ISSN 2282-6483

Alma Mater Studiorum - Università di Bologna
DEPARTMENT OF ECONOMICS

Work-Hour Instability, Occupational Mobility and Gender

Francesco Roncone

Quaderni - Working Paper DSE N° 1201

Work-Hour Instability, Occupational Mobility and Gender *

Francesco Roncone[†]

Version March 2025

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 US 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, male breadwinner role.

JEL Codes: J16, J22, J24, J62.

*I would like to thank Jacob Wong and Qazi Haque for their fruitful discussions, which significantly contributed to improving this paper. I am also grateful to the seminar participants at the University of Adelaide Economics Research Workshop for their insightful comments and suggestions. Special thanks go to the organising committee of the 2023 Econometric Society Australasian Meeting in Sydney, as well as its participants, for their valuable feedback and stimulating discussions. I would also like to express my gratitude for nominating this paper as the Best Paper by a Young Researcher at the 2023 ESAM.

[†]Department of Economics, University of Bologna, Piazza Antonio Scaravilli 2, 40126 Bologna BO, Italy (e-mail: francesco.roncone@unibo.it).

Non-Technical Summary

A growing share of US workers experience unstable and unpredictable work schedules—fluctuating hours from week to week that complicate planning, reduce income certainty, and interfere with family life. Yet despite increasing policy and academic attention to the rise of work-hour instability, we know little about how this volatility shapes broader labour market outcomes, such as occupational mobility. This study examines that link, focusing especially on how men and women respond differently to unstable work schedules.

To do so, I leverage the panel dimension of the Current Population Survey (CPS), which allows me to track individuals over time and observe changes in both their weekly hours and their occupations. I develop a measure of individual work-hour instability based on the variation in reported hours over three months and analyse how this variation correlates with occupational mobility across more than 400 detailed job categories.

The results show a clear and robust pattern: individuals experiencing greater instability in their work hours are significantly more likely to switch occupations. Importantly, this effect is substantially stronger for women. Compared to individuals with stable hours, women in the top quartile of hour volatility are 0.81% more likely to switch occupations in a given month, compared to 0.33% for men. While these percentages may seem modest, they are sizable relative to an average monthly occupational mobility rate of 1.7% in the US labour market.

Two key mechanisms appear to be crucial for explaining the substantial gender gap. First, intra-household specialisation—particularly related to childcare and housework—makes predictable work schedules more valuable for women. Second, work-hour instability seems to be more occupation-specific for women, while for men it is more related to the employer. As switching between employers is usually associated with substantially lower wage losses, it confirms the importance of the male breadwinner role. In other words, women tend to respond to instability by switching occupations, whereas men are more likely to switch employers within the same occupation.

The next part of the study examines whether occupational changes lead to more stable schedules. Using a quasi-experimental design, I find that only workers who initially faced very high work-hour volatility manage to significantly improve their work schedule stability after switching occupations. This suggests that occupational mobility may be a deliberate strategy to escape unstable work conditions.

Taken together, the findings underscore the importance of stable work schedules as a job attribute and highlight how gender-specific preferences and the male breadwinner role shape mobility patterns in ways often overlooked in traditional labour market models. Policymakers concerned with job quality, gender equality, and labour market resilience should pay close attention to work-hour instability, not only as a source of psychological stress and inequality but also as a force that shapes the broader structure of job mobility.

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 US 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 2009) 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 US 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-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 realised occupation choices instead of relying on hypothetical job choice experiments or stated-preference models that depend on constraining 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

[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.

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 the American Time Use Survey (ATUS) data, which documents that women are more likely to specialise in non-working activities (childcare and housework). Such activities are undoubtedly 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 predominantly 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 US 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 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 US 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 predominantly 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 and unpredictability (Finnigan and Hale 2018; LaBriola and Schneider 2020). Third, this study relies upon intra-year work-hour fluctuations, which are more

[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.

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 occupation characteristics other than skills and wages also matter in 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 mobility patterns 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 motivates my empirical analysis by illustrating that a significant part of work-hour instability is occupation-specific. Section 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 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 6 discusses and concludes this study in the context of future research opportunities.

