Labour Market Dynamics in the Twenty-First Century

by

Francesco Roncone

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Department of Economics

School of Economics and Public Policy

The University of Adelaide

Australia

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Abstract

This thesis analyses how workers in the twenty-first century adjust to labour demand changes through mobility between occupations, employers and local labour markets. Technological change systematically replaces routine and manual tasks while complementing cognitive skills. Skill-biased technological change has diverse effects on the workforce. Growing regional employment polarization, declining employment of low-skilled workers, and rising educational wage gaps require deeper investigations in this context. In addition to medium and long-term demand trends, differences between occupations determine workers' relative risk of experiencing short-term labour demand fluctuations. The direct negative effects of work-hour instability on income volatility, work-life imbalances and mental health are well-documented. However, the question remains of how workers' intra-year work-hour instability affects their occupational mobility decisions. The main objective of this thesis is to investigate these topics.

Chapter 2 shows that task changes within occupations are occupation-biased and how this affects the returns to tasks and the overall wage structure of the U.S. labour market. I construct a balanced occupation panel and exploit the updated O*NET ability data to derive two occupation-specific manual and cognitive task intensity measures. The decennial trend analysis shows that mainly non-routine cognitive occupations increased in cognitive intensity. Moreover, non-routine cognitive occupations show a larger decline in manual task intensity. A decomposition of the labour market by workers' education and experience shows that cognitive-intensity-increasing task changes are more prevalent for workers with a college degree, younger and male workers. A returns analysis shows that the polarizing effects of task changes within occupations led to a substantial increase in the return to cognitive intensity between 2008 and 2017.

Although every fifth worker changes their occupation every year, the mechanisms of occupational mobility are still not fully understood. Chapter 3 studies whether the detrimental effects of work-hour instability, such as income volatility and work-life imbalances, potentially influence occupational mobility decisions and whether changing occupations alleviates the work-hour fluctuations of individuals. I construct a measure of individuals' intra-year work-hour variation using the longitudinal dimension of the

monthly Current Population Survey (CPS). To observe occupational transitions, I track individuals through a balanced occupation panel of 430 occupations. The results show that workers with high work-hour fluctuations are likelier to change occupations from month to month. In the highest quartile of hour variation, the marginal effect is almost three times larger for women than men. Deeper investigations of the mechanisms behind the gender gap unveil that men who are married or have children in the household do not change occupations due to work-hour fluctuations. On the contrary, a positive and significant effect is found for women across all household compositions. A difference-in-differences model shows that only workers exposed to highly fluctuating work hours sort themselves systematically into more stable occupations.

To test the supply adjustments of the labour market in response to cognitive-biased task demand changes, Chapter 4 analyses population growth, employment and wage effects of workers with different educational attainment. Therefore, I divide the U.S. labour market into local labour markets using data from the American Community Survey (ACS). The segmentation of the U.S. labour market allows me to use the local industrial specialization for instrumenting my technological change measure based on occupations' task demands. The causal effects show a relative increase in the population of both college and non-college workers in local labour markets with higher exposure to cognitive-biased technological change. Cognitive-biased technological change has detrimental wage and employment effects on non-college workers, including lower employment shares, reduced wages and higher labour force non-participation rates. Moreover, the downward pressure on wages of high-school workers on high-school dropouts increases the college wage premium in regions with more substantial growth in cognitive-biased task demand.

This thesis contributes to the empirical labour and macroeconomic literature by unveiling new findings on heterogeneous task demand changes, work-hour instability and labour mobility. The novel results can help policymakers combat precarious working conditions, rising educational wage gaps, and population polarization between local labour markets.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint award of this degree. I give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

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Dedication

I dedicate this thesis to my grandmother.

For her endless love, support and guidance.

Chapter 1

Introduction

> *The greatest improvements in the productive powers of labour, and the greater part of the skill, dexterity, and judgment, with which it is anywhere directed, or applied, seem to have been the effects of the division of labour.*
>
> *Adam Smith (1776)*

The contemporary labour market is ever-changing, providing new opportunities and posing new challenges to the workforce. This thesis divides the U.S. labour market into detailed occupations to analyse labour demand and supply dynamics in the twenty-first century. On the labour demand side, occupations can be decomposed into complementing tasks. On the labour supply side, workers are endowed with abilities and accumulate skills which enable them to specialise in specific tasks. Advances in cutting-edge technologies progressively reshape the occupational environment while continuous educational upgrading amplifies the competition between and within skill groups. Workers adjust to these changes based on their skill endowment and preferences by resorting between local labour markets, occupations and employers. The dynamic assignment of skills to tasks is one of the cornerstones of the labour market. The main objective of this thesis is to empirically explore these dynamics for a better understanding of the contemporary labour market.

The motivating question of this thesis is whether one can observe a systematic evolution in the task composition of the labour market. And, if so, how does it affect the workforce? Understanding the impact of task demand changes on the workforce is vital to providing appropriate job training, facilitating job search and matching and preparing the labour force for long-term structural changes. While the traditional technological change literature predominately focuses on changes in employment shares between occupations, recent studies find that task changes are more concentrated within occupations (Hershbein and Kahn, 2018; Atalay et al., 2020). Moreover, the studies suggest that task demand changes within occupations systematically favour cognitive skills consistent with the skill-biased technological change literature (see, e.g., Katz and Murphy, 1992; Autor et al., 2006). Although these findings are enlightening, questions remain about how different occupations and workers are affected by task changes within occupations.

Chapter 2 investigates this question using a self-constructed balanced occupation panel and data on occupations' ability requirements from the Occupational Information Network (O*NET). To make the multidimensional O*NET ability data useful for my study, I conduct a principal component analysis to derive composite measures of occupations' cognitive and manual intensity. A trend analysis between 2008 and 2017 shows that task changes within occupations systematically favoured cognitive-intensive over routine-intensive occupations. This observation is linked with heterogeneous effects on the workforce. Young and middle-aged men, workers with college or master's degrees, and workers in STEM occupations experienced the most substantial increases in cognitive task intensity. At the same time, women with high-school degrees show the largest decline in cognitive intensity within occupations. The heterogeneous but systematic task changes within occupations caused a polarisation of cognitive task demand at the top of the wage distribution, which led to an overall increase in the return to cognitive ability by 8.3 per cent between 2008 and 2017. The unveiled increase in the return to cognitive ability contrasts sharply with Castex and Dechter (2014), who report a decline in the demand for cognitive ability in the 2000s but do not include task changes within occupations.

Chapter 3 of this thesis is dedicated to the dynamics of labour supply. Occupational mobility is constantly rising in the U.S. labour market while every fifth worker changes their occupation every year (Kambourov and Manovskii, 2008). Understanding the mechanisms of occupational mobility is crucial because it has medium to long-term effects on workers' human capital and income accumulation. Kambourov and Manovskii (2009) show that five years of occupational tenure are associated with an increase in wages between twelve and twenty per cent. If occupational mobility embarks a risk of losing valuable human capital, why do workers move between occupations at such a high rate? While the literature focuses mainly on the role of wages, my study explores the relationship between work-hour instability and occupational mobility. One way to think about occupational resorting is that workers look for occupations that align with their preferences (Rosen, 1986). If workers have a distaste for work-hour instability, changing occupations could be a way to alleviate the instability in work hours and reconstitute a healthy work-life balance.

I analyse the mobility patterns of men and women separately to consider recent findings that women value jobs with stable work hours more than men (Mas and Pallais, 2017) and that gender differences in preferences potentially lead to different job choices (Wiswall and Zafar, 2018). My results show that women in the top 25 per cent of work-hour variation are 0.81 per cent more likely to switch occupations from month to month compared to women without hour variation. The marginal effect is substantial compared to an average monthly mobility rate in the labour market of 1.71 per cent. In comparison, men in the top 25 per cent have a 0.33 per cent higher probability of switching occupations. Interestingly, the lower but positive and significant effect disappears when men are married and have children. This observation aligns with Akerlof and Kranton (2000) suggesting that gender is crucial for women's and men's specialisation within households. The high sensitivity of female workers to fluctuating work hours shows that it is necessary to create a more stable working environment for women, which allows them to maintain a better balance between non-working activities and work. Fair Workweek laws, which are introduced in some cities and for some specific industries (see, e.g., Kesavan et al., 2022), could be the right tools if implemented efficiently and at a broader scale. The last part of my study shows that workers with high work-hour fluctuations sort themselves systematically into more stable occupations, confirming the importance of hour stability for the workforce.

Chapter 4 builds on the framework of task changes within occupations from Chapter 2 but goes beyond a demand-side analysis by answering if and how workers adjust to the cognitive-biased changes in task demand. Complementing Chapter 3 on occupational mobility, the crucial element of supply changes in Chapter 4 is the mobility of workers between local labour markets. Due to their industrial specialisation, local labour markets are subject to different exposures to biased task demand changes (Autor and Dorn, 2013). If labour is at least partly mobile in the medium run, one would intuitively expect that workers endowed with high cognitive ability systematically reallocate to local labour markets where the cognitive task intensity increases. If the reallocation process were optimal, one would further expect that the supply adjustment of skills equalises wages across labour markets (see, e.g., Beaudry et al., 2010). However, Topel (1994) shows that labour adjustments are not always optimal in response to technology-induced demand shocks. Suboptimal readjustment processes of the workforce potentially lead to wage inequality within local labour markets if technological progress outpaces the supply increase in complementing cognitive skills (Goldin and Katz, 2007).

In the local labour market analysis, I estimate the causal effects of within-occupation cognitive-biased technological change on population growth, employment and wage growth, and the college wage premium between local labour markets. I find that both college and high-school workers move systematically to labour markets with a growing demand for cognitive ability within occupations. I do not find a significant effect on the wage rate of college workers, suggesting that the increase in cognitive skill demand and the rising labour supply of college workers in cognitive-intensity-growing regions have equalising effects on college workers' wages. On the other hand, higher exposure to cognitive-biased technological change creates downward pressure on the wages of high-school workers. The relative decline in the wages of high-school workers leads to rising wage inequality between college and high-school workers in growing labour markets. The adverse wage effects are accompanied by a relative decrease in employment in non-routine-cognitive occupations and higher labour force non-participation rates of workers without a college degree.

The cognitive-biased nature of technological change and the inefficient reallocation of low-skilled workers create population polarisation between local labour markets and increase educational wage gaps within growing local labour markets. Active labour market policies and long-term strategic investments are required to combat these challenges and support disadvantaged workers and local labour markets.

Chapter 5 summarises the findings of this thesis and discusses policy implications and potential future challenges of the U.S. labour market in the twenty-first century.

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Chapter 2

The Changing Nature of Occupations and Returns to Task Intensities*

Francesco Roncone†

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† School of Economics, University of Adelaide, 10/12 Pulteney St, Adelaide SA 5000 (e-mail: francesco.roncone@adelaide.edu.au).

Abstract

The direction of change of the task composition in the contemporary labour market is still not fully understood. By combining detailed and time-varying occupation data with representative U.S. survey data, this paper documents cognitive and manual task intensity changes within occupations between 2008 and 2017. Non-routine cognitive and high-wage occupations increased the most in cognitive intensity, while routine and low-wage occupations decreased in cognitive intensity. The decline in manual task intensity is also more substantial in non-routine-cognitive and high-wage occupations. The differential task demand changes between occupations imply heterogeneous effects on the segmented labour market. Young men, workers with college degrees and workers in STEM occupations experienced the most substantial increases in the demand for cognitive ability. The polarising effects of task changes within occupations are associated with an 8.3% rise in the return to cognitive task intensity in the U.S. labour market between 2008 and 2017.

Keywords: O*NET ability data, principal component analysis, returns to task intensities, wage decomposition.

JEL codes: **J23, J24, J31**.

2.1 Introduction

Task heterogeneity is one of the cornerstones of the versatile U.S. labour market. The Occupational Information Network (O*NET) currently records more than 23.000 different tasks performed across all occupations. For an efficient assignment of workers with different skills and abilities to tasks, as it is conceptualized in the task-based model by Acemoglu and Autor (2011), it is essential to understand the direction of change in the demand for tasks in the aggregate production process. Essentially, there are two channels through which the evolution of tasks is shaped in the labour market: first, relative changes in employment shares between occupations, and second, task changes within occupations.

While aggregate task changes through relative employment shifts are thoroughly analysed and well understood (Autor et al., 2006; Goos et al., 2009; Firpo et al., 2011; Acemoglu and Autor, 2011; Autor and Dorn, 2013), focusing only on this channel requires the assumption that the task content within occupations is constant over time. However, occupations often undergo huge transformations. For example, as described in the *1976 Occupational Outlook Handbook*, "secretaries type, take short-hand and deal with callers" (US Department of Labor, 1976). Two decades later, "secretaries now provide training and orientation to new staff, conduct research on the Internet and learn to operate new office technologies" (US Department of Labor, 2000). Considering task changes only at the 'extensive margin' is, therefore, insufficient, especially because new advanced technologies (ICTs, automation technologies and AI) affect occupations more heterogeneously in the twenty-first century (see, e.g., Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Acemoglu et al., 2020). However, since the path-breaking work by Autor et al. (2003) there has been a shortage of studies providing insights into changes in task content within occupations. This study aims to close this gap.

Combining ability data from different O*NET databases with employment data from the Occupational Employment Statistics (OES) and the Current Population Survey (CPS), I show that between 2008 and 2017, there were systematic changes in occupations' cognitive and manual task intensities. Using hourly wage data from the CPS merged outgoing rotation groups (MORG), a simple counterfactual exercise shows that the return to cognitive task intensity increased by 8.3% in the U.S. labour market and that the entire increase can be attributed to the heterogeneous but systematic task changes within occupations. This observation contrasts sharply with a study conducted by Castex and Dechter (2014), which unveils a decline in the return to cognitive ability in the 2000s but fails to include task changes within occupations. On the other hand, manual task intensities declined for eleven of the twelve major occupation groups. Despite these changes, the return to manual intensity remained relatively constant between 2008 and 2017.

Following up on the unveiled systematic task changes in the 2000s, my study makes two further contributions to the literature. First, I demonstrate the impact of within-occupation changes on workers with different characteristics (education, labour market experience and gender). The descriptive findings establish new facts: (i) the demand for cognitive abilities increased only for individuals with at least a college degree; (ii) increased on average for men but decreased for women; (iii) the increase in cognitive intensity and the decline in manual intensity are more pronounced at the top of the wage distribution. Second, I use an Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973) to quantify the relative contribution of changes in task intensities to the observed wage differentials between 2008 and 2017 compared to other factors (labour unions, industries, education and experience). The results show that task changes are more critical within task-based occupation groups than across all occupations, suggesting that occupations' initial task content was decisive for their recent task evolution in the twenty-first century.

A key component of this study is the systematic usage of the underlying O*NET ability data for measuring task intensities. The O*NET ability rating procedure was profoundly modified in rating cycle 12, which I use as the starting point of my analysis. In rating cycle 12 and all subsequent rating cycles, trained job analysts receive additional information ("stimulus material") concerning changes in occupations' work context, knowledge requirements and task content (Fleisher and Tsacoumis, 2012). The consistent procedure of measuring abilities within occupations over time is a substantial advantage over other O*NET domains, although their inconsistency pitfalls have often been overlooked in other studies. To make the multidimensional O*NET data useful, I follow Yamaguchi (2012) and conduct two Principal Component Analyses (PCAs), one for cognitive and one for manual abilities.[1] In contrast to other studies using PCA to derive composite task scores based on only one specific database, I pool O*NET data from two different years (2008 and 2017) but assign the data to the same employed workforce of 2008. This strategy yields occupation-year-specific scores that can directly be compared relative to the mean score of the 2008 employed population.

Although the literature on task changes within occupations is relatively scarce, some key papers are worth mentioning. Using a survey-based data set from West Germany, Spitz-Oener (2006) analyses the impact of workplace computerisation on skill requirements within and between occupations. Spitz-Oener (2006) provides evidence that tasks requiring mostly cognitive abilities, such as tasks related to research and planning, have gained more importance than routine-intensive tasks from 1979 to 1999. This development was more profound in occupations in which technological breakthroughs took place. In another paper, Handel (2016b) evaluates changes in more than 160 job items across five broad occupation groups using data from two waves of the Survey of Skills, Technology and Management Practices (STAMP). The study finds that the importance of learning new technologies is comparatively low for "lower blue-collar" and "lower white-collar" occupations compared to "upper white-collar" occupations.[2] The observation of heterogeneous task shifts between occupation groups is consistent with my findings based on O*NET data. Another related paper by Freeman et al. (2020) finds that task changes within occupations outweighed changes between occupations between 2005 and 2015 with the help of a shift-share analysis applied to different O*NET job characteristics.[3] My study contributes to this literature by going beyond the micro-level analysis of occupations and analysing the most recent task intensity changes representative of the U.S. labour market and their heterogeneous impact on the workforce.

[1] Other studies that use principal component analysis to derive composite task measures are conducted by Autor et al. (2003), Caines et al. (2017), Guvenen et al. (2020).

[2] Handel (2016b) categorises occupations into five groups whereby "upper white-collar" occupations can be considered non-routine cognitive and "lower white-collar" occupations are equivalent to routine cognitive occupations in my study.

[3] Another strategy is adopted by Hershbein and Kahn (2018) and Atalay et al. (2020). Their studies use job advertisements to analyse changes in task content and skill requirements within occupations, finding substantial importance of within-occupation changes.

Regarding returns estimation, my study is related to a study by Ross (2017), which combines time-variant O*NET data on different work activities with individual data from the Survey of Income and Program Participation (SIPP). The study documents that within-occupation variation let the premium for routine tasks decline while the premium for abstract tasks increased from 2004 to 2013. Boehm (2014) finds evidence of significant changes in relative returns across all occupations through the 1990s and 2000s, whereas Cortes (2016) shows that wages in non-routine cognitive and non-routine manual occupations have significantly increased compared to wages in routine occupations. In the framework of this literature, my study demonstrates the important role of changes within occupations compared to changes between occupations.[4]

In a broader sense, this study is motivated by the accelerating momentum of new technologies in the post-millennium era characterised by major advances in artificial intelligence (Acemoglu and Restrepo, 2018a; Brynjolfsson et al., 2018; Webb, 2019; Tolan et al., 2021), industrial robotics (Acemoglu and Restrepo, 2020) and information technologies (Akerman et al., 2015; Bessen, 2016). The rising implementation of such technologies in various working environments raises the question of how labour markets will be reshaped. Frey and Osborne (2017) use O*NET variables to quantify the probability of different occupations becoming automated. Their analysis suggests that at least half of the jobs in the U.S. are at risk of becoming completely automated in the near future. On the other hand, a study by Tolan et al. (2021) predicts that most artificial intelligence applications will not automate complete work-related tasks soon. Instead, it is more likely that many occupations will become "transformed" rather than completely automated, with new tasks emerging and some tasks only becoming partly automated. However, the extent to which technological change might affect workers in the future is hard to predict. I hope that the new insights that can be obtained from my study help better understand the direction of potential long-term changes in cognitive and manual task demand.

The remainder of this paper is organised as follows: The next section provides conceptual thoughts on task changes grounded on a new task-based model in the theo-

[4] From the studies mentioned above, only Ross (2017) incorporates task shifts within occupations using yearly panel data. Regarding the empirical methodology, my study is more related to Ingram and Neumann (2006) and Boehm (2014).

retical literature. Section 2.2 explains in detail the O*NET data used in this study and how the constructed measures capture changes in occupations' task content. Section 2.3 documents the changes in task intensities within occupations and between broad occupation groups. Moreover, this section sheds light on how workers with different characteristics are affected differently by recent task shifts within occupations. Section 2.4 provides a returns analysis between 2008 and 2017 and highlights the contribution of task changes within occupations. Section 2.5 concludes by summarising and evaluating the main findings of this study.

2.2 Data and Methodology

To analyse changes within occupations representative of the employed labour force, I combine occupation data with individual survey data. The individual survey data comes from the annually Merged Outgoing Rotation Group (MORG) files of the Current Populations Survey[s] (CPS), which contain information on various worker characteristics, for example, workers' hourly wage rate, working hours and detailed job titles. To measure changes in task intensities within occupations, I use updated data on the importance of cognitive and psychomotor abilities obtained from the Occupational Information Network (O*NET). The two O*NET databases used in this study are 16.0 (July 2011) and 25.0 (August 2020).

I undertook two steps to link the occupation data with the individual survey data. First, I constructed a balanced occupation panel of 460 detailed occupations in the CPS-MORG files based on the 2010 Standard Occupational Classification (SOC). Second, I assign the ability data of the finer O*NET occupations to my self-constructed occupation panel. Since only a proportion of O*NET occupations (107 on average) are updated in each rating cycle, most occupations differ in the year of their latest update in a given database. To overcome this hurdle, I centre each of the two O*NET databases on the average year of the occupations' latest updates following Freeman et al. (2020). Based on this procedure, the two databases represent occupations' ability requirements for 2008 and 2017. Finally, I match the O*NET data with the CPS-MORG data of 2008 and 2017, allowing for a cross-sectional trend analysis of the U.S. labour market.

2.2.1 The O*NET Ability Rating Procedure

The Occupational Information Network (O*NET) replaced the Dictionary of Occupational Titles (DOT) in June 2003 with the release of its final analyst database (O*NET 4.0). The O*NET is a dynamic library in contrast to its static predecessor, containing more than 900 O*NET occupations and more than 230 job items across all occupations. However, the data-gathering process for the final analyst database relied mainly on preexisting sources like the DOT. Since 2003, occupation characteristics and related worker requirements have been updated based on a "multiple-method data collection program" (U.S. Department of Labor, 2018). Survey data from job incumbents is the preferential source for equipping most O*NET domains with data (Generalised Work Activities, Work Context, Knowledge, Education and Training, and Work Styles). However, data from job incumbents is often combined with occupation assessments from job experts. Moreover, the dynamic nature of the O*NET comes at the cost of intermingling different data collection methods for the same occupation over time.

Being aware of the diversity of data collection methods in the O*NET, I identified the ability domain as the most reliable data source for consistently measuring changes in task content within occupations. Abilities often represent an abstract construct rather than an apparent working activity that can easily be understood and recognised by workers (U.S. Department of Labor, 2005). For example, evaluating the importance of *inductive reasoning* might be challenging for workers if they cannot directly relate their ability to the tasks they execute on the job. To eliminate a potential survey bias that could arise from the complexity of the ability items, the data collection program of abilities has been consigned to 16 analysts selected based on their education and job experience (Tippins and Hilton, 2010). The analysts are trained by the Human Resources Research Organization (HumRRO) to guarantee a consistent reevaluation of the importance and required level of different abilities, including cognitive abilities and psychomotor abilities. In each rating cycle, the analysts receive stimulus material and rate the importance of the abilities on a scale from 1 ("not important") to 5 ("extremely important") for a set of occupations (Fleisher and Tsacoumis, 2012). The stimulus material includes the following information:

- Occupation title, definition, and vocational preparation ("Job Zone")
- Mean importance of core and supplementary tasks for the targeted occupation[5]
- Mean importance of Generalized Work Activities (GWAs) that (1) have a mean importance for the occupation ≥ 3.0, and (2) require the targeted ability to be performed
- Mean rating of Work Context (WC) statements that (1) have a mean rating for the targeted occupation ≥ 3.0, and (2) require the targeted ability to work in that context
- Mean importance of the ten most important Knowledge domains associated with the occupation with a mean importance rating of ≥ 3.0.

In addition, the trained raters receive specific information on changes in occupation characteristics compared to the last rating cycle. For example, suppose a task (or another occupation characteristic) no longer reaches the "relevance threshold" because the task has partially been automated. In that case, the task is crossed out in the stimulus material. Moreover, if a task has increased in importance or a new task has emerged, the task is highlighted by an asterisk.[6] The consideration of both task automation and the emergence of new tasks is essential for understanding the dynamics of skill demand both within and between occupations (see, e.g., Acemoglu and Restrepo, 2018b, 2019). It is important to note that the trained occupation analysts rate the importance of occupations' abilities on a continuous scale between 1 and 5 instead of an ordinal scale, primarily used for other O*NET domains that rely on job incumbent surveys. This allows researchers to go beyond an ordinal ranking of occupations by considering the exact distance between occupations concerning specific abilities.

[5] Tasks are classified into three categories based on survey answers of at least 15 job incumbents on their relevance and importance: 1) *Core Tasks* with a relevance rating $\geq 67\%$ and a mean importance rating ≥ 3; 2) *Supplementary Tasks* with a relevance rating $> 67\%$ but mean importance rating $<$ 3, or, tasks rated on relevance between 10% and 66% regardless of the mean importance rating; 3) *Non-Relevant Tasks* rated on relevance $< 10\%$. The importance scale of task measures and other occupation characteristics is equivalent to the importance scale of abilities, ranging between 1 and 5.

[6] The highlighting of occupation-specific task changes over time was implemented into the ability rating procedure after the O*NET database 16.0 (2011) release, as most occupations have been rated at least once in the previous rating cycles.

There are two other significant advantages of using O*NET ability data in my study: First, the O*NET ability rating procedure is consistent over time and across all observed occupations, minimising the problem of inaccurate measurement.[7] This is important because intermingling survey data from job incumbents with data from job experts would have distortionary effects on my analysis. Although this issue has been neglected in previous studies relying on O*NET data, such distortions would be particularly severe when identifying slight differences in task changes between occupations. Second, abilities are directly comparable between occupations. In contrast, specific tasks and generalised work activities may differ substantially between occupations. For example, the O*NET ability *problem sensitivity* is crucial for police officers, dentists and psychologists, although they execute entirely different tasks. Likewise, being a firefighter, dishwasher, or fisherman requires a high level of *manual dexterity*. However, the work activities of firefighters do not have much in common with those of fishermen or dishwashers. One objective of this study is to evaluate the dynamics within occupations, considering that task content and worker characteristics are multidimensional and have different relevance across occupations. Using O*NET ability data is a well-suited approach to achieve this goal because the rating procedure of abilities evaluates occupations based on their specific task content, including more than 20.000 different core and complementary tasks, instead of comparing the same task measures across all occupations.

It is worth mentioning that my approach of using O*NET ability data for analysing the evolutionary changes in task demand in the U.S. labour market has some limitations. Most importantly, it does not allow for a direct way of measuring changes in occupations' routine task intensity. While it is intuitive to assume that workers are equipped with manual and cognitive abilities, it is much more challenging to think about a category of abilities favouring particularly routine tasks. Moreover, changes in occupations' routine task intensity cannot be seen as a whole different dimension. Most importantly, the change in occupations' cognitive intensity and occupations' transformation in terms of de-routinisation are mechanically linked based on the construction

[7] The ability rating procedure is built upon the O*NET principles of "interrater agreement" and "interrater reliability" to guarantee rating consistency within and between occupations. See Fleisher and Tsacoumis (2012) for a detailed description of the underlying principles.

of the ability measures. As outlined above, occupation analysts take into account the "importance changes" of the most relevant work context measures when evaluating changes in occupations' ability requirements, including the measures which researchers commonly use to measure the routine task content of occupations ("degree of automation", "importance of repeating same tasks", "structured versus unstructured work", "pace determined by speed of equipment", "spend time making repetitive motions"). Thus, if there is a systematic negative relationship between changes in cognitive task demand and the de-routinisation of tasks, which is shown in Autor et al. (2003) as well as in the more recent literature (see, e.g., Ross, 2017), measuring changes in the demand for cognitive and manual abilities should be sufficient to characterise the development of the current labour market accurately. A similar argument is provided by Yamaguchi (2012), whose study also focuses on the cognitive and manual task dimension of occupations.

2.2.2 Construction of the Task Intensity Measures

For constructing the task intensity measures, I rely on the importance ratings of thirteen cognitive and ten psychomotor abilities from the two O*NET databases, 16.0 (July 2011) and 25.0 (August 2020).[8] More precisely, I use the *verbal, idea generation and reasoning* and *quantitative* ability domains to and the *fine manipulative, control movement* and *reaction time and speed* ability domains for my analysis. A summary of the used O*NET abilities categorised into coarser ability rating domains is shown in Table 2.1. A detailed description of all 23 cognitive and psychomotor abilities is presented in Appendix Table A.2.

If one used all original cognitive and psychomotor abilities, one would assume that thirteen dimensions of cognitive task heterogeneity and ten dimensions of manual task heterogeneity yield an informative representation of the labour market. However, a well-known characteristic of the multidimensional O*NET data is that different items often describe the same unobserved construct rather than describing multiple dimen-

[8] In addition to the importance ratings, every ability item is rated on a level scale (from 0 to 7). However, Handel (2016a) shows that choosing between the importance and level rating is only of minor significance as the same O*NET items evaluated on the different scales are highly correlated ($\rho = 0.92$). This feature makes one of the two scales "redundant".

Table 2.1: Summary of O*NET Cognitive and Psychomotor Abilities

Occupation Group	All		*NRC*		*NRM*		*RC*		*RM*	
	2008	2017	2008	2017	2008	2017	2008	2017	2008	2017
A. Cognitive Ability Domains										
Verbal	3.547	3.552	3.936	3.950	3.166	3.152	3.643	3.631	3.079	3.021
Ideas & Reasoning	3.163	3.177	3.507	3.536	2.878	2.869	3.058	3.012	2.921	2.909
Quantitative	2.555	2.570	2.879	2.888	2.010	2.083	2.717	2.668	2.247	2.262
B. Psychomotor Ability Domains										
Fine Manipulative	2.522	2.431	2.096	1.976	2.869	2.803	2.238	2.184	3.280	3.248
Control Movement	1.968	1.915	1.528	1.469	2.094	2.094	1.615	1.577	2.977	2.949
Reaction Time & Speed	1.689	1.676	1.352	1.355	1.837	1.845	1.416	1.423	2.424	2.392

Notes: The summary of the O*NET ability domains shows the average values of all detailed abilities included in the respective domains. Abilities are rated on an importance scale from one (not important) to five (extremely important). I use CPS employment shares along with CPS "earnings weights" to calculate the average values for the broad occupation groups. The reported occupation groups are non-routine cognitive (NRC), non-routine manual (NRM), routine cognitive (RC) and routine manual (RM) occupations. The mapping of the detailed SOC occupations to the four broad occupation groups is reported in Appendix Table A.1.

sions (Handel, 2007). For example, both *inductive reasoning* and *deductive reasoning* measure the ability to use information for problem-solving. Similarly, both *arm-hand steadiness* and *manual dexterity* measure the ability to control hand movements. A widely used statistical method to reduce the dimensionality of correlated variables that measure the same unobserved construct while keeping the highest possible degree of explanatory value is called Principal Component Analysis (PCA). Under the linearity assumption and given the original variables $x = [x_1 + x_2 + ... + x_p]$, one can estimate components $z = [z_1 + z_2 + ... + z_p]$ which are a linear combination $u = [u_1 + u_2 + ... + u_p]'$ of x that achieve maximum variance. To compute the linear transformation and map the high-dimensional O*NET ability data into a lower-dimensional space, I assume that the two major task categories (cognitive and manual) are fully separable in a way that cognitive abilities only determine the cognitive task intensity of an occupation and manual abilities are only relevant for measuring their manual task intensity. This approach is also employed by Bacolod and Blum (2010) and Yamaguchi (2010, 2012). It requires to conduct two separate analyses for the two major task categories. This approach is particularly suitable for this study, compared to conducting one PCA including all cognitive and manual abilities combined, as it gives the constructed task intensity vectors a clear interpretation.

To test the suitability of the O*NET ability data for the use of PCA, I follow Handel (2007) checking first the pairwise correlations of the abilities and second, "Cronbach's alpha" which is also known as "reliability coefficient" for measuring constructs. Tables A.4 and A.5 show the correlations between the thirteen cognitive abilities and all correlations between the ten manual abilities. The average correlation between cognitive abilities is 70.0%, and the average correlation between manual abilities yields 77.9%. In addition, the reliability coefficients are noticeably high with α=96.8% α=97.2% for cognitive and manual abilities, respectively. The suitability checks proposed by Handel (2007) suggest that a reduced number of components relative to the original number of ability variables can potentially describe a large proportion of the variation in the data.

To account for the fact that employment shares differ between different occupations (for example, high-school teachers and astronomers), one should use representative individual-level data of the employed population to compute the task components. Otherwise, one would weigh all occupations equally, which does not accurately represent the labour market. While using representative survey data of a given year is the standard approach in the literature when using statistical techniques of reducing the dimensionality of ability or skill data (see, e.g., Yamaguchi, 2012; Robinson, 2018; Guvenen et al., 2020), the new feature of my analysis is that I include ability ratings of two different years. Remember that the aim of PCA in this study is to obtain occupation-year-specific task intensity scores to measure task intensity changes within occupations. Particular care must be devoted to achieving this goal and constructing the measures, as there are several pitfalls.

Three different strategies for the use of PCA are evaluated: first, two separate analyses were conducted for 2008 and 2017 using the specific employment shares of the different years. This approach is unsuitable as it yields different factor loadings when computing the task intensity components of 2008 and 2017. It makes a direct comparison over time incomparable both at the aggregate level and for a given occupation. Alternatively, one can conduct PCA with employment weights and ability ratings of 2008 and take the computed ability loadings to reconstruct the same linear combination of abilities for the employed population in 2017. However, with this approach, the issue remains that the task intensity scores of 2008 and 2017 are related to their year-specific occupational structures as different occupation weights are used for 2008 and 2017. To overcome these hurdles, I employ a third approach. More precisely, I use CPS data of the employed population in 2008 and duplicate each individual in the sample. The monotonic transformation of the data leaves the employment shares of occupations unchanged and simultaneously allows the inclusion of occupations with both 2008 and 2017 ability ratings. Next, I standardise the computed composite task intensity scores with zero mean and a standard deviation of one so that aggregate and occupation-specific changes are directly interpretable. This standardisation approach is commonly used in the literature and is preferred as the underlying ability data has no natural scale. Consequently, the occupation-year-specific scores show the deviation from the mean score of all occupations weighted by 2008 employment shares. Equivalently, any change in task intensity is measured in units of standard deviation relative to the mean score in 2008. An overview of the highest and lowest-ranked occupations evaluated at the cognitive and manual intensity scores in 2017 is presented in Appendix Table A.3.

To determine the number of components after conducting PCA, researchers often rely on the so-called "Kaiser Rule" (Kaiser, 1960), which is, in fact, more a heuristic rule. More precisely, it suggests using all components with an eigenvalue greater than one, as they are presumed to capture substantial variation from the underlying data. Figure 2.1 shows the scree plots of the estimated eigenvalues from the two principal component analyses for cognitive and manual abilities. Panel B shows that only one component has an eigenvalue greater than one, explaining 80.4% of the manual ability data variation. On the other hand, the PCA applied to cognitive abilities shows that the first two components have an eigenvalue greater than one (see Panel A). Nonetheless, in this case, I keep only the first component for two reasons: first, there is a large break between the eigenvalue of the first component (9.4) and the eigenvalue of the second component (1.1). Therefore, the first component explains the substantial part of the underlying data variation (72.7%). Second, splitting the cognitive intensity index into two separate components would hamper a meaningful interpretation of the results as one would have to assume that the two components are orthogonal and thus independent.

Such an assumption appears implausible as the underlying data captures abilities of the same ability domain.[9]

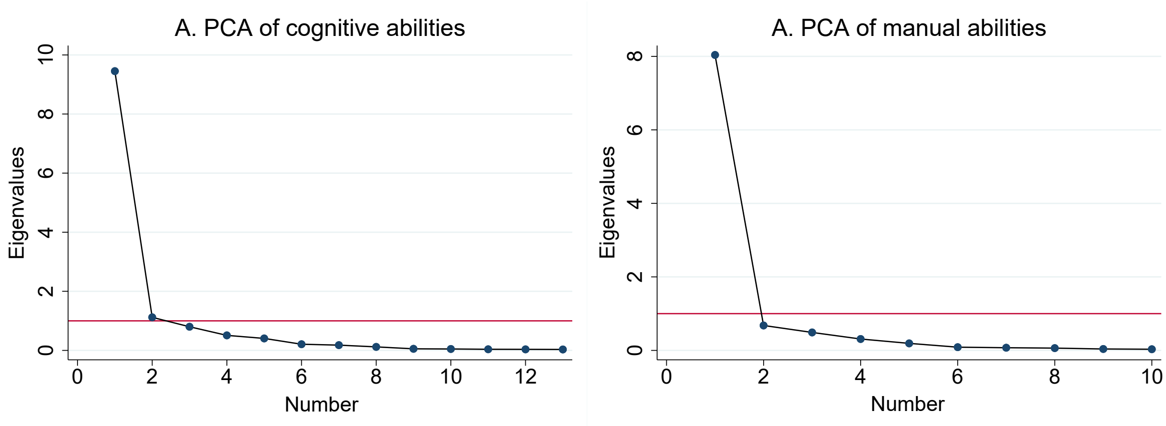

Figure 2.1: Components' Eigenvalues after Principal Component Analysis

2.2.3 CPS-MORG Survey Data

The monthly CPS is the primary source of the official U.S. labour market statistics (US Census Bureau, 2019). Households included in the survey are interviewed for four consecutive months (rotation groups one to four) before they drop out of the sample for eight months and rejoin the sample for four successive months for a second interval (rotation groups five to eight). In addition to the monthly questions, households rotating out of the sample (rotation groups four and eight) answer supplementary questions related to their labour status, hourly wage rate and weekly work hours. Based on the underlying survey design, each household interviewed appears in the outgoing rotation groups only once a calendar year. Every year, the outgoing rotation groups are extracted and merged into a CPS-MORG file, yielding a pooled sample size roughly three times the Annual Social and Economic Supplement (ASEC) survey, which researchers often use for wage analyses of the U.S. labour market. A large sample size is crucial for this study in order to break down the U.S. labour market into 460 detailed occupations. There are two other appealing features of the CPS-MORG data compared to the ASEC data. First, the additional labour questions are related to current pay and hours worked instead of last year's pay and work hours, increasing the accuracy of the

[9] A similar approach of choosing only the first component of multidimensional skill data is used, for example, by Autor et al. (2003), Yamaguchi (2012) and Guvenen et al. (2020).

households' responses. Second, the CPS-MORG data provides information on workers' union coverage, an essential factor to control for in the regression analysis.

This study draws on the CPS-MORG data files provided by the Center for Economic and Policy Research (CEPR).[10] The CEPR modifies the original CPS data to create a consistent and robust hourly wage series. This feature is of major importance for the second part of this study when I analyse occupations' returns to tasks between 2008 and 2017. The adjustment process of the wage series is well described by Schmitt (2003). To account for the CPS survey design, I use the "earnings weights" recommended by the US Census Bureau (2006) for all estimations throughout my study. I restrict the two cross-sectional samples of 2008 and 2017 to the employed labour force and exclude self-employed, unpaid family workers and workers employed in military occupations. Further, I limit the analysis to workers aged 18 to 64. After imposing the sample restrictions, the final sample contains 165,000 and 150,000 observations for 2008 and 2017, respectively.

Table 2.2 provides a summary of employment shares (or employment per-capita), mean wages, educational attainment, experience (age - years of schooling - 6)[11] and other worker characteristics for the employed workforce and by task-based occupation groups. The table shows some noticeable changes between the two analysed sample years. The non-routine cognitive (NRC) employment share increased by 9.4% while the employment shares of routine cognitive (RC) and routine manual (RM) jobs fell altogether. This observation is in line with the finding that technological progress favours non-routine cognitive tasks compared to routine tasks (Autor et al., 2003; Goos and Manning, 2007) and causes a disproportionate reallocation of workers into occupations where non-routine cognitive tasks are more dominant (Cortes, 2016; Cortes et al., 2020). Routine manual occupations experienced a slight upward shift in worker experience. In contrast, non-routine cognitive occupations show a slight reduction in worker experience potentially caused by attracting younger talent (Autor and Dorn, 2009).

[10] CEPR data is maintained by the Center for Economic and Policy Research (CEPR) in Washington, DC. The CEPR CPS-ORG Uniform Extracts are accessible through `www.cepr.net`. The CEPR exclusively uses raw data from the monthly CPS files.

[11] Years of schooling are derived from a consistent education variable in the CEPR ORG files which classifies individuals into 16 categories from no education to a doctoral degree. The used approach of calculating potential labour market experience (age - years of schooling - 6) follows Mincer (1974) and Lemieux (2006).

Regarding education, one can obtain a general upgrading across all broad occupation groups between 2008 and 2017.

Table 2.2: Worker Characteristics of the Employed Labour Force: 2008 and 2017

Occupation Group	All		*NRC*		*NRM*		*RC*		*RM*	
	2008	2017	2008	2017	2008	2017	2008	2017	2008	2017
Employment Share			.358	.392	.165	.172	.247	.221	.229	.215
Mean wage (2019$)	24.79	26.13	34.00	35.48	16.18	16.43	20.43	21.39	21.30	21.73
A. Average Experience (Years) and Education (Fractions within Occupation Groups)										
Years of experience	19.21	19.32	19.23	19.11	17.60	17.87	18.77	18.74	20.81	21.47
LTHS	.080	.062	.008	.007	.153	.121	.044	.035	.178	.141
High-school	.301	.275	.106	.094	.395	.382	.348	.317	.487	.477
Some college	.301	.292	.242	.216	.338	.356	.393	.377	.267	.292
College	.213	.240	.384	.393	.098	.119	.184	.225	.058	.076
Advanced	.105	.131	.258	.290	.015	.022	.030	.047	.010	.014
B. Other Worker Characteristics (Fractions within Occupation Groups)										
Female	.482	.480	.543	.544	.564	.560	.648	.625	.147	.153
Union	.140	.121	.154	.131	.134	.112	.085	.073	.183	.161
Married	.565	.533	.646	.618	.439	.413	.523	.477	.573	.533
White	.673	.617	.755	.701	.560	.496	.690	.628	.610	.549
Black	.117	.126	.092	.099	.165	.175	.124	.138	.112	.126
Hispanic	.147	.176	.073	.099	.212	.248	.130	.165	.233	.270

Notes: I use CPS employment shares and CPS "earnings weights" for my calculations. This table represents the employed labour force in the U.S. aged 18 to 64 years, excluding workers employed in military occupations. The reported occupation groups are non-routine cognitive (NRC), non-routine manual (NRM), routine cognitive (RC) and routine manual (RM) occupations. The mapping of the detailed SOC occupations to the four broad occupation groups is reported in Appendix Table A.1.

Moreover, Table 2.2 shows that men and women are sorted into different occupation groups. In particular, one can see that two-thirds of workers in routine cognitive occupations are women. On the contrary, women make up only 15% of the workforce in routine manual occupations. Considering the substantial male-female differences in employment shares between different occupation groups, it is straightforward to assume that women and men are affected differently by task changes within occupations. One purpose of Section 2.3 is to demographically break down the impact of within-occupation task changes on gender, age and education groups.

2.3 Changes in Cognitive and Manual Task Intensities

This section analyses the heterogeneous changes in cognitive and manual task intensities between occupations and across the employed civilian population in the United States. Figure 2.2 visualises the population-weighted aggregate changes in task intensities smoothed over the 460 occupations. The cognitive intensity distribution of 2017 in Panel A shows two significant differences compared to the distribution of 2008: first, a higher density at the upper end of the distribution, and second, a lower density in the middle part, along with a stretch of the distribution to the left. The first observation seems plausible, considering the recent increase in the proportion of people working in non-routine cognitive occupations (see Table 2.2). The second observation can also partly be explained by relative changes in employment shares between occupations. Most importantly, office and sales occupations decreased substantially in relative employment shares, contributing to the shrinking of the middle part of the distribution.

To completely understand the distributional shift from 2008 to 2017 in Panel A, it is crucial to consider the 'intensive margin' (dashed red line), which shows the distribution of task intensities in 2017, holding the workforce distribution constant at 2008 levels. The intensive margin in Panel A indicates that occupations with comparatively low levels of cognitive intensity in 2008 have further decreased in cognitive intensity (stretching to the left), while the most cognitive-intensive occupations seem to have contributed to the density increase at the upper end of the distribution (stretching to the right). The counterfactual exercise is repeated for the manual intensity distribution in Panel B. In line with past trends of technological change, the manual intensity distribution has shifted to the left over the last decade. However, in contrast to Panel A, the intensive margin does not significantly differ from the actual manual intensity distribution of 2017. This observation suggests that changes in employment shares had no significant role regarding overall manual task shifts between 2008 and 2017. In addition, the joint distribution of cognitive and manual task intensity is plotted and shown in Appendix Figure A.3 weighted by 2008 employment shares in the upper panel and 2017 employment shares in the lower panel.

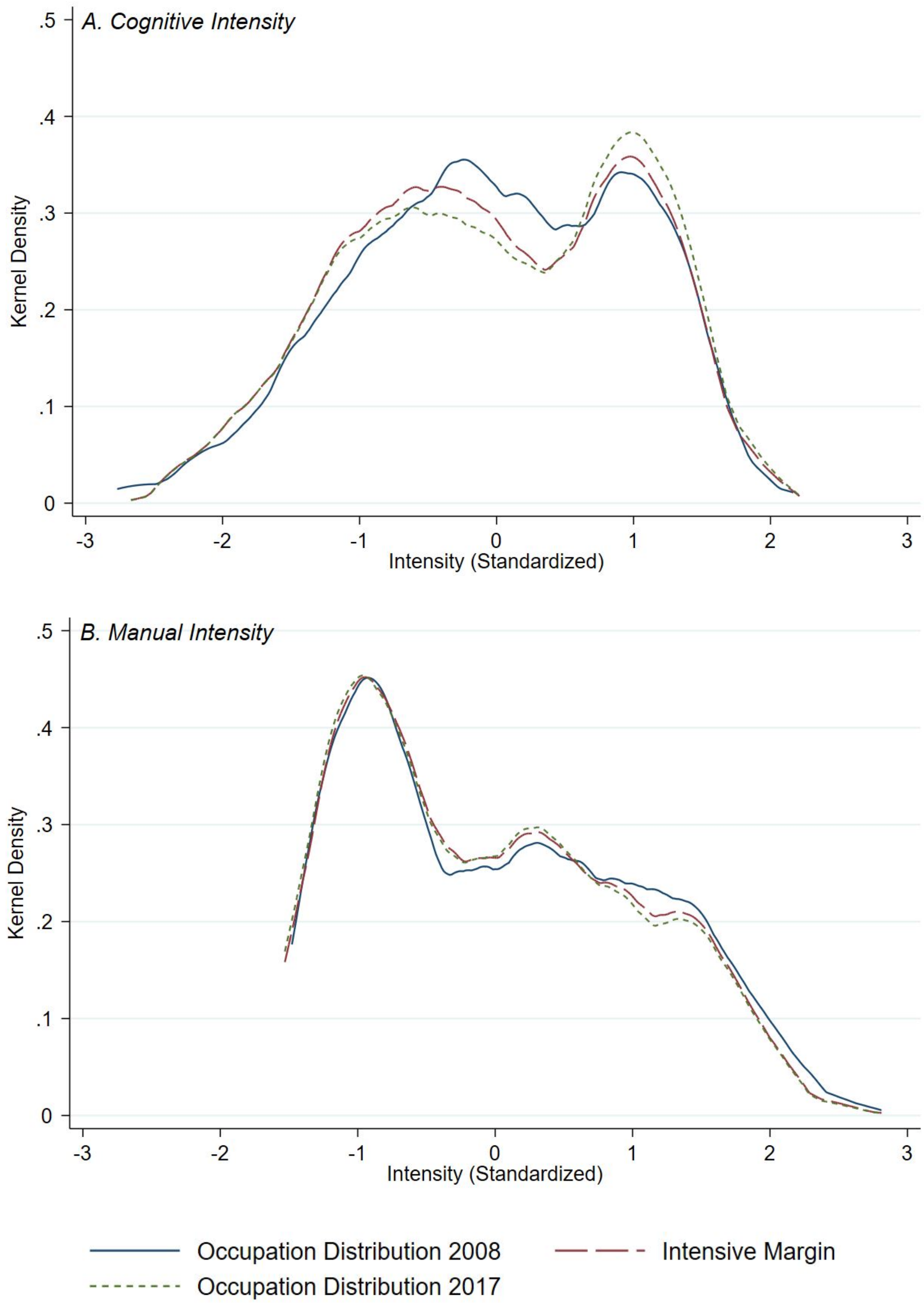

Figure 2.2: Smoothed Cognitive and Manual Intensity Distributions of the Employed Labour Force: 2008 and 2017

Although looking at aggregate distributions provides a good overview of the aggregate task shifts, it obscures the heterogeneity in task intensity developments between occupations. Therefore, the following sections analyse within-occupation changes in more detail to disentangle the presented aggregate changes.

