refers to region dummies.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 51: First Stage Regression about Employment Effects of Automation Across Countries, 2004-2019

	(1)	(2)	(3)	(4)
Dep Var	Robotic Penetration		ICT Intensity	
Robot IV: Predicted Robotic Exposure	1.984***	1.692***		
	(0.175)	(0.159)		
ICT IV: Predicted ICT Exposure			1.291***	1.482***
			(0.317)	(0.091)
Year FE	√	√	√	√
Geographic FE	√	√	√	√
Geographic FE × Year FE	√	√	√	√
Demographics		√		√
N of Economies	65	65	108	108
N of Observations	1026	1026	1728	1728
First Stage F Statistics	127.84	113.38	100.85	136.28
Kleibergen-Paap rk LM statistics	46.30	57.29	10.90	40.33
Cragg-Donald Wald F statistic	1233.14	868.26	100.11	36.50
Kleibergen-Paap rk Wald F statistic	127.85	113.38	100.85	36.28

Notes:
The table presents first stage estimates of the relationship between automation adoption and employment rate across countries, where automation adoption predicted using aging trend is used as the instrument. Dependent variable for Columns 1 and 2 is robotic penetration (Robot), that for Columns 3 and 4 is ICT intensity (ICT), and all of them are based on US data. Independent variables include predicted robotic exposure and ICT exposure. The regressions are weighted by total labour force in 2004. Other demographic controls include country level demographics such as total population in thousands (Population), GDP (Gross Domestic Product) in current thousand US dollars (GDP), percentage of old people (Old) and female people (Female). Geographic FE refers to region dummies. Income levels across countries are measured using GNI per capita in 2019, to avoid the problems of missing values in previous years. Geographic FE refers to Census Divisions.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 52: Robustness Checks for Usual Weekly Working Time and Automation Technologies for UK Workers based on NS-SEC 2010, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Usual Working Hours								
Auto Equip	-2.730***	-2.943***	-1.882***	-1.487***				
	(1.577)	(1.650)	(1.664)	(2.050)				
Computer					-0.667*	-0.550	-0.434	-1.563***
					(0.362)	(0.371)	(0.386)	(0.447)
Auto Equip ×Income				0.383***				
				(0.019)				
Computer ×Income								0.139***
								(0.007)
Task Intensities	√	√	√	√	√	√	√	√
Year FE		√	√	√		√	√	√
Nation FE			√	√			√	√
Occupation FE			√	√			√	√
Demographics			√	√			√	√
R^2	0.028	0.028	0.118	0.117	0.027	0.027	0.117	0.117
N of Observations	141910	141910	141910	141910	141910	141910	141910	141910

Notes:
The table presents within group estimates of the effects of automation technologies on individual working hours. Dependent variable is usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer) The classification of occupation dummies are 3-digit level SOC 2010. Other demographic controls include individual specific characteristics such as sex, age, marital status, and education level. Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 53: Robustness Checks for Weekly Working Time and Automation Technologies for UK Workers based on SIC 2007, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dep Var: Total Actual Hours in Main Job								
Auto Equip	-5.148***	-4.896***	-0.528	-4.702***				
	(0.333)	(0.334)	(0.407)	(0.499)				
Computer					-1.471***	-1.423***	-1.517***	-2.587***
					(0.096)	(0.100)	(0.105)	(0.134)
Auto Equip ×Income				0.424***				
				(0.018)				
Computer ×Income								0.146***
								(0.006)
R^2	0.021	0.022	0.057	0.051	0.020	0.021	0.056	0.056
N of Observations	718123	718123	718123	718123	719030	719030	719030	719030
B. Dep Var: Total Usual Hours in Main Job								
Auto Equip	-6.202***	-5.666***	-1.537***	-2.296***				
	(0.199)	(0.200)	(0.234)	(0.263)				
Computer					-1.315***	-1.023***	-1.621***	-2.529***
					(0.057)	(0.061)	(0.061)	(0.069)
Auto Equip ×Income				0.394***				
				(0.009)				
Computer ×Income								0.136***
								(0.003)
R^2	0.034	0.037	0.146	0.159	0.031	0.032	0.145	0.163
N of Observations	714102	714102	714102	714102	715002	715002	715002	715002
Task Intensities	√	√	√	√	√	√	√	√
Year FE		√	√	√		√	√	√
Nation FE			√	√			√	√
Occupation FE			√	√			√	√
Demographics			√	√			√	√