2 Data Usage and Sample Construction

The monthly Current Population Survey (CPS) is a representative survey conducted by the Bureau of Labour 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.

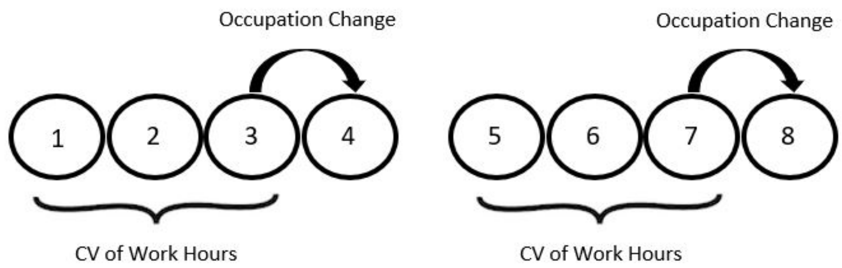

Figure 1: Longitudinal Data Usage of 4 Survey Months in the CPS

Figure 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.

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 categorised 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 work-hour variation' in this study. This term considers the fact that the constructed measure captures a broader spectrum of reasons

[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".

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 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 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-randomised 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 A. The analysis weights are used throughout the empirical analysis.[4]

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

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

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 and Leete 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 since the variance is sensitive to the mean of work hours.

Figure 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

[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.

[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 US Census Bureau.

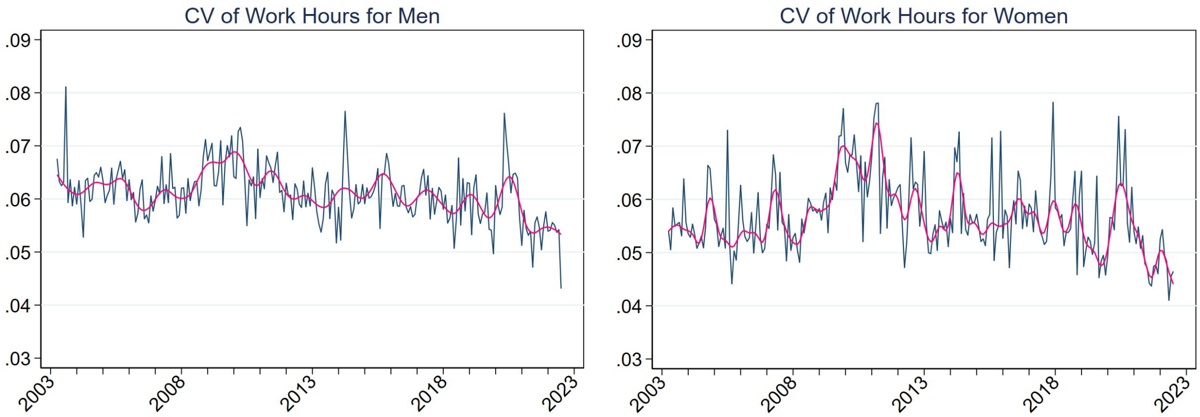

Figure 2: Male and Female Coefficient of Variation of Work Hours: 2003-2022

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 2 indicates that 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.

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 the present. However, the proposed occupation system, which is an update of the occupation system constructed by Meyer and Osborne (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]

At 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 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

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

pooled together in response to job automation and declining employment. For instance, printing machine operators and job printers are now categorised 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, depending 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 to be 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 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 conditionally 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 A.

Table 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 occupational 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 because this study also analyses occupational mobility within employers.

[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)

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

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 US 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 plots the population-weighted trend line of the coefficient of variation (CV) averaged within major occupation groups.[10] Occupations are categorised into five major groups using the Standard Occupational Classification System (SOC). Figure 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 has decreased over the last 20 years in the management, business, and science occupations. On the contrary, all other broad occupation groups show a relatively stable long-term CV development.