2.3.1 Breakdown by Occupation Groups

To shed more light on heterogeneous occupation developments, I break down the aggregate changes into changes within and between smaller occupation groups based on the 2010 SOC structure.[12] In addition, this section aims to pinpoint the contribution of task changes within occupations relative to the contribution of task changes caused by shifts in employment shares. To achieve this goal, I decompose the total intensity changes into a within-component and a between-component by using counterfactual employment shares and task intensities. Table 2.3 documents the results of the task intensity decomposition for different occupation groups.

Non-routine cognitive occupations increased in cognitive intensity from 2008 to 2017 with a positive change of 0.054 units of standard deviation. When splitting non-routine cognitive occupations into smaller occupation groups, one can see that the growing importance of cognitive abilities is mainly driven by computer, engineering and science occupations, with a sizeable increase of 0.233 units of standard deviation. Management, business and finance occupations experienced only a minor positive change in cognitive intensity, while education and legal occupations experienced a minor decrease. Non-routine manual occupations (service occupations) show a modest but negative cognitive intensity shift. Routine cognitive occupations experienced a sizeable reduction in cognitive intensity from 2008 to 2017, with score value changes of -0.118 and -0.097 for sales and office occupations, respectively. A similar picture is unveiled when disentangling task changes in routine manual occupations. On average, production jobs have decreased in cognitive intensity by -0.036 units of standard deviation. During the same time, transportation and material moving jobs show the most severe fall in cognitive in-

[12] The Standard Occupation Classification (SOC) categorises occupations into groups based on similarities in their task content and working activities following the SOC classification principles (Cosca and Emmel, 2010). Detailed information on the 2010 SOC structure can be obtained from the official website of the Bureau of Labour Statistics (`https://www.bls.gov/soc/2010/`).

Table 2.3: Changes in Cognitive and Manual Task Intensities: 2008-2017

	△ Cognitive Intensity			△ Manual Intensity		
Occupation Group	Within	Between	Total	Within	Between	Total
A. Non-Routine Cognitive	**0.052**	**0.007**	**0.054**	**-0.109**	**0.008**	**-0.099**
Management/Business/Finance	0.026	-0.013	0.017	-0.132	-0.004	-0.134
Computer/Engineering/Science	0.212	0.032	0.233	-0.091	-0.038	-0.120
Education/Legal/Comm./Arts/Media	-0.022	0.003	-0.027	-0.033	0.004	-0.027
Healthcare Practitioners and Technical	0.072	0.004	0.077	-0.201	-0.016	-0.223
B. Non-Routine Manual	**0.002**	**-0.016**	**-0.015**	**-0.003**	**-0.016**	**-0.021**
C. Routine Cognitive	**-0.126**	**0.021**	**-0.108**	**-0.056**	**0.001**	**-0.049**
Sales and Related	-0.118	-0.003	-0.118	-0.164	0.014	-0.147
Office and Admin. Support	-0.132	0.043	-0.097	0.028	-0.013	0.015
D. Routine Manual	**-0.024**	**-0.027**	**-0.053**	**-0.050**	**0.002**	**-0.051**
Farming/Fishing/Forestry	-0.049	-0.023	-0.081	-0.098	-0.003	-0.114
Construction and Extraction	0.134	-0.020	0.084	-0.001	0.017	0.001
Installation/Maintenance/Repair	0.023	-0.025	-0.017	-0.107	0.018	-0.099
Production	-0.040	0.002	-0.036	-0.003	0.004	-0.007
Transportation and Material Moving	-0.154	-0.015	-0.158	-0.096	-0.028	-0.116
F. Employed labour Force	**-0.012**	**0.041**	**0.020**	**-0.066**	**-0.026**	**-0.090**

Notes: All intensity changes presented in this table refer to changes in the deviation from the mean score of the entire occupation panel (456 occupations) measured in standard deviation units. I use CPS employment shares and CPS "earnings weights" for all calculations. Within-occupation changes are calculated by holding employment shares constant at the 2017 levels and changing task intensities from 2008 to 2017. Between-occupation changes are computed by holding task intensities within occupations constant at the 2017 levels and changing employment shares from 2008 to 2017.

tensity among all occupation groups with -0.158 units of standard deviation. Moreover, within the group of routine manual occupations, only construction and extraction jobs show a positive change in cognitive intensity with 0.084 units of standard deviation.

When comparing the within-component (column 1) with the between-component (column 2) of the cognitive intensity changes, one can observe that the impact of task changes within occupations is of comparatively larger magnitude for most groups. This finding is in line with Freeman et al. (2020), who find that within-occupation changes dominate between-occupation changes in nine out of ten O*NET job attributes. While their analysis remains at the aggregated level, my study shows that the impact of changes within occupations is substantially more prevalent when splitting the workforce into task-based occupation groups as the dissimilarities in task content between occupations within groups decrease.

The second part of Table 2.3 shows the within, between and total changes in the manual intensity of the presented occupation groups. All groups reveal a decrease in manual intensity between 2008 and 2017, although there is some variation in the magnitudes. When comparing columns 4 and 5, it becomes evident that the intensity changes predominately come from task changes within occupations, as the within-component dominates the between-component in most cases. The impact of changes in employment shares is of comparatively minor importance, and its direction is not clear-cut. At an aggregate level, both within and between-occupation changes contributed to the overall decline in manual intensity.

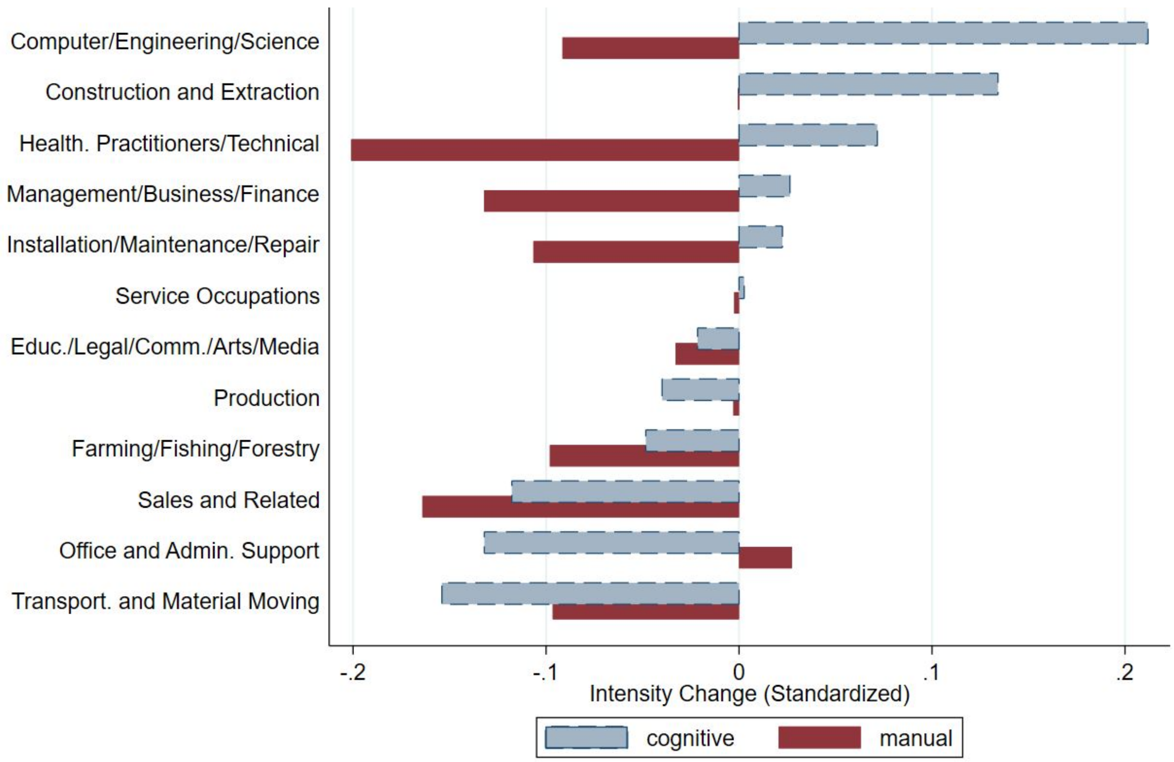

Figure 2.3: Changes in Task Intensities Within Occupations by 2010 SOC Intermediate Aggregation Occupation Groups

To highlight the heterogeneity in occupation changes, I hold the employment shares within occupation groups constant at the 2017 levels and show the isolated effect of task changes within occupations in Figure 2.3. Complementing the results of Table 2.3, one can see a reduction in manual intensity across all occupation groups except for office and administrative support occupations. The figure also illustrates the drifting apart of the labour market regarding the demand for cognitive abilities. The results suggest that non-routine cognitive occupations experienced the most substantial increase, and routine cognitive occupations experienced the largest decline in cognitive intensity through the channel of within-occupation changes.

The results also emphasise that a change in one of the two measured task intensities is not necessarily offset by an opposite change in the other task dimension. In fact, I do not find a systematic relationship between the change in cognitive and manual task intensity at the occupation level. At first glance, this appears counterintuitive, as one could assume that technological change replaces other tasks with new cognitive-intensive tasks (Acemoglu and Restrepo, 2019). However, this assumption does not necessarily contradict the presented results in this section. For example, the cashier job has changed substantially in the last ten to fifteen years due to the introduction of self-service checkouts. While the manual task intensity decreased significantly for cashiers, new tasks now include overlooking the self-service checkout and helping customers occasionally with the new technology. Nonetheless, as long as the newly introduced tasks are not of higher cognitive intensity than the average task performed by cashiers, the new tasks do not cause an increase in the cognitive intensity of the job (except the time spent on the more cognitive-intensive tasks increases as a result of a change in the task composition of the job). Therefore, it depends on the intensity levels of the newly introduced tasks relative to the average task to determine if and by how much the cognitive and manual intensity within occupations change. A decrease in the demand along all different task dimensions is, therefore, equivalent to a decrease in the relevance of an occupation, potentially leading to complete job automation in the future.[13]

Although not the focus of this study, one could also ask whether there are other dimensions to the systematic task intensity changes shown in this section. For example, it is intuitive to assume that industries are affected differently as they differ in their occupational composition. For example, construction industries show the highest increase in cognitive intensity with 0.120 units of standard deviation, while wholesale and retail trade industries experienced the most substantial decrease with -0.086 standard deviation units. Agricultural, forestry, fishing and hunting industries decreased the most in the demand for manual abilities with -0.103, and none of the thirteen major industries

[13] Note that this interpretation is based on focusing on occupations' cognitive and manual intensities. In fact, it is possible that other unobserved abilities and skills have also changed in importance, affecting the overall relevance of an occupation.

increased in the demand for manual abilities between 2008 and 2017. In contrast to the noticeable differences between industries, I do not find a statistically significant difference between the public and private sectors regarding cognitive and manual task intensity changes.

2.3.2 Demographic Breakdown

Based on the finding that different occupations evolve differently over time along with the assumption that individuals sort themselves into occupations based on their skills and abilities (Roy, 1951)[14], the next question to address is: are workers with different characteristics affected differently by within-occupation task changes, and if so, how?

Figure 2.4 shows the standardised cognitive and manual intensity changes due to task shifts within occupations for workers with different educational attainments. Therefore, I hold the employment distribution constant at 2017 levels. It can be seen that recent task shifts within occupations favour workers with high educational attainment over less educated workers. Moreover, the increase in the importance of cognitive abilities among the most educated workers is noticeably more considerable for men than women. Both observations seem to contrast labour market trends during the second half of the twentieth century, where the increase in the demand for non-routine cognitive tasks was pervasive at all educational levels and equally present for both men and women (Autor et al., 2003). However, the diverse effects on different education groups are not surprising when taking into account that the average educational level is significantly higher in occupations that have recently experienced a rapid increase in cognitive intensity, for example, computer, engineering and science occupations. In 2017, almost 30% of all workers employed in non-routine cognitive jobs had a master's or postgraduate degree and 68% held at least a college degree. On the contrary, only 9% of workers in routine manual jobs held a college or master's degree.

Figure 2.5 shows the impact of task changes within occupations on workers with different potential labour market experiences, using the fixed 2017 employment distri-

[14] Following the path-breaking work by Roy (1951), sorting models have been widely used over the last decades to support empirical analyses that are based on employment decisions of individuals (see, e.g., Costinot and Vogel, 2010; Firpo et al., 2011; Autor and Handel, 2013; Jung and Mercenier, 2014; Cortes, 2016).

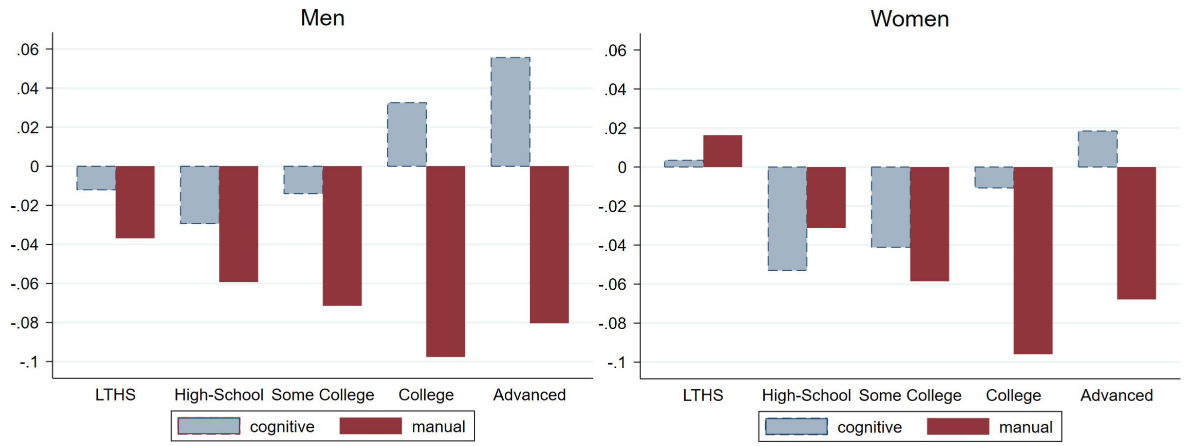

Figure 2.4: Within-Occupation Task Intensity Changes by Education Groups

bution. Workers with the same years of experience are binned into cohorts, and the average changes in cognitive and manual intensity between 2008 and 2017 are calculated for each cohort. The binned scatter plots show a clear pattern of how the potential workforce experience relates to cognitive and manual intensity changes. Workers with five to twenty years of potential labour market experience show a more substantial cognitive intensity increase (or lower cognitive intensity decline for women). Workers with more than thirty years of experience show the largest decline in the demand for cognitive abilities. This observation is likely related to older workers working in routine manual and cognitive occupations more often than other workers. This finding also resonates with a study by Autor and Dorn (2009), which shows that younger workers are more likely to switch from "routine jobs" that are declining in employment shares to "high-skill non-routine jobs". On the other hand, middle-aged and older workers switch more often to "low-skill non-routine jobs". Equivalent to the more substantial decrease in cognitive intensity, the most experienced workers show the lowest reduction in the importance of manual tasks. Likewise, the least experienced workers (zero to five years of experience) also show a substantial decline in cognitive intensity because workers entering the labour market work more often in routine cognitive or manual occupations. It is also worth mentioning that the most experienced women are outliers as they make the only female cohort reaching the 'zero change threshold' regarding the demand for cognitive ability in their jobs.

The reasons why men experienced a more significant increase in cognitive inten-

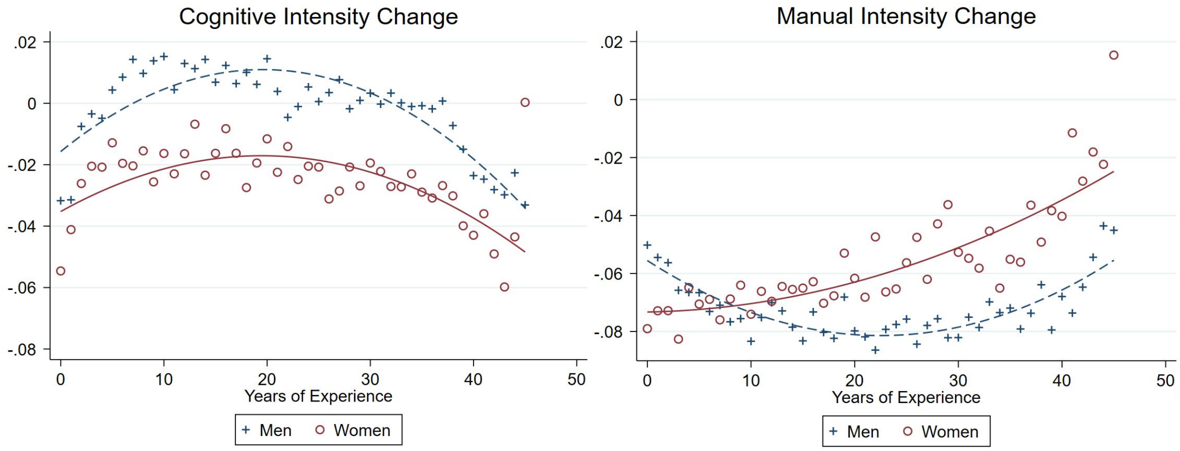

Figure 2.5: Within-Occupation Task Intensity Changes by Years of Experience

sity and simultaneously a more considerable decrease in manual intensity compared to women are manifold: first, women are less often employed in computer, engineering and science occupations, with only 26% in 2017. Simultaneously, these occupations show the most substantial increase in cognitive intensity between 2008 and 2017. Second, women work more often in office and administrative support occupations, with a total share of 72% in 2017. Aside from the sizeable decrease in cognitive intensity, office occupations make the only occupation group which shows an increase in manual intensity (see Table 2.4). Third, women work significantly less often in construction and extraction occupations, with only 3% on average. On the contrary, the disproportionate increase in cognitive intensity in construction and extraction occupations predominately affected male high-school graduates and workers with some college experience.

In addition to the presented findings, the Appendix Tables A.6 and A.7 provide a more detailed picture of the labour market by splitting the employed labour force into 20 experience-education cells separately for men and women and by taking into account both changes within occupations and changes in employment shares. From this more comprehensive perspective, it becomes clear that only a small proportion of workers benefited from task demand changes in the sense that the demand for cognitive ability increased. For men, this includes experienced college graduates and those with an advanced degree but less than 30 years of working experience. Regarding female workers, only those with an advanced degree and moderate working experience (10 to 20 years) show increased cognitive intensity in their jobs. Particular care needs to be taken when interpreting these results as the changes shown in Tables A.6 and A.7 capture both task changes within occupations and occupational resorting between 2008 and 2017. When looking at the weighted average changes, one can observe that the overall change in cognitive intensity is positive for both men and women. However, the effect is noticeably more substantial for men. As illustrated in Figures 2.4 and 2.5, the noticeable difference between men and women stems from task changes within occupations. For example, the overall change in cognitive intensity relative to the pooled sample of male and female workers is negative for women, with -0.025 units of standard deviations when using fixed employment shares of 2017. The same counterfactual exercise for men unveils no significant change in cognitive intensity when holding employment shares constant at 2017 levels.

Regarding the evolution of manual task demand in the male labour market, all 20 experience-education cells show a decline in manual intensity. On the other hand, only the most experienced women without a degree and experienced women with a high school degree but no college experience show substantial increases in manual intensity with 0.079 and 0.057 units of standard deviation, respectively. As shown in panel B and complementing the other findings in this section, both men and women record a substantial decline in manual intensity on average when holding employment shares constant at 2008 or 2017 levels. Interestingly, only men resort to occupations of lower manual intensity, as indicated by the difference of 0.058 standard deviation units between the measured change when using actual employment shares and fixed shares of 2017.

2.4 Task Intensity Changes and Wage Effects

This section analyses how the heterogeneous task demand changes are related to the wage structure in the U.S. and how the changes affected the returns to cognitive and manual task intensity between 2008 and 2017. To understand the relationship between wages and task intensity changes, I split the cross-sectional sample 2017 into 100 equally sized bins based on workers' hourly wage rate to plot the cognitive and manual intensity changes between 2008 and 2017 against the log wages.[15] The left panel of Figure 2.6 shows a systematic and positive relationship between an individual's position in the wage distribution and the change in the importance of cognitive abilities. A log wage of 3.3 (equal to 27 U.S. dollars) is the approximate threshold determining whether individuals work with a lower or higher probability in a cognitive-intensity-increasing occupation. On the contrary, the change in manual intensity is systematically decreasing in the log wage rate, as illustrated in the right panel of Figure 2.6. The importance of manual abilities fell for all calculated bins between 2008 and 2017, whereas the decrease was more significant for individuals with higher wages. It is intuitive to assume that the unveiled systematic relationships have impacted the recent evolution of earnings in the U.S. economy, which is worth analysing in more detail.

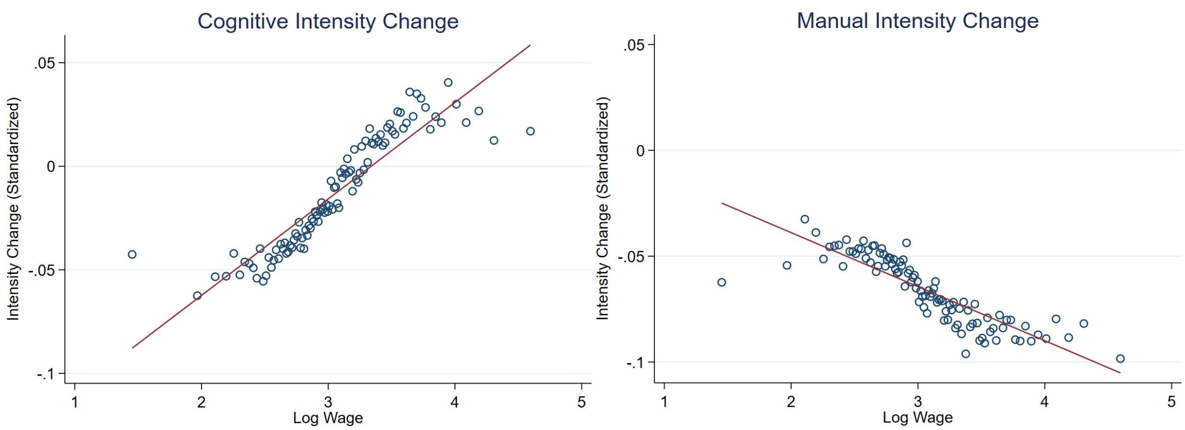

Figure 2.6: Wage Distribution and Within-Occupation Task Intensity Changes of the Employed Labour Force (2017)

2.4.1 Returns to Task Intensities

To check the returns to task intensities in the two cross-sectional samples of 2008 and 2017, I extend the Mincer (1974) earnings equation for my study. The Mincer regression framework relies on a human capital investment model and has been widely used by researchers to analyse the impact of education and experience on earnings (Grossbard, 2006). In the original equation, log earnings are regressed on a linear function of years of

[15] Each bin contains approximately 1,500 individuals independent of their occupation. To ensure that differences in education and experience do not drive the relationship between the log wages and intensity changes, I control for these factors to derive the two partial relationships.

schooling and a quadratic function of labour market experience. Although the original equation has proven to fit the data well in various contexts, Autor and Handel (2013) points out that the original equation is not capable of carrying over returns to tasks as the equation does not include job-specific characteristics but relies entirely on workers' skill endowments. Equation 2.1 includes both the return to general human capital and the returns to occupation-specific task intensities:[16]

$$\ln w_{ij} = \ln w_0 + \delta_1 CI_j + \delta_2 MI_j + \alpha S_i + \beta_1 Exp_i + \beta_2 Exp_i^2 + \sum_{k=1}^{K} \gamma X_i + \varepsilon_{ij} \tag{2.1}$$

$\ln w_{ij}$ is the *log* wage rate of worker i employed in occupation j. CI_j and MI_j are the occupation-specific cognitive and manual intensity. δ_1 and δ_2 estimate the returns to the cognitive and manual intensity. S_i is years of completed schooling, Exp_i is potential labour market experience (age - years of schooling - 6) and X_i is a vector of $k = 1, ..., K$ different worker characteristics.[17]

Table 2.4 shows the estimation results of equation 2.1 for 2008 and 2017. The coefficients represent the returns to task intensities and different worker characteristics. For example, in 2017, the preferred model specification of column 6 predicts that a worker employed in an occupation with one standard deviation higher cognitive intensity receives an hourly wage that is 18.2% higher than the mean wage. In contrast, the coefficient of manual intensity is statistically significant but relatively modest, indicating a 1.1% higher return for one standard deviation higher manual intensity. When comparing the coefficients of task intensities between the two cross-sectional samples, the return to cognitive intensity increased by 8.3% ((0.182-0.168)/0.168). In contrast, the return to manual intensity seems to have stayed the same during the ten-year period.

[16] Checking the relationship of the task intensity levels with the log wages of individual workers suggests that a linear model is the most suitable to regress log wages on task intensities and other regressors. It is important to note that the shown relationship in Figure 2.6, which appears to be non-linear, is not the relationship of interest for the estimated model as it represents occupations' changes in cognitive and manual task intensity instead of the occupation-specific levels used in the model.

[17] Worker characteristics that are controlled for are: gender, union coverage, race (white, black, Hispanic, others) and marital status. In addition, I include thirteen dummies for major industries to control for industry-fixed effects.

Table 2.4: Returns to Task Intensities: 2008 and 2017

	CPS Sample 2008			*CPS Sample 2017*		
	(1)	(2)	(3)	(4)	(5)	(6)
Controls		√	√		√	√
Industry Fixed Effects			√			√
Cognitive Intensity	0.307**	0.179**	0.168**	0.318**	0.194**	0.182**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Manual Intensity	0.055**	0.019**	0.011**	0.052**	0.020**	0.011**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Years of Schooling		0.069**	0.071**		0.066**	0.068**
		(0.001)	(0.001)		(0.001)	(0.001)
Experience		0.030**	0.028**		0.028**	0.026**
		(0.000)	(0.000)		(0.000)	(0.000)
Experience^2		-0.001**	-0.000**		-0.000**	-0.000**
		(0.000)	(0.000)		(0.000)	(0.000)
Female		-0.241**	-0.200**		-0.222**	-0.180**
		(0.003)	(0.003)		(0.003)	(0.003)
Married		0.061**	0.055**		0.066**	0.061**
		(0.003)	(0.003)		(0.003)	(0.003)
Union		0.129**	0.131**		0.111**	0.120**
		(0.004)	(0.004)		(0.004)	(0.004)
Black		-0.108**	-0.103**		-0.129**	-0.122**
		(0.004)	(0.004)		(0.005)	(0.004)
Hispanic		-0.019**	-0.020**		-0.028**	-0.028**
		(0.004)	(0.004)		(0.004)	(0.004)
Other		0.017**	0.019**		0.035**	0.036**
		(0.006)	(0.006)		(0.006)	(0.006)
Constant	3.024**	1.788**	1.664**	3.066**	1.862**	1.881**
	(0.002)	(0.011)	(0.016)	(0.002)	(0.012)	(0.017)
R^2	0.211	0.384	0.403	0.233	0.386	0.404
Observations		164,824			151,652	

Notes: CPS "earnings weights" are used for all estimations. The method for estimating the unknown parameters in the linear regression model is ordinary least squares (OLS). Robust standard errors are shown in parentheses. **/* Significant at the 1%/5% level.

To better understand the role of task changes within rather than between occupations, Table 2.5 shows the results of a falsification exercise by holding the occupation-specific task intensities constant at 2008 levels (columns 5-6). It turns out that the estimated return to cognitive task intensity is insignificantly different from 2008. Thus, not including changes in task intensities within occupations mistakenly leads to the interpretation that the return to cognitive intensity remained unchanged between 2008 and 2017. This interpretation is consistent with the descriptive findings shown in the last sections and stands in contrast to a study conducted by Castex and Dechter (2014), which finds a decline in the return to cognitive ability in the 2000s. On the other hand, the result of the counterfactual exercise is in line with a study by Ross (2017) showing that within-occupation changes let the premium for routine tasks decline and the premium for abstract tasks increase. In contrast, the return to manual intensity shows only a slight drop in the counterfactual exercise from 0.11 to 0.08.

Table 2.5: Returns and Counterfactual Returns to Task Intensities

	CPS Sample 2008		***CPS Sample 2017***		***Counterfactual Sample***	
	(1)	(2)	(3)	(4)	(5)	(6)
Full Controls		√		√		√
Cognitive Intensity	0.195**	0.168**	0.217**	0.182**	0.195**	0.169**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Manual Intensity	0.071**	0.011**	0.068**	0.011**	0.056**	0.008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: CPS "earnings weights" are used for all estimations. The method for estimating the unknown parameters in the linear regression model is ordinary least squares (OLS). Controls include years of schooling, experience, gender, union coverage, race and thirteen industry dummies. Robust standard errors are shown in parentheses. **/* Significant at the 1% and 5% level.

2.4.2 Heterogeneity in Returns to Task Intensities

The objective of this section is to investigate if the systematic task changes within occupations across the wage distribution are also prevalent within the four task-based occupation groups.[18] This exercise helps us to understand if the overall return to cognitive intensity comes from increasing returns within occupation groups or from diverging developments between occupation groups.

Figure 2.7 shows the binned scatter plots of the four task-based occupation groups, which are analogous to the plots in Figure 2.6 using the fixed 2017 employment distribu-

[18] The categorisation of occupations into the four groups is documented in Appendix Table A.1.

tion.[19] One can see that higher wages are associated with a more considerable increase in cognitive intensity for all groups except for non-routine manual occupations. The latter group does not show a clear relationship between an individual's position in the group-specific wage distribution and the change in the importance of cognitive ability. All other occupation groups have a positive slope, indicating a positive relationship between the log wage rate and the change in cognitive task intensity between 2008 and 2017. Non-routine cognitive occupations show a negative relationship between log wages and manual task intensity changes. On the contrary, the wage distributions of routine manual and routine cognitive occupations do not reveal a clear positive or negative relationship with the change in the importance of manual abilities.

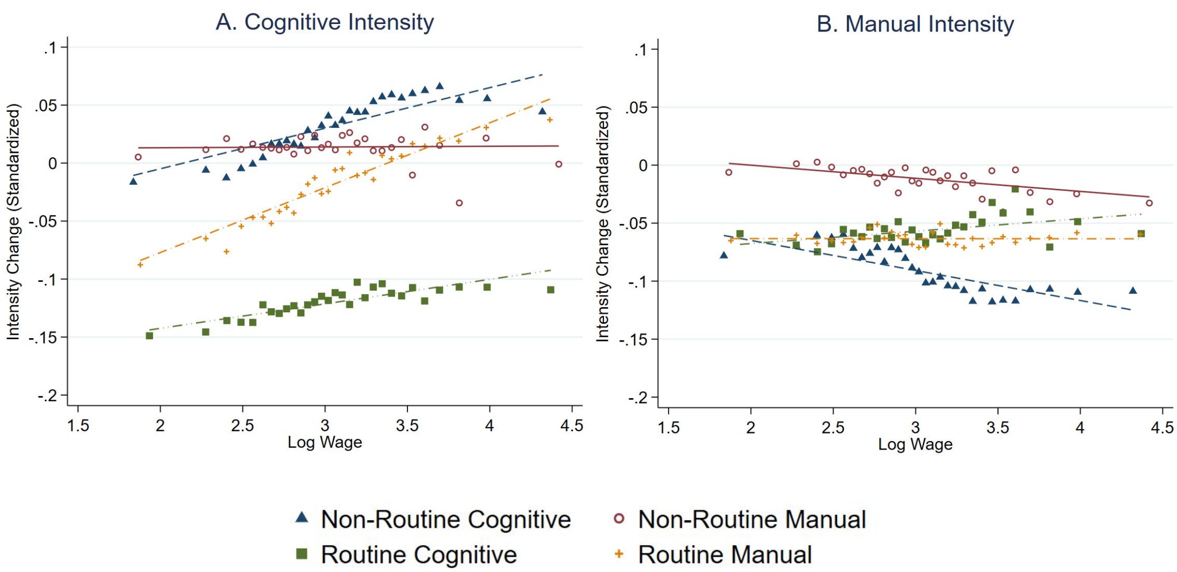

Figure 2.7: Wage Distribution and Within-Occupation Task Intensity Changes by Broad Occupation Groups (2017)

Table 2.6 reports the estimated returns to task intensities, formal education and years of experience based on the different occupation groups.[20] Non-routine cognitive occupations show an increase in the return to cognitive intensity by 7% when measured at the mean. This finding aligns with two stylised facts shown in Section 2.3: first, non-routine cognitive jobs experienced the most significant upward shift in cognitive

[19] I control for labour market experience and years of schooling to find the partial correlation between task intensities and the log wage distribution within the broad occupation groups.

[20] Following the preferred model specification in columns 3 and 6 of Table 2.4, I control for gender, union coverage, race, marital status and industries.

intensity among all occupation groups. Second, recent cognitive-biased task changes favoured individuals employed in computer, engineering and science occupations, which are often located at the upper end of the wage distribution. The largest increase in the return to cognitive intensity is found in non-routine manual occupations (service occupations), with a noticeable increase of 15% between 2008 and 2017. The return to cognitive task intensity also increased for workers employed in routine manual occupations by a noticeable 7%. Routine cognitive occupations record the most substantial decrease in the return to cognitive intensity with -12% between 2008 and 2017. This finding is consistent with the fact that both sales and office administrative occupations show a remarkable reduction in the importance of cognitive abilities (see Figure 2.3).

The return to manual task intensity decreased for non-routine cognitive occupations by 19% between 2008 and 2017, confirming the lessened importance of manual abilities in such jobs. While the return to manual intensity also decreased for routine cognitive occupations, workers employed in both routine and non-routine manual occupations experienced an increase in the return to manual task intensity. From a pure demand-side perspective, the increase in the return to manual intensity for routine and non-routine manual occupations appears inconsistent with the general assumption that primarily manual tasks become automated, which should reduce the relative importance of those tasks and decrease their return. However, it is essential to note that the supply of manual skills most likely decreases over time as workers sort themselves disproportionately into non-routine cognitive occupations (see Table 2.2). This development possibly increases the market value of manual abilities in manual-intensive occupations.

Although the shown results in this section are very informative, the Mincerian approach of regressing log wages on years of schooling, experience and task intensities contains some crucial limitations, as discussed, for example, in Autor (2013). First, the set of tasks a worker performs is not an exogenous state variable but a function of the current wage distribution. In other words, the set of tasks that a worker performs is "simultaneously determined by the worker's stock of human capital and the contemporaneous productivity of the tasks that human capital could accomplish." In this light, it would be more informative to regress wages on workers' skills instead of regressing wages on task intensities measured at the occupation level. In this regard,

Table 2.6: Returns to Task Intensities by Broad Occupation Groups: 2008 and 2017

A. Returns 2008	*NRC*	*NRM*	*RC*	*RM*
Cognitive Intensity	0.141**	0.078**	0.079**	0.134**
	(0.005)	(0.004)	(0.005)	(0.003)
Manual Intensity	0.062**	0.008	-0.036**	0.036**
	(0.003)	(0.007)	(0.005)	(0.005)
Years of Schooling	0.097**	0.042**	0.073**	0.039**
	(0.001)	(0.001)	(0.002)	(0.001)
Experience	0.033**	0.018**	0.030**	0.021**
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.288	0.257	0.294	0.291
Observations	60,145	26,768	40,761	55,573
B. Returns 2017	*NRC*	*NRM*	*RC*	*RM*
Cognitive Intensity	0.151**	0.087**	0.067**	0.144**
	(0.005)	(0.005)	(0.006)	(0.004)
Manual Intensity	0.050**	0.033**	-0.062**	0.042**
	(0.004)	(0.008)	(0.008)	(0.005)
Years of Schooling	0.098**	0.041**	0.071**	0.038**
	(0.002)	(0.001)	(0.002)	(0.001)
Experience	0.031**	0.017**	0.028**	0.019**
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.292	0.240	0.296	0.275
Observations	60,596	25,459	33,181	53,495

Notes: 2008 and 2017 employment shares and task intensities are used to estimate the returns. CPS "earnings weights" are used for all estimations. The method for estimating the unknown parameters in the linear regression model is ordinary least squares (OLS). The reported occupation groups are non-routine cognitive (NRC), non-routine manual (NRM), routine cognitive (RC) and routine manual (RM) occupations. The mapping of the detailed SOC occupations to the four broad occupation groups is reported in Appendix Table A.1. Robust standard errors are shown in parentheses. **/* Significant at the 1%/5% level.

one cannot assume that an occupation's task intensities accurately mirror the underlying skills of all workers employed in that occupation, as occupation choices depend not only on individuals' abilities and skills but also on their preferences (Yamaguchi, 2012). Both workers' abilities and preferences are unobserved. Second, equation 2.1 does not include all relevant occupation characteristics, which could lead to biased estimates of cognitive and manual task intensity measures. This is a well-known problem in the occupation and skill literature. However, entering additional measures of arguably important characteristics, such as occupations' capability to offshore tasks or the routine intensity of occupations, has been proven to cause severe multicollinearity due to significant overlaps in the construction of the different measures when using O*NET data (see, e.g., Yamaguchi, 2012; Autor, 2013). Third, the Mincerian regression approach is not a suitable method to quantify the relative contribution of task shifts to wage changes compared to other factors. The next section's detailed Oaxaca-Blinder decomposition of wage changes between 2008 and 2017 helps address this issue.

2.4.3 Oaxaca-Blinder Decomposition of Wage Changes

This section aims to shed light on the relative contribution of task changes, including task changes within occupations, compared to changes related to socio-demographic factors, industrial composition and labour unions. To answer this question, I use an Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973) applied to the employed labour force and the four different occupation groups.[21] The method decomposes the total effect of mean wage differentials into two separate components: a component that captures the changes in the workforce composition ("composition effect") and another component that can be explained by changes in the market price of worker and job characteristics ("wage structure effect"). The linear wage setting model for the employed labour force in 2008 and 2017 can be written as

$$W_t = X\beta_t + \upsilon_t \quad \text{for} \quad t = 2008, 2017 \tag{2.2}$$

whereby the conditional mean of υ_t is assumed to be zero ($\mathbb{E}[\upsilon_t|X] = 0$). Letting $G = 1$ be an indicator for being in the labour force in 2017 and taking the expectations over X, one can express the mean wage gap as follows:

[21] The Oaxaca-Blinder decomposition approach has been widely used to analyse earnings differentials between men and women, union members and non-union members or related to other worker characteristics (see, e.g., O'Neill and O'Neill, 2006; Fortin et al., 2011). Thanks to the flexibility of the approach, it can also be used to decompose wage gaps between two workforce samples of different years.

$$
\begin{aligned}
\Delta_T^\mu &= \mathbb{E}[W_{2017}|G=1] - \mathbb{E}[W_{2008}|G=0] \\
&= \mathbb{E}[X|G=1]\beta_{2017} - \mathbb{E}[X|G=1]\beta_{2008} + \mathbb{E}[X|G=1]\beta_{2008} - \mathbb{E}[X|G=0]\beta_{2008}
\end{aligned} \tag{2.3}
$$

By replacing the expected values of X with the mean values of the two samples, 2008 and 2017, one can estimate the wage decomposition

$$
\begin{aligned}
\Delta_T^\mu &= \overline{X}_{2017}\hat{\beta}_{2017} - \overline{X}_{2017}\hat{\beta}_{2008} + \overline{X}_{2017}\hat{\beta}_{2008} - \overline{X}_{2008}\hat{\beta}_{2008} \\
&= \overline{X}_{2017}(\hat{\beta}_{2017} - \hat{\beta}_{2008}) + (\overline{X}_{2017} - \overline{X}_{2008})\hat{\beta}_{2008} \\
&= \Delta_S^\mu + \Delta_X^\mu
\end{aligned} \tag{2.4}
$$

to find the wage structure effect Δ_S^μ and the composition effect Δ_X^μ. In the second step, each of the two effects is further decomposed into different factors, quantifying the fraction of the average wage change between 2008 and 2017 attributable to each factor. Based on the assumption that the true wage setting model is linear[22], it is straightforward to estimate the different factor contributions based on the two additive equations

$$
\begin{aligned}
\hat{\Delta}_S^\mu &= (\hat{\beta}_{2017,0} - \hat{\beta}_{2008,0}) + \sum_{k=1}^{K} \overline{X}_{2017,k}(\hat{\beta}_{2017,k} - \hat{\beta}_{2008,k}) \\
\hat{\Delta}_X^\mu &= \sum_{k=1}^{K} (\overline{X}_{2017,k} - \overline{X}_{2008,k})\hat{\beta}_{2008,k}
\end{aligned} \tag{2.5}
$$

where $(\hat{\beta}_{2017,0} - \hat{\beta}_{2008,0})$ is the unexplained difference between the 2008 and 2017 labour force, and $\overline{X}_{2017,k}(\hat{\beta}_{2017,k} - \hat{\beta}_{2008,k})$ and $(\overline{X}_{2017,k} - \overline{X}_{2008,k})\hat{\beta}_{2008,k}$ are the contributions of the kth factor to the wage structure and composition effect, respectively.

[22] To test if the wage setting model of the two underlying samples is linear, I use a reweighted-regression decomposition as proposed by Barsky et al. (2002) and check if the specification error term is close to zero. More specifically, I use Rios-Avila (2020) procedures based on recentered influence functions and find that the linearity assumption is indeed satisfied.

I use the decomposition procedures of linear regression models provided by Jann (2008). The results are shown in Table 2.7.[23] As can be observed from column 1, 32% (0.014 out of 0.043 log points) of the wage change between 2008 and 2017 can be explained by changes in the composition of the workforce, including task changes within and between occupations. Cognitive task intensity changes contribute a positive 25%, and manual task intensity changes a negative 7% to the overall composition effect. The overall contribution of task changes is only of minor importance compared to the effect of formal education, which contributes a noticeable 0.023 log points to the overall change. However, compared to other factors like resorting mechanisms between industries or changes in union coverage, the contribution of cognitive task shifts is of comparable magnitude. Moreover, the contribution of both cognitive and manual intensity changes is highly significant.

The wage structure effect shows very different results. The role of task changes is only of minor importance. Moreover, the effect is insignificant for the manual task intensity. On the contrary, formal education stands out as the factor with the most considerable contribution to the wage structure effect. Interestingly, the contribution of education is negative, with -0.041 log points indicating a decrease in the market price of education between 2008 and 2017. In conjunction with the predicted stagnating return to years of schooling (see Table 2.4), this trend stands in contrast to the increasing demand for formal education and the rising skill premium in the late twentieth century (see, e.g., Goldin and Katz, 2007).

Educational upgrading is also the most important factor regarding the composition effects within broad occupation groups (columns 2-5). Interestingly, the effect of cognitive task intensity changes within groups is noticeably larger than in the total employed population. The noticeable effects can come from either changes within occupations, shifts in employment shares between occupations, or a combination of both. However, the findings in the last sections have unveiled that between-occupation changes play a much less important role when evaluated within major occupation groups. A noticeable and significant 71.2% (0.008 log points out of 0.011) of the composition effect

[23] Table 2.7 shows the results when using the pooled sample as the reference wage structure, which is recommended by Jann (2008). However, the results are robust when using the wage structure of 2017 as the reference structure instead of the pooled sample.

Table 2.7: Oaxaca-Blinder Wage Decomposition Results - Composition Effects and Wage Structure Effects

	Employed LF	*NRC*	*NRM*	*RC*	*RM*
Total Change (×100)	4.277***	3.413***	2.492***	3.273***	1.789***
Composition (×100)	1.352***	1.113***	0.172	0.228	-1.714***
Wage Structure (×100)	2.925***	2.300***	2.320***	3.045***	3.503***
Composition Effects:					
Cognitive Intensity	0.337***	0.792***	-0.121*	-0.807***	-0.721***
Manual Intensity	-0.097***	-0.545***	-0.040***	0.215***	-0.204***
Education	2.289***	1.789***	1.264***	2.039***	1.115***
Experience	-0.454***	-0.712***	-0.170*	-0.665***	-0.200**
Union	-0.239***	-0.113***	-0.404***	-0.156***	-0.525***
Worker Characteristics	-0.290***	-0.157**	-0.168**	-0.061	-0.930***
Industry	-0.194***	0.060	-0.188***	-0.337***	-0.249***
Wage Structure Effects:					
Cognitive Intensity	-0.022***	0.894	-0.768	0.142*	-0.371
Manual Intensity	-0.001	0.764**	0.844**	1.244***	1.931
Education	-4.119***	1.103	-1.506	-2.389	-8.054***
Experience	-0.907**	0.508	0.883	-0.716	-4.799***
Union	0.435**	0.362	0.897	0.513	-0.049
Worker Characteristics	-0.000	0.306	0.365	0.872**	-0.854
Industry	-0.361	-1.581**	2.967*	-1.329	-0.005
Constant	7.900***	-0.057	-1.361	4.709	15.705***

Notes: All log point contributions are multiplied by 100 for convenience of presentation. The factor "Worker Characteristics" represents aggregated decomposition results of a subset of variables, including dummies for marital status, gender and four race categories (white, black, Hispanic and others). Following Yun (2005), all categorical variables are normalized, capturing the deviation contrasts from the aggregated mean. The reported occupation groups are non-routine cognitive (NRC), non-routine manual (NRM), routine cognitive (RC) and routine manual (RM) occupations. The mapping of the detailed SOC occupations to the four broad occupation groups is reported in Appendix Table A.1. CPS "earnings weights" and robust standard errors are used for all estimations. ***/**/* Significant at the 1%/5%/10% level.

in non-routine cognitive occupations can be explained by the change in cognitive intensity. Regarding routine manual and routine cognitive occupations, the contribution of cognitive task shifts is negative and significant, with -0.007 and -0.008 log points, respectively. These findings are consistent with the documented heterogeneous changes in the importance of cognitive abilities between occupation groups (see Table 2.3).

When looking at the wage structure effects within occupation groups, the market price of cognitive intensity evaluated at the group-specific mean has only significantly changed for routine cognitive occupations. On the contrary, the contribution of manual intensity is significant for all groups except for routine manual occupations. Moreover, the impact of manual task shifts is positive and of noticeable magnitude. It is important to mention that this finding is not inconsistent with the recent decreases in manual intensity within most occupation groups. In fact, the total impact on the market price of manual task intensity depends on the interaction between the demand for and supply of manual skills in the labour market. Based on this note, it is well-known and partly shown in this study that the workforce has shifted towards a disproportionate increase in the supply of cognitive skills. If this trend generates a shortage of manual skills, it pushes up their market price.[24] The market price of formal education and labour market experience only shows a significant decline within the group of routine manual occupations, driving the overall considerable decrease in the employed labour force. While the estimated contributions of education and experience (-0.081 and -0.048) to the overall wage structure effect of routine manual occupations are enormous, they are offset by a substantial increase in the constant reflecting an overall higher market price paid to the average worker in routine manual occupations.

Regarding the other factors, one has to consider that the wage structure effects are sensitive to the choice of the base category for categorical variables when applying an Oaxaca-Blinder decomposition to wage changes (Oaxaca and Ransom, 1999). To overcome this issue, I follow Yun (2005) and normalize the categorical variables to represent the deviation contrast from the mean of the pooled sample. The results show that union status does not significantly contribute to the wage structure effects within occupation groups. Industries play an important role only for the two non-routine occupation groups, whereby the industry effect differs substantially between the two groups, contributing a negative 0.016 log points for non-routine cognitive occupations and a positive 0.030 log points for non-routine manual occupations. Moreover, the

[24] There is a large literature that focuses on skill mismatch and skill shortages. See, for example, Brunello and Wruuck (2021) for a good overview.

factor that combines worker-specific characteristics (marital status, race, and gender) substantially contributes only to the wage structure effect for routine cognitive occupations.

2.5 Conclusion

Using the unique features of the O*NET ability rating procedure, this study analysed heterogeneous occupation dynamics by focusing on task changes within occupations between 2008 and 2017. Contrary to the assumption that task changes within occupations monotonically increase the demand for cognitive abilities in the labour market, my results suggest that technological change is ability-biased for some occupations but ability-saving for others.

My results show a disproportionate increase in cognitive intensity in non-routine cognitive occupations and a cognitive intensity decline in routine cognitive and routine manual occupations. Moreover, non-routine cognitive occupations experienced the most impactful decrease in manual intensity between 2008 and 2017. The systematic changes within occupations directly affect the workforce: experienced workers and women who do not hold a college degree experienced the largest decreases in cognitive intensity. The labour market analysis also unveils a systematic relationship between workers' position in the wage distribution and their cognitive and manual task demand changes. High-paying occupations show a more substantial increase in the importance of cognitive tasks, combined with a larger decrease in the importance of manual tasks. These observations are consistent with the labour-increasing effects within non-routine-cognitive occupations manifested through rising employment shares in the twenty-first century.