Notes:
The table presents within group estimates of the effects of automation technologies on individual working hours. Dependent variables include actual weekly working hours measures individual's working time during survey reference week, and usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer) The classification of occupation dummies are 3-digit level SOC 2010. Other demographic controls include individual specific characteristics such as sex, age, marital status, and education level. Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 54: Robustness Checks for Weekly Working Time and Automation Technologies for UK Workers based on SOC 2010, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dep Var: Total Actual Hours in Main Job								
Auto Equip	-4.485***	-3.649***	-1.738***	-1.523***				
	(0.389)	(0.414)	(3.028)	(3.552)				
Computer					-1.901***	-1.629***	-2.051***	-0.786**
					(0.147)	(0.180)	(0.262)	(0.310)
Auto Equip				0.413***				
×Income				(0.018)				
Computer								0.142***
×Income								(0.006)
R^2	0.021	0.021	0.050	0.048	0.021	0.021	0.050	0.048
N of Observations	736005	736005	736005	736005	736005	736005	736005	736005
B. Dep Var: Total Usual Hours in Main Job								
Auto Equip	-2.340***	-2.260***	-1.499***	-1.197***				
	(0.216)	(0.228)	(1.657)	(1.751)				
Computer					-1.124***	-1.349***	-1.715***	-0.405***
					(0.081)	(0.100)	(0.144)	(0.154)
Auto Equip				0.386***				
×Income				(0.009)				
Computer								0.136***
×Income								(0.003)
R^2	0.064	0.065	0.129	0.150	0.065	0.065	0.129	0.150
N of Observations	731692	731692	731692	731692	731692	731692	731692	731692
Task Intensities	√	√	√	√	√	√	√	√
Year FE		√	√	√		√	√	√
Nation FE			√	√			√	√
Occupation FE			√	√			√	√
Demographics			√	√			√	√

Notes:
The table presents within group estimates of the effects of automation technologies on individual working hours. Dependent variables include actual weekly working hours measures individual's working time during survey reference week, and usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer) The classification of occupation dummies are 3-digit level SOC 2010. Other demographic controls include individual specific characteristics such as sex, age, marital status, and education level. Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 55: Robustness Checks for Dynamics about Usual Working Time and Automation based on NS-SEC 2010, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Usual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.236***	-0.212***	0.099	-0.094	0.006	0.006
	(0.020)	(0.023)	(0.092)	(0.099)	(0.057)	(0.057)
$Auto\,Equip_t$	-12.046	-4.553	-43.204	-126.967	-137.829	-137.829
	(10.047)	(14.023)	(84.062)	(142.209)	(121.890)	(121.890)
$Auto\,Equip_t \times Income_t$		0.593***		0.029	0.002	0.002
		(0.133)		(0.401)	(0.428)	(0.428)
N of Observations	38292	38292	38292	38292	38292	38292
R^2	0.028	0.028	0.118	0.117	0.117	0.117
B. Total Usual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.236***	-0.211***	0.085	-0.104	0.004	0.004
	(0.020)	(0.023)	(0.093)	(0.101)	(0.060)	(0.060)
$Computer_t$	-1.424	-0.699	-37.087***	-17.441	-7.623	-7.623
	(2.644)	(3.521)	(12.641)	(73.931)	(24.352)	(24.352)
$Computer_t \times Income_t$		0.229***		0.005	0.025	0.025
		(0.048)		(0.146)	(0.155)	(0.155)
N of Observations	38292	38292	38292	38292	38292	38292
R^2	0.014	0.015	0.051	0.050	0.051	0.050
Task Intensities	√	√	√	√	√	√
Year FE	√	√	√	√	√	