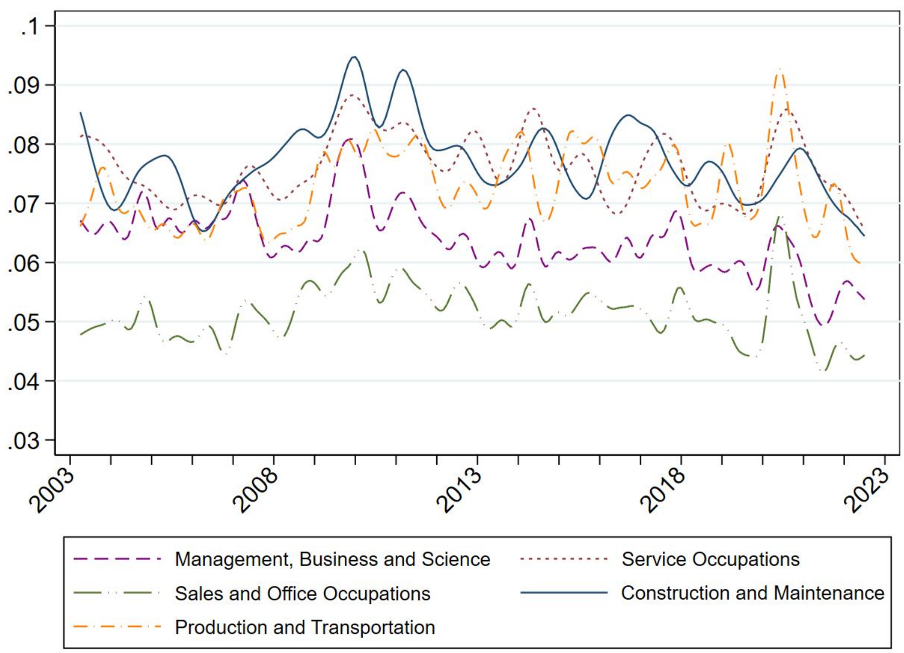

Figure 3: Trend Line of the Coefficient of Variation of Work Hours of Broad Occupation Groups: 2003-2022

Table 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, such as 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

[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 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.

construction jobs such as cement masons, terrazzo workers, and roofers, but also actors, crossing guards, massage therapists, 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: 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 characterise 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 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 ("essentiality") 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 organise 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 Rio-Chanona et al. (2020), which capture occupations' "remote work ability" and their "essentiality".[11]

Figure 4 plots the CV of work hours averaged within occupations against the standardised

[11] To equip occupations with the "remote work ability" and "essentiality" measures provided by 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.