The returns analysis of Section 2.4.1 suggests that the return to cognitive intensity has increased by 8.3 per cent between 2008 and 2017, whereas the increase is entirely attributable to task shifts within occupations. However, when interpreting the percentage change, one has to be aware that it only captures the demand side measured at the occupation level, as individuals' cognitive and manual ability is unobserved. This study is open about this limitation, focusing on changes within occupations rather than unobserved individual characteristics. Finally, an Oaxaca-Blinder wage decomposition shows that it is essential to consider the heterogeneity between different occupation groups to evaluate the impact of task changes within and between occupations on the wage structure.

My study emphasises the importance of task changes within occupations for future research. Although data challenges like inconsistencies in the O*NET data gathering program are often difficult to overcome, not taking into account changes within occupations potentially leads to wrong interpretations of the development of the contemporary labour market.

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Appendix to Chapter 2

A.1 Appendix Tables

Table A.1: Mapping of SOC Occupations to Broad Occupation Groups

Broad Occupation Group	*2010 SOC Major Groups*	*2010 SOC Codes*
Non-Routine Cognitive	Management	11-0000
	Business and Financial Operations	13-0000
	Computer and Mathematical	15-0000
	Architecture and Engineering	17-0000
	Life, Physical, and Social Science	19-0000
	Community and Social Service	21-0000
	Legal Occupations	23-0000
	Education, Training, and Library	25-0000
	Arts, Design, Entertainment, Sports, and Media	27-0000
	Healthcare Practitioners and Technical	29-0000
Non-Routine Manual	Healthcare Support	31-0000
	Protective Service	33-0000
	Food Preparation and Serving	35-0000
	Building and Grounds Cleaning and Maintenance	37-0000
	Personal Care and Service	39-0000
Routine Cognitive	Sales and Related	41-0000
	Office and Administrative Support	43-0000
Routine Manual	Farming, Fishing, and Forestry	45-0000
	Construction and Extraction	47-0000
	Installation, Maintenance, and Repair	49-0000
	Production Occupations	51-0000
	Transportation and Material Moving	53-0000

Notes: All military occupations (SOC Codes 55-0000) are excluded from the sample. This mapping follows the SOC High-Level Aggregation with the only exception that "Natural Resources, Construction, and Maintenance Occupations" (45-49) and "Production, Transportation, and Material Moving Occupations" (51-53) are melted into the group of routine manual occupations.

Table A.2: O*NET Cognitive and Psychomotor Abilities

Ability Domain	ID	Ability Name	Description
1.A.1 Cognitive Abilities			
Verbal	1.A.1.a.1	Oral Comprehension	listen and understand what people say
Verbal	1.A.1.a.2	Written Comprehension	read and understand what is written
Verbal	1.A.1.a.3	Oral Expression	communicate by speaking
Verbal	1.A.1.a.4	Written Expression	communicate by writing
Ideas & Reasoning	1.A.1.b.1	Fluency of Ideas	come up with lots of ideas
Ideas & Reasoning	1.A.1.b.2	Originality	create new and original ideas
Ideas & Reasoning	1.A.1.b.3	Problem Sensitivity	realize when problems happen
Ideas & Reasoning	1.A.1.b.4	Deductive Reasoning	use rules to solve problems
Ideas & Reasoning	1.A.1.b.5	Inductive Reasoning	make general rules to come up with answers from lots of detailed information
Ideas & Reasoning	1.A.1.b.6	Information Ordering	order or arrange things
Ideas & Reasoning	1.A.1.b.7	Category Flexibility	group things in different ways
Quantitative	1.A.1.c.1	Mathematical Reasoning	choose the right type of math to solve a problem
Quantitative	1.A.1.c.2	Number Facility	add, subtract, multiply or divide
1.A.2 Psychomotor Abilities			
Fine Manipulative	1.A.2.a.1	Arm-Hand Steadiness	keep your arm or hand steady
Fine Manipulative	1.A.2.a.2	Manual Dexterity	hold or move items with your hands
Fine Manipulative	1.A.2.a.3	Finger Dexterity	put together small parts with your fingers
Control Movement	1.A.2.b.1	Control Precision	quickly change the controls of a machine, car, truck or boat
Control Movement	1.A.2.b.2	Multilimb Coordination	use your arms and/or legs together while sitting, standing, or lying down
Control Movement	1.A.2.b.3	Response Orientation	quickly decide if you should move your hand, foot, or other body part
Control Movement	1.A.2.b.4	Rate Control	change when and how fast you move based on how something else is moving
Reaction Time & Speed	1.A.2.c.1	Reaction Time	quickly move your hand, finger, or foot based on a sound, light, picture or other command
Reaction Time & Speed	1.A.2.c.2	Wrist-Finger Speed	make fast, simple, repeated movements of your fingers, hands, and wrists
Reaction Time & Speed	1.A.2.c.3	Speed of Limb Movement	quickly move your arms and legs

Source: *Occupational Information Network*, O*NET OnLine.

Table A.3: Occupations with Highest and Lowest Intensity Scores (2017)

Cognitive Intensity	Manual Intensity
A. Highest Ranked Occupations	***C. Highest Ranked Occupations***
1. Astronomers & physicists*	1. Manufact. building & mobile home installers
2. Operations research analysts*	2. Dredge, excavating & load. machine operators
3. Nuclear engineers*	3. Aircraft pilots & flight engineers
4. Chief executives	4. Fire fighters*
5. Biological scientists*	5. Structural iron & steel workers
6. Mining & geological engineers*	6. Industrial & refractory machinery mechanics
7. Architects*	7. Millwrights*
8. Chemical engineers*	8. Heavy vehicle & mobile equipment technicians
9. Civil engineers*	9. Crane & tower operators
10. Actuaries*	10. Locomotive engineers & operators
B. Lowest Ranked Occupations	***D. Lowest Ranked Occupations***
1. Pressers of textile and garment materials	1. Economists
2. Graders & sorters, agricultural products*	2. Purchasing managers
3. Cleaners of vehicles & equipment*	3. Budget analysts
4. Food preparation & serving workers	4. Personal financial advisors
5. Dishwashers*	5. Actuaries
6. Packers & packagers, hand	6. Operations research analysts*
7. Janitors & building cleaners	7. Human resources assistants*
8. Maids & housekeeping cleaners*	8. Procurement clerks
9. Grounds maintenance workers	9. Management analysts*
10. Laundry & dry-cleaning workers*	10. Public relations specialists*

Notes: An asterisk denotes an increase in cognitive or manual intensity between 2008 and 2017; no asterisk indicates an intensity decrease in the presented occupations.

Table A.4: Correlations Between O*NET Cognitive Ability Items

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Oral Comprehension	1.000												
(2) Written Comprehension	0.823	1.000											
(3) Oral Expression	0.948	0.798	1.000										
(4) Written Expression	0.833	0.953	0.826	1.000									
(5) Fluency of Ideas	0.727	0.748	0.743	0.777	1.000								
(6) Originality	0.721	0.717	0.740	0.750	0.963	1.000							
(7) Problem Sensitivity	0.616	0.684	0.587	0.683	0.711	0.679	1.000						
(8) Deductive Reasoning	0.715	0.811	0.699	0.801	0.817	0.779	0.887	1.000					
(9) Inductive Reasoning	0.693	0.798	0.676	0.790	0.777	0.737	0.867	0.948	1.000				
(10) Information Ordering	0.586	0.764	0.540	0.720	0.688	0.646	0.753	0.809	0.794	1.000			
(11) Category Flexibility	0.615	0.758	0.585	0.734	0.735	0.705	0.663	0.761	0.760	0.798	1.000		
(12) Mathematical Reasoning	0.523	0.658	0.497	0.624	0.609	0.572	0.555	0.648	0.607	0.631	0.651	1.000	
(13) Number Facility	0.461	0.581	0.438	0.551	0.532	0.500	0.511	0.578	0.550	0.558	0.590	0.955	1.000

Notes: The presented correlations between the O*NET psychomotor ability measures are based on the MORG CPS 2008 and 2017 samples.

Table A.5: Correlations Between O*NET Psychomotor Ability Items

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Arm-Hand Steadiness	1.000									
(2) Manual Dexterity	0.964	1.000								
(3) Finger Dexterity	0.802	0.793	1.000							
(4) Control Precision	0.863	0.871	0.747	1.000						
(5) Multilimb Coordination	0.877	0.877	0.673	0.870	1.000					
(6) Response Orientation	0.742	0.745	0.597	0.857	0.846	1.000				
(7) Rate Control	0.754	0.771	0.618	0.889	0.850	0.917	1.000			
(8) Reaction Time	0.772	0.774	0.631	0.875	0.856	0.949	0.949	1.000		
(9) Wrist-Finger Speed	0.711	0.735	0.628	0.734	0.661	0.694	0.752	0.711	1.000	
(10) Speed of Limb Movement	0.802	0.803	0.586	0.720	0.878	0.783	0.746	0.791	0.588	1.000

Notes: The presented correlations between the O*NET psychomotor ability measures are based on the MORG CPS 2008 and 2017 samples.

Table A.6: Cognitive and Manual Intensities by Experience-Education Cell for Men

	Cognitive Intensity			Manual Intensity		
	2008	2017	Change	2008	2017	Change
A. By Education and Experience						
Less than high-school:						
0-10	-1.030	-1.037	**-0.007**	0.861	0.728	**-0.133**
11-20	-1.037	-1.065	**-0.028**	1.149	1.072	**-0.077**
21-30	-0.992	-1.050	**-0.058**	1.098	1.075	**-0.023**
31+	-0.993	-1.035	**-0.042**	1.114	1.036	**-0.078**
High-school graduates:						
0-10	-0.742	-0.805	**-0.063**	0.806	0.702	**-0.104**
11-20	-0.552	-0.613	**-0.061**	0.869	0.745	**-0.124**
21-30	-0.523	-0.563	**-0.040**	0.855	0.780	**-0.075**
31+	-0.539	-0.554	**-0.015**	0.835	0.756	**-0.079**
Some college:						
0-10	-0.356	-0.430	**-0.074**	0.416	0.382	**-0.034**
11-20	-0.085	-0.151	**-0.066**	0.502	0.422	**-0.080**
21-30	-0.032	-0.088	**-0.056**	0.478	0.427	**-0.051**
31+	-0.113	-0.128	**-0.015**	0.422	0.370	**-0.052**
College graduates:						
0-10	0.495	0.473	**-0.022**	-0.379	-0.389	**-0.010**
11-20	0.582	0.574	**-0.010**	-0.320	-0.431	**-0.111**
21-30	0.574	0.575	**0.001**	-0.329	-0.417	**-0.088**
31+	0.533	0.548	**0.015**	-0.337	-0.410	**-0.073**
Master and postgraduates:						
0-10	0.907	0.969	**0.062**	-0.631	-0.730	**-0.099**
11-20	0.964	0.972	**0.008**	-0.650	-0.752	**-0.102**
21-30	1.003	1.003	**0.000**	-0.673	-0.743	**-0.070**
31+	0.992	0.968	**-0.024**	-0.711	-0.721	**-0.010**
B. Weighted Average						
Actual Employment Shares:	-0.132	-0.104	**0.028**	0.363	0.233	**-0.130**
2008 Employment Shares:	-0.132	-0.139	**-0.007**	0.363	0.289	**-0.074**
2017 Employment Shares:	-0.104	-0.104	**0.000**	0.305	0.233	**-0.072**

Notes: Intensity Scores are standardized, showing the deviation from the mean score value of the entire sample measured in units of standard deviation. Recommended CPS "earnings weights" are used for all calculations.

Table A.7: Cognitive and Manual Intensities by Experience-Education Cell for Women

	Cognitive Intensity			Manual Intensity		
	2008	2017	Change	2008	2017	Change
A. By Education and Experience						
Less than high-school:						
0-10	-0.757	-0.804	**-0.047**	0.099	0.060	**-0.039**
11-20	-0.953	-0.964	**-0.011**	0.257	0.247	**-0.010**
21-30	-1.039	-1.122	**-0.083**	0.305	0.352	**0.047**
31+	-1.069	-1.094	**-0.025**	0.266	0.345	**0.079**
High-school graduates:						
0-10	-0.442	-0.553	**-0.111**	-0.027	-0.033	**-0.006**
11-20	-0.353	-0.423	**-0.071**	-0.067	-0.082	**-0.015**
21-30	-0.316	-0.382	**-0.066**	-0.123	-0.116	**0.007**
31+	-0.291	-0.379	**-0.088**	-0.189	-0.132	**0.057**
Some college:						
0-10	-0.164	-0.248	**-0.084**	-0.149	-0.153	**-0.004**
11-20	0.114	0.034	**-0.080**	-0.231	-0.224	**0.007**
21-30	0.131	0.060	**-0.071**	-0.282	-0.297	**-0.015**
31+	0.160	0.048	**-0.112**	-0.327	-0.335	**-0.008**
College graduates:						
0-10	0.531	0.482	**-0.049**	-0.505	-0.513	**-0.008**
11-20	0.615	0.580	**-0.035**	-0.490	-0.561	**-0.071**
21-30	0.626	0.547	**-0.079**	-0.464	-0.573	**-0.109**
31+	0.593	0.532	**-0.061**	-0.511	-0.559	**-0.048**
Master and postgraduates:						
0-10	0.948	0.946	**-0.002**	-0.705	-0.678	**0.027**
11-20	0.940	0.953	**0.013**	-0.754	-0.764	**-0.010**
21-30	0.972	0.942	**-0.030**	-0.730	-0.786	**-0.056**
31+	0.919	0.906	**-0.013**	-0.738	-0.744	**-0.006**
B. Weighted Average						
Actual Employment Shares:	0.089	0.100	**0.011**	-0.283	-0.331	**-0.048**
2008 Employment Shares:	0.089	0.053	**-0.036**	-0.283	-0.336	**-0.053**
2017 Employment Shares:	0.125	0.100	**-0.025**	-0.271	-0.331	**-0.060**

Notes: Intensity Scores are standardized, showing the deviation from the mean score value of the entire sample measured in units of standard deviation. Recommended CPS "earnings weights" are used for all calculations.

A.2 Appendix Figures

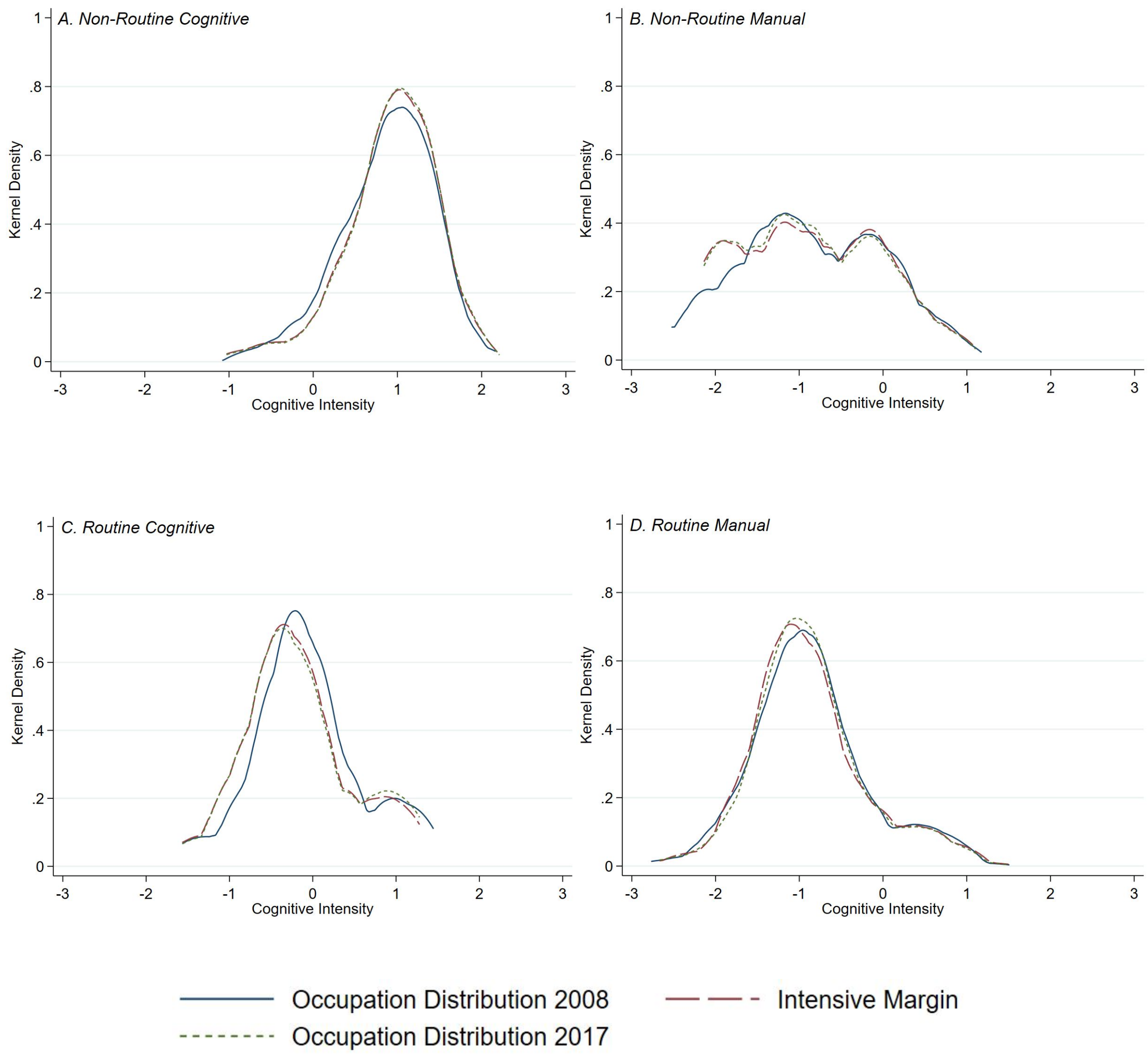


Figure A.1: Smoothed Cognitive Task Intensity Distributions of 2008 and 2017 by Broad Occupation Groups

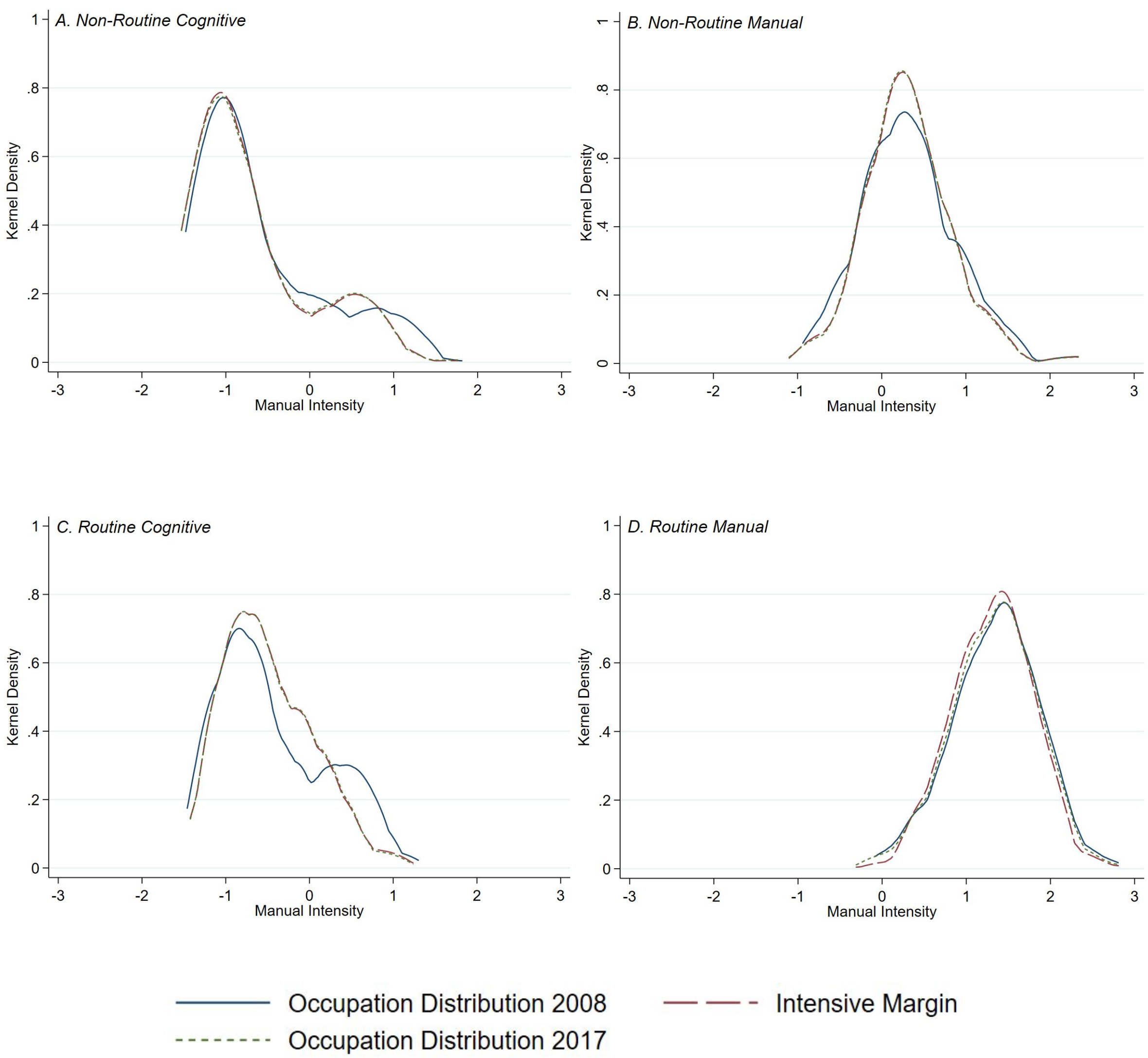
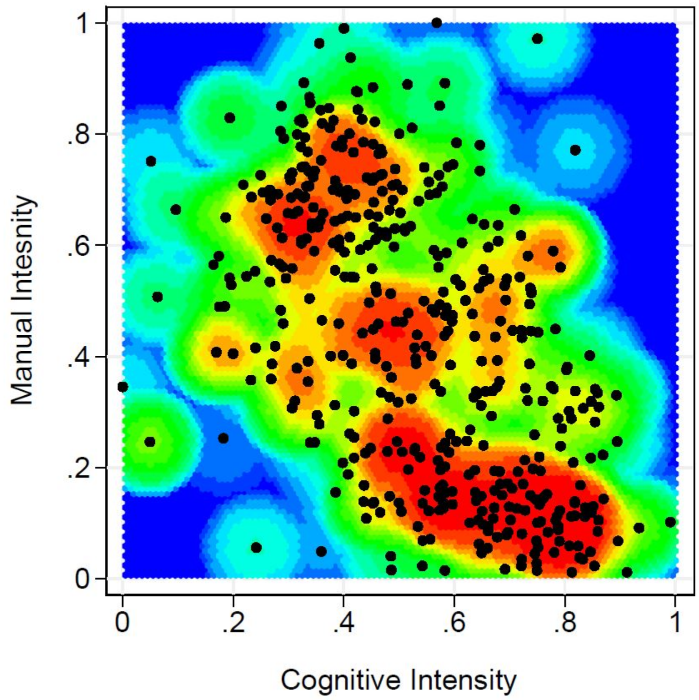


Figure A.2: Smoothed Manual Task Intensity Distributions of 2008 and 2017 by Broad Occupation Groups



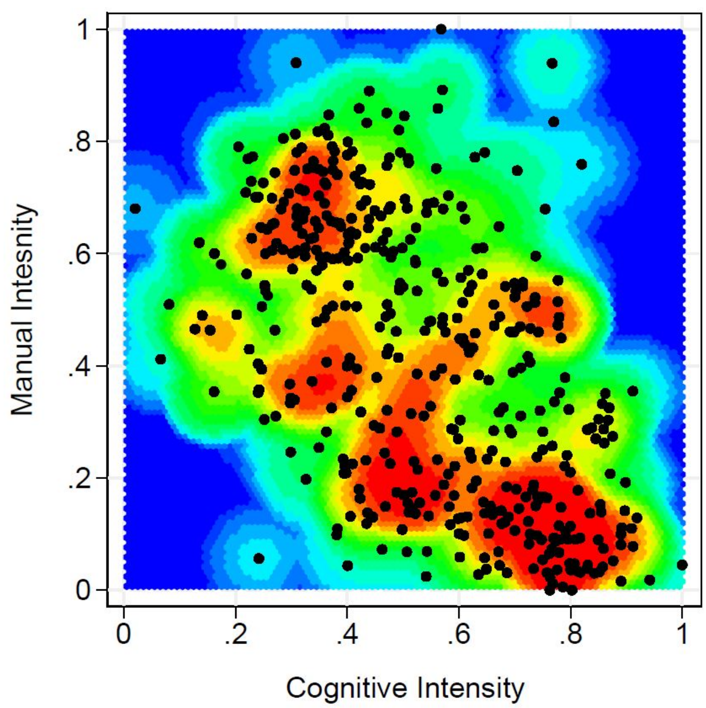


Figure A.3: Joint Distribution of Cognitive and Manual Intensities of 2008 and 2017

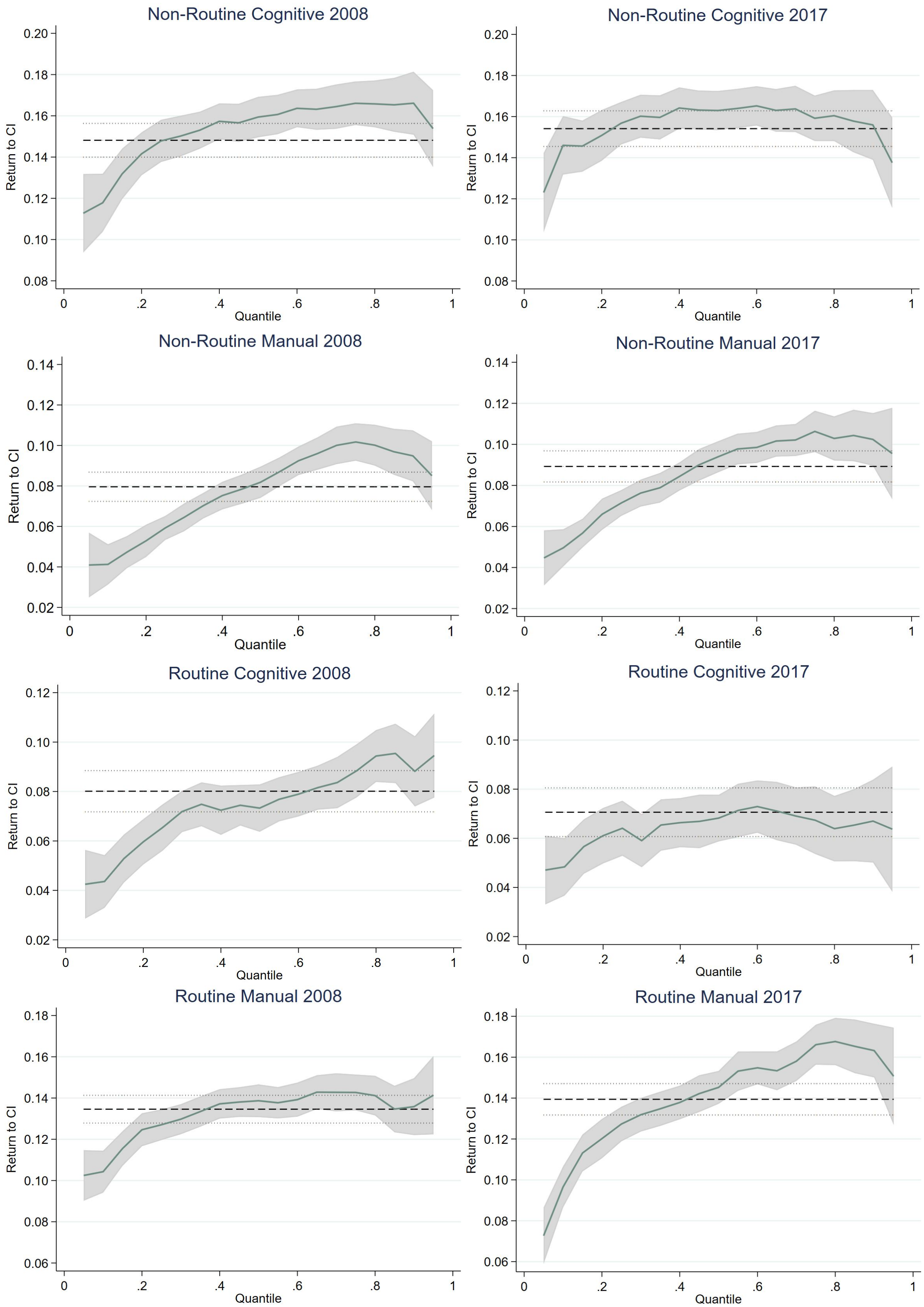


Figure A.4: Returns to Cognitive Task Intensity over Wage Quantiles by Broad Occupation Groups

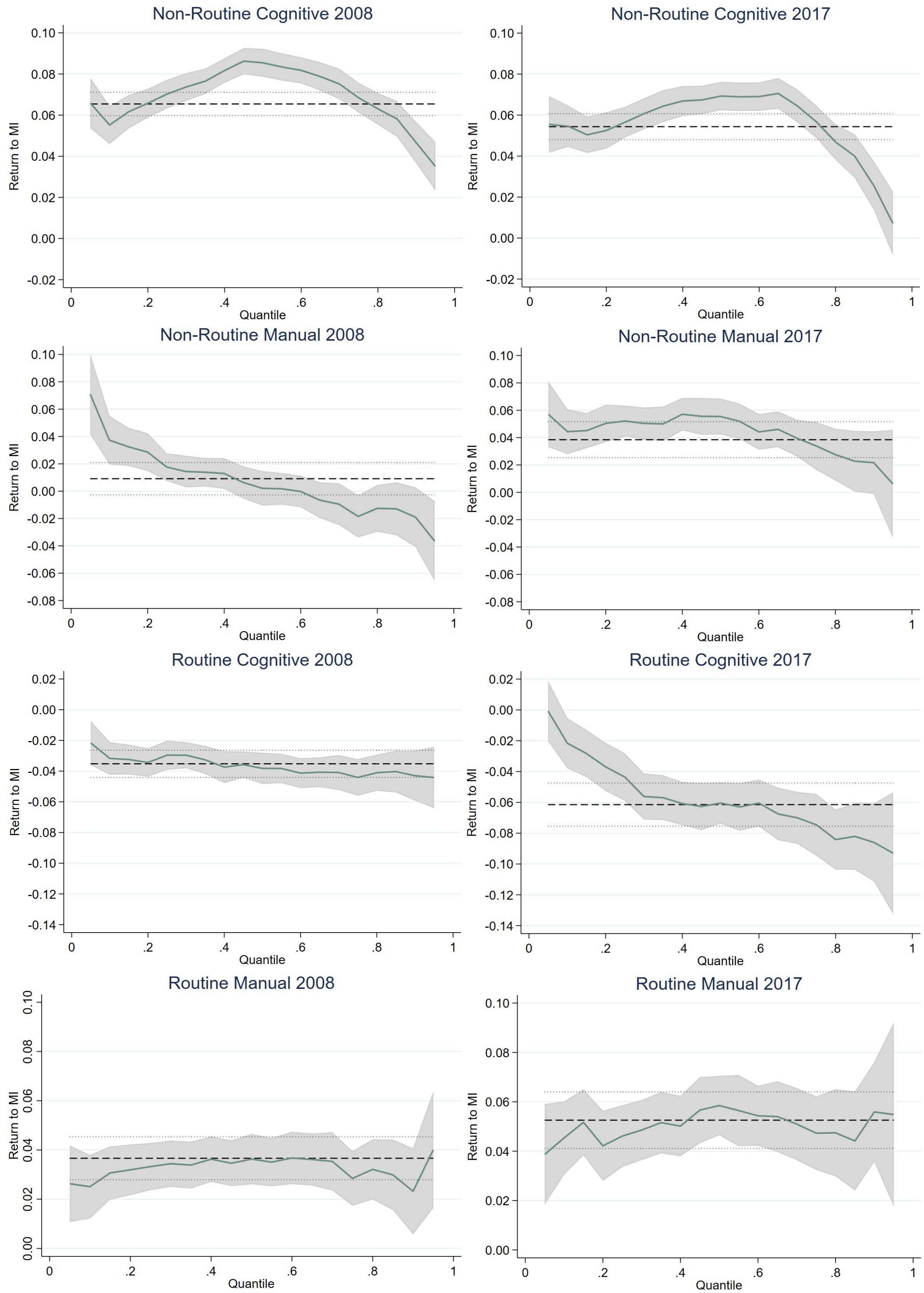


Figure A.5: Returns to Manual Task Intensity over Wage Quantiles
by Broad Occupation Groups

Chapter 3

Work-Hour Instability, Occupational Mobility and Gender*

Francesco Roncone†

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† School of Economics, University of Adelaide, 10/12 Pulteney St, Adelaide SA 5000 (e-mail: francesco.roncone@adelaide.edu.au).

Abstract

Although more than 20 per cent of the workforce changes their occupation every year, we still do not fully understand the mechanisms behind the observed mobility. This paper focuses on analysing the relationship between work-hour instability and occupational mobility in the U.S. labour market. I use the longitudinal dimension of the Current Population Survey (CPS) to measure individuals' intra-year work-hour variation and analyse their mobility through a balanced occupation panel. Being in the highest quartile of work-hour variation is associated with a higher mobility rate of 0.33% for men and 0.81% for women compared to an average monthly mobility rate of 1.71%. Analysing the predicted marginal effects across different household compositions suggests that the substantial gender gap can be explained by the intra-household specialisation of men and women. The last part of this study shows that only workers with highly volatile work hours sort themselves into more stable occupations.

Keywords: work hours, coefficient of variation, occupational resorting, gender.

JEL codes: **J16, J22, J24, J62**.

3.1 Introduction

Work-hour instability and its detrimental effects on the workforce have moved into the focus of political debate[1] and economic research over the last few years. Involuntary fluctuations in work hours affect individuals negatively along two dimensions: first, they cause volatility in earnings (Gottschalk and Moffitt, 2009; Finnigan, 2018), which implies an economic risk for hourly-paid workers in low-wage occupations. Second, work-hour instability negatively affects individuals' health and subjective well-being by increasing personal distress, poor sleep quality, and work-family imbalances (Kelly et al., 2014; Olson et al., 2015; Moen et al., 2016; Schneider and Harknett, 2019).

Despite the growing literature documenting the direct adverse effects of work-hour instability, we still do not fully understand its relationship to women's and men's mobility decisions in the labour market. With about one-fifth of U.S. workers changing their occupations annually (Kambourov and Manovskii, 2008), understanding the mechanisms of occupational mobility is critical for evaluating matching processes between workers and occupations (Groes et al., 2015; Guvenen et al., 2020; Lise and Postel-Vinay, 2020), assessing human capital accumulation and wage growth (Kambourov and Manovskii, 2009a,b) and for the effective implementation of labour market policies. Nonetheless, the existing literature on occupational mobility is far from being conclusive. This paper aims to contribute to closing this gap by creating a link between individuals' work-hour instability and their mobility patterns using representative U.S. survey data.

Exploiting the short but rich panel dimension of the monthly Current Population Survey (CPS), I show that workers who experience high volatility in work hours are more likely to switch between occupations than workers with more stable work hours. This pattern is significantly more dramatic for women than men. The finding of gender-heterogeneous mobility patterns related to work-hour-instability complements a new stream of literature showing that women have comparatively higher preferences for non-

[1] Fair Workweek laws have recently been implemented to address the employer-driven unpredictability and instability of work schedules (Wolfe et al., 2018; Lambert, 2020; Petrucci et al., 2022). However, the enforced laws target only particular regions (Oregon, Seattle, New York City, Philadelphia, San Francisco, Emeryville (California), San Jose, and Chicago), are limited to hospitality, food service and retail industries, and exclude small firms and businesses.

pecuniary positive job attributes (Mas and Pallais, 2017; Maestas et al., 2018; Wiswall and Zafar, 2018). In contrast to these studies, in my work, I observe realized occupation choices instead of relying on hypothetical job choice experiments or stated-preference models that depend on constricting assumptions. For the identification of the gender-specific monthly mobility rates, I track individuals in the CPS for four consecutive months and over sixteen calendar months in total through a self-constructed balanced occupation panel covering 430 detailed occupations from 2003 to 2022. To measure each individual's work-hour instability, I make use of their self-reported weekly working hours (related to the main job) across different survey months and construct the coefficient of variation (CV) following LaBriola and Schneider (2020).

The predicted mobility gap between workers without hour variation and workers in the highest quartile of hour variation is 0.33 per cent for men and 0.81 per cent for women, compared to an average monthly mobility rate of 1.71 per cent. Deeper investigations unveil two potential explanations for the noticeable gender gap: first, family commitments seem to affect men and women differently, as only women who are married or have children show a clear positive relationship between hour fluctuations and occupation choices. On the contrary, men with family commitments are completely unaffected if they have to work significantly different hours across weeks. This finding is supported by American Time Use Survey (ATUS) data documenting that women are more likely to specialise in non-working activities (childcare and housework), which are easier to plan with predictable and stable work schedules. Second, a simple joint model of occupational and employer mobility shows that work-hour instability is predominately occupation-specific for women but employer-specific for men. While the CPS data does not allow me to pinpoint the exact reasons why women are more likely to switch between occupations and men between employers, this finding is nonetheless a significant new contribution to the literature, opening the door for potential future research in this direction.

Based on the uncovered relationship between work-hour instability and mobility in the U.S. labour market, the second part of this study aims to answer whether individuals who switch occupations can achieve higher stability in work hours. If work-hour stability is an important workplace characteristic and at least to some degree occupation-specific, as the first part of this study suggests, we would expect that especially individuals suffering from high work-hour fluctuations target stable occupations. To test this assumption, I use all sixteen calendar months individuals can be tracked in the CPS and link the CPS sample to the Annual Social and Economic Supplement (ASEC) of the CPS to make use of the more reliable "dependent occupation coding" scheme (Polivka and Rothgeb, 1993). After constructing the new dataset, I match individuals with similar characteristics to create a quasi-experimental setting that can be used in a difference-in-differences model with two time periods. By analysing treatment effects at different locations of the work-hour instability distribution, I show that only workers with noticeably high work-hour fluctuations significantly reduce hour instability after transitioning to a different occupation. In line with the results of the first part of this study, this finding suggests that workers value stable work hours in the labour market.

A study related to my work is conducted by Choper et al. (2022), showing that unpredictable and unstable work schedules are associated with an increase in the likelihood of job turnover among retail and food service workers. Their finding aligns with my result that work-hour instability is associated with higher mobility rates in the U.S. labour market. However, my results must be seen differently as the measurement approach and the underlying data differ substantially. First, my study focuses on occupational mobility from month to month. As this approach excludes workers who fall into short-term unemployment before becoming re-employed, it most likely captures predominately voluntary mobility. Robinson (2018) shows that voluntary job changes yield an average improvement in job-matching quality and wage growth. This observation differs from the study by Choper et al. (2022), which shows a "cumulative disadvantage" in turnover when workers' job changes are evaluated based on surveys six months apart.[2] Second, my study is not necessarily limited to low-wage workers with relatively less bargaining power due to lower education levels and union coverage rates. Recent studies have shown that such disadvantages lead to higher work-hour instability

[2] It is worth mentioning that the CPS data does not allow me to directly distinguish between involuntary and voluntary occupation changes as the questionnaire does not ask individuals why they change occupations. However, my approach of using monthly data helps to significantly reduce the risk of measuring occupation changes that cannot be classified as voluntary from the workers' perspective.

and unpredictability (Finnigan and Hale, 2018; LaBriola and Schneider, 2020). Third, this study relies upon intra-year work-hour fluctuations, which are more granular than the qualitative work schedule questions used by Choper et al. (2022).

Concerning occupational mobility, my study is related to Groes et al. (2015) and Robinson (2018), who focus on the "direction" of worker sorting across occupations. The authors conclude that less productive workers and workers laid off by their employers are likelier to be "downgraded" when changing occupations. On the other hand, workers who are more productive in their jobs and who change occupations voluntarily are more likely to move "upward" when changing occupations. While the two studies characterise upward and downward mobility by looking at changes in wages or skill intensities, my study investigates whether voluntary occupational mobility potentially improves the work-hour stability of occupation switchers. In this context, my findings contribute to the literature by showing that other occupation characteristics than skills and wages also matter for individuals' mobility decisions.

This work is also motivated by recent experimental and empirical studies showing significant differences in job preferences between female and male workers. Mas and Pallais (2017) show that women have a noticeably stronger distaste for jobs with unstable weekly work hours but a higher valuation for worker-friendly work arrangements. Wiswall and Zafar (2018) reach similar conclusions based on a hypothetical job choice experiment applied to university students and a follow-up survey to observe their realised occupation choices. Their study shows that gender-specific preferences for different job attributes naturally lead to heterogeneous occupation choices of new labour market entrants. Complementing their findings, my results suggest that gender differences in preferences for occupation characteristics may also be a reason for heterogeneous occupation resorting between men and women. Further explorations show that the differences in "preferences" are strongly related to intra-household specialisation and the traditional male breadwinner role. These findings open the door to further investigating the indicated mechanisms for future research, for example, by using dynamic household decision models.

The remainder of this paper is organised as follows: The next section describes the construction of the measure of work-hour instability and how I overcome the sample selection problem. Section 3.3 motivates my empirical analysis by illustrating that a significant part of work-hour instability is occupation-specific. Section 3.4 shows that the instability in work hours is associated with an increased probability of occupational mobility and that women and men systematically differ in their mobility patterns. In Section 3.5, I exploit additional information from the CPS data on individuals' work hours to estimate the effect of occupational mobility on work-hour stability. Section 3.6 discusses and concludes this study in the context of future research opportunities.

3.2 Data Usage and Sample Construction

The monthly Current Population Survey (CPS) is a representative survey conducted by the Bureau of Labor Statistics and includes roughly 60,000 households. Although the CPS is widely known as a cross-sectional survey, it has a short but rich longitudinal dimension. The rotation pattern of the survey enables researchers to follow the same individuals over 16 calendar months, whereby individuals are not interviewed for eight months between the first and the second 4-month survey interval (Rivera Drew et al., 2014). This study draws on CPS data from the Integrated Public Use Microdata Series (IPUMS) to make use of a unique person identifier variable and longitudinal weights that account for attrition of individuals between different survey months (Flood et al., 2022). To strengthen the validity of individual linkages across survey months, I use the matching criteria proposed by Madrian and Lefgren (2000), including gender, race, and age.

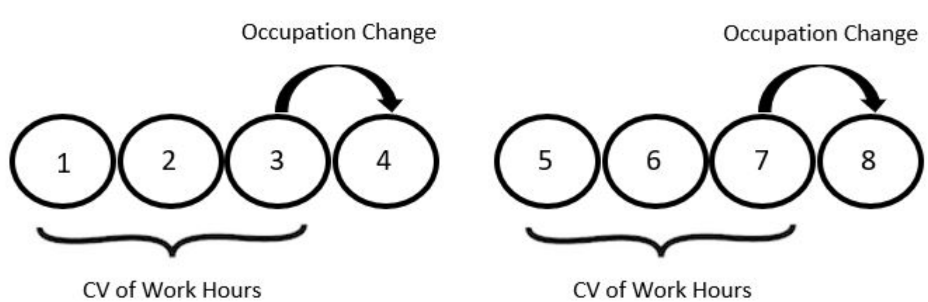

Figure 3.1: Longitudinal Data Usage of 4 Survey Months in the CPS

Figure 3.1 illustrates the longitudinal dimension of the monthly CPS and how it is used in this study. I construct the coefficient of work-hour variation of individuals based on their reported work hours across three consecutive months (1-3 and 5-7) and identify occupational transitions from survey months 3 to 4 and 7 to 8. All individuals are observed two times over four months (1-4 and 5-8) if they do not drop out of the survey for any reason.

3.2.1 Sample Selection

First, I exclude individuals who are not in the labour force, employed in military occupations, unpaid family workers, self-employed, or not between 23 and 61 years of age. Next, I impose additional sample restrictions following LaBriola and Schneider (2020): I exclude all individuals who a) are unemployed in at least one month of a 4-month CPS interval, b) change their employer during the first three months, c) miss work for non-economic reasons or d) work part-time for non-economic reasons during the first three months of a given CPS interval.

Workers who report work-hour fluctuations for "non-economic reasons" are excluded from the sample because the main objective is to measure involuntary work-hour instability. To do so, I exploit the different CPS answer categories for why individuals work part-time or miss work during a given week.[3] Excluding all workers who report having had non-standard work schedules in the last week due to personal obligations is a significant improvement. Despite this improvement, the data still obscures the actual reasons why individuals work different hours across weeks as there is no question in the CPS directly asking for the reasons for working different hours if those reasons can be categorized as "economic reasons". While a related study conducted by LaBriola and Schneider (2020) defines the remaining variation in work hours after implementing equal sample restrictions as "employer-driven," part of the fluctuations could also stem from other firm-specific or macroeconomic factors. Considering the limitations of the knowledge on the variation in work hours, I instead use the term 'involuntary

[3] "Non-economic reasons" for individuals who miss work include the following: vacation/personal days, own illness/injury/medical problems, child care problems, other family/personal obligation, maternity/paternity leave, school/training, civic/military duty and "other". "Non-economic reasons" for working part-time include the following: holiday, own illness, health/medical limitation, vacation/personal day, child care problems, other family/personal obligations, school/training, civic/military duty, and "other".

work-hour variation' in this study. This term considers the fact that the constructed measure captures a broader spectrum of reasons for fluctuations in work hours, including idiosyncratic shocks to the labour market. Nonetheless, I cannot completely rule out that, in some cases, individuals voluntarily work non-standard hours and are therefore not excluded from the sample. The rare occurrence of such cases has to be accepted to create some measurement error.

In addition to the outlined restrictions, which are equivalent to LaBriola and Schneider (2020), I include only e) individuals who do not change occupations during the first three survey months. The additional restrictions are critical to guarantee that the measured work-hour fluctuations are not caused by occupational mobility within employers. Finally, I exclude all individuals who do not self-report their employment information in all four consecutive survey months to avoid measurement error resulting from differences between self-reports and proxy reports in the CPS (see, e.g., Boehm, 1989).

Table 3.1: Retention Rates of the Different Sample Restrictions

		conditional on employment					
	employed	*same employer*	*same occupation*	*did not work PT*	*did not miss work*	*self-report*	*all criteria*
All	94.16%	96.88%	91.69%	76.27%	92.21%	37.07%	21.96%
Men	93.57%	96.88%	91.43%	83.19%	93.73%	33.00%	21.98%
Women	94.79%	96.88%	91.96%	69.10%	90.63%	41.33%	21.95%

Notes: The retention rates are constructed based on the sample after excluding all individuals who are not in the labour force, employed in military occupations, unpaid family workers, self-employed, and not between 23 and 61 years of age. The sample restrictions shown in columns 2-5 are calculated conditional on four continuous months of employment.

Table 3.1 shows the retention rates for women and men based on the described sample restrictions. 22% of all individuals who can be linked across four consecutive survey months simultaneously fulfil all sample restrictions. While the final retention rates are almost identical for men and women, the reasons for attrition differ starkly by gender. Women drop out of the sample more frequently because they work part-time for non-economic reasons in at least one considered month. This observation is in line with Wiswall and Zafar (2018), suggesting that women value schedule flexibility and the availability of part-time work more than men. On the other hand, men have a higher drop-out rate due to not self-reporting their labour force information. This observation can be explained by men's higher labour force participation, which implies that women are more often available to reply to the CPS interview questions.

The imposed sample restrictions could cause selection bias due to non-probability sampling. As Moscarini and Vella (2008) show in their paper on business cycles and occupational mobility, selection into employment is endogenous to mobility. Furthermore, it is plausible to assume that being employed in the same job for three consecutive months is also endogenous to mobility based on the notion that occupational mobility contains a dynamic persistence ("job shopping"), which is especially relevant for young workers who are more likely to mismatch with their first job (Neal, 1999). There are at least three ways to deal with the sample selection problem: first, one could accept that the results only represent a subgroup of the labour force with specific characteristics. Second, one could follow the approach of Moscarini and Vella (2008) and use a control function procedure to restore the orthogonality conditions violated by the non-randomized selection process. Third, one could construct sampling weights that account for the differential likelihood that the selected individuals have different characteristics than those dropped out of the final sample. To remain consistent with my overall strategy, I follow the third approach, which is also used by LaBriola and Schneider (2020).