Notes:
Based on NS-SEC 2010 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 2 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 3 and 4 describe the results of system GMM using Arellano–Bond method, and Columns 5 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 56: Robustness Checks for Dynamics about Usual Working Time and Automation based on SIC 2007, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Usual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.292***	-0.247***	0.010	-0.006	0.002	0.002
	(0.004)	(0.006)	(0.007)	(0.009)	(0.007)	(0.007)
$Auto\,Equip_t$	-4.617***	-2.650***	-5.484***	-2.194*	-2.163*	-2.163*
	(0.657)	(0.863)	(0.849)	(1.141)	(1.144)	(1.144)
$Auto\,Equip_t \times Income_t$		0.714***		0.768***	0.769***	0.769***
		(0.033)		(0.042)	(0.042)	(0.042)
N of Observations	185759	185759	185759	185759	185759	185759
R^2	0.021	0.022	0.057	0.051	0.056	0.056
B. Total Usual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.294***	-0.249***	0.009	-0.007	0.001	0.001
	(0.004)	(0.006)	(0.007)	(0.009)	(0.007)	(0.007)
$Computer_t$	-1.575***	-3.529***	-1.870***	-3.665***	-3.660***	-3.660***
	(0.196)	(0.260)	(0.252)	(0.339)	(0.339)	(0.339)
$Computer_t \times Income_t$		0.250***		0.268***	0.268***	0.268***
		(0.012)		(0.015)	(0.015)	(0.015)
N of Observations	186005	186005	186005	186005	186005	186005
R^2	0.034	0.037	0.146	0.159	0.145	0.163
Task Intensities	√	√	√	√	√	√
Year FE	√	√	√	√	√	

Notes:
Based on SIC 2007 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 2 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 3 and 4 describe the results of system GMM using Arellano–Bond method, and Columns 5 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on SIC 2007. Other control variables regarding task intensities in levels are based on SIC 2007, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 57: Robustness Checks for Dynamics about Usual Working Time and Automation based on SOC 2010, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Usual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.287***	-0.239***	0.006	-0.006	-0.001	-0.001
	(0.004)	(0.005)	(0.007)	(0.009)	(0.007)	(0.007)
$Auto\,Equip_t$	-1.277	-2.245**	-2.484**	-0.718	-0.726	-0.726
	(0.818)	(1.055)	(1.041)	(1.366)	(1.368)	(1.368)
$Auto\,Equip_t \times Income_t$		0.485***		0.497***	0.498***	0.498***
		(0.033)		(0.043)	(0.043)	(0.043)
N of Observations	190304	190304	190304	190304	190304	190304
R^2	0.021	0.021	0.050	0.048	0.050	0.048
B. Total Usual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.287***	-0.239***	0.006	-0.006	-0.001	-0.001
	(0.004)	(0.005)	(0.007)	(0.009)	(0.007)	(0.007)
$Computer_t$	-0.932**	-0.338	-1.516***	-0.194	-0.191	-0.191
	(0.370)	(0.463)	(0.479)	(0.618)	(0.619)	(0.619)
$Computer_t \times Income_t$		0.168***		0.174***	0.174***	0.174***
		(0.012)		(0.015)	(0.015)	(0.015)
N of Observations	190304	190304	190304	190304	190304	190304
R^2	0.064	0.065	0.129	0.150	0.129	0.150
Task Intensities	√	√	√	√	√	√
Year FE	√	√	√	√	√	

Notes:
Based on SOC 2010 job classification system, the table presents within group estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 2 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 3 and 4 describe the results of system GMM using Arellano–Bond method, and Columns 5 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on SOC 2010. Other control variables regarding task intensities in levels are based on SOC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 58: Robustness checks about Usual Working Time, Automation and Education based on NS-SEC, 2011-2018