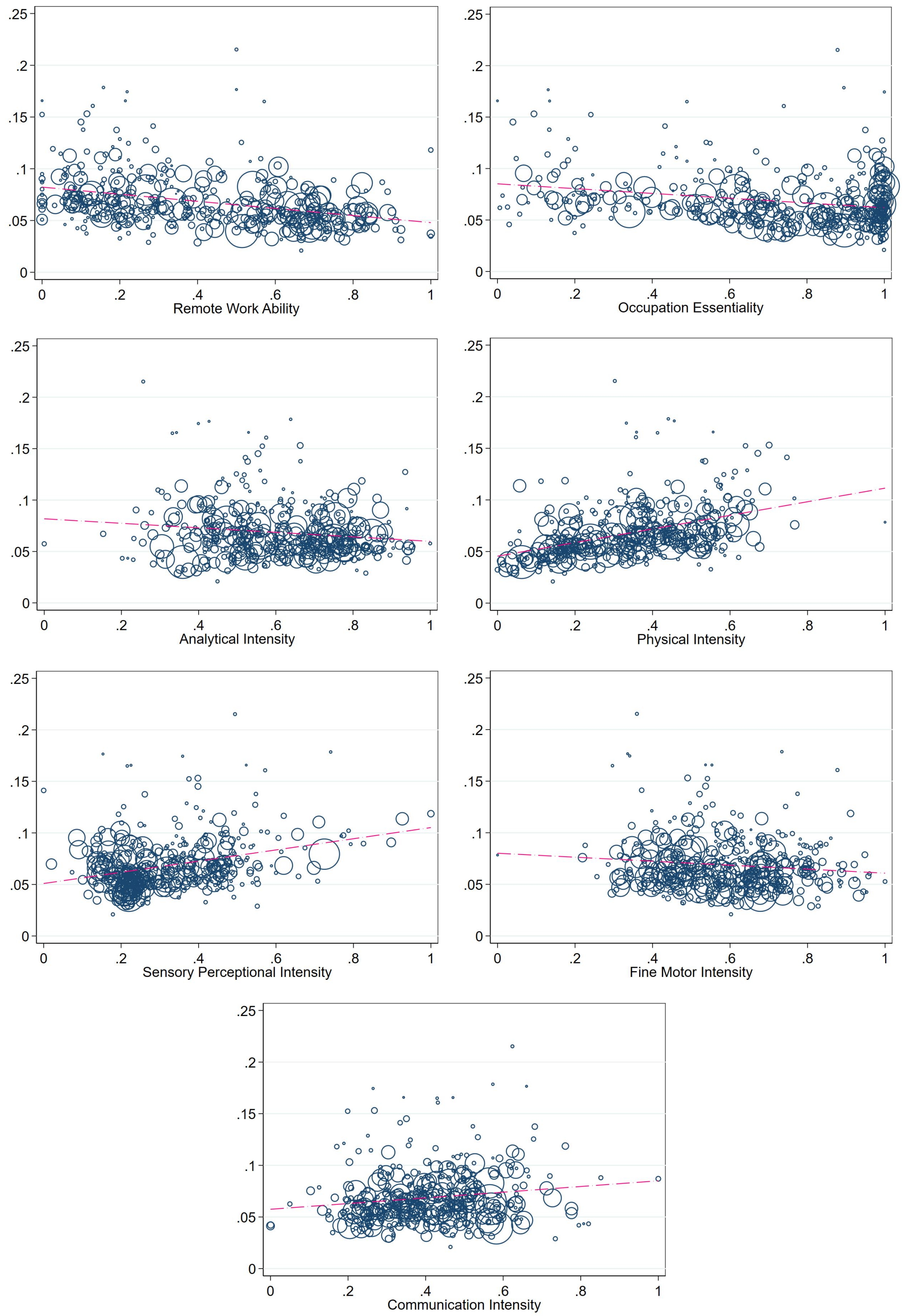

Figure 4: Correlation between Occupation-Specific Characteristics and Occupations' Coefficient of Variation of Work Hours

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 4 reports linear regressions of the form

$$CV_j = \alpha + \sum_{k=1}^{K} \beta X_j + \varepsilon_j \tag{2}$$

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 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.

Table 4 shows that the selected characteristics explain a noticeable proportion of the variation in the occupation-specific CV of work hours. Moreover, the effects are generally robust and

[12] All occupation measures presented in Figure 4 are normalised 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.

significant across the different model specifications. One exception is the ability to work remotely. While the coefficient is negative and significant when 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 4 shows that a 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, the following section investigates whether individuals consider the heterogeneity of occupations regarding their instability in work hours when making mobility decisions.

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 predominantly focuses on skill mismatches, this section investigates whether work-hour fluctuations are a potential determinant of occupational mobility decisions of individuals in the US 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).

4.1 Empirical 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

$$Pr[Switch_i = 1|X_i] = G(x_i'\beta) \tag{3}$$

[13]This section highlights the potential of occupation-specific characteristics to explain differences in 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 is detailed in Appendix C. Based on the observed individuals' decisions to switch occupations $y_i = 1$ or not $y_i = 0$, the log-likelihood function

$$\mathcal{L}_N = \sum_{i=1}^{N} y_i log[G(x_i'\beta)] + (1 - y_i) log[1 - G(x_i'\beta)] \tag{4}$$

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 equations 3 and 4 serves as baseline for the empirical analysis.

One limitation of the baseline model 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 (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 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 1973).