I construct analysis weights based on the IPUMS-CPS longitudinal weights, which account for attrition of responding in four consecutive survey months. First, I adjust the basic weights for differences in the probability of experiencing work-hour fluctuations, becoming unemployed and changing occupations by sequentially including different worker and job characteristics as well as categorical variables for broad occupation and industry groups. Next, I use a probabilistic model to account for differences in the likelihood of self-reporting employment information in the CPS. The weighting procedure is documented in greater detail in Appendix B.1. The analysis weights are used throughout the empirical analysis.[4]

[4] The strategy for constructing the analysis weights is equivalent to LaBriola and Schneider (2020). However, the results are qualitatively and quantitatively robust when using different versions of analysis weights or dropping the weights altogether.

3.2.2 Constructing the Measure of Work-Hour Instability

I measure individuals' work-hour instability as the coefficient of variation (CV) of reported weekly work hours in the main job individuals held over the last three survey months.[5] The reported weekly hours relate to the reference week when the CPS interview is conducted. This week is usually the second week of a given month. For each individual i, the coefficient of variation at time t is

$$CV_{i,t} = \frac{\sqrt{\frac{1}{3} \times ((hours_{i,t-3} - \mu(hours_i))^2 + (hours_{i,t-2} - \mu(hours_i))^2 + (hours_{i,t-1} - \mu(hours_i))^2}}{\mu(hours_i)} \tag{3.1}$$

where $\mu(hours_i)$ is the mean of work hours across the last three months, and the numerator is the standard deviation from the mean. Consequently, a higher coefficient of variation (CV) implies a higher level of work-hour instability. The CV measure has been used in previous studies to analyse households' intra-year income volatility (Bania et al., 2009; Morduch and Siwicki, 2017; Bania and Leete, 2022) and to analyse the heterogeneity in work-hour instability between demographic subgroups in the CPS (LaBriola and Schneider, 2020). The two advantages of the measure are that the measure is scale-insensitive to the mean of work hours and reflects increases in the variation of work hours in direct proportion. These characteristics are advantageous as my study includes both full-time and part-time workers. Using other volatility measures, for example, the variance, would not allow me to directly compare different types of workers as the variance is sensitive to the mean of work hours.

Figure 3.2 plots men's and women's work-hour variation time series from 2003 to 2022.[6] On average, the CV is 9% lower for women, indicating that women are either sorted into more stable occupations or work in more stable jobs within occupations or both. The trend line (purple line) shows a plateau from 2003 followed by a downward trend from 2014 for both men and women. Moreover, Figure 3.2 indicates that

[5] The CPS questionnaire asks individuals how many hours they worked in the last week in their main job ("ahrswork1") in addition to asking about the total hours worked in the last week. I use the variable related to the main job to minimise measurement error from intermingling work hours of different jobs.

[6] To plot the Henderson trend line (purple line) and the seasonally adjusted series (blue line), I use the X-13ARIMA-SEATS Seasonal Adjustment Program provided by the U.S. Census Bureau.

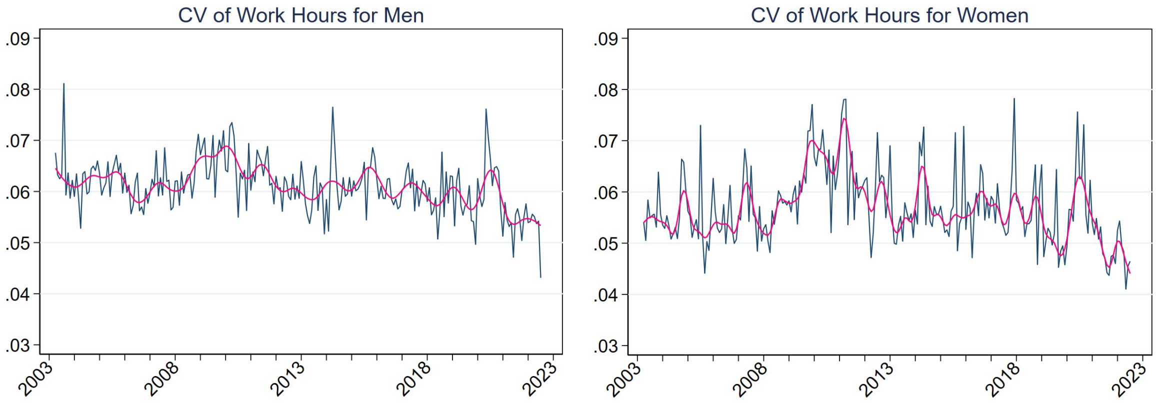

Figure 3.2: Male and Female Coefficient of Variation of Work Hours: 2003-2022

women's work-hour variation, when measured at the aggregate level, is more susceptible to cyclical economic fluctuations over the last twenty years and most noticeably in the aftermath of the financial crisis. From eyeballing the data, it is not obvious what drives the difference in the volatility of work-hour variation between the male and female labour markets. Although a more detailed analysis of this topic seems promising, it is beyond the scope of this study, which exploits variation in the CV of work hours between individuals and within gender-specific labour markets.

3.2.3 Occupational Mobility in the CPS

To measure monthly occupational mobility, I compare individuals' assigned occupation codes between adjacent months in the CPS. IPUMS provides an occupation category system that encompasses occupations from 1976 to today. However, the proposed occupation system, which is an update of the occupation system constructed by Meyer et al. (2005), is unbalanced. This feature causes measurement error as workers are assigned to different occupation codes when occupations are dropped out of the system and would, therefore, mistakenly be classified as occupation switchers. To overcome this hurdle, I use a self-constructed balanced panel of 430 occupations that can be used from 2003 to 2023.[7]

In the beginning of 2003, the CPS changed to the 2000 Census occupation categories. As this marks a significant structural break in occupation coding, it is a natural

[7] The detailed crosswalk of the constructed occupation panel across the different IPUMS CPS data files 2003-2023 is available upon request.

starting point for my analysis. The Census Bureau introduced two other occupation category changes adopted by the CPS in 2011 and 2020. The most common changes that need to be taken care of include splitting single occupations into multiple occupations, dealing with emerging new occupations, and pooling two or more occupations into one. For example, computer occupations have become much more diverse since the beginning of the 2000s. Workers classified very broadly as network analysts have been split into more detailed computer-related occupations like web developers or computer network architects. On the other hand, numerous production occupations have been pooled together in response to job automation and declining employment. For instance, printing machine operators and job printers are now categorized as printing press operators.

Another challenge is identifying valid occupation changes in the noisy CPS data. Although the introduction of a "dependent occupation coding" procedure in 1994 contained a significant part of coding error, it could not solve the problem entirely (Kambourov and Manovskii, 2013).[8] One way to address this issue is to use filters that account for differences in the likelihood that an occupation change is valid dependent on the "occupation trajectory" of individuals in the observed four consecutive survey months. Moscarini and Thomsson (2007) use such filters to design a cleaning algorithm and to identify valid occupation changes between the survey months 2 and 3 in the monthly CPS. They argue that occupation changes are more likely valid if individuals' occupation codes are consistent two months before and two months after a potential change. My sample restrictions for identifying involuntary work-hour instability are similar, requiring both employer and occupational stability between survey months 1 and 3.

Table 3.2 shows that every sample restriction reduces the observed mobility rate in the sample. All sample restrictions in combination yield an unweighted mobility rate of 1.64%, which is significantly lower than the mobility rate of 3.5% found by Moscarini and Thomsson (2007) but closer to Kambourov and Manovskii (2008), who study oc-

[8] Based on the dependent coding procedure, individuals' occupations are only re-coded if they report a change in employer or daily working activities. Before 1994, occupations were re-coded every month based on the blunt interview question "What is your occupation?" (Polivka and Rothgeb, 1993).

Table 3.2: Monthly Occupational Mobility Rates Based on Sample Restrictions

	no restrictions	*same employer*	*same occupation*	*self-report*	*final sample unweighted*	*final sample weighted*
All	4.53	3.73	2.28	3.24	1.64	1.71
Men	4.72	3.82	2.27	3.35	1.61	1.72
Women	4.34	3.65	2.29	3.16	1.66	1.70

Notes: The calculated monthly mobility rates in columns 2 and 3 are based on the condition that individuals are employed in all four consecutive survey months. All other mobility rates are calculated only based on the restrictions shown in the specific table columns. Columns 5 and 6 combine all shown sample restrictions of columns 1-4 and the restrictions that individuals did not miss work or worked part-time for non-economic reasons in the last three months. The construction of the sampling weights applied in column 6 is documented in Appendix B.1.

cupational mobility in the PSID.[9] A lower mobility rate when all sample restrictions are used indicates that my approach excludes a fair proportion of individuals with a higher probability of being incorrectly classified as occupation switchers. Nonetheless, I cannot completely rule out the possibility that my approach simultaneously eliminates a small fraction of valid transitions. Another approach to reducing the measurement error of occupational mobility is to consider an occupation change only valid if it coincides with an employer change (Neal, 1999). However, this strategy is not optimal as this study also analyses occupational mobility within employers.

3.3 Work-Hour Instability and Occupations

To the best of my knowledge, this study is the first that ties the instability of work hours to a detailed occupation system representative of the U.S. labour market. This section aims to motivate the subsequent empirical study by illustrating that a significant part of work-hour instability is specific to occupations. Figure 3.3 plots the population-weighted trend line of the coefficient of variation (CV) averaged within major occupation groups.[10] Occupations are categorized into five major groups using the

[9] Kambourov and Manovskii (2008) calculate a yearly mobility rate of 18%. Without considering time aggregation effects, their found yearly rate is equivalent to a monthly rate of 1.5%.

[10] As this section's purpose is to highlight occupation heterogeneity in work-hour-instability, it does not need to consider occupational mobility between survey months 3 and 4. Therefore, I use individuals' work-hour variation over four consecutive months instead of three months to construct the occupation-specific CV measures. While the occupation-specific CV measure is based on a slightly

Standard Occupation Classification System (SOC). Figure 3.3 shows that white-collar jobs (management, business, science, sales and office) have a comparatively lower CV of work hours. Moreover, one can see that the CV decreased over the last 20 years for management, business and science occupations. On the contrary, all other broad occupation groups show a relatively stable long-term CV development.

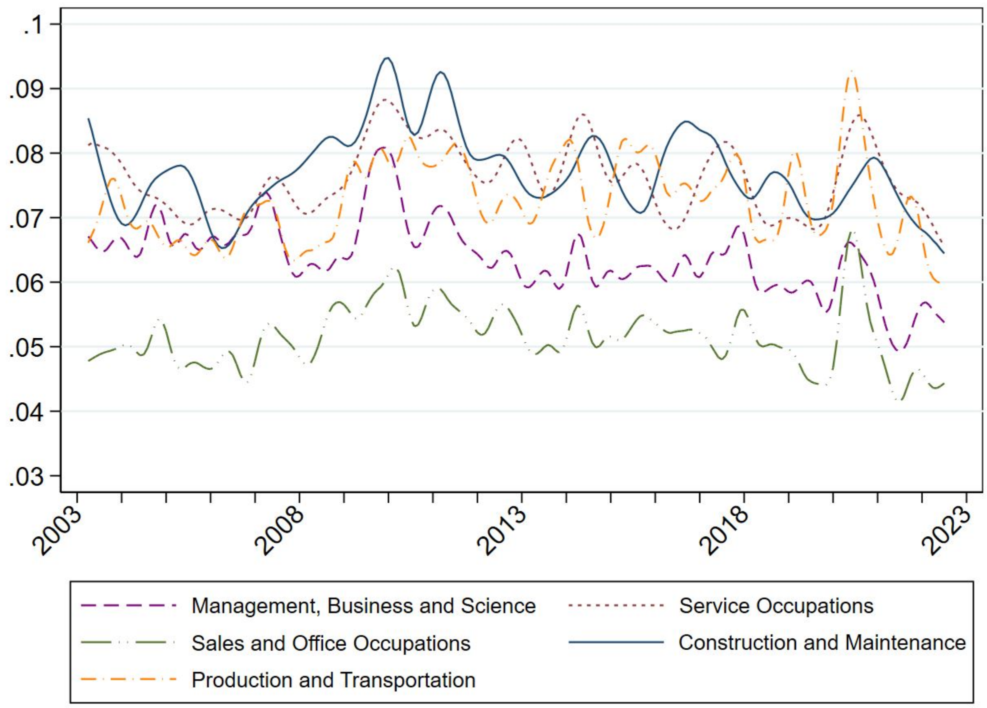

Figure 3.3: Trend Line of the Coefficient of Variation of Work Hours of Broad Occupation Groups: 2003-2022

Table 3.3 shows selected detailed occupations and their average CVs by percentiles of the occupation distribution based on the pooled samples from 2003 to 2022. The table indicates substantial differences in the risk of work-hour instability between occupations at the bottom and the top of the distribution. Administrative support occupations, for example, new accounts, insurance claims, and credit clerks, show the lowest risk of experiencing high hour variation. Other occupations with comparatively low CVs are air traffic controllers, financial examiners, and credit analysts. Occupations at the upper end of the distribution include extraction and construction jobs such as cement masons, terrazzo workers, and roofers, but also actors, crossing guards, massage therapists,

different sample, using this approach increases the measurement accuracy of occupations' CVs when averaged across individuals. All other sample restrictions described in the last section also apply to constructing the occupation-specific CV measure used in this section.

janitors, fishing and hunting workers, and sailors. The occupation ranking suggests that the risk of unstable work hours is prevalent across different occupation groups and industries.

Table 3.3: Selected Occupations by Percentiles of Work-Hour Variation

Percentiles	**Detailed Occupation**	**CV**
Lowest	New accounts clerks	**.021**
1%	Insurance claims and policy processing clerks	**.032**
10%	Budget analysts	**.043**
25%	Logisticians	**.052**
50%	Security guards and gaming surveillance officers	**.062**
75%	Driver/sales workers and truck drivers	**.079**
90%	Millwrights	**.099**
99%	Fishing and hunting workers	**.166**
Highest	Crossing guards	**.215**

Notes: The 430 detailed occupations are ranked based on their population-weighted coefficient of variation (CV) of work hours obtained from the pooled sample 2003-2022.

In the next step, I explore why occupations differ in their risk of work-hour instability. One way to characterize occupations is based on the conception that each occupation combines different tasks while workers are assigned to tasks based on their skills and abilities (Acemoglu and Autor, 2011). I use occupation-specific data on 52 required abilities from the Occupational Information Network (O*NET) and map the importance ratings of the abilities (from 1 "not important" to 5 "extremely important") to the matched occupations of my self-constructed panel. Next, I apply an exploratory factor analysis to derive broader and more meaningful task categories (factors) from the multidimensional ability data following Ingram and Neumann (2006) and Poletaev and Robinson (2008). Appendix B.2 documents the exploratory factor analysis procedure in more detail. The factor analysis results suggest that five task categories can explain most of the variation in the original ability data. The five categories relate to occupations' 'physical', 'analytical', 'sensory perceptional', 'fine motor', and 'communication' intensity.

Other occupation-specific characteristics plausibly related to the work-hour instability of occupations are the ability to work remotely and the social importance ("essen-

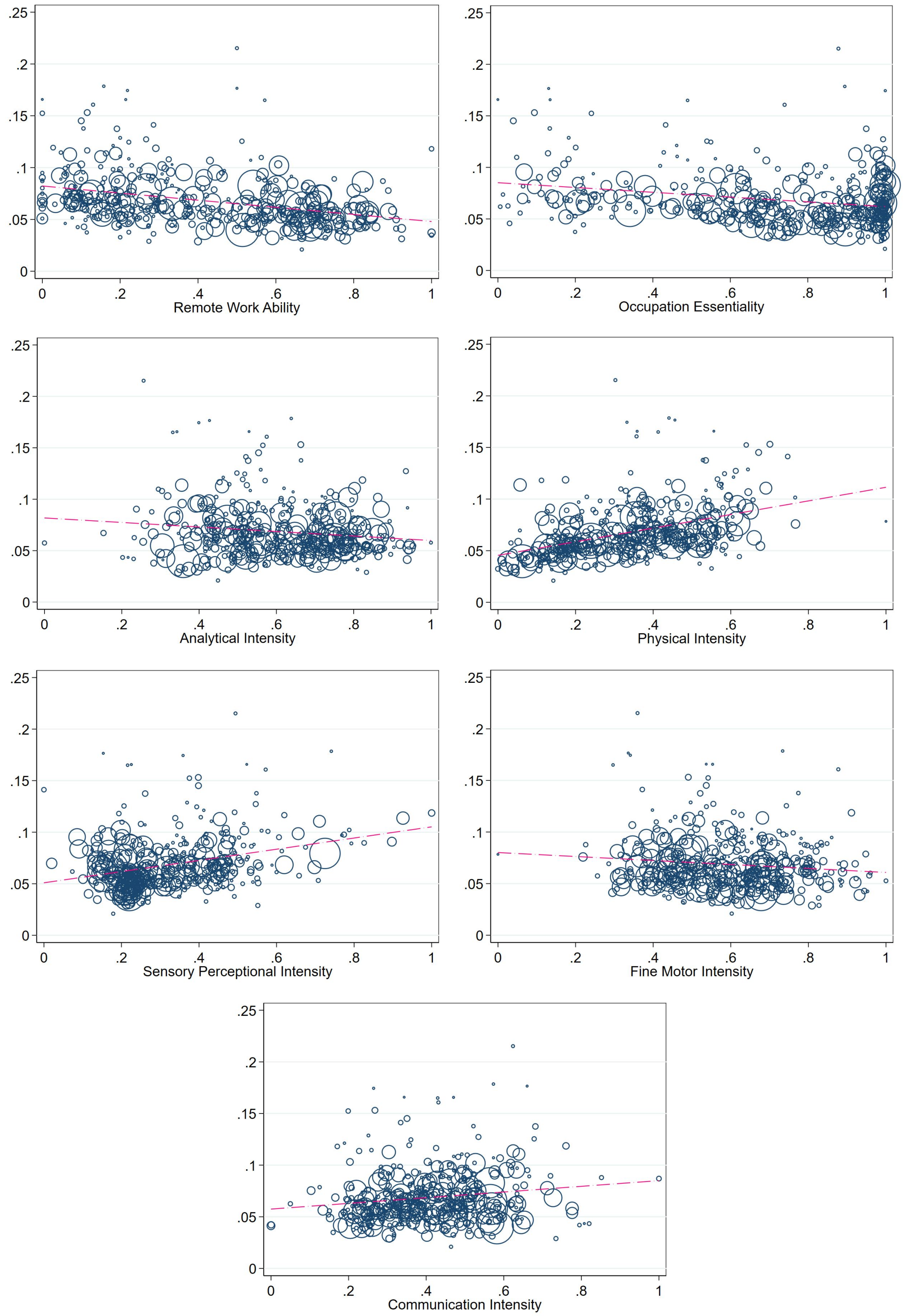

Figure 3.4: Correlation between Occupation-Specific Characteristics and Occupations' Coefficient of Variation of Work Hours

tiality") of occupations. Jobs that can be done from home provide workers with more flexibility. If workers dislike high fluctuations in work hours, as the prevalent literature suggests, one would assume that remote workers organize their tasks in such a way that it leads to more stable weekly work hours across adjacent months. I make use of the constructed measures in del Rio-Chanona et al. (2020), which capture occupations' "remote work ability" and their "essentiality".[11]

Figure 3.4 plots the CV of work hours averaged within occupations against the standardized population-weighted scores of the different occupation-specific characteristics.[12] Occupations' instability of work hours is negatively related to their remote work ability and essentiality. Concerning task content, higher physical, sensory perceptional and communication task intensities seem to increase occupations' risk of high work hour fluctuations. On the contrary, a higher intensity in analytical or fine motor tasks is related to lower work-hour fluctuations. To test the robustness of the relationships, Table 3.4 reports linear regressions of the form

$$CV_j = \alpha + \sum_{k=1}^{K} \beta X_j + \varepsilon_j \tag{3.2}$$

where CV_j is the coefficient of variation of occupation j, and X_{kj} is a vector of the standardized occupation characteristics $k = 1, ..., K$, which are entered separately (columns 1-3) and in combination (columns 4-5) into the regression model. In addition, I enter five occupation group dummies to account for the possibility that the entered occupation characteristics do not capture systematic differences between broad occupation groups.

Table 3.4 shows that the selected characteristics explain a noticeable proportion of variation in the occupation-specific CV of work hours. Moreover, the effects are generally robust and significant across the different model specifications. One exception is the ability to work remotely. While the coefficient is negative and significant when

[11] To equip occupations with the "remote work ability" and "essentiality" measures provided by del Rio-Chanona et al. (2020), I conduct a reversed mapping of their occupation scores to the original O*NET occupation codes. In the second step, I assign the O*NET occupation codes to the balanced occupation panel.

[12] All occupation measures presented in figure 3.4 are normalized between zero and one. Occupations are plotted in relative size based on employment shares in January 2012, marking the focal point of the monthly CPS data used in this study.

Table 3.4: Predicting the Coefficient of Work-Hour Variation of Occupations

	(1)	(2)	(3)	(4)	(5)
Remote Work Ability	-0.0343***			0.0044	0.0105
	(0.0043)			(0.0097)	(0.0098)
Essentiality		-0.0233***		-0.0155***	-0.0162***
		(0.0050)		(0.0055)	(0.0055)
Physical			0.0105***	0.0098***	0.0097***
			(0.0011)	(0.0019)	(0.0019)
Analytical			-0.0039***	-0.0026	-0.0065***
			(0.0011)	(0.0017)	(0.0021)
Sensory Perceptional			0.0063***	0.0069***	0.0084***
			(0.0013)	(0.0016)	(0.0019)
Fine Motor			-0.0037***	-0.0036***	-0.0019
			(0.0011)	(0.0012)	(0.0013)
Communication			0.0025**	0.0034***	0.0032**
			(0.0011)	(0.0013)	(0.0013)
Broad Occupation Group FE	X	X	X	X	✓
R^2	0.112	0.064	0.300	0.321	0.359
Observations	430	430	430	430	430

Notes: The dependent variable is the coefficient of variation of work hours averaged within occupations. The estimation method is ordinary least squares (OLS). Robust standard errors are shown in parentheses. ***/**/* Significant at the 1%/5%/10% level.

entered individually, it turns positive and insignificant when controlling for other task intensities. This result is potentially related to the fact that occupations' task content simultaneously predicts their work-hour variation and the ability to work remotely. I confirm this assumption by conducting a simple linear regression of occupations' remote work ability on the five-dimensional task vector, yielding an *R-squared* of 0.77.

Column 5 of Table 3.4 shows that one standard deviation higher level of analytical task intensity is associated with a reduced occupation-specific CV of work hours by 0.007. This is equivalent to a 12% lower CV relative to the sample mean. On the contrary, one standard deviation higher level of physical, sensory perception, and communication task intensity is associated with an elevated CV of work hours by 0.010, 0.008, and 0.003 (14%, 12%, and 5%), respectively. The results suggest that their work context and task content can predict a significant part of occupations' susceptibility to work-hour instability.[13] Based on this section's motivational and descriptive analysis,

[13] This section highlights the potential of occupation-specific characteristics to explain differences in

the following section investigates whether individuals consider the heterogeneity of occupations regarding their instability in work hours when making mobility decisions.

3.4 Relationship Between Work-Hour Instability and Occupational Mobility

The analysis in this section builds on the intuition that workers sort themselves into occupations based on their preferences for pecuniary and non-pecuniary job attributes (Rosen, 1986). While theoretical models traditionally assume that workers have perfect information about the labour market and their preferences, empirical evidence suggests that workers often mismatch with occupations. This induces resorting mechanisms to "correct" for previous mismatches (see, e.g., Groes et al., 2015; Guvenen et al., 2020). While the literature predominately focuses on skill mismatches, this section investigates whether work-hour fluctuations are a potential determinant of occupational mobility decisions of individuals in the U.S. labour market. In this context, it is important to mention that this section does not claim any causality between work-hour volatility and mobility but establishes an economically important relationship that has so far been overlooked in the literature. I conduct the following empirical analysis separately by gender based on new evidence that women value "positive" job attributes more than men (Mas and Pallais, 2017), which leads to systematic differences in occupation choices (Wiswall and Zafar, 2018).

3.4.1 Identification Strategy

First, I fit a probabilistic choice model with a binary outcome variable of occupational mobility. The probability of observing $Switch_i = 1$ for individual i in occupation j is

$$Pr[Switch_i = 1|X_i] = G(x_i'\beta) \tag{3.3}$$

occupations' work-hour instability. The tested variables appear to be reliable predictors of occupations' work-hour instability. However, the used variables can arguably be considered an arbitrary choice, whereas other omitted characteristics could be equally important.

where $G(\cdot)$ is the cumulative distribution function given individual i's characteristics X_i including $i's$ preferences for job attributes - such as work-hour stability, average work hours, job security, expected wages, the ability to work remotely - and occupation-specific mobility costs. The intuition of using the model variables and their construction are detailed in Appendix B.3. Based on the observed individuals' decisions to switch occupations $y_i = 1$ or not $y_i = 0$, the log-likelihood function

$$\mathcal{L}_N = \sum_{i=1}^{N} y_i log[G(x_i'\beta)] + (1 - y_i) log[1 - G(x_i'\beta)] \tag{3.4}$$

can be estimated for the pooled cross-sectional sample. I assume $G(x_{ij}'\beta)$ to be a standard normal *cdf*, which naturally leads to a probit model. However, I find no differences in how well a normal or logistic distribution fits the data when comparing different model selection criteria.[14] The model shown in equation 3.4 is the baseline model for the empirical analysis.

One limitation of the baseline model shown in equation 3.4 is that it does not account for the fact that work-hour instability measured at the individual level is sometimes more specific to the employer than the occupation. Moreover, occupation and employer changes cannot be classified as independent labour market outcomes. The data unveils that 37% of all job turnovers are associated with simultaneous occupation and employer changes. Using a model that does not consider the mobility between employers could lead to upward-biased estimates if mobility decisions were mainly related to precarious working conditions within employers. Moreover, switching between employers automatically leads to a new "independent" coding of workers' occupations in the CPS, which is another source of measurement error and potential upward bias (see, e.g., Polivka and Rothgeb, 1993).[15] To address these issues, I use a joint employer and occupational mobility model, which helps to disentangle and better understand the different mobility

[14] I use the deviance information criterion (DIC) of Spiegelhalter et al. (2003) for model comparison. In addition, I compare the Akaike information criterion (AIC) and pseudo R-squared and fitted log-likelihood values between the two models. None of the different criteria suggests either a logit or probit model. A robustness check confirms that using a logit model instead of a probit model leads to similar results both quantitatively and qualitatively.

[15] The independent coding refers to an assignment of new occupation codes independent of the last occupation, which might or might not have changed due to the change of employer. Section 3.5.1 provides a more detailed explanation of this issue.

decisions in the labour market.

The commonly used models to jointly identify two different labour market outcomes are the bivariate probit model and the multinomial logit model. I do not find clear evidence that either model is preferred based on the different selection criteria proposed by Hahn and Soyer (2005). Therefore, I choose to work with a bivariate probit model because it allows for relaxation of the Independence of Irrelevant Alternatives (IIA) assumption, which is restrictive for the multinomial logit model (McFadden et al., 1973).

Starting from the latent variable framework, one can write

$$\begin{aligned} y^*_{1,i} &= (x'_{1,i}\beta_1) + \epsilon_{1,i} \\ y^*_{2,i} &= (x'_{2,i}\beta_2) + \epsilon_{2,i} \end{aligned} \tag{3.5}$$

where $\epsilon_{1,i}, \epsilon_{2,i}$ are joint normal with means zero, unit variances and correlation ρ. The bivariate probit model specifies the observed outcomes related to occupational and employer mobility to be

$$\begin{aligned} y_{1,i} = 1 \quad \text{if} \quad y^*_{1,i} > 0 \quad \text{and} \quad = 0 \quad \text{, otherwise} \\ y_{2,i} = 1 \quad \text{if} \quad y^*_{2,i} > 0 \quad \text{and} \quad = 0 \quad \text{, otherwise} \end{aligned} \tag{3.6}$$

allowing us to write down the probability for each realisation of the pairs $y_{1,i}$ and $y_{2,i}$. For instance, for a simultaneous change of occupation and employer, we have

$$\begin{aligned} Pr[Y_{1,i} = 1, Y_{2,i} = 1] &= Pr[y^*_{1,i} > 0, y^*_{2,i} > 0] \\ &= Pr[-\epsilon_{1,i} < x'_{1,i}\beta_1, -\epsilon_{2,i} < x'_{2,i}\beta_2] \\ &= \int_{\infty}^{x'_1\beta_1} \phi(z_1, z_2, \rho) dz_1 dz_2 \\ &= \Phi(x'_1\beta_1, x'_2\beta_2, \rho) \end{aligned} \tag{3.7}$$

where $\phi(z_1, z_2, \rho)$ and $\Phi(x'_1\beta_1, x'_2\beta_2, \rho)$ are the standardised bivariate normal density and cdf for (z_1, z_2) with zero means, unit variances, and correlation ρ. The general expression for the other possible outcomes is

$$
\begin{aligned}
p_{j,k} &= Pr[Y_{1,i} = j, Y_{2,i} = k] \\
&= \Phi(q_{1,i}x_1'\beta_1, q_{2,i}x_2'\beta_2, \rho)
\end{aligned}
\tag{3.8}
$$

where $q_{s,i}$ = 1 if $y_{s,i}$ = 1 and $q_{s,i}$ = -1 if $y_{s,i}$ = 0, for s = 1, 2. In Section 3.4.3, I particularly focus on documenting the predicted marginal effects. The objective is to quantify how much the probability of switching occupation (and/or employer) differs when characteristic k differs by one unit for continuous variables and by one category for categorical variables. Standard errors are adjusted for clustering at the individual level, as individuals can potentially be observed twice in the sample.

3.4.2 Descriptive Statistics

Table 3.5 presents the workforce characteristics of the baseline category, including all workers with no work-hour variation ($CV = 0$), and of the highest quartile of positive work-hour variation.[16] Table 3.5 illustrates how individuals differ between these two groups at the poles and by gender. First, it is noticeable that the mobility rates are markedly higher in the highest quartile, whereby the gap between the base category and the highest quartile is more substantial for women. For example, the propensity of job turnover, including both employer and occupation changes, is 41% higher for women and 23% higher for men in the highest quartile compared to women and men without hour variation. Simultaneously, workers in the highest quartile of hour variation face a higher job loss probability and fewer opportunities to work remotely. Moreover, the highest quartile shows a higher 'mean task distance', which implies higher task-specific mobility costs.[17] Appendix B.3 documents the construction of the included worker and occupation characteristics in detail.

[16] Note that Table 3.5 does not include workers of the first, second and third quartile of positive work-hour variation. How I categorize workers into quartiles of work-hour variation is explained in detail in Appendix B.3.

[17] The 'mean task distance' of an occupation is its unweighted average of the Euclidean distances of the five different task categories derived from the factor analysis (analytical, physical, sensory perception, fine motor and communication) relative to the population-weighted means of the task categories. Consequently, a higher mean task distance implies that an occupation is more specific in its task composition than others. A higher task specificity leads, in turn, to higher mobility costs due to a more substantial loss of task-specific human capital. See Appendix B.3.3 for the construction of the occupation-specific mean task distance measure.

Table 3.5: Characteristics of Workers without Hour Variation and Workers in the Highest Quartile of Hour Variation

	No Hour Variation		*Highest Quartile*	
Worker Characteristics	Men	Women	Men	Women
Job Change in %	2.08	1.95	2.55	2.74
Occupation Change in %	1.65	1.52	1.93	2.16
Employer Change in %	1.01	0.99	1.62	1.79
Avg. Hour Volatility (CV)	0	0	0.236	0.225
Avg. Work Hours	41.35	39.85	44.55	38.26
Avg. Occupation Wage	26.76	24.28	25.42	23.26
Job Loss Probability in %	3.46	2.76	3.92	3.03
Remote Jobs in %	28.93	41.60	21.27	31.06
Mean Task Distance	0.963	0.947	1.005	0.955
Age	42.50	43.23	42.08	43.37
Non-White in%	23.08	24.10	17.80	22.16
Married in %	67.94	58.49	63.54	52.86
College Degree in %	48.78	48.92	43.75	49.68
Government Worker in %	16.26	21.38	14.69	20.60
Part-Time Worker in %	1.23	3.35	9.29	23.86
Shares in High-Level Occupation Groups				
% in Management, Business, Science, Arts	39.22	43.84	32.98	43.94
% in Service	13.46	16.80	16.61	26.26
% in Sales and Office	16.49	33.43	12.75	21.75
% in Resources, Construction, Maintenance	15.10	0.78	18.08	0.99
% in Production and Transportation	15.73	5.16	19.57	7.05
Observations	96,411	101,106	33,445	30,013

Notes: The worker characteristics are constructed for the pooled sample 2003-2022. The construction of the different worker and occupation characteristics is documented in Appendix B.3. The mobility rates (Job Change, Occupation Change, and Employer Change) are obtained from the unweighted sample. All other presented characteristics of men and women with different work-hour variations are calculated using the analysis weights shown in Appendix B.1.

Both female and male workers are less likely to be married when exposed to extremely high work-hour variation. Regarding education, the proportion of men with at least a college degree is 5% lower in the highest quartile of hour variation. In contrast, women are slightly better educated in the highest quartile. One plausible reason for this observation is that a comparatively high share of women experience extreme hour variation work in management, business, science, and arts occupations. Entry into such occupations typically requires a college degree. Moreover, one can see that the composition of the five broad occupation groups differs remarkably between the baseline category and the upper quartile for both men and women. This observation confirms the documentation in Section 3.3 that different occupations vary significantly in their average work-hour variation.

In accordance with previous empirical research on unpredictable work scheduling practices, Table 3.5 suggests that workers in service occupations and part-time workers are more often sorted into jobs with very high work-hour variation. It is worth mentioning that the share of women in the upper quartile who work part-time is noticeably larger at 24% compared to 9% for male workers. Based on this observation, it is plausible to assume that the larger share of women in part-time jobs could drive the results of the subsequent analysis, hampering a fair comparison between women and men. Therefore, I exclude all individuals who usually work part-time in one of the robustness checks shown in Appendix B.4. The results show that the differential sorting into part-time jobs is not the driving factor of the gender-heterogeneous results presented in the following sections.

3.4.3 Results

Baseline Model Results

All tables and figures presented in the following sections are based on the preferred model specification, including all occupation-specific and demographic control variables and year, month, state, and industry-fixed effects (see Appendix B.3 for detailed variable description). Table 3.6 shows the predicted occupational mobility rates based on the baseline probit regression model displayed in equations 3.3 and 3.4. The reference category contains all workers without work-hour variation ($CV = 0$). Columns 1-3 present the results for the benchmark categorization of workers into quartiles across all occupations, whereas columns 4-6 are based on the worker categorization into quartiles of work-hour variation within 2-digit SOC occupations (see Appendix B.3.1 for a description of the two different categorization strategies). The difference in the predicted mobility rate between those with a coefficient of variation (CV) equal to zero and the highest quartile is substantial. More precisely, individuals with stable work schedules show a predicted monthly mobility rate of 1.59%. In contrast, the mobility rate is 2.18% for individuals in the highest quartile of work-hour variation. The predicted gap of 0.59% is about one-third of the average mobility rate of the final sample, including both men and women.

Table 3.6: Predicted Monthly Rates of Occupational Mobility by Quartiles of Work-Hour Variation

	Quartiles Across All Workers			*Quartiles Within Occupations*		
	All	Men	Women	All	Men	Women
CV=0	1.59%	1.71%	1.47%	1.59%	1.72%	1.47%
	(0.0004)	(0.0006)	(0.0005)	(0.0004)	(0.0006)	(0.0005)
1. Quartile	1.61%	1.66%	1.59%	1.58%	1.62%	1.53%
	(0.0008)	(0.0010)	(0.0011)	(0.0007)	(0.0010)	(0.0011)
2. Quartile	1.76%	1.73%	1.75%	1.73%	1.64%	1.82%
	(0.0007)	(0.0010)	(0.0011)	(0.0007)	(0.0010)	(0.0011)
3. Quartile	1.69%	1.47%	1.99%	1.80%	1.62%	1.95%
	(0.0007)	(0.0012)	(0.0011)	(0.0007)	(0.0009)	(0.0010)
4. Quartile	2.18%	2.04%	2.28%	2.15%	2.02%	2.32%
	(0.0009)	(0.0011)	(0.0014)	(0.0009)	(0.0011)	(0.0015)

Notes: The first category contains all workers without work-hour variation (CV=0). The four quartiles of work-hour variation are constructed for the subsample of workers with a positive work-hour variation. The demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household, and five education groups. The occupation controls include average wages, job loss probabilities, remote work ability, task distance and five occupation categories of vocational preparation. The model controls for time, state and industry fixed effects. Standard errors are clustered at the individual level and shown in parentheses.

The second approach of categorizing workers within 2-digit occupations shows the effect of work-hour variation on mobility conditional on the initial occupation. This approach follows the intuition that workers are more likely to compare themselves with other workers in their field when making mobility decisions. Thus, treating the heterogeneity in individual-level work-hour instability as exogenous variation appears more plausible when comparing workers in relative terms within occupations. It is reassuring that the predicted mobility rates estimated within occupations are essentially congruent to those presented in columns 1-3, as seen from Table 3.6.

Turning to the predicted marginal effects presented in Table 3.7, one can see that the estimated gap in mobility between the base category and the highest quartile of hour variation is statistically significant at the 1%-level for both men and women. Concerning the second and third quartiles, the coefficients are only positive and significant for female workers. In numbers, being in the second, third, and fourth quartile of work hour variation is associated with an elevated probability of switching occupations by 0.27%, 0.52% and 0.80%, respectively. The predicted marginal effects are substantial compared to an average monthly female switching rate of 1.70%. Moreover, the estimated marginal effects are robust when categorizing women into work-hour variation quartiles within 2-digit occupations instead of across all occupations.

The relationship between work-hour variation and occupational mobility is less clear-cut for men. Although being in the highest quartile predicts men's occupational mobility rate to be elevated by 0.33%, it appears counterintuitive that being in the third quartile is associated with a lower switching probability compared to the base category. The differences in the predicted marginal effects between women and men (with 95% confidence intervals) are illustrated by Figure 3.5. The substantial gender differences are also robust across various sample constructions, as shown in the Appendix Figures B.1-B.2.

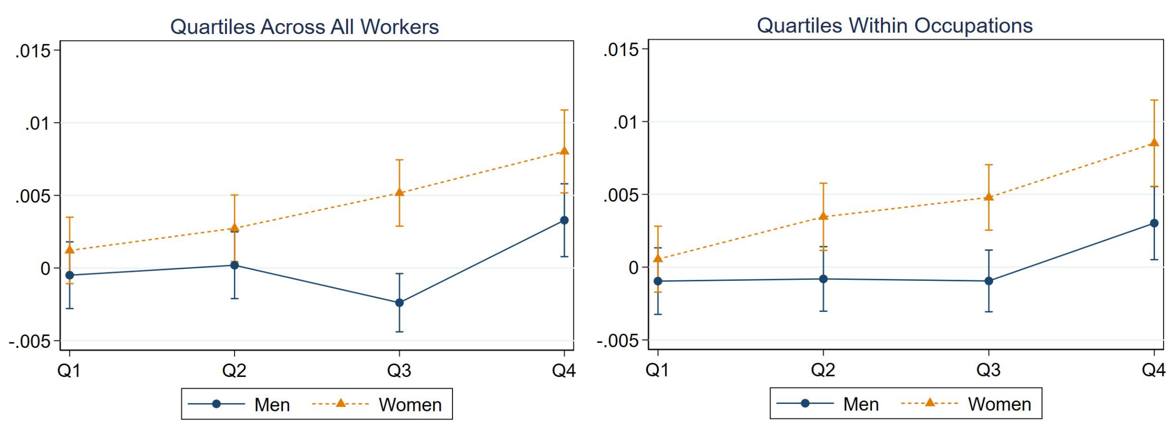

Figure 3.5: Marginal Effects of Work-Hour Variation on the Probability of Occupational Mobility by Quartiles

Concerning the predicted marginal effects of other occupation-specific characteristics, the results confirm the importance of both pecuniary and non-pecuniary determi-

Table 3.7: Marginal Effects of Work-Hour Variation on Occupational Mobility

	Quartiles Across All Workers		*Quartiles Within Occupations*	
	Men	Women	Men	Women
Hour Variation (Baseline: CV=0)				
1. Quartile	-0.0005	0.0012	-0.0010	0.0005
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
2. Quartile	0.0002	0.0027**	-0.0008	0.0035***
	(0.0012)	(0.0012)	(0.0011)	(0.0012)
3. Quartile	-0.0024**	0.0052***	-0.0009	0.0048***
	(0.0010)	(0.0012)	(0.0011)	(0.0011)
4. Quartile	0.0033***	0.0080***	0.0030**	0.0085***
	(0.0013)	(0.0015)	(0.0013)	(0.0015)
Average Working Hours	-0.0030***	-0.0023***	-0.0026***	-0.0023***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Occupation Wage	-0.0019**	0.0012	-0.0022***	0.0007
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
Probability of Job Loss	0.0011**	0.0024***	0.0013**	0.0024***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Remote Work Ability	0.0033***	0.0018**	0.0035***	0.0016*
	(0.0012)	(0.0008)	(0.0012)	(0.0008)
Task Distance	-0.0049***	-0.0042***	-0.0047***	-0.0040***
	(0.0014)	(0.0015)	(0.0014)	(0.0015)
Occupation Categories (Baseline=1)				
Occ Category 2	0.0004	-0.0018	0.0002	-0.0024
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Occ Category 3	0.0018	-0.0035	0.0017	-0.0038
	(0.0026)	(0.0028)	(0.0027)	(0.0028)
Occ Category 4	0.0011	-0.0070**	0.0010	-0.0071**
	(0.0030)	(0.0029)	(0.0029)	(0.0030)
Occ Category 5	-0.0017	-0.0079**	-0.0020	-0.0079**
	(0.0034)	(0.0033)	(0.0034)	(0.0034)
Demographic Controls	√	√	√	√
Year and Month Fixed Effects	√	√	√	√
State Fixed Effects	√	√	√	√
Industry Fixed Effects	√	√	√	√
Observations	232,339	222,769	232,339	222,769

Notes: The four quartiles of work-hour variation are constructed for the subsample of workers with a positive work-hour variation. The baseline category includes all workers who report no work-hour variation during the last three months. The demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household, and five education groups. Standard errors are clustered at the individual level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

nants. Moreover, some predicted marginal effects differ starkly by gender, which aligns with other studies on preferences for occupation characteristics (Arcidiacono et al., 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2018). Table 3.7 shows that an increased job loss probability by one standard deviation from the gender-specific mean is linked to an elevated likelihood of switching occupations by 0.24% for women but only by 0.11% for men. In contrast to job security, the expected wage rate appears to be only a driving factor for the mobility decisions of male workers. Regarding working from home, potential remote workers show a higher probability of occupational mobility. This observation is significant for both women and men. Moreover, Table 3.7 unveils that labour market frictions are negatively related to individuals' mobility. One standard deviation higher mean task distance predicts an increased probability of switching occupations from month to month by 0.42% for women and 0.49% for men. Compared to task-related mobility costs, task-unrelated mobility costs appear to affect only female workers. For example, the female monthly mobility rate is reduced by 0.70% for women working in the second-highest occupation category, requiring at least a college degree.

It is important to note that the cross-sectional CPS data cannot control for unobserved individual characteristics. This could lead to an omitted variable problem as other individual-specific but unobserved job characteristics likely correlate with the involuntary work-hour variation of individuals.[18] To address this issue under the given limitations of the CPS data, I include a battery of occupation-specific characteristics and other controls in a stepwise manner and evaluate the sensitivity of the coefficient of work-hour variation. The results shown in the Appendix Tables B.2-B.3 confirm the stability of the estimated effects of work-hour variation on occupational mobility. Moreover, the coefficient of interest remains highly significant for women with high levels of work-hour instability throughout all model specifications. The effects are also relatively robust to different sample constructions, as shown in the Appendix Figures B.1-B.2. The found robustness across different samples at least partly eliminates doubts that the substantial difference in the predicted mobility effect between male and female

[18] This issue is well-known in the related literature. A recent study by Wiswall and Zafar (2018) accentuates that any empirical cross-sectional model based on realised job choices potentially does not include all variables for identifying worker preferences.

workers is driven by the fact that women work more often part-time. Part-time jobs generally provide a more dynamic working landscape, making occupational mobility easier. Especially women in the third quartile of work-hour variation are significantly more likely to switch occupations than men, irrespective of the sample construction.

The predicted marginal effects are also robust when estimated within occupations instead of across all occupations. Although measuring work-hour variation within occupations cannot eliminate potential bias stemming from within-occupation-group differences, it eradicates any bias arising from differences in unobserved occupation characteristics. For example, shift work is a work model typically prevalent in production and service occupations. Simultaneously, shift work is likely to be correlated with work-hour variation across weeks. Investigating the relationship between work-hour instability and mobility within occupations is, therefore, helpful to reduce potential bias from that correlation. Nonetheless, at least partly, the unobserved variation between individuals within occupations remains an issue and must be considered when interpreting the results. In particular, wage differences within occupations are potentially problematic regarding the goal of unbiased estimates. Lower wages are positively correlated with both work-hour instability (see, e.g., LaBriola and Schneider, 2020) and occupational mobility (Groes et al., 2015). Controlling for average occupation wages can only partly address this issue.

Joint Model Results

The results of this section are based on equations 3.5-3.8, analysing individuals' occupational and employer mobility jointly. Every month, the CPS asks the question if an individual "still works for the same employer" compared to the previous month. This information can be exploited to identify workers' direct transitions between employers. If survey respondents do not provide information on their previous or current employer, I exclude them from the following analysis.[19]

[19] As pointed out by Fujita et al. (2020), one can observe a significant increase in the fraction of individuals who do not share their employer details if they do not self-report their employment information since 2007. However, this is not a problem in this study as the imposed sample restrictions only consider individuals in the CPS who self-report all employment information. The rate of employer non-responses in the sample conditional on the used restrictions is only 1.5%.

Table 3.8: Marginal Effects of Work-Hour Variation on the Probability of Occupational Mobility and/or Employer Change

	Men			Women		
Change in	*Only Employer*	*Only Occupation*	*Employer & Occupation*	*Only Employer*	*Only Occupation*	*Employer & Occupation*
1. Quartile	-0.0002	0.0008	0.0002	-0.0000	0.0013*	0.0007
	(0.0004)	(0.0007)	(0.0011)	(0.0005)	(0.0007)	(0.0005)
2. Quartile	0.0004	0.0004	0.0006	0.0008	0.0014**	0.0015***
	(0.0005)	(0.0007)	(0.0011)	(0.0006)	(0.0007)	(0.0005)
3. Quartile	0.0009*	-0.0012**	0.0000	0.0009	0.0028***	0.0025***
	(0.0005)	(0.0006)	(0.0011)	(0.0006)	(0.0007)	(0.0006)
4. Quartile	0.0035***	0.0006	0.0035***	0.0021***	0.0040***	0.0044***
	(0.0006)	(0.0007)	(0.0014)	(0.0006)	(0.0009)	(0.0007)

Notes: The omitted category is the baseline category of workers with no hour variation (CV=0). The demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household, and five education groups. The occupation controls include average wages, job loss probabilities, remote work ability, task distance and five occupation categories of vocational preparation. The model controls for time, state and industry fixed effects. Standard errors are clustered at the individual level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

Table 3.8 and Figure 3.6 document the predicted marginal effects for changing (i) employer within occupation, (ii) occupation within employer, and (iii) changing both employer and occupation. All presented results in this section are for the baseline categorization of workers into quartiles across all occupations. The results reveal some interesting patterns which differ clearly by gender. Men with extreme fluctuations in work hours are more likely to change their employer from month to month. On the contrary, I do not find evidence that men are more likely to change occupations within employers if they are subject to unstable work hours. On the other hand, women show a higher probability of switching occupations within employers in all quartiles of positive hour variation. The described differences between men and women are also noteworthy in magnitudes. Female workers in the highest quartile only show a 0.21% higher propensity to change their employer without an occupation change. In comparison, the job-switching propensity within occupations is 0.35% higher for male workers compared to their baseline category. Regarding mobility within employers, I find a significantly higher mobility rate for women across all quartiles of positive work-hour fluctuations compared to the base category. In numbers, the mobility propensities in the female labour market are elevated by 0.13%, 0.14%, 0.28%, and 0.40% for the first, second, third, and fourth quartile, respectively. For evaluating these results, it is worth mentioning that occupational mobility within employers is not a phenomenon predominately prevalent in the segregated female labour market. In numbers, 52% of men and 51% of women who switch occupations do not change their employers simultaneously.