	College Educated Workers			Non-College Educated Workers		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Total Usual Hours in Main Job and Automated Equipments						
$Hour_{t-1}$	-0.212***	-0.094	0.006	-0.209***	-0.090	0.004
	(0.023)	(0.099)	(0.057)	(0.025)	(0.094)	(0.058)
$Auto\,Equip_t$	-4.553***	-1.270***	-1.378*	-1.121	-1.468	-1.543
	(1.402)	(0.142)	(1.219)	(0.143)	(1.380)	(1.222)
$Auto\,Equip_t \times Income_t$	0.593***	0.290***	0.200***	0.604***	0.013	0.001
	(0.133)	(0.040)	(0.042)	(0.138)	(0.395)	(0.425)
N of Observations	72374	72374	72374	69535	69535	69535
R^2	0.051	0.050	0.028	0.028	0.051	0.050
B. Total Usual Hours in Main Job and Computerisation Complexities						
$Hour_{t-1}$	-0.211***	-0.104	0.004	-0.209***	-0.101	-0.002
	(0.023)	(0.101)	(0.060)	(0.025)	(0.099)	(0.059)
$Computer\_t$	-0.699	-1.744**	-0.762***	-0.275	-2.300	-0.671
	(3.521)	(0.739)	(0.244)	(3.474)	(7.718)	(2.292)
$Computer_t \times Income_t$	0.229***	0.500***	0.025*	0.235***	0.010	0.026
	(0.048)	(0.015)	(0.016)	(0.050)	(0.148)	(0.156)
N of Observations	72374	72374	72374	69535	69535	69535
R^2	0.027	0.027	0.051	0.050	0.051	0.050
Task Intensities	√	√	√	√	√	√
Year FE	√	√	√	√	√	√

Notes:
Based on NS-SEC 2010 job classification system, the table presents within group and IV estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Columns 1 and 4 are estimated based on Equation 4.2 with dependent variable of individual hours worked, and Columns 2 and 5 describe the results of system GMM using Arellano–Bond method, and Columns 3 and 6 describe the results of system GMM using Blundell-Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 59: Robustness Checks for Usual Working Time, Automation by Regions based on NS-SEC, 2011-2018

	Within London		Outside London	
	(1)	(2)	(3)	(4)
Dependent Variable: Usual Working Hours				
$Hour_{t-1}$	-0.271***	-0.277***	-0.206***	-0.205***
	(0.068)	(0.067)	(0.026)	(0.026)
$Auto\,Equip_t$	-6.686***		-2.267*	
	(0.491)		(1.521)	
$Computer\_t$		-1.159***		0.825
		(0.104)		(3.725)
$Auto\,Equip_t \times Income_t$	0.250***		0.609***	
	(0.051)		(0.143)	
$Computer_t \times Income_t$		0.100***		0.232***
		(0.019)		(0.052)
N of Observations	2846	2846	28247	28247
R^2	0.219	0.214	0.149	0.150
Task Intensities	√	√	√	√
Year FE	√	√	√	√

Notes:
Based on NS-SEC 2010 job classification system, the table presents IV estimates of the dynamic effects of automation technologies on individual working hours, accounting for lagged effects of explained variables. Based on Equation 4.2 with dependent variable of individual hours worked, this table describe the results of system GMM using Arellano–Bond method. First difference estimation of system GMM could result in missing numbers of observations, and time-invariant variables including nation specific effects and industry factors would also be cancelled out. Dependent variables include usual weekly working hours reflecting individual habits on work schedule. Explanatory variable are degree of automated equipments, and degree of computerisation complexities. Income levels across workers are measured using natural logarithm of gross pay last time (Government scheme or employer). The degree of automated equipments, computerisation complexities, and task intensities are occupation-level based on NS-SEC 2010. Other control variables regarding task intensities in levels are based on NS-SEC 2010, and they are quadratic form including degree of repetitiveness (Repeat), analytical skill (Analytical), interpersonal skill (Interpersonal), and manual skill (Manual). Those regarding education level include full time at school (School Full), full time at university or college (College Full), part time at school (School Part), and part time at university or college (College Part). The rest of control variables include whether female people (Female), age (Age), and marital status (Marry). Geographic FE refers to nation dummies (England, Wales, Scotland, Scotland North of Caledonian Canal Northern Ireland).
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$