Starting from the latent variable framework, one can write

$$\begin{aligned} y_{1,i}^* &= (x_{1,i}'\beta_1) + \epsilon_{1,i} \\ y_{2,i}^* &= (x_{2,i}'\beta_2) + \epsilon_{2,i} \end{aligned} \tag{5}$$

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

[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 5.1.1 provides a more detailed explanation of this issue.

$$
\begin{aligned}
y_{1,i} &= 1 \quad \text{if} \quad y^*_{1,i} > 0 \quad \text{and} \quad = 0 \quad \text{, otherwise} \\
y_{2,i} &= 1 \quad \text{if} \quad y^*_{2,i} > 0 \quad \text{and} \quad = 0 \quad \text{, otherwise}
\end{aligned} \tag{6}
$$

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

$$
\begin{aligned}
Pr[Y_{1,i} = 1, Y_{2,i} = 1] &= Pr[y^*_{1,i} > 0, y^*_{2,i} > 0] \\
&= Pr[-\epsilon_{1,i} < x'_{1,i}\beta_1, -\epsilon_{2,i} < x'_{2,i}\beta_2] \\
&= \int_{\infty}^{x'_1\beta_1} \phi(z_1, z_2, \rho) dz_1 dz_2 \\
&= \Phi(x'_1\beta_1, x'_2\beta_2, \rho)
\end{aligned} \tag{7}
$$

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

$$
\begin{aligned}
p_{j,k} &= Pr[Y_{1,i} = j, Y_{2,i} = k] \\
&= \Phi(q_{1,i}x'_1\beta_1, q_{2,i}x'_2\beta_2, \rho)
\end{aligned} \tag{8}
$$

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 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.

4.2 Descriptive Statistics

Table 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 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]

[16] Note that Table 5 does not include workers of the first, second and third quartile of positive work-hour variation. How I categorise workers into quartiles of work-hour variation is explained in detail in Appendix C.

[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

Table 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 C. 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 A.

Appendix C documents the construction of the included worker and occupation characteristics in detail.

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

C.3 for the construction of the occupation-specific mean task distance measure.

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 that different occupations vary significantly in their average work-hour variation.

In accordance with previous empirical research on unpredictable work scheduling practices, Table 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 D. 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.

4.3 Results

4.3.1 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 C for detailed variable description). Table 6 shows the predicted occupational mobility rates based on the baseline probit regression model displayed in equations 3 and 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 C.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.

The second approach of categorising 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 6.

Turning to the predicted marginal effects presented in Table 7, one can see that the estimated gap in mobility between the base category and the highest quartile of hour variation is statistically

Table 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.

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 categorising 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 5. The substantial gender differences are also robust across various sample constructions, as shown in the Appendix Figures 10-11.

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

Table 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.

observation is significant for both women and men. Moreover, Table 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.