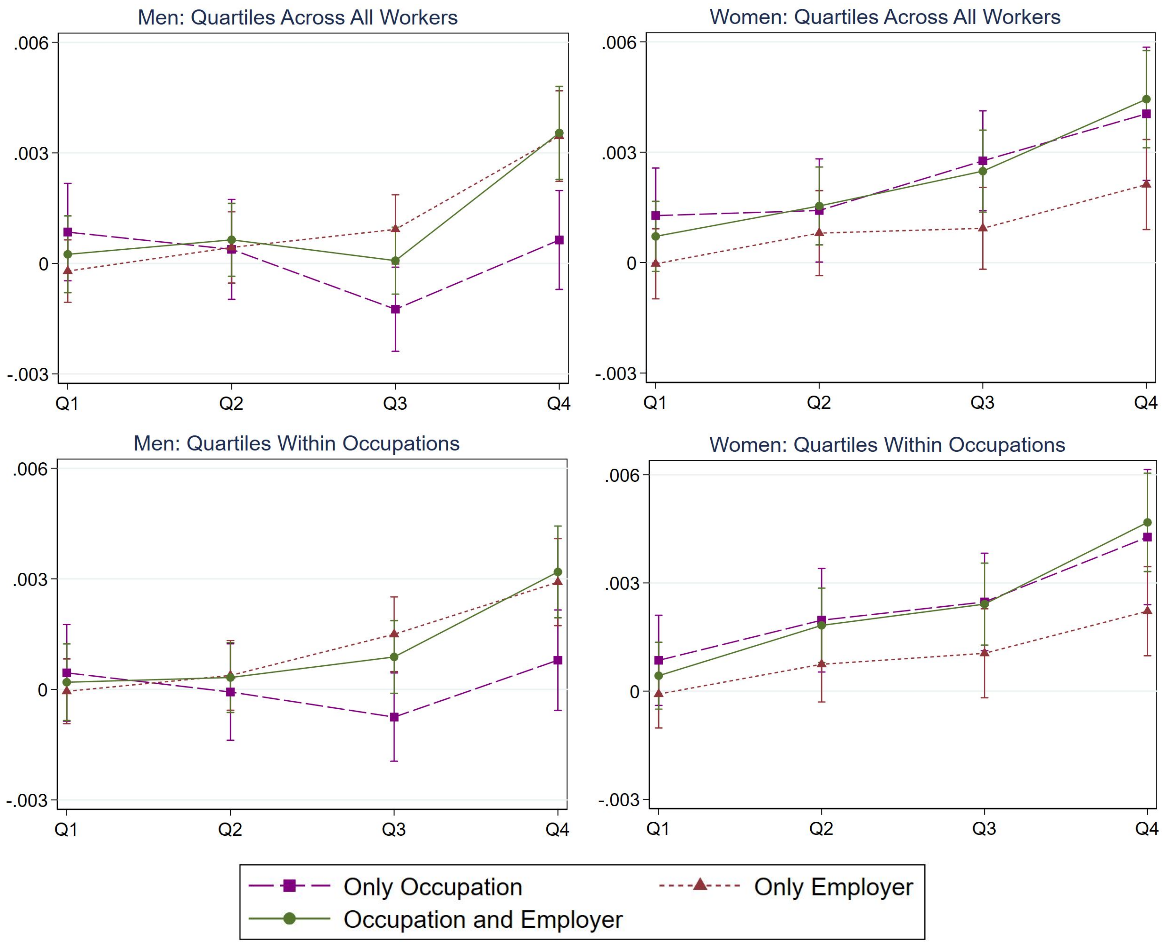

Figure 3.6: Marginal Effects of Work-Hour Variation on the Probability of Occupational Mobility and/or Employer Change

The two different channels of occupational mobility (within and between employers) are discussed, for example, by Moscarini and Thomsson (2007) and Kambourov and Manovskii (2008). However, these studies do not examine differences in mobility patterns between male and female workers due to work-hour instability. This section unveils that work-hour instability is more occupation-specific for women and employer-specific for men regarding their job mobility. The gender-heterogeneous mobility patterns shown in the last two sections require deeper investigations. Why are women more likely to switch occupations when they face high levels of involuntary work-hour variation? The subsequent section's objective is to shed light on this question.

Gender Disparities

In this section, I exploit information on individual and household characteristics provided by the CPS to narrow down and discuss why women are apparently more affected by fluctuating work hours regarding their occupational mobility decisions. A natural way to think about the gender differences relates to time allocation between work and work-unrelated obligations (i.e. housework and childcare). Data from the American Time Use Survey (ATUS) shows that women in 2021 spent on average 51% more time on household activities[20] and 94% more time on caring for household members, including children. On the contrary, men spent more time on working and work-related activities, such as commuting between home and workplace. These observations align with the "gender identity theory" proposed by Akerlof and Kranton (2000), based on the core idea that gender is central to individuals' specialization within households.

Table 3.9 reports the predicted marginal effects on occupational mobility for women and men in the highest quartile of work-hour variation across different household compositions. For the subsample regressions, I use the model equations 3.3 and 3.4. The results show positive and statistically significant coefficients across all household compositions when the full sample is included. The same model applied to gender-segregated labour markets shows that only unmarried men and men without children living in the household have a higher propensity to switch occupations when exposed to extreme hour fluctuations. For men in all other household compositions, the coefficients are insignificant and, for the most part, insignificantly different from zero. On the contrary, women show significant and positive predicted marginal effects across all household compositions. The fact that men are more likely to specialize in working activities within households and are more often the main breadwinners seems to be a plausible explanation for these findings. Another possible explanation could be related to

[20] Household activities in the American Time Use Survey (ATUS) include housework, food preparation and cleanup, lawn and garden care, and household management.

Table 3.9: Marginal Effect of Being in the Highest Quartile of Work-Hour Variation on Occupational Mobility by Household Composition

					Unmarried		
	Unmarried	Married	No Children in HH	Children in HH	No Children in HH	1 Child in HH	>1 Children in HH
Marginal Effects of Highest Quartile of Hour Variation							
All	0.0084***	0.0042***	0.0072***	0.0047***	0.0074***	0.0086***	0.0125***
	(0.0013)	(0.0014)	(0.0014)	(0.0013)	(0.0015)	(0.0031)	(0.0038)
Men	0.0083***	0.0004	0.0065***	-0.0005	0.0086***	0.0047	0.0008
	(0.0020)	(0.0016)	(0.0018)	(0.0018)	(0.0021)	(0.0058)	(0.0065)
Women	0.0083***	0.0078***	0.0079***	0.0082***	0.0062***	0.0092***	0.0125***
	(0.0017)	(0.0022)	(0.0022)	(0.0018)	(0.0021)	(0.0034)	(0.0042)
Number of Observations							
Men	117,732	114,607	143,369	88,970	100,295	9,273	6,083
Women	130,200	92,569	114,731	108,038	78,411	26,963	24,826

Notes: This table presents the marginal effects of the highest quartile compared to the base category of workers without work-hour variation on the monthly occupational mobility rates. The demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household, and five education groups. The occupation controls include average wages, job loss probabilities, remote work ability, task distance and five occupation categories of vocational preparation. The model controls for time, state and industry fixed effects. Standard errors are clustered at the individual level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

gender-specific discrimination in the workplace. However, contradicting the 'female discrimination hypothesis', McCrate et al. (2019) finds that neither women nor men are compensated for employer-driven work schedule unpredictability.[21]

A complementing pattern can be observed from columns 5-8, showing the predicted marginal effects for unmarried women and men with no children, one child and more than one child. While the female switching probability positively varies with the number of children, the opposite effect is true for men. A closer look into the household-level CPS data shows that women who are unmarried and have children live more often without a partner (single mothers), implying an additional burden regarding balancing work duties and childcare. On the contrary, men with more than one child living in the household usually live with a partner in the same household. As occupational mobility contains the risk of human capital loss (Kambourov and Manovskii, 2009b), men could have a higher tolerance regarding precarious working conditions in terms of work-hour

[21] It is worth mentioning that the study by McCrate et al. (2019) can only give an indication of possible compensation mechanisms in the U.S. labour market as the study focuses on the compensation for work schedule unpredictability in the Canadian labour market. However, the similarities between the two labour markets, such as the high labour market flexibility in the U.S. and Canada, make a comparison reasonable.

instability in order to fulfil the male breadwinner role. Related to this suggestion, a recent study by Gonalons-Pons and Gangl (2021) shows that the "importance of male-breadwinner norms is strongest among couples for whom the male-breadwinner identity is most salient."

Table 3.10: Marginal Effect of Being in the Highest Quartile of Work-Hour Variation on Occupational Mobility by Age-Education Cells

	No College Degree			College Degree		
	Age <= 35	Age 36-50	Age 51-61	Age <= 35	Age 36-50	Age 51-61
Marginal Effects of Highest Quartile of Hour Variation						
All	0.0167***	0.0042**	0.0034**	0.0058**	0.0017	0.0013
	(0.0034)	(0.0017)	(0.0018)	(0.0023)	(0.0017)	(0.0019)
Men	0.0122***	0.0005	0.0018	0.0024	0.0011	-0.0026
	(0.0039)	(0.0022)	(0.0026)	(0.0031)	(0.0023)	(0.0026)
Women	0.0198***	0.0078***	0.0052**	0.0095***	0.0017	0.0046*
	(0.0055)	(0.0025)	(0.0026)	(0.0033)	(0.0022)	(0.0027)
Number of Observations						
Men	32,522	47,432	31,590	39,218	50,438	30,796
Women	24,983	43,394	34,368	36,241	51,006	32,724

Notes: This table presents the marginal effects of the highest quartile compared to the base category of workers without work-hour variation on the monthly occupational mobility rates. The demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household, and five education groups. The occupation controls include average wages, job loss probabilities, remote work ability, task distance and five occupation categories of vocational preparation. The model controls for time, state and industry fixed effects. Standard errors are clustered at the individual level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

Another perspective of how work-hour instability might be linked to mobility becomes visible when splitting the sample based on workers' education and potential labour market experience. Both labour market experience and education enhance the matching quality between workers and jobs and decrease the propensity of occupational mobility. In addition, Addison et al. (2020) find that women mismatch more often than men. Table 3.10 reveals that the predicted marginal effects are indeed significantly different between young male and female workers with at least a college degree. Women have a higher propensity of changing occupations of 0.95% compared to the gender-specific base category of no work-hour variation. On the other hand, male college workers do not show statistically significant changes in their propensity to switch occupations when exposed to different levels of work-hour instability. Regarding workers without a college degree, I find that the predicted marginal effect is positive and significant for women in all age cohorts. However, the predicted difference to the base category is noticeably more substantial for younger women, with 1.98%. Recall that the average monthly mobility rate in the female labour market is 1.71%. Regarding men, a positive and significant predicted marginal effect is only found for young workers but not middle-aged and older workers without a college degree. Therefore, as gender differences persist even in more experienced cohorts, the gender-specific household specialization theory by Akerlof and Kranton (2000) seems to be the more coherent explanation for the observed gender-heterogeneous mobility patterns.

3.5 Do Workers Switch to Stable Occupations?

The findings of the last section show a clear relationship between workers' instability in work hours and occupational mobility. However, it remains unclear so far if workers sort themselves into different occupations because they potentially seek a more stable working environment.[22] This section's main objective is to shed new light on this question by analysing the potential effect of occupational mobility on individuals' variation in weekly work hours.

3.5.1 Identification Strategy

To test if workers move to more stable occupations requires two measures of individuals' work-hour variation: one associated with their occupation before the change and one with the new occupation after the change. My previous identification strategy of following individuals over four consecutive months is not ideal for the purpose in this section. Instead, I exploit the complete eight survey months of the panel dimension in the CPS by measuring occupation changes between survey months 4 and 5. This strategy allows me to construct two detailed measures of work-hour variation, each

[22] While studies usually focus on the impact of occupational resorting on the level of wages and wage growth (see, e.g., Groes et al., 2015; Guvenen et al., 2020), the literature does not look at work-hour instability in this context.

combining four weekly work-hour observations. The modified approach is visualized in Figure 3.7.

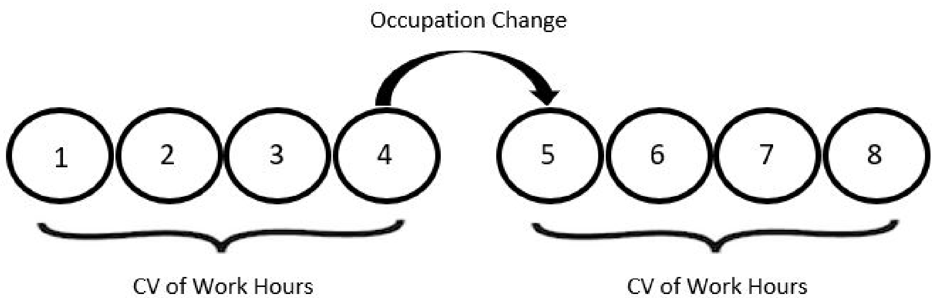

Figure 3.7: Longitudinal Data Usage of 8 Survey Months in the CPS

Combining Monthly CPS and ASEC CPS Data

One drawback of the CPS structure is that individuals are not included in the survey for eight months after month four before re-entering the survey. Because of the drop-out for eight months, new occupation codes are assigned to individuals who re-enter the survey independent of job information known from survey month 4.[23] In comparison, the more reliable "dependent coding" technique, which is used between survey months 2-4 and 6-8, assigns a new occupation code to workers only if they report an employer change or a change in daily work activities compared to the last calendar month. However, such information is unavailable for individuals in survey month 5 as they were not observed in the last calendar month. Instead, CPS staff code occupations independently based on the blunt interview question "What is your occupation?" (Polivka and Rothgeb, 1993). This procedure leads to spurious occupational transitions, especially at the 6-digit occupation level.[24]

Figure 3.8 illustrates the scope of the overestimated mobility rate measured between survey months 4 and 5. The adjusted monthly mobility rate based on independent

[23] A more detailed discussion on the "independent occupation coding" issue is provided in Polivka and Rothgeb (1993).

[24] One plausible reason for the invalid classification of individuals into 6-digit occupations is that the occupation definition provided by respondents is often not detailed enough to map it to the fine Census Occupation Codes used by CPS coders. For a more detailed discussion about potential occupation coding errors in the CPS, see, for example, Moscarini and Thomsson (2007) or Kambourov and Manovskii (2013).

Figure 3.8: Monthly Occupational Mobility Rates in the CPS Based on Different Occupation Coding Techniques

occupation coding is almost three times higher than the rate based on the dependent coding technique (1.7% compared to 4.6%).[25] To overcome this issue, I identify valid occupation changes between CPS months 4 and 5 by linking individuals with the Annual Social and Economic Supplement (ASEC) data files. The ASEC is also called the March CPS because the supplementary questions are only asked to all CPS survey respondents in March. Most importantly, the questionnaire asks about the current job and the longest main job held in the last year using an equivalent procedure of "dependent coding" as in the CPS months 2-4 and 6-8.

First, I link individuals in the CPS across all sixteen calendar months (equivalent to eight survey months) following the same procedure described in Section 3.2. The attrition rate for linking individuals across all eight survey months is significantly higher since individuals are dropped out of the CPS for eight calendar months between survey months 4 and 5.[26]. Next, I construct individuals' work-hour variation (CV) coefficients based on the complete 4-month intervals by imposing the sample restrictions described in Section 3.2.1. In the next step, I use a unique person identifier constructed by Flood and Pacas (2017) to link individuals between the March CPS data files and the supplementary ASEC CPS data files. Because only four out of twelve yearly CPS

[25] Every monthly observation of the time series based on independent coding is divided by nine to make the time series comparable to the monthly time series based on dependent coding. The transformation of the time series is required as the series measures occupational mobility between nine calendar months due to the dropout of individuals for eight months between survey months 4 and 5.

[26] For detailed documentation of the expected attrition rates in the CPS when linking individuals across different survey months based on the identifier "cpsidp", see Rivera Drew et al. (2014).

cohorts undergo the ASEC questionnaire each year, I have to drop the eight cohorts that cannot be linked between the CPS and the ASEC data files. As a result, the original sample shrinks by about 65% to 23,100 individual observations. Finally, the analysis weights are appropriately adjusted to account for the higher attrition rate for linking individuals across all eight survey months (see Appendix B.1).

Table 3.11: Occupation Switching Indicators in the Monthly CPS and ASEC (March) CPS Files

	ASEC Indicator		
Monthly CPS Indicator	$Switch = 0$	$Switch = 1$	Total
$Switch = 0$	12,927	558	13,485
$Switch = 1$	8,823	819	9,642
Total	21,750	1,377	23,127

Notes: The indicator numbers are based on all individuals in the final sample linked between monthly CPS and yearly ASEC (March) CPS data files for 2003-2022.

Based on the matched sample, I can check the validity of occupational transitions in the monthly CPS by comparing individuals' occupation codes in the monthly CPS data files with those in the yearly ASEC CPS data files. Table 3.11 shows that the occupation switching indicator is not harmonious for a significant proportion of individuals between the two surveys. The main reason is related to the different occupation coding techniques outlined above. A second possible reason is that the ASEC questionnaire asks individuals about the longest main job held in the last year instead of the job held twelve months ago.[27] A straightforward approach to eliminate spurious occupational transitions is to consider only individuals for whom the two switching indicators are congruent by using a double flag to identify valid occupation switchers and non-switchers. Table 3.11 shows that the constructed double flag identifies 12,900 non-switchers (control group) and 800 switchers (treatment group), yielding 13,700 observed individuals in total. This sample is the underlying sample used for the empirical

[27] For example, consider individuals whose work-hour variation is measured in year X between December and March. In practice, they may switch occupations between April and May while remaining in the new occupation till March (or longer) next year. When asked in the March CPS of year X+1 if they still work in the "same job compared to the longest job held in the last year", they are supposed to answer "yes". Nonetheless, they should be classified as occupation switchers if compared to last year's CPS in March.

analysis in the next section.[28]

A Propensity-Score Matching Quantile Difference-in-Differences Model

The modified sample construction provides a simple setting for using a difference-in-differences model with two groups (treated and untreated) and two time periods (pre-treatment and post-treatment) for each combination of two adjacent years from 2003 to 2022. The selective treatment occurs between CPS survey months 4 and 5 when realized occupation changes are observed. The pre-treatment period is the first 4-month interval, and the post-treatment period is the second 4-month interval. Each of the two intervals contains a measure of work-hour variation, as visualized in Figure 3.7. I estimate the following difference-in-differences model at the mean as well as at specified quantiles of pre-treatment work-hour variation:

$$CV(WorkHours_i) = \alpha + \beta Post_i + \gamma Mob_i + \delta Post_i * Mob_i + \eta Year_i + \epsilon_i \qquad (3.9)$$

The dependent variable is individual i's coefficient of variation (CV) of work hours, $Post_i$ is an indicator variable taking the value of zero in the pre-treatment period and the value of one in the post-treatment period, Mob_i is the treatment indicator, and the interaction term of $Post_i$ and Mob_i captures the difference-in-differences effect. In addition, I control for year-fixed effects captured by $Year_i$ to account for variation in the treatment probability over time.

The identification strategy could raise concerns regarding sample selection and causal inference, which must be addressed appropriately. First, as I work with observational data, I must ensure that the sample construction does not cause selection bias. In other words, the sample selection should not depend on unobserved potential outcomes (Ho et al., 2007). Selection bias could arise because the sample only includes individuals who work for the same employer and in the same occupation for at least

[28] It is worth mentioning that this approach relies on the assumption that eliminating all individuals who do not match between the two surveys follows a random selection process. Careful examination of the data does not show systematic differences in characteristics between matched and unmatched individuals. Therefore, I proceed without adjusting the analysis weights at this stage and treat the matched sample as a random sample selected from the main sample.

four consecutive months before the treatment occurs. It is intuitive to assume that working for the same employer over a more extended period increases workers' bargaining power, which could be related to their potential outcomes of work-hour stability. To address this issue, I use the analysis weights described in Appendix B.1 to give more weight to individuals with underrepresented characteristics due to the underlying selection procedure.

Second, observing individuals over two 4-month intervals does not allow me to test whether the instability of work hours follows the same trend for the treated and control groups before the treatment. Although the parallel trend assumption cannot directly be replaced in theory, I can improve the validity of the estimates and reduce their bias by exploiting the rich information from the pre-treatment control variables X_i through the use of a propensity score matching procedure (Rubin, 1973; Angrist and Pischke, 2009; Imbens and Rubin, 2015). I predict individuals' probability of treatment (propensity scores) based on selected covariates[29], $p_i = E(Z_i = 1|X_i)$, and match workers with similar scores in order to construct kernel weights following Heckman et al. (1997). In the second step, the kernel weights are integrated into the difference-in-differences model, yielding an adjusted treatment effect conditional on the given covariates.[30]

Table 3.12 compares the baseline characteristics between the treated and control group for the unadjusted and the propensity-score adjusted sample. The matched sample reports a significant reduction in deviation for most covariates. Moreover, the balancing t-test shows that the calculated deviation remains statistically significant only for age and union coverage. Although this implies that individuals in the treated group are younger and less often covered by union agreements, the clear deviation reductions by 50.9% and 64.2% help improve the initially more enormous imbalances between the two groups. From an economic point of view, more experienced workers and workers covered by union agreements have more bargaining power, which is negatively correlated with work-hour instability (Finnigan and Hale, 2018; LaBriola and Schneider, 2020).

[29] The covariates include three continuous variables (age, hourly wages and average work hours), seven categorical variables (female, white, married, children, college degree, union coverage and hourly paid), and controls for regional, time, occupation and industry fixed effects.

[30] Stata codes for implementing the kernel propensity-score matching DiD and the kernel propensity-score matching quantile DiD are provided by Villa (2016). I use a logit model along with an epanechnikov kernel function with a bandwidth of 0.06 to construct the weights. However, my results are not sensitive to choosing different functions and/or bandwidths.

Table 3.12: Comparison of Baseline Balance in Individual Characteristics Between Unmatched (U) and Propensity-Score Matched (M) Sample

		Mean		deviation		t-test	
		Treated	Control	% total	% reduction	t	$p > \|t\|$
CV of Work Hours	U	0.080	0.086	-7.2		-2.21	0.027
	M	0.080	0.084	-4.8	33.9	-1.08	0.282
Age	U	42.282	44.909	-26.4		-8.07	0.000
	M	42.301	43.591	-12.9	50.9	-2.86	0.004
% Female	U	0.429	0.452	-4.6		-1.41	0.157
	M	0.430	0.436	-1.2	73.6	-0.27	0.785
% White	U	0.821	0.863	-11.5		-3.71	0.000
	M	0.822	0.832	-2.7	76.7	-0.57	0.566
% Married	U	0.363	0.428	-13.3		-4.03	0.000
	M	0.362	0.397	-7.3	45.6	-1.62	0.105
% Children in HH	U	0.423	0.406	3.5		1.06	0.288
	M	0.424	0.407	3.5	-2.3	0.79	0.431
% College Degree	U	0.520	0.576	-11.3		-3.48	0.001
	M	0.521	0.537	-3.1	72.4	-0.69	0.490
Wage Rate	U	26.645	28.976	-13.4		-4.14	0.000
	M	26.654	27.481	-4.8	64.5	-1.08	0.282
Average Work Hours	U	43.337	44.106	-9.3		-2.84	0.004
	M	43.337	43.846	-6.2	33.7	-1.40	0.162
% Union Coverage	U	0.098	0.179	-23.6		-6.54	0.000
	M	0.098	0.127	-8.5	64.2	-2.04	0.041
% Hourly Paid	U	0.511	0.470	8.3		2.54	0.011
	M	0.511	0.480	6.3	24.6	1.39	0.164

Notes: Workers without work-hour variation (CV=0) are excluded from the sample. The sample includes 8,417 individuals in the control group and 496 in the treatment group. The balancing t-test is conducted with the weighted covariates. The % deviation is the % difference of the sample means in the treated and control groups as a percentage of the average standard deviation of the two groups following (Rosenbaum and Rubin, 1985).

Thus, it is most likely that the lower age and union coverage rate of individuals in the treated group lead to an underestimation of the treatment effect of occupational mobility on work-hour instability. This has to be considered for interpreting the results in the following section.

Table 3.12 also reports the baseline level of work-hour variation for the unmatched and matched samples. Although individuals' pre-treatment work-hour variation is not included in the propensity-score estimation, the difference in pre-treatment work-hour variation between the treated and control groups decreases and becomes statistically insignificant due to the matching procedure. This result is a valuable improvement as it helps to account for the fact that the treatment assignment is potentially selective in that workers with higher fluctuations in work hours have higher incentives to sort themselves into more stable jobs.

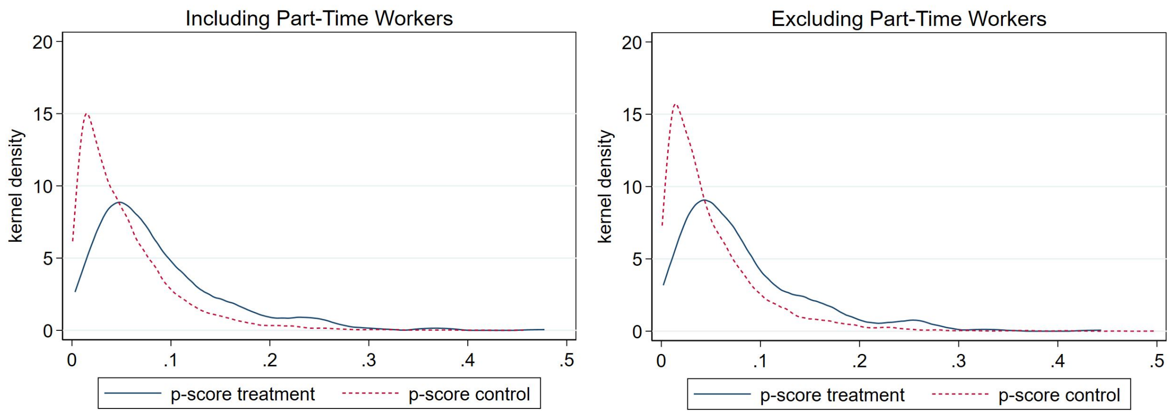

Figure 3.9: Propensity Score Densities of the Treatment and Control Group

To further strengthen the internal validity of the results, I restrict the identification to the "common support" for propensity scores between the treated and control groups. Figure 3.9 illustrates the propensity score densities of the treatment and control groups. The sizeable overlapping area indicates that both groups have comparable and positive treatment probabilities. A fraction of individuals with very low propensity scores who do not change occupations are dropped from the analysis as they cannot be matched with individuals in the treatment group.

3.5.2 The Effect of Occupational Mobility on Work-Hour Instability

Table 3.13 reports the difference-in-differences effects evaluated at the mean and different quantiles for the entire sample (columns 1-2) and the restricted sample (columns 3-4). The restricted sample excludes part-time workers and multiple job holders in order to remove the possibility that occupation changes between part-time and full-time jobs as well as between first and second jobs affect the treatment effect.[31]

[31] Note that workers who report to work usually full-time (35 hours or more) but are observed to work only part-time due to "economic reasons" are not excluded. In fact, this is the variation in work hours I aim to investigate in this study (involuntary work-hour variation).

Table 3.13: The Effect of Occupational Mobility on Work-Hour Instability

	Treatment Effect (includes part-time workers and multiple job holders)		*Treatment Effect (excludes part-time workers and multiple job holders)*	
Estimation Method	*DiD*	*Matching & DiD*	*DiD*	*Matching & DiD*
Mean	-0.006	-0.011**	-0.003	-0.010*
	(0.008)	(0.005)	(0.008)	(0.005)
0.5 Quantile	-0.009	-0.009	-0.007	-0.008
	(0.005)	(0.005)	(0.006)	(0.007)
0.75 Quantile	-0.011	-0.011	-0.009	-0.008
	(0.007)	(0.007)	(0.008)	(0.008)
0.9 Quantile	-0.024*	-0.025*	-0.033**	-0.030**
	(0.014)	(0.014)	(0.015)	(0.014)
Control Group	8,417	8,293	6,480	6,232
Treatment Group	496	495	346	346
Off Support	-	125	-	248

Notes: Workers without work-hour volatility (CV=0) are excluded from the samples. Robust standard errors for the mean regression model and bootstrap standard errors (1,000 replications) for the quantile regression model are shown in parentheses. ***/**/* are significant at the 1% 5% and 10% level.

Table 3.13 shows a negative effect of occupational mobility on work-hour instability for both the unadjusted (columns 1 and 3) and the propensity-score matching adjusted (columns 2 and 4) difference-in-differences model. The effect evaluated at the mean is statistically significant only for the adjusted samples. In numbers, individuals' average coefficient of variation (CV) decreases by 0.011 (column 2) and 0.10 (column 4) after being treated. This result is equivalent to a decline in work-hour variation by about 13% compared to individuals who remain in the same occupation. Moreover, the effect is only significant at the highest quantile, showing that only workers with extreme fluctuations in work hours sort themselves into more stable occupations. The significant and negative effect is more substantial when part-time workers and multiple job holders are excluded from the sample.

As mentioned above, the results presented in this section must be interpreted with caution because I cannot directly test the parallel trends assumption, which is fundamental for difference-in-differences models. Instead, my approach relies on the "conditional independence" assumption (see, e.g., Imbens and Wooldridge, 2009). I further strengthen the internal validity of the results through the common support of matched individuals. Relying on the conditional independence assumption, the robustness of the negative effect for workers exposed to extreme work-hour instability across the different samples and model specifications indicates that occupational mobility could be an important driver for improving their work-hour stability.

However, despite the illuminating findings, the question remains of why individuals with high fluctuations of work hours switch occupations and if the estimated improvement in work-hour stability comes as a side effect of other unobserved mechanisms or if individuals specifically target more stable occupations. It is important to note that this section does not restrict the analysed sample to individuals who switch occupations due to the harmful effects of work-hour instability. Instead, I observe occupational transitions of matched individuals and their corresponding change in hour variation after transitioning. This is a clear limitation stemming from the CPS data, which does not allow for pinpointing the exact reason for mobility. In this regard, it would be highly beneficial for researchers if the U.S. Bureau of Labour Statistics included further questions in the CPS to help identify the reasons for the mobility of those who switch occupations from month to month (without unemployment spells). Such information would help better understand the mechanisms of the discovered mobility patterns related to the instability of work hours.

3.6 Discussion and Conclusion

This study provides a novel perspective on occupational mobility by linking individuals' instability in work hours to their realised occupation changes based on representative U.S. survey data. First, this study illustrates that occupations' task content and other occupation-specific characteristics can explain a significant fraction of workers' intra-year work-hour variation. In the second part of this study, I use a probabilistic model to establish a relationship between work-hour instability and occupational mobility. The positive relationship between work-hour instability and mobility is most significant for workers in the highest quartile of hour variation and noticeably more substantial for female workers. In the last part of this study, I show that only workers at the highest quantile of work-hour variation move to more stable jobs.

The findings of the second part of this study are partly in line with a study by Choper et al. (2022), which analyses the effect of unstable and unpredictable work schedules on job turnover in retail and food service industries. While work-hour instability is assumed to be more concentrated in "low-wage" occupations as well as in retail and food service industries (LaBriola and Schneider, 2020), my study suggests that it is a far more widespread phenomenon than anticipated in the literature, predicting the mobility decisions of different types of workers. Therefore, policymakers should consider extending current labour market policies that have the potential to reduce the risk of work-hour instability in all industries and occupations. Although the efficiency of recently introduced Fair Workweek laws remains to be seen, broader implementations of such laws at the state or country level could be a potential tool for containing the related adverse effects on the workforce, including the loss of occupation-specific human capital.

This study also contributes to the literature on gender-specific preferences for working arrangements. While most studies predominately build on experimental designs or hypothetical job choice models (see, e.g., Mas and Pallais, 2017; Wiswall and Zafar, 2018), my results suggest that women have a stronger distaste for unstable work schedules based on observational survey data. Investigations of the household composition role let me conclude that the traditional breadwinner role provides a plausible explanation for the gender disparities. This assumption is also confirmed by American Time Use Data (ATUS), which shows that women are more specialised in non-working activities than men. The probabilistic model also sheds light on workers' preferences for other occupation–specific characteristics suggesting that women tend to have higher preferences for employment stability and remote work opportunities. This is in line with previous research.

Besides the limiting knowledge about the reasons for occupational mobility in the CPS data, another limitation of this study relates to potential omitted variable bias. Although I exploit the longitudinal dimension of the Current Population Survey (CPS) for constructing the work-hour instability measure, I draw on a pooled cross-sectional sample for the probabilistic regression analysis. It would be of high value if one could use panel data to investigate further the relationship between work-hour instability and mobility patterns in the labour market. Further, this would allow researchers to evaluate the long-term individual effects of hour variation on wage growth and human capital accumulation - an understudied field of research. Unfortunately, no reliable high-frequency data on individuals' work hours is available for the U.S. labour market. The most promising survey seems to be the Survey of Income and Program Participation (SIPP), which collects weekly and monthly data on individuals' working arrangements. However, an exploration of the data shows that individuals' reported weekly work hours suffer from extreme "seam bias" since the survey is conducted in quarterly or yearly waves instead of on a regular monthly basis (Moore, 2008). Therefore, using the longitudinal dimension of the more reliable CPS data is a reasonable compromise at this point. Overall, further explorations in this area of research are warranted, given the strong relationship between work-hour instability and occupational mobility.

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Appendix to Chapter 3

B.1 Analysis Weights

For the construction of the analysis weights, my approach follows LaBriola and Schneider (2020) with some essential adjustments. For the analysis in Sections 3.3 and 3.4, I use the CPS individual basic weight WTFINL, and for Section 3.5, I use the earnings weight EARNWT as basic weights for the construction of the final analysis weights. The earnings weight is recommended if the CPS earner study variables are included in the analysis. Recall that I use data on individual wages, union coverage and whether an individual is paid by the hour in the kernel propensity score matching procedure, which requires the usage of the earnings weight.

The Integrated Public Use Microdata Series (IPUMS) provides two longitudinal weights based on WTFINL accounting for attrition during the first four survey months (LNKFWMIS14WT) and the second four survey months (LNKFWMIS58WT). To maintain a simpler notation, I define the two longitudinal weights as w_i^1 for the construction of the final analysis weights in Sections 3.3 and 3.4. For the analysis in Section 3.5, I link individuals across all eight CPS survey months. While IPUMS provides the longitudinal weight LNKFW8WT to account for attrition during all eight survey months, I need to modify LNKFW8WT such that it is based on EARNWT instead of WTFINL:

$$w_i^2 = \frac{LNKFW8WT_i * EARNWTi}{WTFINLi} \tag{B.1}$$

Next, I adjust w_i^1 and w_i^2 for each individual i in the sample in two more steps: first, I adjust the weights for systematic differences in individuals' personal and job characteristics between those who are dropped out of the sample and those who remain in the final sample. This step aims to give more weight to individuals whose characteristics are underrepresented in the analysis sample conditional on the imposed sample restrictions described in Section 3.2.1. This procedure accounts for differences in the probability of experiencing work-hour variation across different months and the likelihood of switching occupations. For each individual i, the categorical variables are used sequentially for the construction of the adjusted weight:

$$w_i^3 = w_i^{1,2} \prod_{n=1}^{N} \frac{Pr(x_t^n = x_{i,t}^n \mid \text{In labour force})}{Pr(x_t^n = x_{i,t}^n \mid \text{Under sample restrictions})} \tag{B.2}$$

where $x^n_{i,t}$ is a vector of n categorical variables including race, sex, age, education, marital status, number of children in household, union coverage, wage quartile, broad occupation and broad industry.[1]. This procedure is repeated for each monthly CPS survey separately denoted by the time subscript t. The calculated relative probabilities are multiplied by w^1_i and w^2_i.

In the next step, w^3_i is adjusted for the probability that individuals who fulfil all sample restrictions self-report their labour force information across all four (or eight) survey months. At the end of this procedure, all individuals who do not self-report their work hours are dropped. To achieve the weight adjustment, I use a probit regression model (by using the adjusted individual weight w^3_i) with a dependent indicator variable equal to 1 if a person does self-report information across all months and equal to 0 otherwise. I include the same categorical variables for each individual i as in equation B.2 to predict the probability of self-reporting:

$$Pr(SR_i = 1) = \Phi(X_i\beta) \tag{B.3}$$

Finally, I amend the weights by dividing w^3_i by individuals' probability of self-reporting to give more weight to those who remain in the sample but are less likely to self-report their labour force information based on their individual and job characteristics X_i:

$$w^4_i = \frac{w^3_i}{Pr(SR_i = 1)} \tag{B.4}$$

The final analysis weights w^4_i are used in all empirical analyses in this paper.

[1] The broad occupation groups include 22 different 2-digit occupation categories based on the 2010 SOC occupation structure. The broad industry groups are based on the consistent IND1990 variable provided by IPUMS. I reclassify the more detailed industry categories into 13 broader groups following LaBriola and Schneider (2020). These groups are: agriculture, forestry, and fisheries (10-32); mining (40-50); construction (60); manufacturing (100-392); transportation, communications, and other public utilities (400-472); wholesale trade (500-571); retail trade (580-691); finance, insurance, and real estate (700-712); business and repair services (721-760); personal services (761-791); entertainment and recreation services (800-810); professional and related services (812-893); public administration (900-932).

B.2 Exploratory Factor Analysis of O*NET Data

The basic idea for conducting a factor analysis is that the 52-dimensional O*NET ability data can be reduced to a significantly lower number of more meaningful task categories (factors). To achieve this goal, I draw on the 25.0 O*NET database (November 2020), the latest updated database based on the 2010 Standard Occupational Classification (SOC) structure. Job analysts rate all ability items through two different scales. The "importance" scale ranges from 1 to 5, and the "level" scale from 0 to 7. However, Handel (2016) shows that the different ratings for the same ability items are highly correlated ($r = 0.95$), making one of the two scales redundant. This study uses the importance rating for the factor analysis, but the results are insensitive to this choice.

The O*NET occupation classification is more detailed (970 occupations) than this study's balanced occupation system (430 occupations). Therefore, I take the unweighted average of O*NET occupations' ability rating if more than one occupation is matched with an occupation in my panel. Next, one has to choose a sample for conducting the factor analysis. Although one could use the unweighted occupation panel, this strategy would not accurately represent the labour force as some occupations have significantly larger employment shares (e.g. elementary and middle school teachers) than others (e.g. marine engineers and architects). Instead, I map the 52 occupation-specific ability ratings to the employed workforce in the January 2012 Current Population Survey (CPS).[2]

Before conducting the factor analysis, all ability scores are standardised with zero mean and a standard deviation of one using the January 2012 workforce sample of the CPS. Next, I run the factor analysis of the correlation matrix to produce "principal factors" which are orthogonal to each other and, thus, contain independent information of the underlying ability data.[3] The orthogonal (uncorrelated) factors are produced by using a "varimax rotation" procedure (Costello and Osborne, 2005). Finally, one has to decide how many principal factors to retain. Following Kaiser (1960), I keep all factors with Eigenvalues greater than one. The five derived factors can be characterised as 'physical', 'analytical', 'sensory perceptional', 'fine motor' and 'communication' task intensities based on carefully examining the ability factor loadings.

[2] The factor analysis includes all employed individuals who are not self-employed or work in military occupations. The factor analysis sample is further restricted to workers between 23 and 61 years of age to maintain consistency with the overall sample construction in this study.

[3] The principal factor method is recommended if the assumption of multivariate normality cannot be guaranteed (Fabrigar et al., 1999; Costello and Osborne, 2005). A multivariate normality test of the underlying ability data rejects the multivariate normality assumption.

B.3 Construction of Probit Model Variables

B.3.1 Work-Hour Instability

To systematically use the coefficient of variation (CV) measure, which is constructed for each individual as described in Section 3.2.2, I first divide the sample by gender. Next, all female and male workers are assigned to one of two categories: first, workers with positive work-hour variation, and second, workers without work-hour variation (CV=0). I set the second category as the base category for the empirical analysis. In the next step, I sort all individuals with positive hour variation into population-weighted quartiles. This approach allows me to compare workers from different quartiles of work-hour instability to the base category of workers without hour variation, providing a more meaningful interpretation than an evaluation of work-hour instability at the mean. Male and female workers are sorted separately into quartiles within years to avoid unobserved and time-varying confounders affecting the categorization.

In addition to the baseline strategy, I categorize individuals into quartiles within 2-digit SOC occupations in each year-gender cell.[4] The categorization of individuals within occupations accounts for the possibility that workers are more likely to compare their working conditions with colleagues or workers in similar occupations. For example, one could argue that comparing bricklayers and insurance clerks is not very useful because they work in substantially different occupational environments. On the other hand, comparing insurance clerks and new account clerks, or bricklayers and roofers, seems more plausible as they are subject to very similar working conditions. To illustrate the robustness of my findings, I show the results of both categorizations.

B.3.2 Average Work Hours

Following the two measurement approaches of work-hour instability, I construct two measures of individuals' average work hours: first, by taking the average of self-reported work hours across the last three months and standardizing the average work hours of individuals within year-gender cells. In the second approach, average work hours are standardized within year-gender-occupation cells.

[4] The 22 different 2-digit occupation groups based on the 2010 Standard Occupational Classification (SOC) include: Management Occupations (11-), Business and Financial Operations (13-), Computer and Mathematical Occupations (15-), Architecture and Engineering Occupations (17-), Life, Physical and Social Science Occupations (19-), Community and Social Service Occupations (21-), Legal Occupations (23-), Education, Training and Library Occupations (25-), Arts, Design, Sports and Media Occupations (27-), Health Care Practitioners and Technical Occupations (29-), Health Care Support Occupations (31-), Protective Service Occupations (33-), Food Preparation and Serving Related Occupations (-35), Building and Grounds Cleaning and Maintenance Occupations (37-), Personal Care and Service Occupations (39-), Sales and Related Occupations (41-), Office and Administrative Support Occupations (43-), Farming, Fishing and Forestry Occupations (45-), Construction and Extraction Occupations (47-), Installation, Maintenance and Repair Occupations (49-), Production Occupations (51-), Transportation and Material Moving Occupations (53-).

B.3.3 Mobility Costs

I include two types of mobility costs to account for the fact that human capital is, at least to some part, occupation-specific and not transferable between different occupations (Kambourov and Manovskii, 2009b; Sullivan, 2010). First, switching between occupations is not frictionless because occupations differ in their task content. Second, legal requirements such as degrees, certificates and work experience create additional barriers preventing workers from switching occupations without proper vocational preparation.

To account for mobility costs related to differences in task content between occupations, for example, preparing a meal in a kitchen and laying bricks, I follow previous studies using measures of "task distance" between occupation pairs (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Cortes and Gallipoli, 2018; Robinson, 2018). I use the derived five task categories (physical, analytical, sensory perception, fine motor, and communication) to construct the mean task distance for each occupation. First, the five task categories are standardized based on employment shares in the January 2012 CPS. Next, I combine the five standardized task distance measures of each occupation to construct their 'mean task distance' based on the following Euclidean distance formula:

$$\mu_j(edist5) = \sqrt{dist_{1j}^2 w_1 + dist_{2j}^2 w_2 + dist_{3j}^2 w_3 + dist_{4j}^2 w_4 + dist_{5j}^2 w_5} \tag{B.5}$$

where $dist_{kj} = \frac{task_{kj} - \mu(task_k)}{\sigma(task_k)}$ is the standardized distance of occupation j from the population mean in task category k. I use equal weights ($w = 0.2$) for each of the five different task categories.[5] The mean task distance $\mu_j(edist5)$ of occupation j is equal to λ when there is a change of λ standard deviations in each of the five task distances $dist_{kj}$.

In addition to task-related costs, mobility costs can be occupation-specific but "task-unrelated" (Cortes and Gallipoli, 2018). I measure such costs based on occupations' required vocational preparation adopted from the "O*NET Job Zones". Let us call them 'occupation categories' hereafter to avoid any confusion. As higher occupation categories are associated with a higher level of vocational preparation and a more specific degree, it is intuitive that the loss of occupation-specific human capital is more significant if workers of higher categories switch occupations. Table B.1 shows the category system, including some example occupations for each category.[6]

B.3.4 Occupation Characteristics

Three additional occupation characteristics are added to the model: expected wages, job loss probabilities, and occupations' ability to work remotely. To construct the ex-

[5] As a robustness check, I construct a measure with different weights based on the proportion of explained variation in task content proposed by the factor analysis (see Appendix B.3). Both measures of the mean task distance provide very similar results. All reported results in the body of this study are based on the benchmark measure with equal weights.

[6] Because the occupation codes of the O*NET SOC system are finer compared to the used occupation system in this study, I take the unweighted average of the occupation category values if multiple O*NET occupations are mapped to one occupation.

Table B.1: Occupation Categories from O*NET Job Zones

	SVP Range	**Required Degree**	**Examples**
Category 1	Up to 3 months	Less than high school	dishwashers, landscaping workers, baristas
Category 2	3 months to 1 year	High school diploma	counter clerks, security guards, orderlies
Category 3	1-2 years	Vocational training	barbers, electricians, court reporters
Category 4	2-4 years	Bachelor degree	sales managers, art directors, graphic designers
Category 5	Over 4 years	Graduate degree	lawyers, biologists, astronomers

Notes: The occupation category system is based on the O*NET Job Zones.

pected occupation wages, I use hourly wage data from the earner study of the monthly outgoing rotation groups in the CPS.[7] I use the Consumer Price Index adjustment factors provided by IPUMS to construct a consistent wage series. Reported hourly wages below one and higher than 200 U.S. dollars are censored following Schmitt (2003). One problem of constructing average occupation wages in the CPS is the low number of observations of some occupations for a given year. I overcome this hurdle by constructing a five-year moving average wage series for each occupation. In the last step, the average occupation wages are standardized within year-gender cells. Consequently, the marginal effects shown in Table 3.7 report the change in the predicted probability of occupational mobility when the expected wage rate in occupation j increases by one standard deviation relative to the gender-specific mean in a given year.

To construct the job loss probabilities, I first identify all individuals in the monthly CPS who are unemployed due to involuntary job termination, including “job losers” and those who are “temporarily laid off”. Next, I calculate the proportion of involuntarily unemployed relative to the total workforce within each occupation in a given year. I construct a five-year moving average series of job loss probability for each occupation in an equivalent manner to the expected occupation wages. Finally, all occupation-specific job loss probabilities are standardized within year-gender cells.

I use the binary measure constructed by Dingel and Neiman (2020) to account for differences between occupations’ ability to work remotely. The measure is based on survey responses to selected O*NET “Work Context” and “Generalized Working Activities” questions. These questions relate to the frequency of email communication, the importance of working with heavy machinery, and the exposure to hazardous materials at work. The measure takes a value of one if all tasks can be performed remotely and zero otherwise. I map the O*NET occupations into my balanced occupation panel using crosswalks that assign O*NET SOC codes to Census occupation codes.[8] The binary measure suggests that 112 out of 430 occupations in my panel can be done entirely from home.

[7] If workers are not paid by the hour, they report their weekly earnings instead. To calculate their hourly wage rate, I divide their weekly earnings by their reported “usual hours worked per week”.

[8] I classify occupations in my panel as ‘remote work occupations’ only if all assigned O*NET occupations are also classified as such. I also use a more granular measure provided by del Rio-Chanona et al. (2020) as a robustness check. The results are very similar quantitatively and qualitatively. However, I present only the results of the Dingel and Neiman (2020) measure as interpreting the binary variable is more straightforward.

B.3.5 Control Variables

The control variables for demographic characteristics include four race categories, five education categories, a cubic polynomial of age, marital status, and the number of children in a household. Further, I include three dummy variables for classifying individuals as head of the household, part-time worker, and government worker. In addition, I control for year and month-fixed effects, state-fixed effects based on 51 different Census states, and industry-fixed effects, including 13 different major industries.