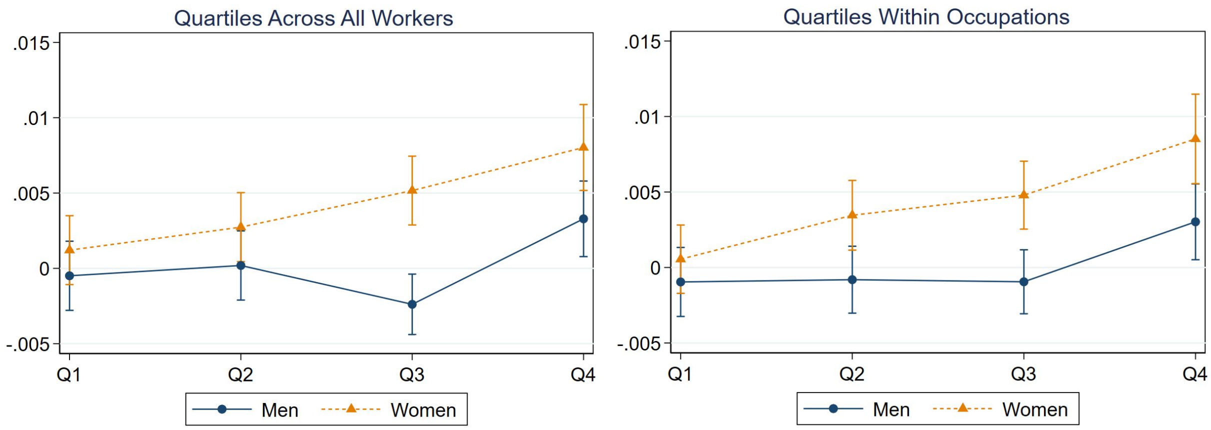

Figure 5: Marginal Effects of Work-Hour Variation on the Probability of Occupational Mobility by Quartiles

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 because 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 15-16 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 10-11. The robustness across different samples at least partly eliminates doubts that the substantial difference in the predicted mobility effect between male and female 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. Moreover, it stands out that women in the third quartile of work-hour variation are especially 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 po-

[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.

tential 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 (LaBriola and Schneider 2020) and occupational mobility (Groes et al. 2015). Controlling for average occupation wages can only partly address this issue.

4.3.2 Joint Model Results

The results of this section are based on equations 5-8, 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]

Table 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 8 and Figure 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 categorisation 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

[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%

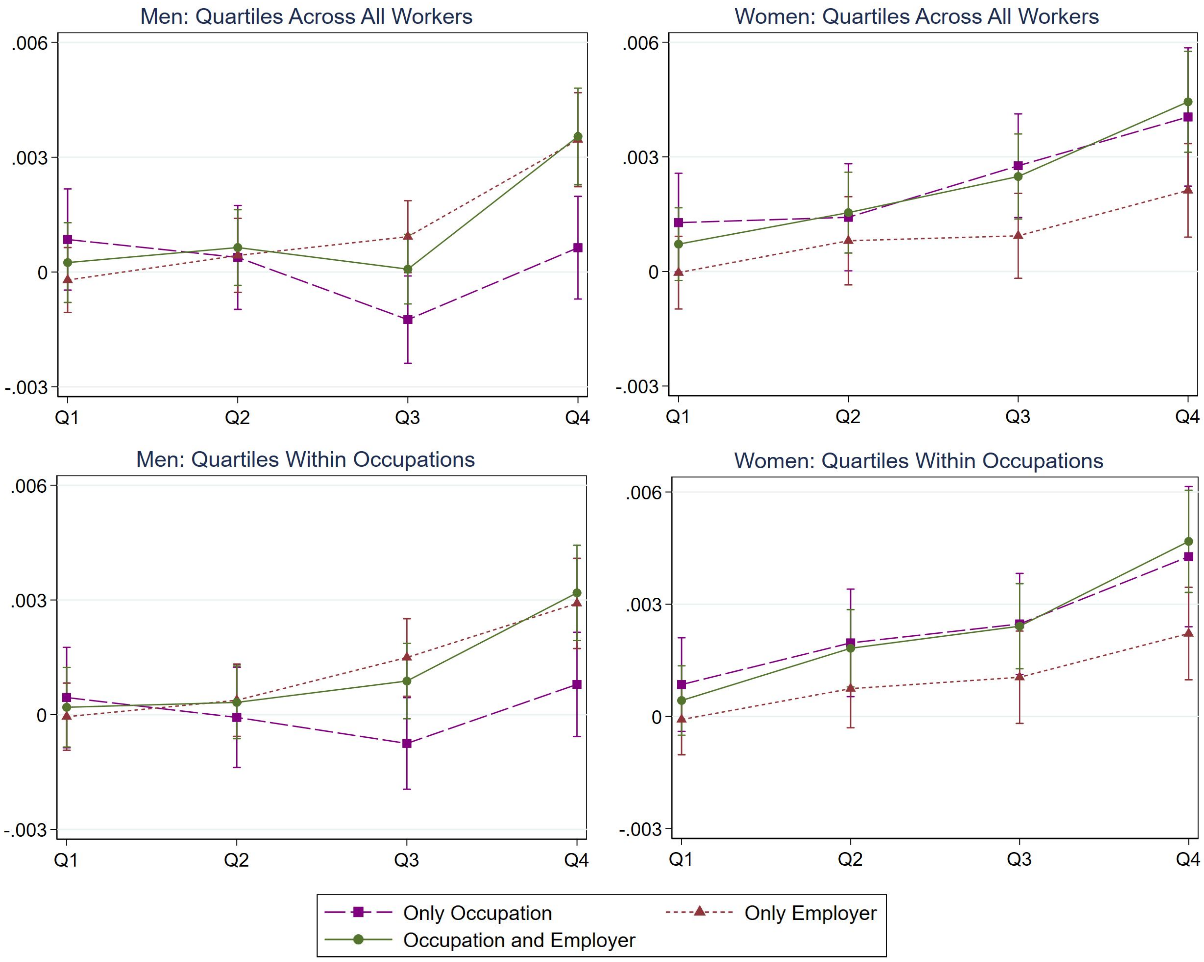

Figure 6: Marginal Effects of Work-Hour Variation on the Probability of Occupational Mobility and/or Employer Change

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 differences between men and women described are also noteworthy in magnitude. 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. In evaluating these results, it is worth mentioning that occupational mobility within employers is not a phenomenon that is predominantly 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.

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.

4.3.3 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' specialisation within households.

Table 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 and 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 specialise 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 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 complementary 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

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

[21]It is worth mentioning that the study by McCrate et al. (2019) can only give an indication of possible compensation mechanisms in the US 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 US and Canada, make a comparison reasonable.

Table 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.

occupational mobility contains the risk of human capital loss (Kambourov and Manovskii 2009), men could have a higher tolerance regarding precarious working conditions in terms of work-hour 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."

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 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.

Table 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.

Therefore, as gender differences persist even in more experienced cohorts, the gender-specific household specialisation theory by Akerlof and Kranton (2000) seems to be the more coherent explanation for the observed gender-heterogeneous mobility patterns.

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 systematically sort themselves into different occupations because they seek a more stable working environment.[22] This section's main objective is to answer this question by identifying the effect of occupational mobility on individuals' variation in weekly work hours.

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-

[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.

hour variation, each combining four weekly work-hour observations. The modified approach is visualised in Figure 7.

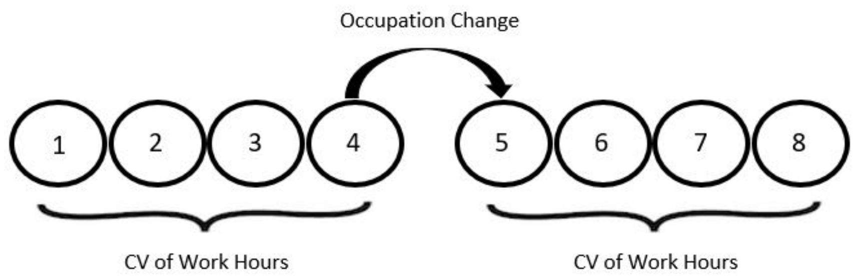

Figure 7: Longitudinal Data Usage of 8 Survey Months in the CPS

5.1.1 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. 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.[23]

Figure 8 illustrates the scope of the overestimated mobility rate measured between survey months 4 and 5. The adjusted monthly mobility rate based on independent occupation coding is almost three times higher than the rate based on the dependent coding technique (1.7% compared to 4.6%).[24] 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 of 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 2. The attrition rate for linking

[23]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).

[24]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.

Figure 8: Monthly Occupational Mobility Rates Based on Different CPS Coding

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.[25]. Next, I construct individuals' work-hour variation (CV) coefficients based on the complete 4-month intervals by imposing the sample restrictions described in Section 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 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 A).

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 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.[26] 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 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 analysis in the next section.[27]

[25] 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).

[26] 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.

[27] 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

Table 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 who are linked between monthly CPS and yearly ASEC (March) CPS data files 2003-2022.