B.4 Robustness Checks of the Probit Model Results

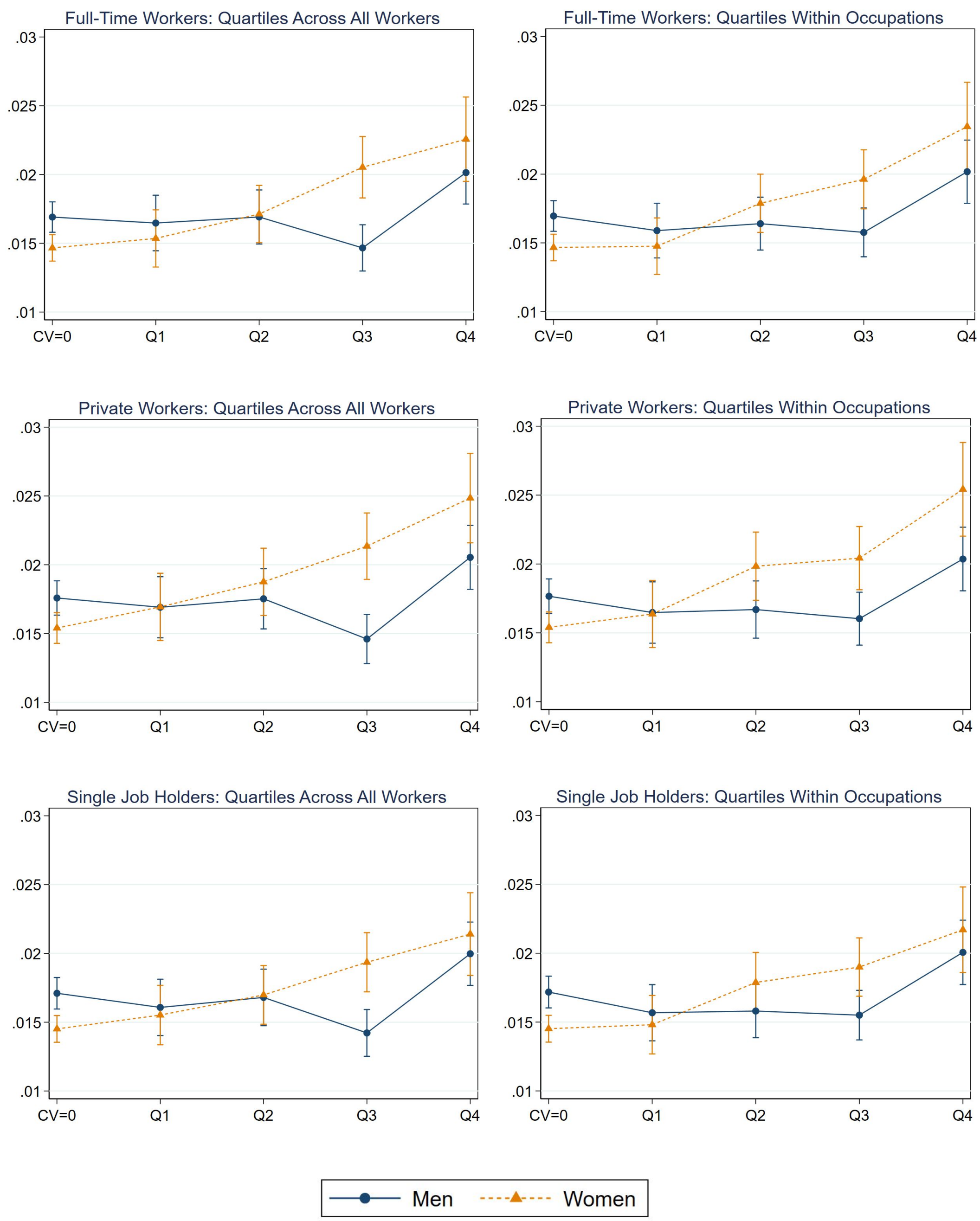

Figure B.1: Predicted Occupational Mobility Rates for Different Types of Workers

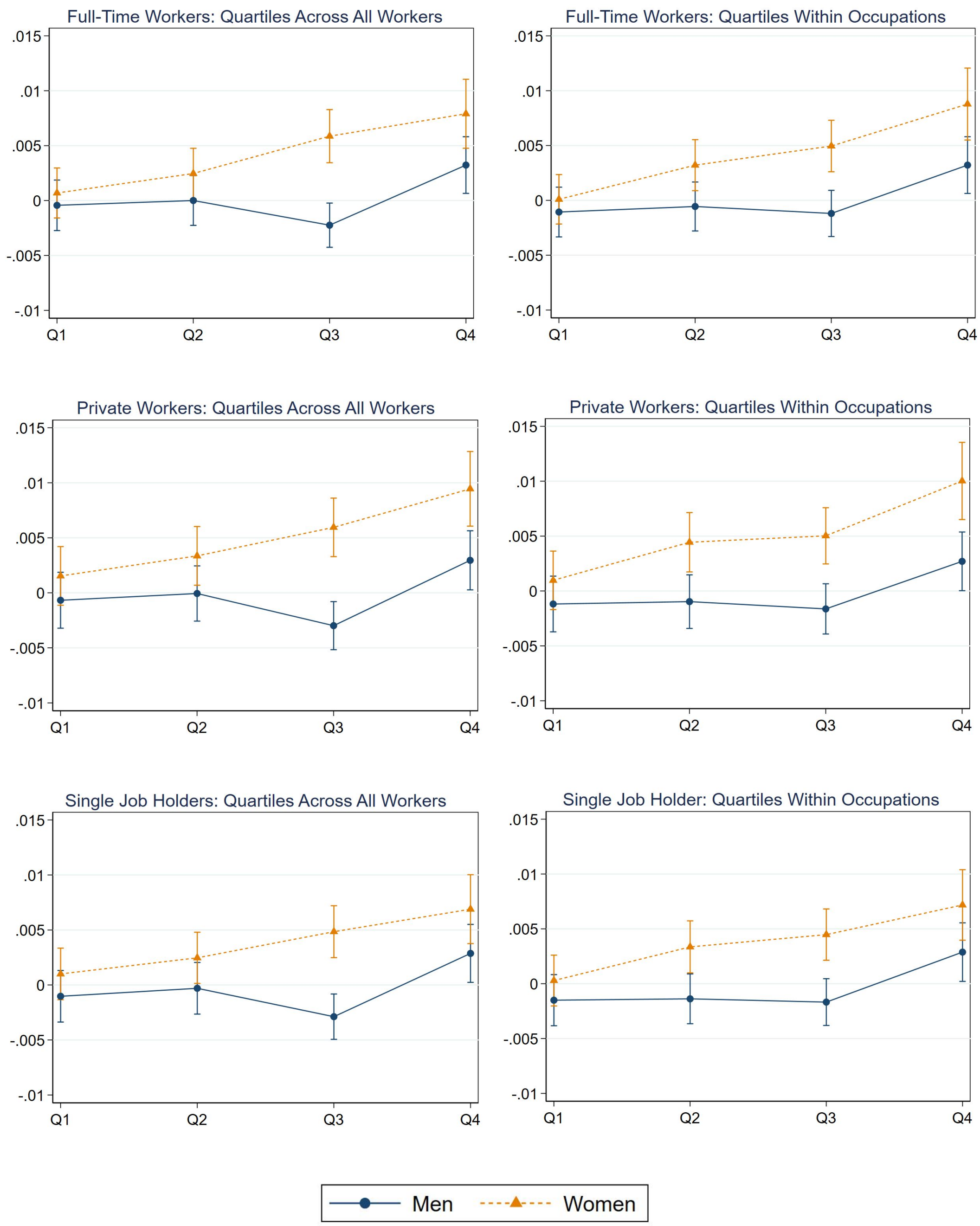

Figure B.2: Marginal Effects of Work-Hour Instability for Different Types of Workers

Table B.2: Entering Control Variables Stepwise for Women

	Entering Occupation Characteristics and Mobility Costs					Entering Other Controls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hour Variation (Baseline: CV=0)								
1. Quartile	0.0015	0.0013	0.0014	0.0015	0.0014	0.0013	0.0013	0.0012
2. Quartile	0.0031***	0.0031***	0.0030**	0.0031***	0.0031***	0.0028**	0.0028**	0.0027**
3. Quartile	0.0051***	0.0051***	0.0049***	0.0050***	0.0051***	0.0052***	0.0052***	0.0052***
4. Quartile	0.0077***	0.0076***	0.0073***	0.0074***	0.0077***	0.0079***	0.0081***	0.0080***
Average Working Hours	-0.0019***	-0.0016***	-0.0016***	-0.0016***	-0.0017***	-0.0023***	-0.0023***	-0.0023***
Occupation Wage		-0.0013***	0.0005	0.0004	0.0027***	0.0022***	0.0012	0.0012
Probability of Job Loss			0.0027***	0.0027***	0.0026***	0.0026***	0.0024***	0.0024***
Remote Work Ability				0.0009	0.0015*	0.0019**	0.0018**	0.0018**
Task Distance					-0.0044***	-0.0042***	-0.0041***	-0.0042***
Year and Month Fixed Effects	√	√	√	√	√	√	√	√
Occupation Categories	X	X	X	X	√	√	√	√
Demographic Controls	X	X	X	X	X	√	√	√
Industry Fixed Effects	X	X	X	X	X	X	√	√
Regional Fixed Effects	X	X	X	X	X	X	X	√

Notes: Robust standard errors are clustered at the individual level and shown in parentheses. Results with ***/**/* are Significant at the 1% 5% and 10% level. Demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household and five education groups. We include 13 dummies for different broad industries and regional fixed effects at the state level.

Table B.3: Entering Control Variables Stepwise for Men

	Entering Occupation Characteristics and Mobility Costs					Entering Other Controls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hour Variation (Baseline: CV=0)								
1. Quartile	-0.0001	-0.0003	-0.0003	-0.0003	-0.0003	-0.0007	-0.0007	-0.0005
2. Quartile	0.0005	0.0004	0.0004	0.0004	0.0004	0.0001	0.0001	0.0002
3. Quartile	-0.0025**	-0.0026***	-0.0026***	-0.0026**	-0.0025**	-0.0026**	-0.0025**	-0.0024**
4. Quartile	0.0032***	0.0028**	0.0028**	0.0029**	0.0032***	0.0030**	0.0032**	0.0033***
Average Working Hours	-0.0033***	-0.0030***	-0.0030***	-0.0030***	-0.0030***	-0.0030***	-0.0030***	-0.0030***
Occupation Wage		-0.0014***	-0.0013***	-0.0023***	-0.0020***	-0.0018***	-0.0019**	-0.0019**
Probability of Job Loss			0.0002	0.0003	0.0006	0.0008	0.0012**	0.0011**
Remote Work Ability				0.0046***	0.0044***	0.0039***	0.0034***	0.0033***
Task Distance					-0.0051***	-0.0048***	-0.0050***	-0.0049***
Year and Month Fixed Effects	√	√	√	√	√	√	√	√
Occupation Categories	X	X	X	X	√	√	√	√
Demographic Controls	X	X	X	X	X	√	√	√
Industry Fixed Effects	X	X	X	X	X	X	√	√
Regional Fixed Effects	X	X	X	X	X	X	X	√

Notes: Robust standard errors are clustered at the individual level and shown in parentheses. Results with ***/**/* are Significant at the 1% 5% and 10% level. Demographic controls include a cubic polynomial of age, categorical variables for the head of household, marital status, class of worker (government or private), number of children in the household and five education groups. We include 13 dummies for different broad industries and regional fixed effects at the state level.

Chapter 4

Within-Occupation Technological Change and Local Labour Markets*

Francesco Roncone†

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† School of Economics, University of Adelaide, 10/12 Pulteney St, Adelaide SA 5000 (e-mail: francesco.roncone@adelaide.edu.au)

Abstract

Why do regions with growing populations in the United States suffer from rising wage inequality? This paper provides a novel explanation by showing the differential effects of directed technological change on worker mobility, employment and wages between local labour markets. The identification strategy is twofold: first, using detailed occupation data, I construct a systematic measure of cognitive-biased technological change. Second, I use an industry shift-share design to estimate the causal effects of the biased technology shocks on the labour market. The results show that the low- and high-skilled working-age population increases in local labour markets with higher exposure to cognitive-biased technological change. Despite the labour-augmenting effects, low-skilled workers experience adverse wage effects and relative employment rate declines. While I do not find a significant effect on the wages of high-skilled workers, the negative impact on low-skilled workers' wages leads to an increase in the college wage premium. The rise in the college wage premium is most pronounced within non-routine cognitive occupations.

Keywords: directed technological change, task demand changes, worker mobility, college wage premium.

JEL codes: **E24, J21, J24, J31, O11.**

4.1 Introduction

Technological change affects workers by automating or complementing the tasks they perform. Task-biased technological change in the second half of the twentieth century systematically replaced routine tasks but complemented cognitive tasks, leading to employment and wage polarization in the U.S. labour market (Autor et al., 2003) as well as within local labour markets (Autor and Dorn, 2013). However, compared to the last episode, new advanced technologies are capable of affecting a much more comprehensive range of tasks and occupations (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Bessen, 2019; Tolan et al., 2021), making it difficult to determine the direction of technological change in the twenty-first century.

At the same time, economists observe a flattening employment growth in non-routine cognitive occupations (Autor and Price, 2013; Beaudry et al., 2014, 2016) and decreasing returns to cognitive ability (Castex and Dechter, 2014), often referred to as the "great reversal" (Beaudry et al., 2016) of the demand for cognitive skills in the 2000s. The increasing relative importance of other skills, such as social skills (see, e.g., Deming, 2017; Aghion et al., 2023) and non-cognitive skills (see, e.g., Edin et al., 2022), is one plausible explanation.[1] Social tasks are complicated to automate as technology does not yet understand the "rules" of such tasks. However, this explanation seems incomplete, given the continuous rise in the supply of cognitive skills in the labour market and the simultaneous (although flattened) increase in relative wages of college-educated workers. Moreover, the college wage premium increase has recently been more substantial in regions that attract comparatively more college-educated workers. This relationship is depicted in Figure 4.1, representing all U.S. states weighted by their working-age population. The existing literature fails to provide a conclusive explanation for the observed regional supply dynamics potentially related to task-biased demand changes.

The core idea of this paper to address this puzzle is to look within occupations. By examining newspaper job advertisements and online job postings, two recent studies conducted by Hershbein and Kahn (2018) and Atalay et al. (2020) find that most changes can be observed within occupations rather than between them. Moreover, the

[1] The term "non-cognitive skills" in the study conducted by Edin et al. (2022) relates to a psychologist-assessed measure of teamwork and leadership skills.

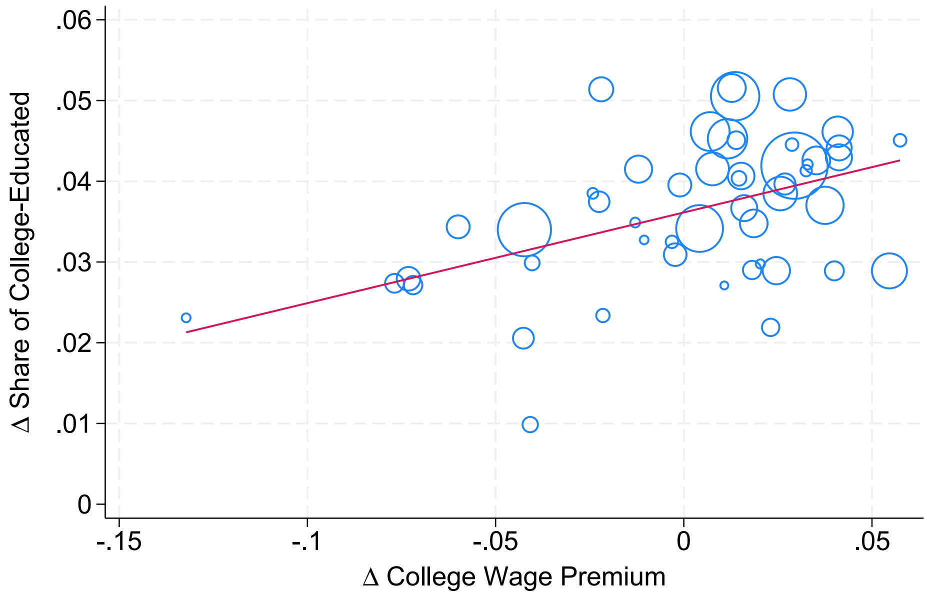

Figure 4.1: Relationship Between the Change in the College-Educated Share and College Wage Premium at State Level: 2006-2017

changes appear to systematically favour cognitive skills consistent with the skill-biased technological change literature (see, e.g., Katz and Murphy, 1992; Autor et al., 2006). Analysing the interaction of skill supply and demand solely based on changes in relative employment shares, consequently, underestimates the true effect of technological change on cognitive skill demand. By using time-varying ability data from the Occupational Information Network (O*NET), I isolate the channel of task changes within occupations between 2008 and 2017. I find that the relative demand for cognitive ability, when measured within occupations rather than through changes in relative employment shares, increases in all local labour markets but with substantial variation between them. Next, I use this finding by exploiting the exogenous spatial variation in cognitive-biased shock exposure between local labour markets using an industry shift-share design (Bartik, 1991; Borusyak et al., 2022). The results show that higher exposure crowds in both low-skilled (high-school or no degree) and high-skilled (college degree) workers but does not affect middle-skilled (some college experience) workers. The heterogeneous and potentially imperfect supply adjustments have adverse wage effects on low-skilled workers, increasing the college wage premium in regions with higher exposure to cognitive-biased task demand changes. Moreover, the share of low-skilled workers declines in more exposed regions as they are systematically crowded out of non-routine cognitive occupations (business, management, and science occupations). In the medium term, the crowding-out effect is mirrored by higher rates of labour force exit of low-skilled workers but is not associated with higher unemployment rates.

A key feature of this study is the approach of measuring task changes within occupations. This approach is grounded on the theoretical model by Acemoglu and Restrepo (2018, 2019), according to which the change in the task input mixture depends on two factors: first, the automation of tasks, and second, the emergence of new tasks whereby new tasks are assumed to be cognitive-intensive and to complement high-skilled workers. Based on this notion, I draw on the updated O*NET ability rating procedure (Fleisher and Tsacoumis, 2012). Every year, trained job analysts evaluate occupations' required abilities based on various measures of occupations' work context, knowledge requirement and task content. The essential feature of the updated rating procedure used in this study is that job analysts take into account detailed information on changes in the task content of occupations compared to their last rating. The possibility of tracking back changes within occupations enables them to consider the automation of tasks and the emergence of new tasks when evaluating their up-to-date ability requirements. To make use of the multidimensional O*NET ability data, I conduct a 'pooled factor analysis' for the years 2008 and 2017, building on but extending the approaches of Ingram and Neumann (2006) and Robinson (2018). Including two years into the factor analysis enables me to compute year-specific composite task scores (factors) for the 430 detailed occupations under scrutiny. Based on the cognitive and non-cognitive (manual, physical, coordination and communication) task intensity scores, I construct a novel measure that captures the change in the cognitive task bias within occupations.

Very few researchers attempted to identify the recent effects of task changes within occupations on the U.S. labour market. Although their findings are illuminating, most studies mainly remain on the demand side, precluding, to a large extent, labour mobility and the supply of skills (see, e.g., Atalay et al., 2020; Freeman et al., 2020). On the other hand, studies that consider both demand and supply changes usually operate at the occupation level. Ross (2017) uses different O*NET databases between 2003 and 2014 to construct a panel of task content, finding that the wage returns to cognitive tasks increased while the return to routine tasks declined over the same period. Cortes et al. (2021) focuses instead on long-distance changes in occupations' task content using the Dictionary of Occupational Titles (DOT) 1977 in combination with O*NET 2016 databases in a similar fashion as Autor et al. (2003).[2] Two other studies draw on a unique individual-level data set from West Germany. Spitz-Oener (2006) finds that within-occupation task changes can explain a significant part of educational upgrading since the 1970s. Using the same dataset, Antonczyk et al. (2009) examines the impact of within-occupation task changes on the German wage structure, finding that task developments within occupations are not associated with rising wage inequality at the aggregate level. My study significantly expands the existing literature on within-occupation changes by going beyond an aggregate or occupation-level analysis and studying worker adjustments across local labour markets covering the entirety of the United States.

In contrast to studies conducted at the aggregate level, analysing the differential growth of wages and wage inequality between local labour markets requires the consideration of the mobility of labour. Despite the traditional conception that high-skilled workers are more mobile than low-skilled workers (Topel, 1986; Bound and Holzer, 2000; Notowidigdo, 2020), my study shows that both high-skilled and low-skilled workers are equally drawn into local labour markets with increasing cognitive task demand. The consequent adverse effects on low-skilled workers are consistent with a study by Topel (1994), finding that technological change favours disproportionately high-skilled workers and increases wage inequality in regions where the "labour force quality" does not adjust to the differential changes in skill demand. In line with their results, I find that the downward pressure on low-skilled workers' wages causes a differential increase in the college wage premium by 2.1 log points measured between the 80th and 20th percentile of exposure to cognitive-biased technological change. Another related study conducted by Beaudry et al. (2010) analyses the impact of computer adoption across different metropolitan areas on the returns to skills but does not find significant support for their hypothesis that the uncovered wage equalisation effects across local labour markets between 1980 and 2000 are driven by changes in relative skill supply.

[2] The study conducted by Cortes et al. (2021) focuses, in particular, on the growing importance of social task content and the increasing tendency of women to sort themselves into social-task-intensity-increasing occupations.

Finally, my study builds upon and closely relates to Autor and Dorn (2013). Similar to the observed mobility patterns in my study, the authors also find relative population growth of both highly educated (college or advanced) and the least educated (high-school or no degree) workers compared to workers with some college experience in regions exposed to more rapid technological change. However, one has to be careful in comparing my results with Autor and Dorn (2013) as well as with other studies' results, as the existing literature focuses either on skill demand changes due to shifts in employment shares or based on start-of-analysis skill or task endowments. In contrast, my technological change measure captures a more profound dimension by reflecting task changes within occupations. This strategy is more appropriate to analyse the contemporary labour market in which technological change affects a considerable variety of tasks (see, e.g., Brynjolfsson and McAfee, 2014) and is more concentrated within occupations (see, e.g., Atalay et al., 2020) in the twenty-first century. My results confirm this assumption by showing that cognitive-biased task changes within occupations are a powerful predictor of population growth, skill composition changes, and wage inequality between skill groups.

The remainder of this paper is organised as follows: The next section describes in detail the features of the O*NET ability rating procedure and how they are used to construct the measure of within-occupation technological change. In addition, it illustrates the systematic task changes within occupations in the twenty-first century. Section 4.3 describes the identification strategy of exploiting the spatial variation in industrial specialisation and national employment shares within industries. Section 4.4 documents the main results regarding differential population growth, skill composition changes and the rise in the college wage premium between local labour markets. Section 4.5 concludes this study and discusses relevant policy implications.

4.2 Measuring Task Changes Within Occupations

Occupations are the natural dimension to measure the impact of technology on task demand, providing deeper insights compared to changes in relative employment shares between occupations. For example, the cashier job has changed substantially in the last ten to fifteen years due to the introduction of self-service checkouts. However, the invention and implementation of self-service checkouts have not completely automated the job of cashiers. Instead, new tasks now include overlooking the self-service checkout and helping customers occasionally with the new technology. This example is similar to the earlier invention of the automatic teller machine, which led to transforming the bank teller job in a way that oriented more toward customer service. Despite the general conception that technological change has become more concentrated within occupations in the twenty-first century (see, e.g., Brynjolfsson and McAfee, 2014), a systematic approach to measuring technology's impact on task demand within occupations is barely available It is one objective of this paper to close this gap by proposing a novel measure of directed technological change based on the 2011 updated O*NET ability rating procedure (Fleisher and Tsacoumis, 2012).

4.2.1 The O*NET Ability Rating Procedure

The Occupational Information Network (O*NET) regularly updates occupations along different O*NET domains, including Education and Training, Knowledge, Work Activities, Work Context, Work Styles, Skills and Abilities. The standard approach in the existing literature is to characterize occupations by selecting single measures that arguably correspond well to a particular task dimension (e.g. using "finger dexterity" to proxy routine manual tasks) or constructing composite measures by combining different occupation characteristics of a given O*NET database. Such an approach is unsuitable for this study as the objective is to identify task changes within occupations over time. The essential criterion regarding the data selection to achieve this goal is that all occupations are updated in a consistent manner. However, using time-varying O*NET data in longitudinal studies is problematic as the multi-method O*NET data collection program makes comparisons between occupations as well as within occupations over time difficult. Occupation ratings obtained by surveying employees in different firms are frequently intermingled with ratings from job experts, whereby the rating procedure often changes between rating cycles, even within the same occupation. An exception is the O*NET ability domain, which is based on a systematic rating procedure described in the following paragraphs.

Abilities are "relatively enduring attributes of an individual's capability for performing a particular range of different task" (Donsbach et al., 2003). Due to the complexity of the ability items, the ability rating procedure has been consigned to specialised analysts selected based on their education and job experience (Tippins and Hilton, 2010). The selected job analysts are further trained by the Human Resources Research Organization (HumRRO) to guarantee a consistent evaluation of occupations' ability requirements: first, for a given ability across occupations ("interrater agreement"), and second, for the relative importance of different abilities within occupations ("interrater reliability"). The interrater principles include the computation of standard errors and other consistency parameters - for example, the Shrout and Fleiss (1979) intraclass correlations coefficients - for maintaining a reliable measurement both regarding the ordering of occupations and the relative distance between occupations by rating occupations' abilities on an importance scale between 1 (not important) and 5 (extremely important). I choose to work with the importance rating of abilities rather than with their level rating because the level anchors often relate to arbitrary examples of specific occupations instead of relating to uniform anchors.[3] As documented by Handel (2016), this leads in many cases to a violation of the "equal interval assumption" between the anchors of the level rating scale. The arbitrary choice of scale anchors is also mirrored by higher standard errors and lower values in consistency parameters for ability ratings (see, Noble et al., 2003). On the contrary, the more transparent anchors of the importance rating (from "not important" to "extremely important") are especially useful for a reliable measurement of changes in occupation distances, which is crucial for this study.

The key feature of the ability rating procedure exploited in this study to measure changes within occupations was introduced in 2011 (rating cycle 12). Before the establishment of the updated rating procedure (cycles 1-11), occupations were only partly rated by trained job analysts but partly by so-called "legacy analysts" based on sources

[3] For example, related to the ability "critical thinking", one of the level anchors shows the example "Write a legal brief challenging a federal law" for a level of 6 from a range between 0 and 7. Clearly, the mentioned example does not relate to the task content of many occupations, making it difficult to use it for orientation when evaluating their abilities. Nonetheless, the level and importance ratings are highly correlated with an average correlation of 0.92 (Handel, 2016). Therefore, the results presented in this study are insensitive to using either the level or importance rating scale.

such as the DOT - the predecessor of the O*NET. As discussed above, this hampers comparing the same abilities between different occupations in earlier released databases. From rating cycle 12, as the vast majority of O*NET occupations had been rated at least once by trained job analysts in the previous cycles, additional information on changes in occupations' most important tasks as well as other relevant changes in occupation characteristics compared to their last rating is made available to the job analysts. For example, in step 2 of the 7-step rating procedure, job analysts evaluate information on relevant core and supplementary tasks related to a specific occupation.[4] More precisely, all tasks that reach the minimum relevance or importance threshold for that occupation are presented to the raters. In addition, new tasks are highlighted, while tasks that do not reach the minimum threshold anymore are crossed out. Only once they have reviewed all current occupation information as well as all relevant changes between the previous and current rating cycle do analysts enter their final importance rating. The dynamic nature of the new rating procedure enables job analysts to consider both the automation of job tasks and the emergence of new tasks - the two critical elements for the evolution of occupations Acemoglu and Restrepo (2018, 2019).

4.2.2 Factor Analysis

In this study, I use the O*NET ability data from the databases 16.0 (July 2011) and 25.0 (August 2020). Before making systematic use of the data with factor analysis, I undertake two data-preparatory steps. First, I construct a balanced occupation panel in the American Community Survey (ACS) that better reflects the contemporary labour market compared to previously constructed occupation panels (see, e.g., Meyer et al., 2005; Dorn, 2009). Second, I assign the O*NET ability data to my occupation panel by taking the weighted average of the finer O*NET occupations based on employment counts from the 2008 Occupation and Employment Statistics (OES). The two steps are

[4] For each occupation, the provided information ("stimulus material") in the 7-step rating procedure includes 1) the mean importance of Generalized Work Activities (GWAs) with (1) a rating ≥ 3, and (2) that require the evaluated ability to perform the GWA; 2) the mean rating of Work Context (WC) statements that (1) have a rating ≥ 3, and (2) require the evaluated ability to work in that context; 3) the mean importance of the ten most important Knowledge domains with a mean importance rating ≥ 3; 4) tasks classified into three categories (core tasks, supplementary tasks and non-relevant tasks) based on survey answers of at least 15 job incumbents on their relevance and importance. All relevance and importance ratings are based on a scale from 1 to 5.

described in more detail in Appendix C.1. The occupation crosswalk is documented in Appendix C.2.

There are two approaches for using the 52 different O*NET abilities assigned to each occupation in the occupation panel: first, constructing composite task measures using a subset of preselected abilities in a principal component analysis (PCA), and second, considering all abilities simultaneously using factor analysis (FA). As pointed out by Yamaguchi (2012), it seems impossible to determine which approach is "better" as they rely on completely different assumptions.[5] The first approach assumes that a subset of abilities is only relevant for explaining one particular task dimension. For example, abilities that are useful for explaining the cognitive task intensity of occupations do not explain any variation of other task dimensions. This requires prior knowledge of the assignment of abilities to tasks, which appears to be a limitation given the complex nature of some of the ability measures. The second approach relies on the assumption that all abilities potentially contain valuable information on multiple underlying task constructs. This paper draws on the second approach, allowing me to exploit all dimensions of variation prevalent in the O*NET ability data.

Because only a proportion of O*NET occupations (107 on average) are updated in each O*NET rating cycle, most occupations differ in the year of their latest update in a given database. To overcome this hurdle, I centre each of the two O*NET databases (16.0 and 25.0) at the midpoint of the occupations' latest updates following Freeman et al. (2020). Based on this approach, the two data files represent occupations' ability requirements of 2008 and 2017. As the key target of my study is to analyse task changes within occupations, I assign the ability ratings of the two different years to the same employed working-age population, using the American Community Survey (ACS) 2008.[6] This is equivalent to treating occupations equipped with 2017 ability scores as different occupations from 2008 while holding the occupation distribution constant. This approach yields occupation-year-specific factor scores relative to the 2008 population-weighted mean scores. Another method would be to conduct two

[5] The first approach is used, for example, by Autor et al. (2003), Yamaguchi (2012), Caines et al. (2017), Guvenen et al. (2020) and Aghion et al. (2023). The second approach is used by Ingram and Neumann (2006), Poletaev and Robinson (2008) and Robinson (2018).

[6] Self-employed, workers employed in military occupations and unpaid family workers are excluded.

Table 4.1: Highest O*NET Ability Factor Loadings and Highest Ranked Occupations

Highest Factor Loadings		*Highest Ranked Occupations in 2008 by Factor*	
*O*NET Ability*	*Loading*	*Occupation*	*Factor Score*
Factor 1: Physical Intensity			
Stamina	0.904	1. Dancers and choreographers	4.19
Gross Body Coordination	0.889	2. Structural iron and steel workers	2.28
Trunk Strength	0.850	3. Recreation and fitness workers	2.27
Extent Flexibility	0.839	4. Masons and reinforcing iron workers	2.20
Dynamic Strength	0.838	5. Practical and vocational nurses	2.14
Factor 2: Cognitive Intensity			
Deductive Reasoning	0.882	1. Astronomers and physicists	2.79
Problem Sensitivity	0.876	2. Architects (except naval)	2.71
Inductive Reasoning	0.863	3. Environmental engineers	2.31
Speed of Closure	0.838	4. Physical scientists, n.e.c.	2.05
Flexibility of Closure	0.838	5. Dentists	2.04
Factor 3: Coordination Intensity			
Night Vision	0.942	1. Aircraft pilots and flight engineers	4.94
Peripheral Vision	0.940	2. Taxi drivers and chauffeurs	4.28
Glare Sensitivity	0.906	3. Bus drivers	4.24
Spatial Orientation	0.901	4. Ship and boat captains and operators	3.86
Sound Localization	0.891	5. Motor vehicle operators, n.e.c.	3.72
Factor 4: Communication Intensity			
Speech Recognition	0.658	1. Announcers	3.18
Speech Clarity	0.631	2. Telephone operators	2.86
Time Sharing	0.607	3. Communication equipment operators, n.e.c.	2.64
Oral Expression	0.565	4. Switchboard operators	2.61
Oral Comprehension	0.548	5. Bailiffs, correctional officers, and jailers	2.42
Factor 5: Manual Intensity			
Finger Dexterity	0.661	1. Data entry keyers	4.35
Wrist-Finger Speed	0.532	2. Dentists	3.55
Perceptual Speed	0.523	3. Optometrists	3.11
Control Precision	0.438	4. Aircraft pilots and flight engineers	3.03
Manual Dexterity	0.419	5. Medical and dental laboratory technicians	2.91

Notes: The presented factor scores are standardized, showing occupations' standard deviation from their population-weighted mean of 2008. The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.96.

separate factor analyses for 2008 and 2017. However, this would lead to different factor loadings between the two years, making a direct comparison of year-specific factor scores of occupations implausible.

Table 4.1 summarises the factor analysis output. The derived factors are by construction orthogonal and represent different dimensions of task input.[7] Five factors selected based on the Kaiser-Rule that their eigenvalue must be greater than one (Kaiser, 1960) explain 90% of the total variation of the 52-dimensional O*NET ability data. The factor with the highest explanatory power (27%) is related to physical abilities such as body strength and flexibility. The second factor (26%) reflects the cognitive intensity of occupations with problem-solving and reasoning abilities as the highest factor loadings. The third factor (24%) is associated with sensory perceptional abilities that are important for coordination. The two other factors provide comparatively less additional explanatory power with 7% each. These two factors can be categorised as communication and manual task intensity. I additionally check the highest-ranked occupations of each factor to confirm the plausibility of the selected factor definitions. For example, dancers, fitness workers, and construction workers rank highest on physical intensity, while physicists, architects, and engineers have the highest cognitive intensity scores.

Four of the five factors which are related to physical, cognitive, coordination and manual intensity are in line with the four task dimensions derived by Ingram and Neumann (2006) and Robinson (2018) using data from the DOT. Although the computed factors cover various dimensions, it is worth mentioning that they probably do not represent all relevant task dimensions in the labour market. Especially social skills, which have received much attention in recent research studies (see, e.g., Deming, 2017; Cortes et al., 2021; Aghion et al., 2023), are seemingly not directly captured by the five factors due to the lack of underlying data on social skills in the O*NET ability domain. Although the O*NET skill domain provides different measures related to social skills, such as “Social Perceptiveness” and “Coordinate or Lead Others”, skills are only recently measured in a similar consistent manner as abilities. This prevents me from including skill measures in the factor analysis, as the identification strategy relies upon

[7] The orthogonality assumption is achieved by applying the principle factor method and a “varimax rotation” of factors (Fabrigar et al., 1999; Costello and Osborne, 2005).

the consistency of the measurement of abilities between the two chosen databases. Despite the non-inclusion of social skill measures, it is well-known that leadership skills, often associated with social skills, are highly correlated with general cognitive abilities. Therefore, the cognitive intensity factor presumably captures partly social task intensity. Moreover, the communication intensity factor mainly captures oral communication abilities. While such abilities are crucial to performing some social tasks, the communication task intensity of occupations should not be confused with their social task intensity, as social skills are not directly observed in the underlying data.

4.2.3 Cognitive-Biased Task Changes Within Occupations

In this section, I document occupations' task intensity changes between 2008 and 2017. To get a better understanding of the relative importance of task changes within occupations compared to task changes between occupations due to shifts in employment shares, I decompose the measured task changes by using the following equation:[8]

$$\overline{TI}_{i,2017} = \overline{TI}_{i,2008} + \sum_{k=1}^{K} \theta_{k,2008}(\widetilde{TI}_{i,k,2017} - \widetilde{TI}_{i,k,2008}) + \sum_{k=1}^{K} (\theta_{k,2017} - \theta_{k,2008})\widetilde{TI}_{i,k,2017} \quad (4.1)$$

In equation 4.1, the weighted average task intensity i in 2017 is equal to the average task intensity in 2008, adjusted by the within-occupation task intensity changes and occupations' shifts in relative shares of total working hours between 2008 and 2017. Therefore, $\widetilde{TI}_{k,2008}$ and $\widetilde{TI}_{k,2017}$ are the year-specific task intensities of occupation k, and $\theta_{k,2008}$ and $\theta_{k,2017}$ are the corresponding 'effective employment shares'.

Table 4.2 shows a systematic trend of cognitive-intensity-increasing labour demand between 2008 and 2017. On average, the cognitive intensity of the U.S. labour force increased by 0.076 units of standard deviation compared to the weighted mean of the workforce in 2008.[9] Task changes within occupations account for almost half of the

[8] The decomposition shown in equation 4.1 is used by Atalay et al. (2020).

[9] To increase the ease of interpretation of the measured changes in the standardised factors (task intensities), one can evaluate them relative to their 75/25 population-weighted percentile values: cognitive [-0.81:0.81]; physical [-0.86:0.80]; manual [-0.73:0.77]; communication [-0.81:0.68]; coordination [-0.62:0.41].

Table 4.2: Task Intensity Changes by Task-Based Occupation Groups: 2008-2017

		Δ ***Non-Cognitive Task Intensities***				
Occupation Group	Δ ***Cognitive Task Intensity***	*All Non-Cognitive*	*Physical*	*Coordination*	*Inter-personal*	*Manual*
Total	0.076	-0.134	0.071	-0.083	-0.249	-0.274
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Within	0.036	-0.114	0.066	-0.052	-0.233	-0.236
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Between	0.040	-0.020	0.006	-0.031	-0.015	-0.037
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: The task intensity changes refer to changes in the deviation from the mean score of the self-constructed occupation panel (430 occupations) measured in standard deviation units. Non-cognitive task intensity changes are the unweighted average changes of the physical, coordination, communication and manual tasks. Occupations are categorized into task-based groups following Acemoglu and Autor (2011) and Autor and Dorn (2013). Occupations are weighted by the provided population weights of the American Community Surveys 2008 and 2017 multiplied by yearly working hours. Excluded are all self-employed individuals, those who work in military occupations, or are younger than 16 or older than 64 years. Standard errors are shown in parentheses.

total cognitive intensity increase. The relative contribution is approximately in line with Autor et al. (2003), which compares job characteristics between the DOT of 1977 and the updated DOT version of 1991. On the other hand, the average importance of non-cognitive task input declined by 0.134 units of standard deviation, with more than 80 per cent of the decrease caused by within-occupation changes. This result is closer to a more recent study by Atalay et al. (2020), which analyses changes in occupations' task content based on job advertisements. Among all non-cognitive task intensities, the most substantial decreases are associated with communication and manual abilities.

The demand for coordination-intensive tasks decreased on average but only by one-third of the magnitude of communication and manual tasks. This observation aligns with the view that machines and robots cannot yet successfully replace visual and perceptional abilities. Such abilities have particular importance for navigating motor vehicles, for example. However, it can be expected that the accelerating technological progress in autonomous driving will soon challenge specialised workers in this task domain. The most surprising finding of Table 4.2 is the increased importance of physical task content. One plausible explanation could be that employers reassign workers from communication and manual tasks to more physically intensive tasks as they are less susceptible to automation. This finding is in line with Ingram and Neumann (2006) showing that the return to physical tasks increased over the last decades.

Following the conception of Acemoglu and Autor (2011), occupations can be defined as bundles of tasks. To put more structure on the observed task changes within occupations, let us consider only two bundles of tasks that can characterise each occupation: cognitive and non-cognitive. While the cognitive task intensity is derived from the factor analysis, the four remaining task dimensions can be considered non-cognitive, including physical, coordination, communication and manual tasks. One can define occupation k's 'non-cognitive task intensity' as

$$\widetilde{NCTI}_{k,t} = \frac{1}{4}\sum_{i=1}^{4}\widetilde{TI}_{k,i,t} \tag{4.2}$$

whereas workers' time spent on cognitive and non-cognitive tasks may change over time due to task automation and the emergence of new tasks (Acemoglu and Restrepo, 2019). Recall that task automation and the emergence of new tasks are directly integrated into the underlying ability rating procedure presented in Section 4.2.1. Related to this intuition, occupation $k's$ cognitive bias of task changes can be defined as

$$\Delta WOCB_{k,2017} = (\widetilde{CTI}_{k,2017} - \widetilde{CTI}_{k,2008}) - (\widetilde{NCTI}_{k,2017} - \widetilde{NCTI}_{k,2008}) \tag{4.3}$$

where $\Delta WOCB_{k,2017}$ is the change of the within-occupation cognitive bias that can be decomposed into a 'direct effect' and a 'replacement effect'. The direct effect is occupation $k's$ change in cognitive task intensity ($\Delta\widetilde{CTI}$). The replacement effect is $k's$ change in non-cognitive task intensity ($\Delta\widetilde{NCTI}$). By construction, the bias is zero if both effects go in the same direction with the same magnitude. However, if the estimated increase in cognitive intensity is larger than the increase in non-cognitive intensity (or if the non-cognitive intensity decreases), task changes within occupation k will be positively cognitive-biased.

Table 4.3 shows the occupations with the most substantial changes in cognitive task bias. While Panel A shows occupations with the largest increase and decrease

Table 4.3: Occupations with the Largest Increases and Decreases in Within-Occupation Cognitive Bias Between 2008 and 2017

Largest Increases		*Largest Decreases*	
Occupation	*Change*	*Occupation*	*Change*
A. Total Cognitive Bias			
Construction laborers	1.601	Library assistants, clerical	-0.850
Graders and sorters, agricultural products	1.151	Office machine operators, exc. computer	-0.716
Maids and housekeeping cleaners	1.096	Ushers, lobby attendants, ticket takers	-0.667
Cabinetmakers and bench carpenters	1.074	Lodging managers	-0.653
Public relations managers	0.920	Industrial/refractory machinery mechanics	-0.643
B. Direct Effect			
Graders and sorters, agricultural products	1.359	Parking attendants	-0.926
Maids and housekeeping cleaners	1.263	Office machine operators, exc. computer	-0.869
Construction laborers	1.257	Environmental engineers	-0.712
Embalmers and crematory operators	1.155	Automotive glass installers	-0.697
Photographic process workers	0.805	Industrial/refractory machinery mechanics	-0.684
C. Replacement Effect			
Technical writers	0.479	Public relations managers	-0.675
Atmospheric and space scientists	0.438	Cabinetmakers and bench carpenters	-0.661
Security and fire alarm systems installers	0.432	Computer and information systems managers	-0.615
Door-to-door sales/news/street vendors	0.431	Environmental engineers	-0.597
Advertising sales agents	0.409	Coin/vending/amusement machine repairers	-0.573

Notes: The change in the occupation-specific cognitive bias is calculated as the direct effect minus the replacement effect following equation 4.3. The changes are measured in units of standard deviation from the occupation-weighted mean 2008. Based on the updated ability rating procedure, 15 out of 430 occupations of my self-constructed panel have not been re-evaluated. Consequently, their change in cognitive bias is expected to be equal to zero.

in total cognitive bias, Panels B and C show occupations with the largest direct and replacement effects changes. Panel A shows that construction labourers, graders and sorters of agricultural products, maids and housekeeping cleaners benefited the most from cognitive-biased task changes. On the other hand, library assistants, office machine operators, ushers, lobby attendants and ticket takers experienced the largest decreases in the measured cognitive task bias. Only 133 out of 430 occupations experienced a decline in cognitive task bias, confirming the general nature of task changes within occupations highlighted in Table 4.2.

A more systematic picture of cognitive-biased task changes within occupations can be obtained from Figure 4.2. The red bar shows the standardized change in within-occupation cognitive task intensity (direct effect), and the green bar illustrates the within-occupation change in non-cognitive task intensity (replacement effect) averaged

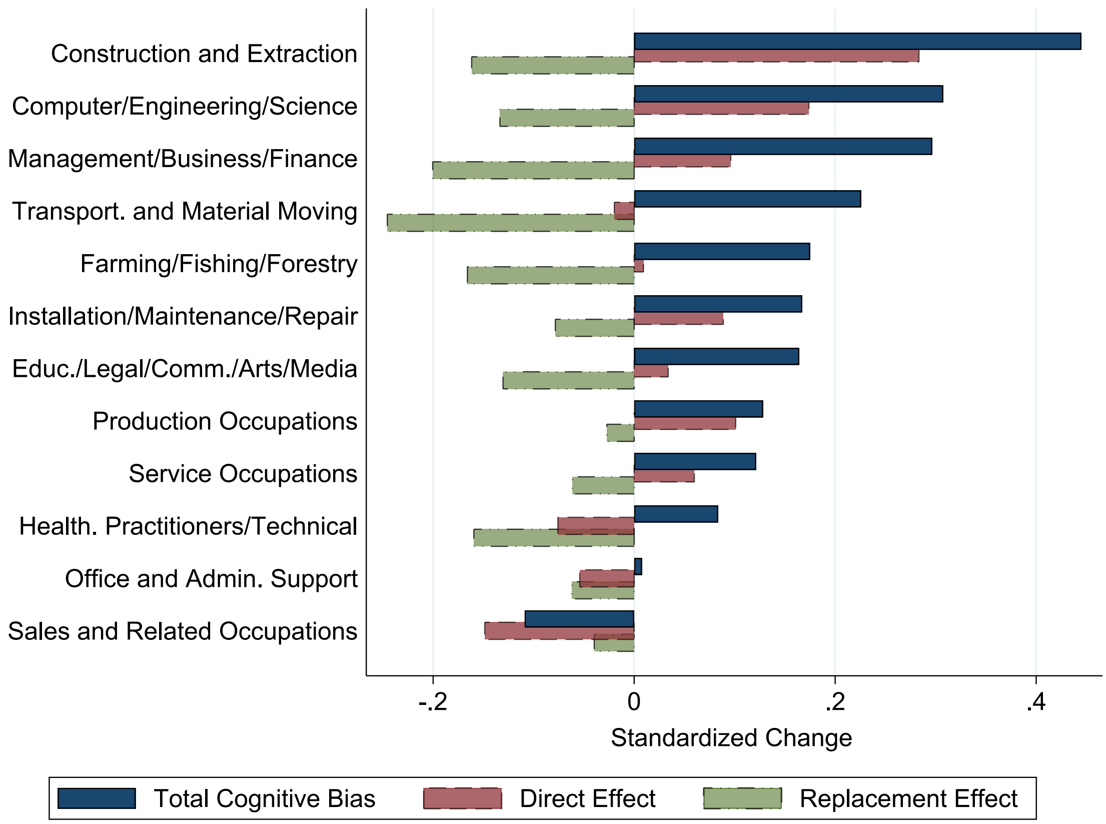

Figure 4.2: Within-Occupation Cognitive and Non-Cognitive Task Intensity Changes by SOC Intermediate Aggregation Occupation Groups

within SOC Intermediate Occupation Groups. The direct effect is most substantial for construction and extraction occupations and computer, engineering and science occupations. On the other hand, the replacement effect is most dominant in transportation, material-moving, management, business, and finance occupations. The blue bar represents the total change in cognitive bias within occupations. Notably, the total cognitive task bias change is positive for all occupation groups except for sales occupations. Moreover, Figure 4.2 illustrates that the growth variation in cognitive task bias is substantial even between aggregated occupation groups. The observed occupation heterogeneity is a crucial element of my identification strategy, described in the next section.

4.3 Data and Identification Strategy

Studying local labour markets requires a large sample size to represent the segmented workforce accurately. My analysis draws on the IPUMS American Community Survey

(ACS) 1% population samples (Ruggles et al., 2023). To increase the sample size, I make use of the combined ACS 3% sample of 2005-2007 and the ACS 5% sample of 2015-2019. The pooled samples match the two focal points of the constructed task intensity measures obtained from the O*NET ability data as accurately as possible. The start-of-analysis sample of 2005-2007 does not perfectly match the start-of-analysis task intensity measures for 2008. However, the 2005-2007 population sample is preferred over the 2007-2009 sample as the latter coincides with the direct effects of the financial crisis. This could lead to measurement error and biased estimates due to the related short-term labour market fluctuations, which are not the focus of this study.

The underlying sample comprises the U.S. working-age population aged 16-64, excluding individuals who are part of "institutional group quarters" (e.g. mental institutions and prisons) or categorized as unpaid family workers. In addition, workers employed in military occupations are excluded as the O*NET does not provide occupation data for military occupations. Labour supply is measured by multiplying individuals' weeks worked in the last twelve months by their reported weekly working hours. To construct the analysis weights of the employed workforce, I multiply ACS sampling weights by the effective labour supply units. For the computation of wages and the college wage premium, I restrict the sample to 'full-time year-round workers' who worked at least 35 hours a week on average and not less than 48 weeks (including paid time off) during the last twelve months.[10] The yearly pre-tax wage and salary incomes used for constructing the wage series are top-coded based on state-specific IPUMS top codes. Hourly wages below the first percentile of the hourly wage distribution are set equal to the first percentile. All wages are adjusted to constant 2010 U.S. dollars.

4.3.1 Public Use Microdata Areas (PUMAs)

In the American Community Survey, local labour markets can be approximately defined by the boundaries of Public Use Microdata Areas (PUMAs).[11] PUMAs represent

[10] Between 2008 and 2018, the ACS reports individuals' weeks worked in intervals. I centre the two intervals, 48-49 and 50-52, at their midpoint for calculating hourly wages. Including individuals who worked less than 48 weeks a year would yield much less precise wage estimates as the intervals become much coarser. Therefore, my wage analysis is restricted to full-time year-round workers.

[11] My study includes all 50 US states, including Alaska, Hawaii, and the District of Colombia. Puerto Rico and island areas that do not reach sufficient population counts are excluded from my analysis.

the smallest identifiable regional units, are state-dependent and follow the boundaries of county groups but are split into multiple units if a single county exceeds 200,000 residents (Coggins and Jarmin, 2021). A well-known challenge for making direct use of PUMAs is the fact that they are delineated for each decennial Census (see, e.g., Dorn, 2009) depending on changes in their population sizes. To address the issue of time-varying PUMA boundaries, IPUMS created a consistent panel of 1,078 PUMAs from the Census 2000 onward. The panel is constructed by aggregating 2000 Census PUMAs such that they align closely with aggregated 2010 Census PUMAs "within a 1% population mismatch tolerance". The new computational aggregation algorithm used for the construction of consistent PUMAs marks a substantial improvement. On the contrary, the previous method relied on researchers who visually identified boundaries and "hand-selected" sets of PUMAs that appeared to be closely aligned with each other.

The crucial advantage of using a consistent PUMA panel linked with ACS data is the accurate and consistent assignment of housing units to regional units, as the household locations are directly recorded by the Census Bureau when conducting the survey. In a more indirect approach, researchers often assign smaller regional units from survey data to self-constructed consistent "labour market areas" (Tolbert, 1987; Tolbert and Sizer, 1996) or "commuting zones" (Dorn, 2009; Autor and Dorn, 2013; Autor et al., 2013). As pointed out by Greenland et al. (2019), this contains a risk of substantial measurement error as the identified regional units (for example, counties or PUMAs) often overlap with multiple units of the self-constructed local labour markets. On the other hand, commuting zones are a better representation of local labour markets in areas that are only sparsely populated because the delineation of consistent PUMA boundaries depends, among others, on areas' population sizes. Consequently, three sparsely populated states (Idaho, Montana and South Dakota) cannot be split into more than one consistent PUMA. On the other hand, the highest number of PUMAs can be found in the state of New York (123). PUMAs in the centre of major cities such as New York or Boston cover only small geographical areas. Therefore, they may not always accurately represent the typical concept of local labour markets. The only way to address this issue would be to combine multiple PUMAs within other defined urban statistical areas, for example, Metropolitan Statistical Areas (SMAs). Again, this approach would lead to substantial measurement error as PUMA boundaries do often not align with the boundaries of metropolitan area units either (see, e.g., Schroeder and Pacas, 2021, for a discussion on the regional variables). For this study, I find it more important to eliminate the measurement error stemming from random assignment of households to overlapping regional units, which is why I rely on consistent PUMA boundaries throughout this study.

Overall, most U.S. states contain a reasonable number of PUMAs, providing a good approximation of local labour markets. On average, a state includes 21 consistent PUMAs, allowing me to include state-fixed effects and analyse within-state differences in labour market outcomes unaffected by state-dependent policies or interventions. To account for differences in population sizes, I weigh all models in Section 4.4 by PUMAs' population shares.

4.3.2 Measuring Within-Occupation Cognitive-Biased Technological Change of PUMAs

Local labour markets are specialized in different industries, requiring specialized workers of different occupations. Consequently, the occupational composition differs between local labour markets. The spatial variation in occupational composition, together with the differential changes in cognitive task bias between different occupations, can be exploited for my analysis. The PUMA-specific measure of within-occupation cognitive-biased technological change ('WO-CBTC' hereafter) is constructed as

$$WOCBTC_{j,t} = \sum_{k=1}^{K} \Phi_{j,k,t-1} \left[(\widetilde{CTI}_{k,t} - \widetilde{CTI}_{k,t-1}) - (\widetilde{NCTI}_{k,t} - \widetilde{NCTI}_{k,t-1}) \right] \quad (4.4)$$

where the technological change measure, $WOCBTC_{j,t}$, depends on the shares of total working hours Φ of occupations $k = 1, ..., K$ in PUMA j and the occupation-specific changes in cognitive task bias measured between $t-1$ and t. Recall that k's change in non-cognitive task intensity, $(\widetilde{NCTI}_{k,t} - \widetilde{NCTI}_{k,t-1})$, is equivalent to the average change of physical, coordination, communication and manual task intensity. As the shares of total working hours within PUMAs are held constant at $t-1$, the constructed measure predicts j's exposure to cognitive-biased technological change stemming exclusively from task shifts within occupations.

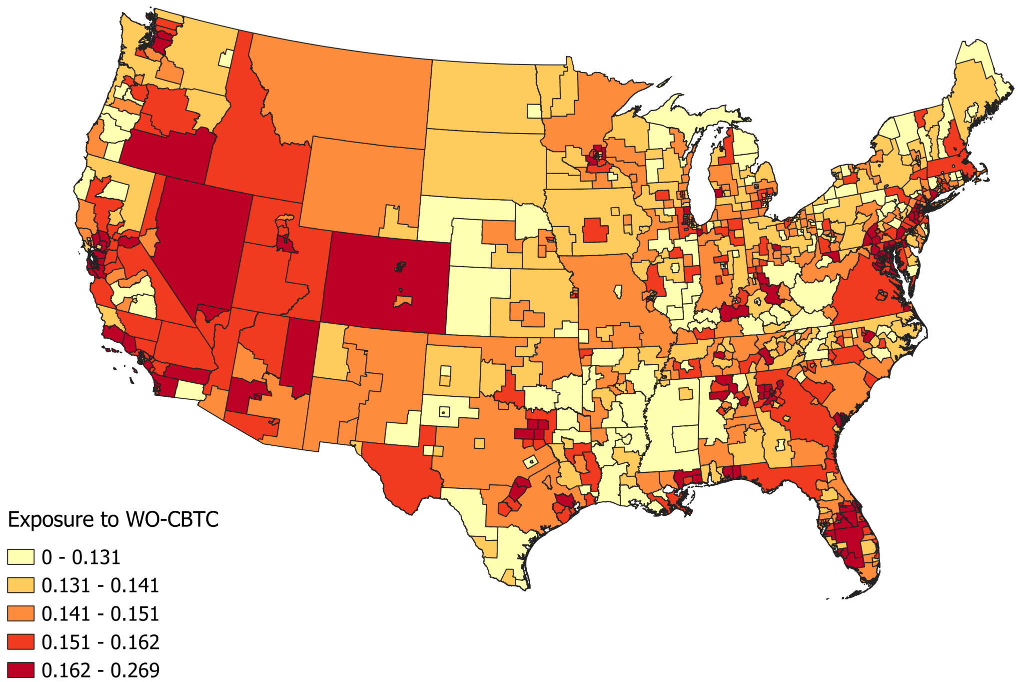

Figure 4.3: PUMA's Exposure to Within-Occupation Cognitive-Biased Technological Change Based on Occupation Shares in 2005-2007

Figure 4.3 visualizes the differential impact of WO-CBTC in the United States by categorizing PUMAs into quintiles with darker colours representing higher exposure to technological change.[12] The exposure to WO-CBTC is positive across all PUMAs, underpinning the systematic increase in cognitive task input in the U.S. economy. The variation between PUMAs ranges from 0.059 to 0.269, measured in units of standard deviation from the national occupation-weighted mean of cognitive bias in 2008. The population-weighted 80/20 percentile range is 0.030 with $WOCBTC^{P20} = 0.134$ and $WOCBTC^{P80} = 0.164$.

Due to the novelty of my measurement approach based on factor analysis and equa-

[12] For a more convenient display, Alaska and Hawaii are excluded from Figure 4.3 due to their far-off locations. The two states are split into four and eight separate PUMAs, respectively.

tion 4.4, I check the robustness of the results shown in Section 4.4 by using two modified specifications of the WO-CBTC measure. First, I use a hand-picked selection of O*NET cognitive abilities instead of deriving a composite measure from factor analysis. Second, I use only occupations' direct cognitive bias instead of the derived compound measure that combines occupations' direct and replacement effects. The two alternative approaches lead to qualitatively and quantitatively similar results.[13]

Is the measure of within-occupation technological change just another static routine-biased technological change (RBTC) measure in disguise? To shed light on this question, I use O*NET data to reconstruct an updated version of the routine-intensity index of Autor et al. (2003) and check its correlation with my WO-CBTC measure.[14] The weak correlation of $\rho = -0.123$ unveils that occupations' routine intensity is not a reliable predictor of their cognitive task bias evolution. In addition, I check the correlation with three other occupation-specific technology measures, finding only weak relationships throughout all tested measures, including automation technologies ($\rho = -0.142$), artificial intelligence ($\rho = 0.089$) and ICT technologies ($\rho = 0.092$).[15] The weak correlations - although they are of a descriptive nature - suggest that cognitive-biased task changes within occupations capture a different dimension of technological change.

4.3.3 Instrumental Variable Approach

The measure constructed in the last section captures PUMAs' exposure to cognitive-biased technological change based on two characteristics: first, occupation-specific task-intensity changes between 2008 and 2017, and second, PUMAs' occupational composition in 2005-2007. The occupational composition 2005-2007 is potentially subject to contemporary economic disturbances. Technically, this causes measurement error and leads to upward or downward-biased estimates. Second, and more fundamentally,

[13] The codes for replicating the different robustness checks are available upon request.

[14] The updated automation/routinization measure is constructed following Firpo et al. (2011) and is described in more detail in Section 4.4.1.

[15] The AI measure is from Felten et al. (2018) while the measure of automation is from Frey and Osborne (2017). The ICT index is reconstructed based on Firpo et al. (2011). All used measures are built based on O*NET data, increasing the risk of high correlation. I do not find substantial relationships between the different static technology measures and my measure of task changes within occupations.

Acemoglu (1998) shows that a sustained increase in the supply of skills induces technological progress to become more skill-complementary as more market opportunities for skill-complementary technologies arise. If the directed technology effect is strong enough, this increases the relative wages of high-skilled workers in the long run. According to this perspective, the causal relationship goes - at least partly - from skill supply to skill-biased technological change to changes in the skill premium.

To address the described potential measurement error and reverse causality, I need to identify some exogenous variation that is correlated with my technology measure but uncorrelated with other contemporary confounders that potentially affect the measure. Therefore, I use the quasi-fixed industry specialization of local labour markets following Autor and Dorn (2013).[16] First, I calculate the employment share Ω of each industry n in PUMA j based on the lagged workforce distribution obtained from the 5% sample of the 2000 Census.[17] Second, I calculate each industry's expected change in cognitive task bias based on the national occupational composition within industries of the year 2000, excluding the state that includes PUMA j.[18] The product of the two measures predicts j's exposure to WO-CBTC dependent on its preexisting industrial structure together with the national occupational structure within industries:

$$\widehat{WOCBTC}_{j,t} = \sum_{n=1}^{N} \Omega_{n,j,2000} \times \mathbb{E}\left[WOCBTC_{n,-j,2000}\right] \tag{4.5}$$

Although using Census data from half a decade before the start of the analysis potentially removes substantial short-term labour market disturbances, the claim for validity of the shift-share instrument must rely on some assumptions. There are essentially two ways of establishing validity. Goldsmith-Pinkham et al. (2020) formalizes an approach that relies on the assumption that exposure shares are exogenous ("share exogeneity"). Using a different framework, Borusyak et al. (2022) leverages exogenous

[16] The approach of using a shift-share ("Bartik") instrument to measure the exogenous variation of shock exposure at the regional level follows Bartik (1991). More recent studies relying on that approach include Autor et al. (2013), Acemoglu et al. (2016) and Diamond (2016).

[17] Workers of the 2000 Census are assigned to industries based on the 1990 Census Bureau industrial classification scheme including 224 different industries.

[18] Following Autor and Duggan (2003), I exclude the state that includes PUMA j from the construction of the instrument to avoid a mechanical correlation between the instrument and the endogenous measure of technological change.

variation in the underlying shocks but allows exposure shares to be endogenous ("shock exogeneity"). The identification strategy in this study is based on the second approach because the industry shares within PUMAs can barely be regarded as being exogenous due to other unobserved industry shocks influencing PUMA-level outcomes through the same mixture of industry shares. Shock exogeneity, in contrast, seems more plausible in the context of my study.

To evaluate the plausibility of the central assumption that shocks are "quasi-randomly assigned" to PUMAs, I implement a shock-orthogonality falsification test following Borusyak et al. (2022). More precisely, I separately regress the shift-share instrument on various potential confounders, including a constant but no other covariates. The included controls that account for the socio-demographic structure of the working-age population are basically in line with Autor et al. (2013) and Autor and Dorn (2013). These are the start-of-analysis share of college-educated, the fraction of employment among women and the share of the foreign-born population. In addition, I check the relationship between the instrument and the share of young as well as old workers to take into account the heterogeneous sorting of workers of different cohorts into industries and occupations. I also test the shock balance regarding PUMAs' manufacturing share and exposure to offshoring as well as their exposure to different technologies, including automation, ICT and artificial intelligence.

Table 4.4 shows the relationships between eleven potential confounders related to regional supply and demand shocks and my shift-share instrument. As indicated by the correlation checks in Section 4.3.2, the results of Table 4.4 confirm that the shock orthogonality assumption holds for all included specific technologies. Overall, only two out of eleven regional balance variables show a significant relationship with the constructed shift-share instrument.[19] Nonetheless, the significant results for the share of foreign-born and young workers imply that these groups may be subject to different labour supply dynamics. The sensitivity analysis in the next section will further explore the role of these potential confounders, showing that they do not affect the significance

[19] This result is similar to the shock balance test that is conducted by Borusyak et al. (2022) to evaluate the shock orthogonality assumption in the context of the China shock study by Autor et al. (2013).

Table 4.4: Shock Balance Tests at PUMA Level
(Dependent Variable: Industry Shift-Share Instrument)

Regional Balance Variable	Coefficient	Standard Error
Start-of-analysis % of college-educated population	0.421	(0.490)
Start-of-analysis % of employment among women	-0.976	(1.039)
Start-of-analysis % of foreign-born population	1.369	(0.641)
Start-of-analysis % of working-age population ≤ 25	-4.976	(1.258)
Start-of-analysis % of working-age population ≥ 55	-4.282	(2.634)
Start-of-analysis % of manufacturing employment	-2.024	(1.262)
Start-of-analysis exposure to offshoring	0.083	(0.067)
Start-of-analysis routine intensity	-0.090	(0.065)
Start-of-analysis exposure to automation	0.018	(0.067)
Start-of-analysis exposure to ICT	0.010	(0.072)
Start-of-analysis exposure to artificial intelligence	0.034	(0.059)

Notes: This table reports coefficients from regressions of PUMA-level covariates on the shift-share instrument. 1,078 Public Use Microdata Areas (PUMAs) are used for the estimation, and the shift-share instrument is standardized with zero mean and unit variance. All models include a constant and are weighted by PUMAs' population shares at the start of analysis in 2006. Robust standard errors are clustered at the state level and shown in parentheses. The offshoring and ICT measures are constructed following Firpo et al. (2011). The routine intensity measure is an updated version of the manual routine index of Autor and Dorn (2013). The measure of exposure to artificial intelligence is based on Felten et al. (2018). The index capturing exposure to job automation is re-constructed following Frey and Osborne (2017). All technology measures are initially measured at the occupation level and mapped into the balanced occupation panel. The average regional exposure values are standardized between PUMAs with zero mean and standard deviation of one.

nor the economic interpretation of the effect of WO-CBTC on labour mobility.[20]

One concern that remains is that PUMAs' industrial specialization observed in 2000 may be influenced by the supply of skills in earlier decades. It is not possible to directly check the shock orthogonality condition for preceding changes in skill supply because PUMAs are only inconsistently defined before the year 2000. However, I can exploit variation at the state level to get an idea if preceding skill supply changes could be an underlying causal factor confounding my results. Using measures of changes in the fraction of college-educated workers across U.S. states between 1980 and 2000, I do not find

[20] To ensure that the young and foreign population does not systematically affect the results, I exclude these two groups from the underlying sample, which yields robust results for the conducted labour market analysis. The results of the robustness checks are provided upon request.

evidence that the cross-state historical evolution of relative skill supply well predicts cognitive-biased task changes within occupations in the twenty-first century. This observation also aligns with Section 4.4.1, showing that PUMAs with higher exposure to WO-CBTC experience a more substantial population inflow of college and non-college workers. These observations confirm the validity of my instrumental variable approach.

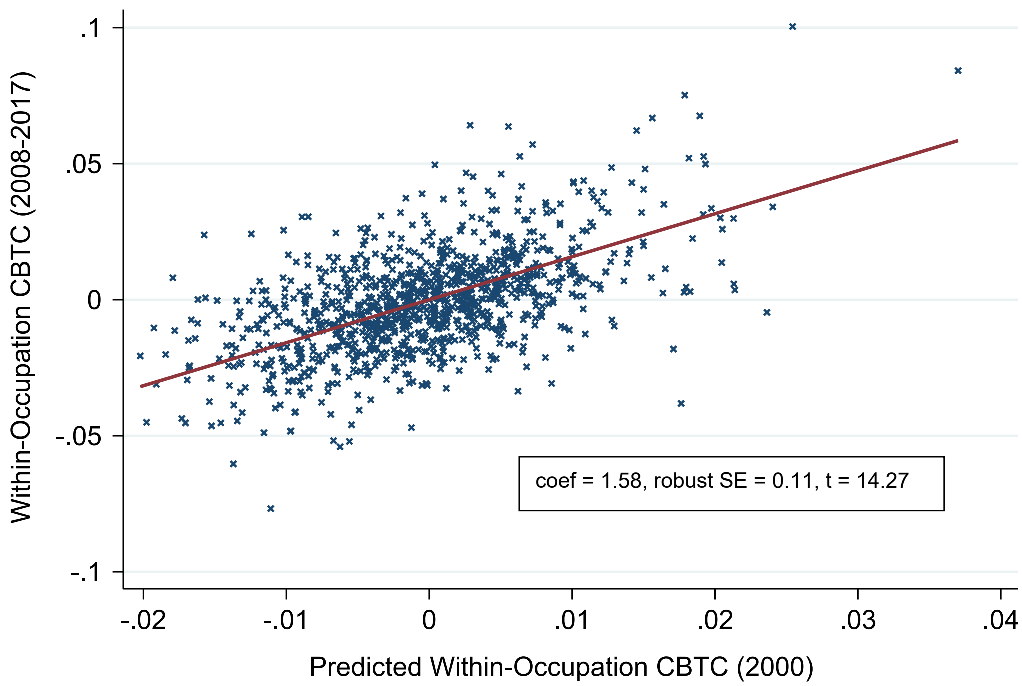

Figure 4.4: Partial Correlation of Predicted Within-Occupation CBTC and Measured Within-Occupation CBTC

Finally, I want to check the first-stage relevance of the shift-share instrument. Figure 4.4 shows the partial correlation between PUMAs' predicted exposure to WO-CBTC and measured exposure to WO-CBTC based on the first-stage regression equation 4.5 and by including state dummies as additional covariates. The predictive value of the shown relationship is highly significant, with a t-ratio of 14.27 underpinning the relevance of my instrument. More precisely, a one per cent increase in predicted exposure to WO-CBTC corresponds to an increase of 1.58 percentage points in measured exposure to WO-CBTC. The following empirical analysis focuses mainly on presenting 2SLS estimation results but also shows OLS estimates for comparison.

4.4 Labour Market Analysis

As a starting point, let us consider that the observed cognitive-biased task shifts within occupations shown in Section 4.2.3 potentially increase the return to cognitive ability for a given supply of skills in the labour market. This assumption can be tested in a falsification exercise by holding the workforce distribution constant at 2008 levels and changing the task intensity measures from 2008 to 2017 to estimate the counterfactual returns to task intensities. Therefore, I use hourly wage data from the merged outgoing rotation groups (MORG) of the Current Population Survey (CPS). In the estimated wage equations, I enter the five task intensity measures derived in Section 4.2.2 and additionally control for years of schooling, experience, gender, union coverage, race and industries. I find that the observed within-occupation task changes lead to an increase in the return to cognitive ability by 6.5 percentage points in the U.S. labour market.

Based on the observation that PUMAs are subject to heterogeneous WO-CBTC, does the return to cognitive ability also change differently across PUMAs? If this is the case, it is intuitive to assume that it leads to a reassignment of skills to tasks along two dimensions: first, workers with different skill endowment reallocate between local labour markets (Topel, 1986; Beaudry et al., 2010; Greenland et al., 2019; Notowidigdo, 2020). Second, workers resort between occupations as well as between employment, unemployment and non-participation within local labour markets (Autor and Dorn, 2013; Autor et al., 2013, 2015). This section's main objective is to analyse the local labour market dynamics along these two dimensions in response to the predicted heterogeneous within-occupation task demand shocks.

4.4.1 Population Growth Effect

For ease of interpretation, the following labour market analysis refers to changes between 2006 and 2017, the two years which reflect the midpoints of the used ACS samples. Figure 4.5 presents the population-weighted bivariate relationship between PUMAs' exposure to WO-CBTC and their change in *log* population counts. The first panel includes all PUMAs, whereas the second panel includes PUMAs with a minimum national population share of 0.1 per cent. The figure unveils a positive relationship between WO-CBTC and population growth between 2006 and 2017. However, the indicative relationship in Figure 4.5 does not account for start-of-analysis population characteristics, nor does it take into account that the differential exposure to biased task demand changes is not exogenous. A more systematic representation of how differential WO-CBTC affects population growth is documented in Table 4.5 based on regression equations of the form

$$\Delta Pop_{j,s,t} = \gamma_0 + \beta_1 \times WOCBTC_{j,s,t} + \beta_2 X_{j,s,t_0} + \delta_s + e_{j,s,t} \tag{4.6}$$

where the dependent variable is the change in *log* population counts between 2006 and 2017 in PUMA j in state s, and $WOCBTC_{j,s,t}$ is the measured within-occupation cognitive-biased technological change which is instrumented by its predicted value $\widehat{WOCBTC}_{j,s,t}$ based on j's industry shares in 2000. Census state dummies δ_s are included to control for state-dependent institutional factors such as unionization, the minimum wage and labour laws. Thus, the exploited variation associated with the results shown in columns 2-6 of Table 4.5 stems from the differential exposure to WO-CBTC within states between PUMAs. In addition, I control for the start-of-analysis labour market and population characteristics summarized by X_{j,s,t_0}. All models include a constant, and standard errors are clustered at the state level.

The coefficients shown in Table 4.5 are multiplied by the factor 10/11 to represent a decennial change in *log* population counts. In the baseline model, which includes only an intercept and the WO-CBTC variable, the OLS model predicts a decennial increase of 1.769 *log* population counts for PUMAs that are exposed to one standard deviation higher WO-CBTC relative to the mean of the appointed population-weighted occupation distribution. Recall that the 80/20 percentile range is 0.03 standard deviations. For a more convenient interpretation of the result, I multiply the estimated coefficient of 1.769 by the 80/20 range to obtain the 80/20 differential increase in *log* population counts, which yields 0.053. At face value, the 80/20 differential is substantial compared to the U.S. average increase in *log* population counts of 0.051.

To validate the significance of the effect of WO-CBTC on regional population growth, I include a battery of population and labour market characteristics that could

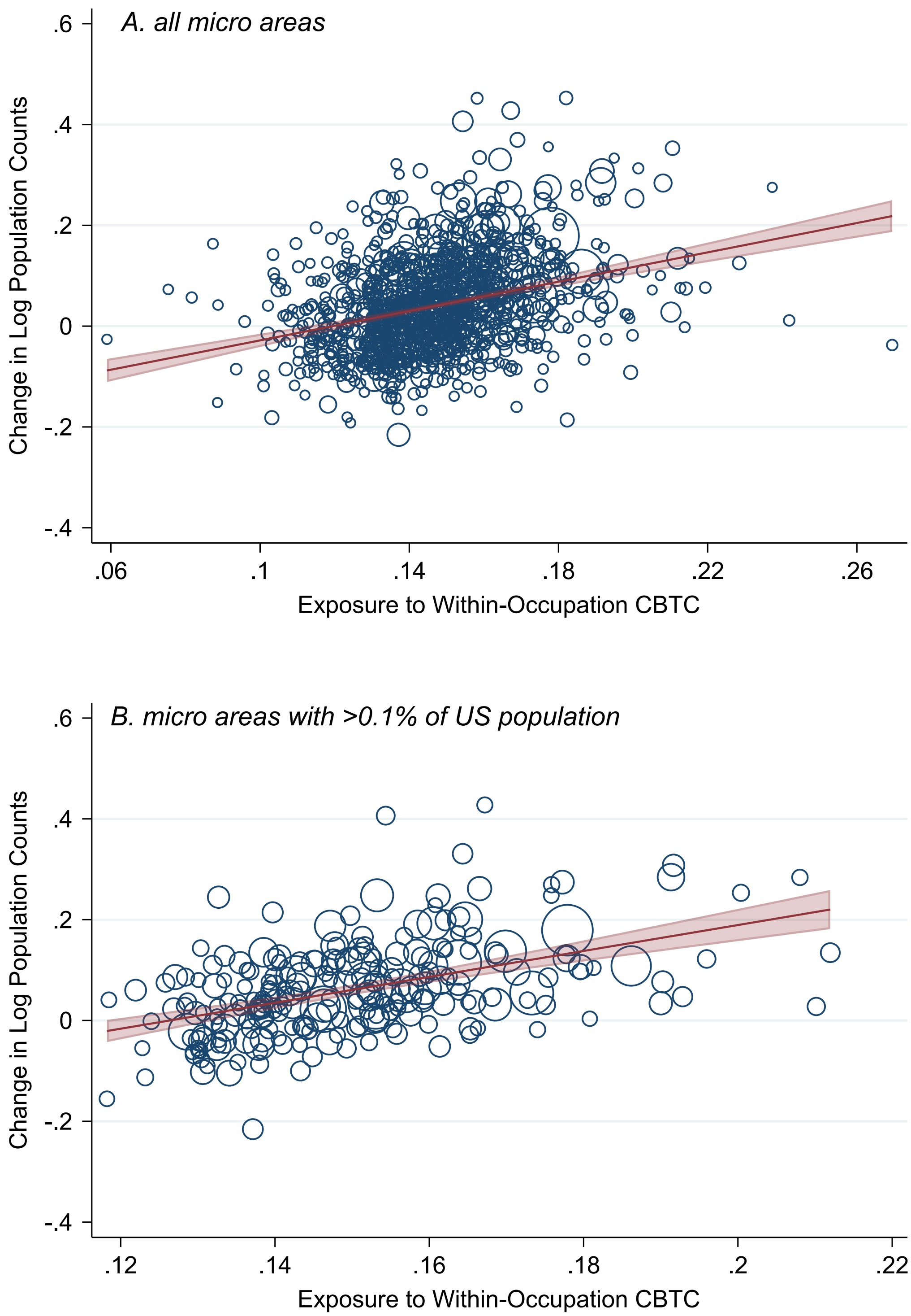

Figure 4.5: Relationship Between PUMAs' Exposure to Within-Occupation CBTC and Change in Log Working-Age Population: 2006-2017

Table 4.5: Exposure to Within-Occupation CBTC and Population Growth of PUMAs
(Dependent Variable: 10 × Annual Log Working-Age Population Change)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. OLS Estimates						
WO-CBTC$_t$	1.769***	1.103***	0.609**	0.727***	0.695**	0.584**
	(0.297)	(0.284)	(0.274)	(0.221)	(0.311)	(0.266)
College/pop$_{t-1}$			0.039			-0.298***
			(0.056)			(0.080)
Female empl/ female pop$_{t-1}$			0.232**			0.259***
			(0.113)			(0.092)
Foreign/pop$_{t-1}$			0.144***			-0.059**
			(0.029)			(0.028)
Age $\leq$ 25/pop$_{t-1}$				-0.263***		-0.178*
				(0.075)		(0.099)
Age $\geq$ 55/pop$_{t-1}$				-1.722***		-1.618***
				(0.191)		(0.206)
manufact/empl$_{t-1}$					-0.273***	-0.072
					(0.082)	(0.087)
Exposure to offshorability of occs$_{t-1}$					0.025***	0.006
					(0.007)	(0.008)
Exposure to de-routinization of occs$_{t-1}$					0.011	-0.039***
					(0.007)	(0.009)
Census state dummies	X	√	√	√	√	√
R^2	0.160	0.463	0.500	0.592	0.514	0.635
Panel B. 2SLS Estimates						
WO-CBTC$_t$	2.612***	1.130***	0.801**	1.066***	1.229***	1.070***
	(0.386)	(0.353)	(0.384)	(0.334)	(0.355)	(0.352)
R^2	0.124	0.463	0.499	0.588	0.506	0.630

Notes: N = 1,078 Public Use Microdata Areas (PUMAs). The dependent variable is the first difference of the *log* working-age population between 2006 and 2017 multiplied by 10/11 to represent a 10 × annual change. The technological change measure (WO-CBTC) represents the within-occupation technological change averaged within PUMAs. Other covariates are expressed in levels of 2006. All models include a constant and are weighted by PUMAs' population shares in 2006. Robust standard errors are clustered at the state level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

simultaneously be correlated with the technology measure and the outcome variable. The state dummies included in column 2 capture unobserved regional heterogeneity, dampening the effect of WO-CBTC on population growth without affecting its significance level. Column 3 introduces population characteristics measured at the start of the analysis in 2006: college-educated relative to the total working-age population, employed female relative to the female working-age population and the share of foreign-born in the working-age population. In addition, column 4 controls for the demographic structure of local labour markets. Controlling for population characteristics decreases the coefficient of WO-CBTC. One plausible explanation for this observation is that the population structure - at least in part - jointly predicts PUMAs' exposure to technological change and population growth. Nonetheless, the variable of interest remains highly significant, at least at the 5% level in all OLS model specifications.

Column 5 includes three variables capturing the industrial and occupational composition of PUMAs: first, the start-of-analysis manufacturing employment share based on the observation that labour markets with a larger fraction of workers in manufacturing industries are more susceptible to trade shocks (Autor et al., 2013). Such shocks potentially cause workers in manufacturing industries to lose their jobs and to resort between local labour markets (see, e.g., Greenland et al., 2019). Moreover, column 5 includes two measures of PUMAs' start-of-analysis occupational composition. The two measures are constructed based on static O*NET data following Firpo et al. (2011) and standardised across PUMAs with a mean of zero and a standard deviation of one. The first measure captures the offshoribility of occupations. The second measure is an updated version of the "manual routine index" of Autor et al. (2003) to address the concern that the routine task intensity of occupations could be an unobserved causal factor of both labour mobility and cognitive-biased task changes within occupations.[21] As can be seen from columns 5 and 6, including the de-routinisation, manufacturing and offshoribility index does not affect the significance of the WO-CBTC measure.

When the WO-CBTC measure is instrumented by the interaction between PUMAs' industry specialisation and precedent national occupation shares within industries, the estimated effect increases noticeably throughout all regression specifications, as can be observed from Panel B. In this regard, the instrumental variable approach most likely removes substantial attenuation bias by diminishing the effects of contemporary labour market disturbances. In the following analysis, I focus on 2SLS estimations to assure

[21] To construct the occupation-specific offshorability measure, I take the unweighted average of different "face-to-face contact" and "on-site job" characteristics from the O*NET 16.0 database. For the construction of an occupation-specific de-routinisation measure, I calculate the unweighted average of the O*NET work context attributes "degree of automation", "importance of repeating same tasks", "structured versus unstructured work (reverse)", "pace determined by speed of equipment", and "spend time making repetitive motions". In the second step, the occupation-specific scores are averaged within PUMAs based on start-of-analysis employment shares.

consistency and to avoid downward-biased coefficients arising from co-dependencies between the WO-CBTC measure and start-of-analysis labour market characteristics - a problem that is emphasised and investigated by Aydemir and Borjas (2011) in the context of migration and wage effects.

Table 4.6: Within-Occupation CBTC and Population Growth by Gender & Education
(2SLS Estimation. Dependent Variable: 10 $\times$ Annual Log Working-Age Population Change)

	LTHS	High-School	Some College	College	Advanced
Panel A. Working-Age Population					
WO-CBTC$_t$	1.905***	1.066***	0.377	1.102**	1.481***
	(0.564)	(0.389)	(0.440)	(0.443)	(0.507)
R^2	0.318	0.515	0.591	0.402	0.405
Panel B. Men					
WO-CBTC$_t$	1.375***	0.732*	0.535	0.839*	1.291*
	(0.564)	(0.416)	(0.466)	(0.485)	(0.680)
R^2	0.250	0.441	0.483	0.340	0.347
Panel C. Women					
WO-CBTC$_t$	2.568***	1.371***	0.229	1.374***	1.797***
	(0.614)	(0.417)	(0.457)	(0.470)	(0.492)
R^2	0.332	0.497	0.589	0.387	0.382

Notes: N = 1,078 Public Use Microdata Areas (PUMAs). The dependent variable is the first difference of the *log* working-age population between 2006 and 2017 multiplied by 10/11 to represent a 10 $\times$ annual change. The technological change measure (WO-CBTC) represents the within-occupation technological change averaged within PUMAs. All 2SLS regressions include the complete set of controls from column 6 of Table 4.5. Observations are weighted by PUMAs' population shares in 2006. Robust standard errors are clustered at the state level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

While table 4.5 demonstrates a robust relationship between WO-CBTC and relative population growth between different areas in the United States, it is silent on what skill types potentially move to areas with increasing demand for cognitive task input. Table 4.6 answers this question by splitting the working-age population into ten gender-education cells. The table shows that individuals with a college or advanced degree and those with high school or no degree reallocate systematically to areas with higher exposure to WO-CBTC. The population growth effects are significant for both men and women. At first glance, this seems counterintuitive as low-skilled workers are less mobile than high-skilled workers (Topel, 1986; Bound and Holzer, 2000; Notowidigdo, 2020). Moreover, it contradicts the general assumption that WO-CBTC is associated with an increase in the relative productivity of high-skilled labour and, thus, a relative productivity decline of low-skilled labour.

The only skill group not showing increased population growth in response to within-occupation task demand shocks includes individuals with some college experience. One possible explanation for the skill polarization is that WO-CBTC has labour-augmenting effects on low-skill workers due to rising demand for different goods and services in population-growing areas. This could create job opportunities for workers specialized in non-cognitive task content. Moreover, it has to be taken into account that the low-skilled relative to high-skilled employment effects depend on the elasticity of substitution between different skills as pointed out by Acemoglu and Autor (2011). The objective of the following sections is to explore the labour market effects related to the differential WO-CBTC and skill polarization in more detail.

4.4.2 Crowding-Out Effect

The results of Section 4.4.1 show a simultaneous increase in low-skilled (high-school or no degree) and high-skilled workers (college or advanced degree) in areas with high exposure to WO-CBTC. The skill-polarising population growth leaves the relative skill supply basically unaffected but increases the labour supply at both ends of the cognitive skill spectrum. Holding the relative supplies of skills constant, the task-based model of Acemoglu and Autor (2011) predicts that technological change that complements cognitive skills increases the proportion of tasks performed by high-skilled workers. Or, to put it differently, low-skilled workers are assumed to be crowded out by high-skilled workers due to high-skilled workers' relative productivity increase ('crowding-out effect').

The results in Table 4.7 confirm the model predictions using 2SLS estimations based on equation 4.6 but with the share of college workers as the dependent variable. The share of college workers is measured in relative total hours of workers with a college degree or a higher degree compared to those without a college degree using the employed workforce obtained from the pooled ACS samples 2005-2007 and 2015-2019. When the complete set of controls is included in the model, PUMAs at the 80th percentile of

WO-CBTC experience a 0.5% differential decennial increase (0.03*0.161) in the share of college-educated workers compared to PUMAs at the 20th percentile.

Table 4.7: The Causal Effect of Within-Occupation CBTC on College Worker Shares
(2SLS Estimation. Dependent Variable: 10 × Annual Change in Share of College Workers)

		Δ College Share Within Occupation Groups			
	ΔCollege Share of Employed Pop	*Non-Routine Cognitive*	*Routine Cognitive*	*Non-Routine Manual*	*Routine Manual*
Panel A. Census state dummies included					
WO-CBTC$_t$	0.240**	0.238**	0.175	0.072*	-0.032
	(0.097)	(0.098)	(0.125)	(0.043)	(0.168)
R^2	0.166	0.103	0.186	0.134	0.068
Panel B. Full controls included					
WO-CBTC$_t$	0.161**	0.204***	0.071	0.030	-0.074
	(0.075)	(0.058)	(0.102)	(0.072)	(0.179)
R^2	0.284	0.223	0.282	0.230	0.123

Notes: N = 1,078 Public Use Microdata Areas (PUMAs). The dependent variable is the first difference of the college share of the employed working-age population between 2006 and 2017 multiplied by 10/11 to represent a 10 × annual change. The technological change measure (WO-CBTC) represents the within-occupation technological change averaged within PUMAs. Regressions of Panel A include an intercept and 51 Census state dummies, whereas regressions of Panel B include the complete set of controls from column 6 of Table 4.5. Observations are weighted by PUMAs' population shares in 2006. Robust standard errors are clustered at the state level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

In addition, Table 4.7 shows the effect of within-occupation technological progress on the college share within the four major task-based occupation groups. The results indicate that the overall positive effect between PUMAs is entirely driven by the disproportionate increase in the share of high-skilled workers in non-routine cognitive occupations. This observation is in line with Roy (1951) models according to which workers with high cognitive abilities sort themselves systematically into occupations that maximize their productivity, namely occupations with the comparatively highest demand for cognitive abilities.

Table 4.8 shows the causal effect of WO-CBTC on employment, unemployment and non-participation shares for both college and non-college workers. College workers in PUMAs at the 80th percentile show a 0.4% differential increase (0.03*0.128) in their employment share compared to the 20th percentile. Moreover, the total increase in relative employment is completely offset by a 0.4% differential decrease (0.03*0.128) in the non-participation rate. The results for the college-educated workforce are robust to entering state dummies and the complete set of controls from column 6 of Table 4.5. Conversely, the effect of cognitive-biased task changes within occupations on the working-age population without a college degree leads to a relative decline in employment of the same magnitude as the increase in college employment. The effect on the non-participation rate is positive and significant when entering the control vector into the model. These observations complement the findings in Table 4.7 that low-cognitive workers are crowded out of the labour market in the medium run due to cognitive-biased task changes within occupations.

Table 4.8: The Causal Effect of Within-Occupation CBTC on Labour Force Shares
(2SLS Estimation. Dependent Variable: 10 × Annual Change in Shares of Employment Status)

	College Degree			*No College Degree*		
	Employed	*Unemployed*	*NILF*	*Employed*	*Unemployed*	*NILF*
Panel A. Census state dummies included						
WO-CBTC$_t$	0.144***	0.001	-0.145***	-0.097*	0.022	0.075
	(0.049)	(0.016)	(0.041)	(0.055)	(0.032)	(0.060)
R^2	0.145	0.131	0.139	0.154	0.259	0.120
Panel B. Full controls included						
WO-CBTC$_t$	0.128***	-0.000	-0.128**	-0.131**	0.008	0.124**
	(0.058)	(0.018)	(0.049)	(0.055)	(0.030)	(0.058)
R^2	0.175	0.157	0.173	0.336	0.309	0.265

Notes: $N = 1{,}078$ Public Use Microdata Areas (PUMAs). The dependent variable is the first difference of the shares of employment status between 2006 and 2017 multiplied by 10/11 to represent a 10 × annual change. The technological change measure (WO-CBTC) represents the within-occupation technological change averaged within PUMAs. Regressions of Panel A include an intercept and 51 Census state dummies, while regressions of Panel B include the complete set of controls from column 6 of Table 4.5. Observations are weighted by PUMAs' population shares in 2006. Robust standard errors are clustered at the state level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

The fact that one cannot find significant effects on unemployment is potentially related to the large time gap between 2006 and 2017. As it is pointed out by Autor et al. (2015), who disentangle the effect of routine-biased technological change and trade shocks on employment, the direct effects on unemployment are most likely visible in the short run but vanish in the medium to long run due to labour force exit. This assumption is consistent with the findings presented in Table 4.8. In addition to medium-run labour market adjustments within PUMAs, low-skilled workers who become unemployed in PUMAs that are decreasing in demand for cognitive skills potentially move to areas with better job opportunities. This hypothesis is reasonable considering the low-skilled population growth in PUMAs with more considerable cognitive-biased task demand changes, as shown in the last section. However, the labour-increasing but cognitive-biased task demand changes in population-growing areas also appear to push low-skilled workers out of the labour market due to the rising supply of high-skilled labour.

4.4.3 Skill Composition Effect

This section aims to deepen the understanding of how the skill composition between labour markets evolves based on the observed differential supply changes of different skills. Therefore, I hold the task intensities within occupations constant at the start-of-analysis levels and change only PUMAs' occupation shares between 2006 and 2017. The counterfactual distribution reflects the 'extensive margin' of skill composition changes in local labour markets.

Figure 4.6, which shows the evolutionary change of the five task intensity scores relative to the start-of-analysis population-weighted standardized mean scores, unveils an important pattern: cognitive-biased technological progress also manifests through resorting of workers across occupations. To better understand the magnitudes of the presented changes, Figure 4.6 categorizes PUMAs into three groups based on their population-weighted exposure to WO-CBTC. The increase in cognitive intensity is 0.047 for the lowest quintile, 0.060 for the combined mid-three quintiles and 0.081 units of standard deviation for the highest quintile. In addition, the highest quintile of PUMAs shows a more substantial decline in communication- and physical-intensive task input and a less significant decrease in manual task input due to changes in relative employment shares between occupations.

A deeper exploration of the data shows that the 'extensive task intensity changes' are the outcome of two different mechanisms: first, mobility within task-based occupation groups, and second, mobility between non-routine cognitive and other occupations. Regarding the latter, the share of non-routine cognitive occupations (management,

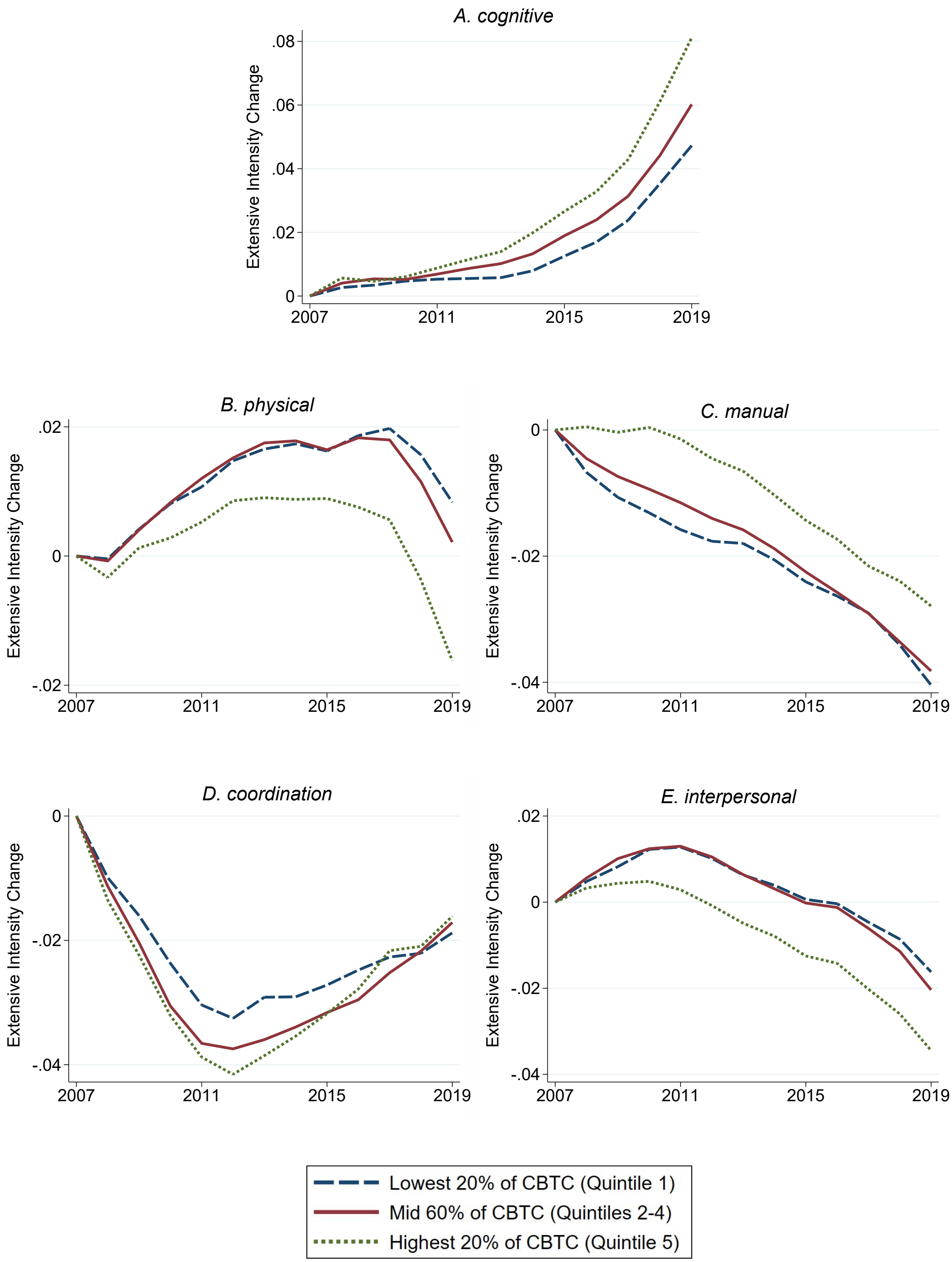

Figure 4.6: Changes in PUMAs' Average Task Intensities from Changes in Relative Employment Shares Between Occupations

business, science, and arts) increased from 0.33 to 0.38 for the highest quintile but only from 0.25 to 0.28 for the lowest quintile of WO-CBTC. However, there is no difference between the highest and lowest quintiles when the changes in non-routine cognitive occupation shares are evaluated in percentage growth rates. Moreover, the figures must be interpreted cautiously as it seems not entirely plausible that task changes between and within occupations can be considered two completely different phenomena.[22] Therefore, this section relies entirely on a descriptive representation which intends to complement the causal effects of the last sections and the following section.

4.4.4 Wage Effect and the College Wage Premium

A substantial finding of this study is that cognitive-biased technological change within PUMAs attracts both high-skilled and low-skilled workers. Moreover, the last two sections predict that non-college workers are crowded out of highly exposed local labour markets. In this section, I investigate how within-occupation cognitive-biased task changes shape the wage growth of high and low-skilled workers across local labour markets. In contrast to the last sections, workers with some college experience but no degree are excluded from this section as the findings of the previous sections do not unveil a significant impact of WO-CBTC on this group. Moreover, workers with some college experience but no degree cannot be clearly classified as either college or high-school workers. Therefore, their inclusion would hamper the interpretation of the college wage premium in this section. To identify the effect of WO-CBTC on the differential wage growth of skill group g, I estimate equations of the form

$$\Delta w_{j,s,g,t} = \gamma_0 + \beta_1 \times WOCBTC_{j,s,t} + \beta_2 X_{j,s,t_0} + \beta_3 \Delta z_{j,s,t} + \delta_s + e_{j,s,g,t} \tag{4.7}$$

where the dependent variable is the change in the *log* hourly wage rate between 2006 and 2017 in PUMA j in state s. $WOCBTC_{j,s,t}$ is instrumented by its predicted value $\widehat{WOCBTC}_{j,s,t}$. The original start-of-analysis population characteristics of PUMA j

[22] This intuition makes the usage of my instrument for estimating the effect of WO-CBTC on task shifts between occupations implausible as the latter - likewise to task changes within occupations - depend on the historical occupational composition.

are amended by the vector $z_{j,s,t}$, which controls for changes in relative employment shares between the four task-based major occupation groups. The vector is included to take into account the findings of the last section, along with the intuition that larger growth of non-routine cognitive occupations could be systematically related to faster wage growth within PUMAs.[23] To obtain a more detailed picture of the predicted wage changes due to cognitive-biased task changes within occupations, I additionally estimate equation 4.7 by gender and occupation groups.

Panel A of Table 4.9 presents the results of the estimated wage equations. PUMAs at the 80th percentile of WO-CBTC show a 1.3 log point differential decennial decline (0.03*(-0.433)) in high-school wages compared to PUMAs at the 20th percentile, whereby the differential decrease is almost twice the magnitude in non-routine cognitive occupations with 2.4 log points (0.03*(-0.807)). No significant effect on the wages of high-school workers is found in other occupation groups. This finding complements the considerable decline in the share of non-college workers in non-routine cognitive occupations shown in Table 4.7. On the contrary, Table 4.9 does not show a significant effect on the wages of college workers despite the expected relative productivity increase of high-skilled workers in local labour markets more exposed to WO-CBTC.

The different wage effects on college and high-school workers are consistent with my previous findings on population growth of different skill groups between local labour markets (see Section 4.4.1). While high-skilled workers reallocate to regions with increasing demand for cognitive ability, the increased labour supply potentially has equalizing effects on their wages compared to less exposed regions. On the other hand, low-skilled potentially face declining relative productivity effects and higher competition with high-skilled workers in more exposed PUMAs. As a result, the growing low-skilled working-age population and the increased supply of non-cognitive abilities possibly push down workers' wages with only a high-school degree or no degree.

Differences between the effects on men (columns 3-4) and women (columns 5-6) can be observed within the group of routine cognitive occupations. Only male high-school and female college workers experienced significantly less wage growth between 2006 and 2017 in more exposed PUMAs. In addition, female high school workers employed in

[23] The results are robust when excluding the occupation share vector.

Table 4.9: The Causal Effect of Within-Occupation CBTC on Wages and the College Wage Premium

(2SLS. Dependent Variable: 10 × Annual Change in Log Wages and Log College Premium)

	All		*Men*		*Women*	
	College	*High-School*	*College*	*High-School*	*College*	*High-School*
Panel A. Change in log hourly wages (for all occupations and within groups)						
(i) all occupations	-0.044	-0.433**	-0.046	-0.386	0.201	-0.527***
	(0.184)	(0.211)	(0.235)	(0.250)	(0.184)	(0.199)
(ii) non-routine cognitive	0.082	-0.807***	0.116	-1.168**	0.356*	-0.420
	(0.233)	(0.305)	(0.321)	(0.502)	(0.198)	(0.477)
(iii) routine cognitive	-0.591*	-0.192	-0.214	-0.878**	-0.747**	0.260
	(0.359)	(0.223)	(0.471)	(0.368)	(0.365)	(0.298)
(iv) non-routine manual	-0.129	-0.312	-0.188	-0.139	0.172	-0.415
	(0.623)	(0.269)	(0.615)	(0.310)	(0.921)	(0.313)
(v) routine manual	1.403	-0.103	0.589	0.075	1.045	-1.084**
	(0.948)	(0.366)	(1.089)	(0.534)	(1.682)	(0.474)
Panel B. Change in log college wage premium (for all occupations and within groups)						
(i) all occupations	0.693**		0.755		0.985***	
	(0.329)		(0.473)		(0.340)	
(ii) non-routine cognitive	1.539***		1.957**		1.067**	
	(0.465)		(0.775)		(0.484)	
(iii) routine cognitive	-0.064		0.902		-0.807	
	(0.537)		(0.728)		(0.628)	
(iv) non-routine manual	0.566		0.552		0.264	
	(0.629)		(0.569)		(1.200)	
(v) routine manual	1.253		0.165		2.564	
	(1.062)		(1.209)		(1.772)	

Notes: N = 1,078 Public Use Microdata Areas (PUMAs). The dependent variable in Panel A is the first difference of the *log* hourly wage rate between 2006 and 2017. The college wage premium in Panel B is the *log* of the average hourly wage rate of workers with at least a college degree divided by the average hourly wage rate of workers with a high-school degree or no degree. All coefficients are multiplied by 10/11 to represent a 10 × annual change. The table shows the estimated causal effect of PUMAs' within-occupation cognitive-biased technological change (WO-CBTC) on wages and the wage premium. All regressions include the complete set of controls from column 6 of Table 4.5 and additional controls to account for the relative changes in employment shares between four major occupation groups (non-routine cognitive, routine cognitive, non-routine manual and routine manual). The underlying sample includes all "full-time year-round workers" who are not self-employed. Hourly wages are calculated by dividing the yearly pre-tax wage and salary income (including wages, salaries, commissions, cash bonuses, tips, and other income received from an employer) by the number of weeks worked multiplied by the usual hours worked per week. The pre-tax wage income is top-coded based on IPUMS state and year-specific pre-tax labour income top codes. Hourly wages below the first percentile of the wage distribution are set equal to the wage rate at the first percentile. Observations are weighted by PUMAs' population shares in 2006. Robust standard errors are clustered at the state level and shown in parentheses. ***/**/* significant at the 1% 5% and 10% level.

routine manual occupations show a significant relative wage decline if they reside in PUMAs with higher exposure to cognitive-biased task changes. No such effect can be observed for men. Besides these differences, the results align with the general findings in columns 1 and 2.

Panel B of Table 4.9 documents the differential changes in the college wage premium between PUMAs of different technology exposure. For the estimation of the college wage premium, I use equation 4.7 but with the first difference of the *log* college wage premium

(w_c/w_{hs}) as the dependent variable. Complementing the decreased wages of high-school workers, I find that PUMAs at the 80th percentile of WO-CBTC experienced a 2.1 log points differential decennial increase (0.03*0.693) in the college wage premium compared to PUMAs at the 20th percentile. Consistent with previous findings, the overall college wage premium increase is driven by non-routine-cognitive occupations, which show a differential increase in the college wage premium of 4.6 log points. To put these numbers into context, Autor et al. (1998) find an average annual increase in the college wage premium of 0.25 log points from 1950 to 1996. The estimated decennial 80/20 differential growth rate is comparable in size, although measuring the college premium between local labour markets instead of aggregate changes over time. Regarding gender disparities, the overall effect on the skill wage premium is positive for both men and women, although the effect is only significant for women. Both men and women show significantly increased college wage premiums within non-routine cognitive occupations.

4.5 Conclusion

This study shows that task changes within occupations systematically increase the demand for cognitive ability but with substantial heterogeneity between different occupations and across local labour markets. I exploited the differential changes in occupations' cognitive task bias together with local labour markets' preexisting industrial specialization to estimate the causal effect of local labour markets' exposure to within-occupation technological change on population growth, employment and wages by skill group. Between 2006 and 2017, the population of high-skilled workers increased in local labour markets with higher exposure to cognitive-biased technological change. At the same time, highly exposed labour markets show a disproportionate increase in the working-age population of low-skilled workers. At first glance, this trend seems counterintuitive as the relative productivity of low-skilled workers in highly exposed regions would be expected to diminish compared to the other areas. A plausible explanation for the substantial population growth of low-skilled workers in cognitive-intensity-increasing regions could be that workers anticipate negative wage or employment effects in areas that show slower growth rates in cognitive task demand. The conception that workers adjust between local labour markets in anticipation of skill demand changes is pointed out by Topel (1986) and Beaudry et al. (2010) - two studies closely related to my work.

The technology-induced low-skilled population growth combined with the potentially declining relative productivity puts downward pressure on the wages of high-school workers and high-school dropouts. With the wages of high-skilled workers being equalized through skill supply adjustments across local labour markets, the downward pressure on the wages of low-skilled workers leads to rising college wage premiums. This trend is most substantial within non-routine cognitive occupations. Moreover, cognitive-biased within-occupation technological change crowds workers without a college degree out of non-routine cognitive occupations. The crowding-out effect is consistent with the finding that non-routine cognitive occupations experienced the most significant increase in the importance of cognitive ability. Finally, this leads to higher employment shares of college workers and higher labour force non-participation rates of non-college workers.

The results suggest that cognitive-biased technological progress adversely affects dislocated low-skilled workers. Active labour market policies such as efficient job training and skill improvement are necessary to address these issues and combat growing educational wage gaps. Another challenge in the long run will be to combat growing inequality between local labour markets. The U.S. Department of Commerce recently announced that "Geographic income inequality has risen more than 40% between 1980 and 2021". My study suggests that the diverging developments between local labour markets could contribute to this trend. Making population-decreasing local labour markets more attractive to high-skilled workers and investing in labour-enhancing technologies could be the supporting instruments to tackle this problem.

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Appendix to Chapter 4

C.1 O*NET and IPUMS ACS Occupation Data

To make systematic use of the O*NET data in this study, I undertake two steps: first, this study needs to work with a balanced occupation panel as it aims to investigate task changes within detailed occupations and their effects on the U.S. labour market. While a balanced occupation panel applied to the IPUMS Census and American Community Survey (ACS) data has been carefully constructed by Dorn (2009), it only covers the years between 1980 and 2005 and is based on an outdated Census occupation classification of 1990 following Meyer et al. (2005). The standard strategy of researchers who work with more recent ACS data files is to extend this occupation panel (see, e.g., Deming, 2017). However, this is not an optimal solution for my analysis, which starts after 2000, marking an essential break in the Census-based occupation structure. As a result, the number of tractable occupations in the ACS dramatically increased since the 2000s. As dropping a large proportion of occupations would cause a loss of valuable information, I constructed a new balanced occupation panel ('occ2010fr'), which can be used from 2000 onward. The new occupation panel includes 430 different occupations and better reflects the contemporary labour market. Appendix B.2 documents the conducted occupation crosswalk in the ACS.

Second, I map the O*NET ability importance ratings of the 16.0 and 25.0 databases into the occupation panel. As the target is to measure changes within occupations, I can only use O*NET occupations available in both databases, allowing me to include 862 different O*NET occupations. Although the O*NET occupation classification is finer (8-digit) than the classification in the ACS (6-digit), both systems can be linked with the Standard Occupation Classification System (SOC) to map the finer O*NET data into my panel. To achieve this goal, I use a "weighted crosswalk" approach using start-of-analysis population counts from the 2008 Occupation and Employment Statistics (OES) provided by the Bureau of Labour Statistics. The population weights are held constant at 2008 levels as I do not want to intermingle changes in ability requirements within occupations with shifts in relative employment shares between the finer O*NET occupations that are grouped into broader occupations in my panel.

C.2 Balanced Occupation Panel: 2000-2023

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
	Management Occupations					
10	Chief executives/legislators	10	10	10	10	10
		30	10	10	10	10
20	General and operations	20	20	20	20	20
40	Advertising/promotions	40	40	40	40	40
50	Marketing/sales	50	50	50	50	51
						52
60	Public relations	60	60	60	60	60
100	Admin. services	100	100	100	100	101
						102
110	Computer/info. systems	110	110	110	110	110
120	Financial	120	120	120	120	120
130	Human resources	130	130	135	135	135
				136	136	136
				137	137	137
140	Industrial production	140	140	140	140	140
150	Purchasing	150	150	150	150	150
160	Transport./storage/distribution	160	160	160	160	160
205	Farmers/ranchers/agricultural	200	200	205	205	205
		210	210			
220	Construction	220	220	220	220	220
230	Education admin.	230	230	230	230	230
300	Architectural/engineering	300	300	300	300	300
310	Food service	310	310	310	310	310
330	Entertainment/recreation	330	330	330	330	335
340	Lodging	340	340	340	340	340
350	Medical/health services	350	350	350	350	350
360	Natural sciences	360	360	360	360	360
410	Property/real estate/community assoc.	410	410	410	410	410
420	Social/community service	420	420	420	420	420
430	Managers, nec	400	430	430	430	440
		430				705
	Business and Financial Operations Occupations					
500	Agents of artists/perform./athletes	500	500	500	500	500
510	Purchasing agents, farm products	510	510	510	510	510
520	Retail buyers, exc. farm products	520	520	520	520	520
530	Purchasing agents, exc. retail/farm	530	530	530	530	530
540	Claims adjusters/appraisers/examiners	540	540	540	540	540
560	Compliance officers	560	560	565	565	565
600	Cost estimators	600	600	600	600	600
620	Human resources specialists	620	620	630	630	630
				640	640	640
				650	650	650
700	Logisticians	700	700	700	700	700
710	Management analysts	710	710	710	710	710
720	Meeting/convention/event planners	720	720	725	725	725
740	Business operations specialists, nec	730	730	425	425	425
				740	740	750
800	Accountants/auditors	800	800	800	800	800
810	Property appraisers/assessors	810	810	810	810	810
820	Budget analysts	820	820	820	820	820
830	Credit analysts	830	830	830	830	830
840	Financial analysts	840	840	840	840	845
850	Personal financial advisors	850	850	850	850	850
860	Insurance underwriters	860	860	860	860	860
900	Financial examiners	900	900	900	900	900
910	Loan counselors/officers	910	910	910	910	910
930	Tax examiners/collectors/revenue agents	930	930	930	930	930
940	Tax prepares	940	940	940	940	940

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
950	Financial specialists, nec	950	950	950	950	960
	Computer and Mathematical Occupations					
1000	Computer scientists/systems analysts	1000	1000	1005	1005	1005
		5800	5800	1006	1006	1006
				1107	1107	1108
				5800	5800	
1010	Computer programmers	1010	1010	1010	1010	1010
1020	Software developers	1020	1020	1020	1020	1021
						1022
1060	Database admin.	1060	1060	1060	1060	1065
1100	Network/computer systems admin.	1040	1040	1050	1050	1050
		1100	1100	1105	1105	1105
		1110	1110	1007	1007	1007
				1106	1106	1106
				1030	1030	1031
						1032
1200	Actuaries	1200	1200	1200	1200	1200
1220	Operations research analysts	1220	1220	1220	1220	1220
1240	Mathematicians/statisticians	1210	1240	1240	1240	1240
		1230				
		1240				
	Architecture and Engineering Occupations					
1300	Architects, exc. naval	1300	1300	1300	1300	1305
						1306
1310	Surveyors/cartographers/photogrammetrists	1310	1310	1310	1310	1310
1320	Aerospace engineers	1320	1320	1320	1320	1320
1340	Agricultural/biomedical engineers	1330	1340	1340	1340	1340
		1340				
1350	Chemical engineers	1350	1350	1350	1350	1350
1360	Civil engineers	1360	1360	1360	1360	1360
1400	Computer hardware engineers	1400	1400	1400	1400	1400
1410	Electrical/electronic engineers	1410	1410	1410	1410	1410
1420	Environmental engineers	1420	1420	1420	1420	1420
1430	Industrial engineers	1430	1430	1430	1430	1430
1440	Marine engineers	1440	1440	1440	1440	1440
1450	Materials engineers	1450	1450	1450	1450	1450
1460	Mechanical engineers	1460	1460	1460	1460	1460
1520	Petroleum/mining/geological engineers	1500	1520	1520	1520	1520
		1520				
1530	Engineers, nec	1510	1530	1530	1530	1530
		1530				
1540	Drafters	1540	1540	1540	1540	1541
						1545
1550	Engineering technicians, exc. drafters	1550	1550	1550	1550	1551
						1555
1560	Surveying/mapping technicians	1560	1560	1560	1560	1560
	Life, Physical, and Social science Occupations					
1600	Agricultural/food scientists	1600	1600	1600	1600	1600
1610	Biological scientists	1610	1610	1610	1610	1610
1640	Conservation scientists/foresters	1640	1640	1640	1640	1640
1650	Medical scientists	1650	1650	1650	1650	1650
1700	Astronomers/physicists	1700	1700	1700	1700	1700
1710	Atmospheric/space scientists	1710	1710	1710	1710	1710
1720	Chemists/materials scientists	1720	1720	1720	1720	1720
1740	Environmental scientists	1740	1740	1740	1740	1745
						1750
1760	Physical scientists, nec	1760	1760	1760	1760	1760
1800	Economists	1800	1800	1800	1800	1800
1810	Market/survey researchers	1810	1810	735	735	735
				1815	1815	
1820	Psychologists	1820	1820	1820	1820	1821
						1822

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
						1825
1840	Urban/regional planners	1840	1840	1840	1840	1840
1860	Sociologists/social scientists, nec	1830	1860	1860	1860	1860
		1860				
1900	Agricultural/food science techs	1900	1900	1900	1900	1900
1910	Biological techs	1910	1910	1910	1910	1910
1920	Chemical techs	1920	1920	1920	1920	1920
1970	Life/physical/social science techs, nec	1930	1930	1930	1930	1935
		1940	1940	1940	1940	1970
		1960	1960	1950	1950	
				1965	1965	
	Community and Social Service Occupations					
2000	Counselors	2000	2000	2000	2000	2001
						2002
						2003
						2004
						2005
						2006
2010	Social workers	2010	2010	2010	2010	2011
						2012
						2013
						2014
2020	Community/social service specialists, nec	2020	2020	2015	2015	2015
				2016	2016	2016
				2025	2025	2025
2040	Clergy	2040	2040	2040	2040	2040
2050	Directors, religious activities/education	2050	2050	2050	2050	2050
2060	Religious workers, nec	2060	2060	2060	2060	2060
	Legal Occupations					
2100	Lawyers/judges/magistrates	2100	2100	2100	2100	2100
		2110				
2160	Legal support workers	2140	2140	2105	2105	2105
		2150	2150	2145	2145	2145
				2160	2160	2170
						2180
						2862
	Education, Training, and Library Occupations					
2200	Postsecondary teachers	2200	2200	2200	2200	2205
2300	Preschool/kindergarten teachers	2300	2300	2300	2300	2300
2310	Elementary/middle school teachers	2310	2310	2310	2310	2310
2320	Secondary school teachers	2320	2320	2320	2320	2320
2330	Special education teachers	2330	2330	2330	2330	2330
2340	Teachers and instructors, nec	2340	2340	2340	2340	2350
						2360
2400	Archivists/curators/museum techs	2400	2400	2400	2400	2400
2430	Librarians	2430	2430	2430	2430	2435
2440	Library techs	2440	2440	2440	2440	2440
2540	Teacher assistants	2540	2540	2540	2540	2545
2550	Education/training/library workers, nec	2550	2550	2550	2550	2555
	Arts, Design, Entertainment, Sports, and Media Occupations					
2600	Artists	2600	2600	2600	2600	2600
2630	Designers	2630	2630	2630	2630	2631
						2632
						2633
						2334
						2335
						2336
						2340
2700	Actors	2700	2700	2700	2700	2700
2710	Producers/directors	2710	2710	2710	2710	2710

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
2720	Athletes/coaches/umpires	2720	2720	2720	2720	2721
						2722
						2723
2740	Dancers/choreographers	2740	2740	2740	2740	2740
2750	Musicians/singers	2750	2750	2750	2750	2751
						2752
2760	Entertainers/performers, nec	2760	2760	2760	2760	2755
						2770
2800	Announcers	2800	2800	2800	2800	2805
2810	News analysts/reporters/correspondents	2810	2810	2810	2810	2810
2820	Public relations specialists	2820	2820	2825	2825	2825
2830	Editors	2830	2830	2830	2830	2830
2840	Technical writers	2840	2840	2840	2840	2840
2850	Writers/authors	2850	2850	2850	2850	2850
2860	Media/communication workers, nec	2860	2860	2860	2860	2861
						2865
2905	Broadcast/sound engineering techs	2900	2900	2900	2900	2905
		2960				
2910	Photographers	2910	2910	2910	2910	2910
2920	Television/video camera operators/editors	2920	2920	2920	2920	2920
	Healthcare Practitioners and Technical Occupations					
3000	Chiropractors	3000	3000	3000	3000	3000
3010	Dentists	3010	3010	3010	3010	3010
3030	Dietitians/nutritionists	3030	3030	3030	3030	3030
3040	Optometrists	3040	3040	3040	3040	3040
3050	Pharmacists	3050	3050	3050	3050	3050
3060	Physicians/surgeons	3060	3060	3060	3060	3090
						3100
3110	Physician assistants	3110	3110	3110	3110	3110
3120	Podiatrists	3120	3120	3120	3120	3120
3130	Nurses	3130	3130	3255	3255	3255
				3256	3256	3256
				3258	3258	3258
3140	Audiologists	3140	3140	3140	3140	3140
3150	Occupational therapists	3150	3150	3150	3150	3150
3160	Physical therapists	3160	3160	3160	3160	3160
3200	Radiation therapists	3200	3200	3200	3200	3200
3210	Recreational therapists	3210	3210	3210	3210	3210
3220	Respiratory therapists	3220	3220	3220	3220	3220
3230	Speech-language pathologists	3230	3230	3230	3230	3230
3245	Therapists, nec	3240	3240	3245	3245	3245
3250	Veterinarians	3250	3250	3250	3250	3250
3260	Health diagnosing/treating, nec	3260	3260	3260	3260	3261
						3270
3300	Clinical laboratory techs	3300	3300	3300	3300	3300
3310	Dental hygienists	3310	3310	3310	3310	3310
3320	Diagnostic related techs	3320	3320	3320	3320	3321
						3322
						3323
						3324
						3330
3400	Emergency medical techs/paramedics	3400	3400	3400	3400	3401
						3402
3420	Health practitioner support techs	3410	3410	3420	3420	3421
						3422
						4323
						3424
						3430
3500	Licensed practical/vocational nurses	3500	3500	3500	3500	3500
3510	Medical records/health information techs	3510	3510	3510	3510	3515
3520	Opticians, dispensing	3520	3520	3520	3520	3520
3530	Health techs, nec	3530	3530	3535	3535	3545
3540	Healthcare practitioners, nec	3540	3540	3540	3540	1980
						3550

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
	Healthcare Support Occupations					
3600	Nursing/psychiatric/home health aides	3600	3600	3600	3600	3601
						3603
						3605
3610	Occupational therapist assistants	3610	3610	3610	3610	3610
3620	Physical therapist assistants	3620	3620	3620	3620	3620
3630	Massage therapists	3630	3630	3630	3630	3630
3640	Dental assistants	3640	3640	3640	3640	3640
3650	Medical assistants, nec	3650	3650	3645	3645	3645
				3646	3646	3646
				3647	3647	3647
				3648	3648	3648
				3649	3649	3649
				3655	3655	3655
	Protective Service Occupations					
3700	Supervisors of correctional officers	3700	3700	3700	3700	3700
3710	Supervisors of police/detectives	3710	3710	3710	3710	3710
3720	Supervisors of fire fighters	3720	3720	3720	3720	3720
3730	Supervisors of protective services, nec	3730	3730	3730	3730	3725
3740	Fire fighters	3740	3740	3740	3740	3740
3750	Fire inspectors	3750	3750	3750	3750	3750
3800	Bailiffs/correctional officers/jailers	3800	3800	3800	3800	3801
						3802
3820	Detectives/criminal investigators	3820	3820	3820	3820	3820
3840	Law enforcement officers	3830	3840	3840	3840	3840
		3840				
3870	Police officers	3850	3850	3850	3850	3870
		3860				
3900	Animal control workers	N/A	3900	3900	3900	3900
3910	Private detectives/investigators	3910	3910	3910	3910	3910
3930	Security guards/gaming surveillance	3920	3920	3930	3930	3930
3940	Crossing guards	3940	3940	3940	3940	3940
3950	Protective service workers, nec	3950	3950	3945	3945	3945
				3955	3955	3946
						3960
	Food Preparation and Serving Related Occupations					
4000	Chefs/head cooks	4000	4000	4000	4000	4000
4010	Supervisors of food serving workers	4010	4010	4010	4010	4010
4020	Cooks	4020	4020	4020	4020	4020
4030	Food preparation workers	4030	4030	4030	4030	4030
4040	Bartenders	4040	4040	4040	4040	4040
4055	Fast food/counter workers	4050	4050	4050	4050	4055
		4060	4060	4060	4060	
4110	Waiters/waitresses	4110	4110	4110	4110	4110
4120	Food servers, non-restaurant	4120	4120	4120	4120	4120
4140	Dishwashers	4140	4140	4140	4140	4140
4150	Hosts and hostesses, restaurant	4150	4150	4150	4150	4150
4160	Food preparation/serving workers, nec	4130	4130	4130	4130	4130
		4160				4160
	Building and Grounds Cleaning and Maintenance Occupations					
4200	Supervisors of janitorial workers	4200	4200	4200	4200	4200
4210	Supervisors of landscaping workers	4210	4210	4210	4210	4210
4220	Janitors/building cleaners	4220	4220	4220	4220	4220
4230	Maids/housekeeping cleaners	4230	4230	4230	4230	4230
4240	Pest control workers	4240	4240	4240	4240	4240
4250	Grounds maintenance workers	4250	4250	4250	4250	4251
						4252
						4153
	Personal Care and Service Occupations					
4330	Supervisors of personal care workers	4300	4300	4300	4300	4330

occ2010fr	Occupation Group and Title	ACS Occupation Codes 2000	2005	2010	2012	2018
		4320	4320	4320	4320	
4340	Animal trainers	4340	4340	4340	4340	4340
4350	Non-farm animal caretakers	4350	4350	4350	4350	4350
4400	Gaming services workers	4400	4400	4400	4400	4400
4420	Ushers/lobby attendants/ticket takers	4420	4420	4420	4420	4420
4435	Entertainment attendants, nec	4430	4410	4410	4410	4435
			4430	4430	4430	
4460	Embalmers/crematory operators	4460	4460	4460	4460	4461
4465	Morticians/undertakers/funeral directors	320	320	4465	4465	4465
4500	Barbers	4500	4500	4500	4500	4500
4510	Hairdressers/hairstylists/cosmetologists	4510	4510	4510	4510	4510
4520	Personal appearance workers, nec	4520	4520	4520	4520	4521
						4522
						4525
4530	Baggage porters/bellhops/concierges	4530	4530	4530	4530	4530
4540	Tour/travel guides	4540	4540	4540	4540	4540
4600	Childcare workers	4600	4600	4600	4600	4600
4610	Personal/home care aides	4610	4610	4610	4610	3602
4620	Recreation/fitness workers	4620	4620	4620	4620	4621
						4622
4640	Residential advisors	4640	4640	4640	4640	4640
4650	Personal care/service workers, nec	4650	4650	4650	4650	4655
	Sales and Related Occupations					
4700	Supervisors of retail sales	4700	4700	4700	4700	4700
4710	Supervisors of non-retail sales	4710	4710	4710	4710	4710
4720	Cashiers	4720	4720	4720	4720	4720
4740	Counter/rental clerks	4740	4740	4740	4740	4740
4750	Parts salespersons	4750	4750	4750	4750	4750
4760	Retail salespersons	4760	4760	4760	4760	4760
4800	Advertising sales agents	4800	4800	4800	4800	4800
4810	Insurance sales agents	4810	4810	4810	4810	4810
4820	Securities/commodities/financial sales agents	4820	4820	4820	4820	4820
4830	Travel agents	4830	4830	4830	4830	4830
4840	Sales representatives. of services, nec	4840	4840	4840	4840	4840
4850	Sales representatives, wholesale/manufacturing	4850	4850	4850	4850	4850
4900	Models/demonstrators/product promoters	4900	4900	4900	4900	4900
4920	Real estate brokers/sales agents	4920	4920	4920	4920	4920
4930	Sales engineers	4930	4930	4930	4930	4930
4940	Telemarketers	4940	4940	4940	4940	4940
4950	Door-to-door sales/news/street vendors	4950	4950	4950	4950	4950
4960	Sales workers, nec	4960	4960	726	726	726
				4965	4965	4965
	Office and Administrative Support Occupations					
5000	Supervisors of office/admin. support	5000	5000	5000	5000	5000
5010	Switchboard operators	5010	5010	5010	5010	5010
5020	Telephone operators	5020	5020	5020	5020	5020
5030	Communications equipment operators, nec	5030	5030	5030	5030	5040
5100	Bill/account collectors	5100	5100	5100	5100	5100
5110	Billing/posting clerks	5110	5110	5110	5110	5110
5120	Bookkeeping/accounting/auditing clerks	5120	5120	5120	5120	5120
5140	Payroll/timekeeping clerks	5140	5140	5140	5140	5140
5150	Procurement clerks	5150	5150	5150	5150	5150
5160	Tellers	5160	5160	5160	5160	5160
5220	Court/municipal/license clerks	5220	5220	5220	5220	5220
5230	Credit authorizers/checkers/clerks	5230	5230	5230	5230	5230
5240	Customer service representatives	5240	5240	5240	5240	5240
5250	Eligibility interviewers, govt programs	5250	5250	5250	5250	5250
5260	File Clerks	5260	5260	5260	5260	5260
5300	Hotel/motel/resort desk clerks	5300	5300	5300	5300	5300
5310	Interviewers, exc. eligibility/loan	5310	5310	5310	5310	5310
5320	Library assistants, clerical	5320	5320	5320	5320	5320
5330	Loan interviewers/clerks	5330	5330	5330	5330	5330
5340	New accounts clerks	5340	5340	5340	5340	5340

occ2010fr	Occupation Group and Title	ACS Occupation Codes				
		2000	2005	2010	2012	2018
5350	Correspondence/order clerks	5210	5350	5350	5350	5350
		5350				
5360	Human resources assistants, exc. payroll	5360	5360	5360	5360	5360
5400	Receptionists/information clerks	5400	5400	5400	5400	5400
5410	Reservation/transportation agents	5410	5410	5410	5410	5410
5420	Information/record clerks, nec	5200	5200	5200	5200	5420
		5420	5420	5420	5420	
5500	Cargo/freight agents	5500	5500	5500	5500	5500
5510	Couriers/messengers	5510	5510	5510	5510	5510
5520	Dispatchers	5520	5520	5520	5520	5521
						5522
5530	Meter readers, utilities	5530	5530	5530	5530	5530
5540	Postal service clerks	5540	5540	5540	5540	5540
5550	Postal service mail carriers	5550	5550	5550	5550	5550
5560	Postal service mail sorters/operators	5560	5560	5560	5560	5560
5600	Production/planning/expediting clerks	5600	5600	5600	5600	5600
5610	Shipping/receiving/traffic clerks	5610	5610	5610	5610	5610
5620	Stock clerks/order fillers	5620	5620	5620	5620	9645
5630	Weighers/measurers/checkers/samplers	5630	5630	5630	5630	5630
5700	Secretaries/administrative assistants	5700	5700	5700	5700	5710
						5720
						5730
						5740
5810	Data entry keyers	5810	5810	5810	5810	5810
5820	Word processors/typists	5820	5820	5820	5820	5820
5840	Insurance claims/policy processing clerks	5840	5840	5840	5840	5840
5850	Mail clerks/machine operators, exc. postal	5850	5850	5850	5850	5850
5860	Office clerks, general	5860	5860	5860	5860	5860
5900	Office machine operators, exc. computer	5900	5900	5900	5900	5900
5910	Proofreaders/copy markers	5910	5910	5910	5910	5910
5920	Statistical assistants	5920	5920	5920	5920	5920
5930	Office/administrative support, nec	5130	5130	5130	5130	5165
		5830	5930	5165	5165	5940
		5930		5940	5940	
	Farming, Fishing, and Forestry Occupations					
6000	Supervisors of farming/fishing/forestry	6000	6000	6005	6005	6005
6010	Agricultural inspectors	6010	6010	6010	6010	6010
6040	Graders/sorters, agricultural products	6040	6040	6040	6040	6040
6050	Agricultural workers, nec	6020	6050	6050	6050	6050
		6050				
6115	Fishing/hunting workers	6100	6100	6100	6100	6115
		6110				
6120	Forest/conservation workers	6120	6120	6120	6120	6120
6130	Logging workers	6130	6130	6130	6130	6130
	Construction and Extraction Occupations					
6200	Supervisors of construction/extraction	6200	6200	6200	6200	6200
6210	Boilermakers	6210	6210	6210	6210	6210
6220	Brickmasons/blockmasons/stonemasons	6220	6220	6220	6220	6220
		6500	6500	6500		
6230	Carpenters	6230	6230	6230	6230	6230
6240	Carpet/floor/tile installers	6240	6240	6240	6240	6240
6250	Cement masons/terrazzo workers	6250	6250	6250	6250	6250
6260	Construction laborers	6260	6260	6260	6260	6260
6305	Construction equip. operators	6300	6300	6300	6300	6305
		6310	6320	6320	6320	
		6320				
6330	Drywall/ceiling tile installers/tapers	6330	6330	6330	6330	6330
6350	Electricians	6350	6350	6355	6355	6355
6360	Glaziers	6360	6360	6360	6360	6360
6400	Insulation workers	6400	6400	6400	6400	6400
6410	Painters/paperhangers	6420	6420	6420	6420	6410
		6430	6430	6430		
6440	Pipelayers/plumbers/pipefitters	6440	6440	6440	6440	6441

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
						6442
6460	Plasterers/stucco masons	6460	6460	6460	6460	6460
6510	Roofers	6510	6510	6515	6515	6515
6520	Sheet metal workers	6520	6520	6520	6520	6520
6530	Structural iron/steel workers	6530	6540	6530	6530	6530
6600	Helpers, construction trades	6600	6600	6600	6600	6600
6660	Construction/building inspectors	6660	6660	6660	6660	6660
6700	Elevator installers/repairers	6700	6700	6700	6700	6700
6710	Fence erectors	6710	6710	6710	6710	6710
6720	Hazardous materials removal workers	6720	6720	6720	6720	6720
6730	Highway maintenance workers	6730	6730	6730	6730	6730
6740	Rail-track laying/maintenance operators	6740	6740	6740	6740	6740
6760	Construction workers, nec	6750	6760	6540	6540	6540
		6760		6765	6765	6765
6800	Derrick operators, oil/gas/mining	6800	6800	6800	6800	6800
		6920				
6820	Earth drillers, except oil/gas	6820	6820	6820	6820	6825
6830	Explosives workers	6830	6830	6830	6830	6835
6850	Underground mining operators	6840	6840	6840	6840	6850
		9730				
6950	Extraction workers, nec	6910	6940	6940	6940	6950
		6930				
		6940				
	Installation, Maintenance, and Repair Occupations					
7000	Supervisors of mechanics/repairers	7000	7000	7000	7000	7000
7010	Computer/automated teller repairers	7010	7010	7010	7010	7010
7020	Radio/tele equip. repairers	7020	7020	7020	7020	7020
7030	Avionics techs	7030	7030	7030	7030	7030
7040	Electric motor/power tool repairers	7040	7040	7040	7040	7040
7100	Electrical repairers, industrial/utility/vehicles	7050	7100	7100	7100	7100
		7100	7110	7110	7110	
		7110				
7120	Electronic home entertain equip. installers	7120	7120	7120	7120	7120
7130	Security/fire alarm systems installers	7130	7130	7130	7130	7130
7140	Aircraft mechanics/service techs	7140	7140	7140	7140	7140
7150	Automotive body repairers	7150	7150	7150	7150	7150
7160	Automotive glass installers	7160	7160	7160	7160	7160
7200	Automotive service techs/mechanics	7200	7200	7200	7200	7200
7210	Bus/truck/diesel engine mechanics	7210	7210	7210	7210	7210
7220	Heavy vehicle/mobile equipment mechanics	7220	7220	7220	7220	7220
7240	Small engine mechanics	7240	7240	7240	7240	7240
7260	Vehicle/mobile equip. mechanics/repairers, nec	7260	7260	7260	7260	7260
7300	Control/valve installers/repairers	7300	7300	7300	7300	7300
7310	Heating/air conditioning/refrigeration mechanics	7310	7310	7315	7315	7315
7320	Home appliance repairers	7320	7320	7320	7320	7320
7330	Industrial/refractory machinery mechanics	7330	7330	7330	7330	7330
7340	Maintenance/repair workers, general	7340	7340	7340	7340	7340
7350	Maintenance workers, machinery	7350	7350	7350	7350	7350
7360	Millwrights	7360	7360	7360	7360	7360
7410	Electrical power-line installers	7410	7410	7410	7410	7410
7420	Telecommunications line installers	7420	7420	7420	7420	7420
7430	Precision instrument/equipment repairers	7430	7430	7430	7430	7430
7510	Coin/vending/amusement machine repairers	7510	7510	7510	7510	7510
7540	Locksmiths/safe repairers	7540	7540	7540	7540	7540
7560	Riggers	7560	7560	7560	7560	7560
7610	Helpers - installation/maintenance/repair	7610	7610	7610	7610	7610
7640	Installation/maintenance/repair, nec	7520	7550	7550	7630	7640
		7550	7620	7630		
		7600				
		7620				
	Production Occupations					
7700	Supervisors of production workers	7700	7700	7700	7700	7700
7720	Electrical/electronics assemblers	7720	7720	7720	7720	7720

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
7730	Engine/machine assemblers	7730	7730	7730	7730	7730
7740	Structural metal fabricators/fitters	7740	7740	7740	7740	7740
7750	Assemblers/fabricators, nec	7710	7710	7710	7710	7750
		7750	7750	7750	7750	
7800	Bakers	7800	7800	7800	7800	7800
7810	Butchers/meat processing workers	7810	7810	7810	7810	7810
7830	Food/tobacco/baking operators	7830	7830	7830	7830	7830
7840	Food batchmakers	7840	7840	7840	7840	7840
7850	Food cooking machine operators	7850	7850	7850	7850	7850
7900	Computer control programmers, metal/plastic	7900	7900	7900	7900	7905
7925	Forming machine operators, metal/plastic	7920	7920	7920	7920	7925
		7930	7930	7930	7930	
		7940	7940	7940	7940	
8025	Machine tool operators, metal/plastic, nec	7950	7950	7950	7950	7950
		7960	7960	7960		8000
		8000	8000	8000		8025
		8010	8010	8010		
		8020				
8030	Machinists	8030	8030	8030	8030	8030
8040	Metal furnace/kiln operators	8040	8040	8040	8040	8040
8100	Molders, metal/plastic	8060	8060	8060	8100	8100
		8100	8100	8100		
8130	Tool/die makers	8130	8130	8130	8130	8130
8140	Welding/soldering/brazing workers	8140	8140	8140	8140	8140
8225	Metal/plastic workers, nec	8120	8150	8150	8220	8225
		8150	8200	8200		
		8160	8210	8210		
		8200	8220	8220		
		8210				
		8220				
8250	Prepress techs/workers	8250	8250	8250	8250	8250
8260	Printing operators	8230	8230	8255	8255	8255
		8240	8240	8256	8256	8256
		8260	8260			
8300	Laundry/dry-cleaning workers	8300	8300	8300	8300	8300
8310	Pressers, textile/garment	8310	8310	8310	8310	8310
8320	Sewing machine operators	8320	8320	8320	8320	8320
8335	Shoe and leather workers/repairers	8330	8330	8330	8330	8335
		8340	8340	8340		
8350	Tailors/dressmakers/sewers	8350	8350	8350	8350	8350
8365	Textile machine setters/operators	8360	8400	8400	8400	8365
		8400	8410	8410	8410	
		8410	8420	8420	8420	
		8420				
8450	Upholsterers	8450	8450	8450	8450	8450
8465	Textile/apparel/furnishings workers, nec	8430	8460	8460	8460	8465
		8440				
		8460				
8500	Cabinetmakers/bench carpenters	8500	8500	8500	8500	8500
8510	Furniture finishers	8510	8510	8510	8510	8510
8530	Sawing machine operators, wood	8530	8530	8530	8530	8530
8540	Woodworking machine operators, exc. sawing	8540	8540	8540	8540	8540
8555	Woodworkers, nec	8520	8550	8550	8550	8555
		8550				
8600	Power plant operators	8600	8600	8600	8600	8600
8610	Stationary engineers/boiler operators	8610	8610	8610	8610	8610
8620	Water/liquid waste plant operators	8620	8620	8620	8620	8620
8630	Plant/system operators, nec	8630	8630	8630	8630	8630
8640	Chemical processing machine operators	8640	8640	8640	8640	8640
8650	Crushing/grinding/polishing workers	8650	8650	8650	8650	8650
8710	Cutting workers	8710	8710	8710	8710	8710
8720	Extruding/pressing machine operators	8720	8720	8720	8720	8720
8730	Furnace/kiln/oven/drier/kettle operators	8730	8730	8730	8730	8730
8740	Inspectors/testers/sorters/samplers	8740	8740	8740	8740	8740
8750	Precious stone/metal workers	8750	8750	8750	8750	8750
8760	Medical/dental/ophthalmic laboratory techs	8760	8760	8760	8760	8760
8800	Packaging/filling machine operators	8800	8800	8800	8800	8800

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
8810	Painting workers	8810	8810	8810	8810	8810
8830	Photographic process workers	8830	8830	8830	8830	8830
8850	Adhesive bonding machine operators	8850	8850	8850	8850	8850
8910	Etchers/engravers	8910	8910	8910	8910	8910
8920	Molders/shapers/casters, exc. metal/plastic	8920	8920	8920	8920	8920
8930	Paper goods machine operators	8930	8930	8930	8930	8930
8940	Tire builders	8940	8940	8940	8940	8940
8950	Helpers - production	8950	8950	8950	8950	8950
8990	Production workers, nec	8840	8860	7855	7855	7855
		8860	8960	8860	8965	8990
		8900		8965		
		8960				
	Transportation and Material Moving Occupationss					
9000	Supervisors of transportation/material moving	9000	9000	9000	9000	9005
9030	Aircraft pilots/flight engineers	9030	9030	9030	9030	9030
9040	Air traffic controllers/specialists	9040	9040	9040	9040	9040
9050	Transportation attendants	4550	4550	9050	9050	9050
				9415	9415	9415
9110	Ambulance drivers/attendants	N/A	9110	9110	9110	9110
9120	Bus drivers	9120	9120	9120	9120	9121
						9122
9130	Driver/sales workers and truck drivers	9130	9130	9130	9130	9130
9140	Taxi drivers/chauffeurs	9140	9140	9140	9140	9141
						9142
9150	Motor vehicle operators, nec	9150	9150	9150	9150	9150
9200	Locomotive engineers/operators	9200	9200	9200	9200	9210
9240	Railroad conductors/yardmasters	9240	9240	9240	9240	9240
9265	Rail transportation workers, nec	9230	9230	9230	9260	9265
		9260	9260	9260		
9300	Sailors/marine oilers/ship engineers	9300	9300	9300	9300	9300
		9330				
9310	Ship/boat captains/operators	9310	9310	9310	9310	9310
9350	Parking attendants	9350	9350	9350	9350	9350
9410	Transportation inspectors	9410	9410	9410	9410	9410
9430	Transportation workers, nec	9340	9360	9360	9360	9365
		9360	9420	9420	9420	9430
		9420				
9510	Crane/tower operators	9510	9510	9510	9510	9510
9570	Conveyor/dredge/hoist/winch operators	9500	9520	9520	9520	9570
		9520	9560	9560	9560	
		9560				
9600	Industrial truck/tractor operators	9600	9600	9600	9600	9600
9610	Cleaners of vehicles/equipment	9610	9610	9610	9610	9610
9620	Laborers and freight/stock/material movers, hand	9620	9620	9620	9620	9620
9630	Machine feeders/offbearers	9630	9630	9630	9630	9630
9640	Packers/packagers, hand	9640	9640	9640	9640	9640
9650	Pumping station operators	9650	9650	9650	9650	9650
9720	Refuse/recyclable material collectors	9720	9720	9720	9720	9720
9760	Material moving workers, nec	9740	9750	9750	9750	9760
		9750				

Chapter 5

Conclusion

The accelerating momentum of new technologies, rising competition among high-skilled workers and heterogeneous workplace preferences in a constantly changing society have reshaped the labour market during the last two decades. At the same time, highly mobile workers adjust to long-term demand changes and temporary disturbances by reallocating between regions, occupations and employers. The limited knowledge of the mechanisms behind the supply adjustments in such a flexible labour market prompted me to explore these topics more thoroughly. My thesis contributes to the empirical labour and macroeconomic literature on the evolution of skill demand, labour mobility and wage inequality.

In Chapter 2, I analysed the impact of task demand changes on different occupation groups and workers with different characteristics in the U.S. labour market. I derived occupation-specific composite measures of manual and cognitive task intensity for the years 2008 and 2017 by using the updated O*NET ability rating procedure. Combining the task intensity measures with representative U.S. survey data revealed very heterogeneous developments in cognitive task demand between occupation groups. The theoretical literature often assumes that technology mainly automates tasks of lower complexity while newly emerging tasks are of higher complexity and, therefore, more cognitive-intensive. Although I find a systematic decline in the demand for manual tasks across all occupation groups, my results suggest that this development does not automatically imply a replacement of manual-intensive tasks by cognitive-intensive tasks. Instead, task changes within occupations are cognitive-biased for non-routine cognitive occupations but cognitive-saving for routine manual and routine cognitive occupations.

The heterogeneous task changes within occupations led to a polarisation of cognitive intensity at the top of the wage distribution and increasing returns to cognitive intensity in the U.S. labour market between 2008 and 2017.

In Chapter 3, I analysed the impact of transitory work-hour fluctuations on occupational mobility in the U.S. labour market using the longitudinal dimension of the monthly Current Population Survey (CPS). My results show that women's propensity to change occupations from month to month increases by 47 per cent when they are in the highest quartile of work-hour fluctuations compared to an increase of 19 per cent for men. While the recent literature focuses mainly on work schedule practices in hospitality, food service and retail industries, my findings show that the positive effects on mobility are significant for the entire U.S. labour market. My results further suggest that workers with extreme work-hour fluctuations use the channel of occupational mobility to alleviate their work-hour instability.

As occupational mobility includes the risk of losing crucial human capital, implementing Fair Workweek laws at a broader regional and industry level could help to protect workers from employer-driven work-hour instability. Besides the general importance of better protecting the workforce from precarious working conditions, the gender differences unveiled in Chapter 3 suggest that female workers require particular assistance. American Time Use Survey (ATUS) data and my results of different household compositions suggest that women face more severe challenges balancing working and non-working activities. Further research is warranted to better understand the intra-household specialisation between women and men and the implications on occupation choices.

In Chapter 4, I analysed the effects of local labour markets' differential exposure to within-occupation cognitive-biased technological change on mobility, wage changes and employment of workers with different educational attainment. The results show that regions with higher exposure grew faster in their working-age population between 2006 and 2017 by attracting both college and high-school workers. The increasing demand for cognitive ability and the simultaneous increase in the labour supply of college workers in growing regions neutralised the wage effects on college workers. On the other hand, wages of high-school workers decreased in areas more exposed to cognitive-biased technological change. At the same time, the employment rates of non-college workers declined while their labour force non-participation rates went up in more exposed regions. The adverse employment effects are driven by the crowding out of non-college workers in non-routine cognitive occupations. This observation is consistent with the finding that non-routine cognitive occupations show the most substantial increase in cognitive task bias.

The results of Chapter 4 indicate challenges related to medium-term and long-term trends of increasing local labour market inequality, rising educational wage gaps and the crowding out of low-skilled workers in local labour markets with higher exposure to cognitive-biased technological change. To combat these challenges, the U.S. Department of Labor plays an instrumental role in efficiently implementing active labour market policies to help disadvantaged and dislocated workers. Boosting high-school workers' skills, providing better job training, and facilitating job search and matching are the necessary tools for a better alignment of labour demand and supply of the workforce in growing regions.

Besides helping low-skilled workers who are dislocated to growing regions, it is crucial to support regions with declining populations and to attract new high-skilled workers. A long-term strategic approach could be to invest more systematically in new technologies that complement workers' skills rather than replace them. However, the potential dynamics of new technologies such as artificial intelligence (AI) are difficult to predict, making long-term approaches to supporting local labour markets challenging. It appears that the current tendency to develop new technologies is to foster further task automation instead of creating new tasks. Moreover, the faster pace of technological progress in recent years suggests that new machine-learning algorithms, autonomous driverless cars, and industrial robots will soon be able to automate a much broader scale of tasks compared to the routine-biased technological change in the last decades. However, some tasks related to perception, complex problem-solving, creativity and social intelligence seem challenging to automate. To maintain a healthy labour market in the future, we need to support workers in accumulating the complementary skills to such tasks.