5.1.2 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 realised 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 illustrated in Figure 7. I estimate the following difference-in-differences model at the mean as well as at specified quantiles of pre-treatment work-hour variation:

$$CV(WorkHours_i) = \alpha + \beta Post_i + \gamma Mob_i + \delta Post_i * Mob_i + \eta Year_i + \epsilon_i \tag{9}$$

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 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 A to give more weight to individuals with underrepresented characteristics due to the underlying selection procedure.

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.

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[28], $p_i = E(Z_i = 1|X_i)$, 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.[29]

Table 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). 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 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.

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 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.

[28] 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.

[29] 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 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
Wagerate	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).

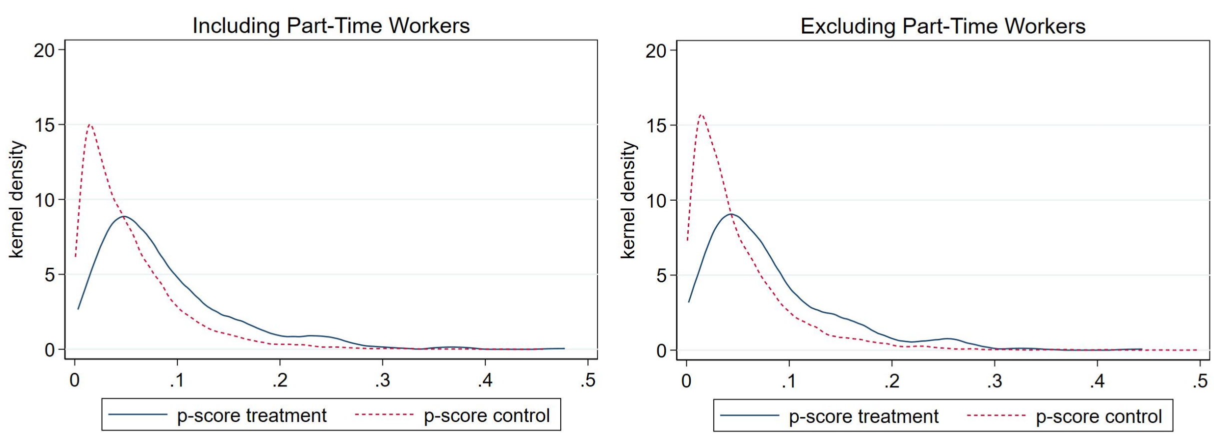

Figure 9: Propensity Score Densities of the Treatment and Control Group

5.2 The Effect of Occupational Mobility on Work-Hour Instability

Table 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.[30]

Table 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 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, the average coefficient of variation (CV) decreases by 0.011 (column 2) and 0.10 (column 4) after treatment. 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

[30] 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).

(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 study 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 US 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.

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 US 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 predominantly 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 limited 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 US 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.

References

Acemoglu, Daron and David Autor (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings". In: *Handbook of Labor Economics*. Vol. 4B. Elsevier, pp. 1043–1171.

Addison, John T., Liwen Chen, and Orgul D. Ozturk (2020). "Occupational Skill Mismatch: Differences by Gender and Cohort". In: *ILR Review* 73.3, pp. 730–767.

Akerlof, George A. and Rachel E. Kranton (2000). "Economics and Identity". In: *The Quarterly Journal of Economics* 115.3, pp. 715–753.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Arcidiacono, Peter, V. Joseph Hotz, Arnaud Maurel, and Teresa Romano (2014). *Recovering Ex Ante Returns and Preferences for Occupations Using Subjective Expectations Data*. Tech. rep. Working Paper 20626. National Bureau of Economic Research.

Bania, Neil and Laura Leete (2009). "Monthly Household Income Volatility in the U.S., 1991/92 vs. 2002/03". In: *Economics Bulletin* 29.3, pp. 2100–2112.

Bania, Neil and Laura Leete (2022). “Monthly Income Volatility and Health Outcomes”. In: *Contemporary Economic Policy* 40.4, pp. 636–658.

Boehm, L. M. (1989). “Reliability of Proxy Response in the Current Population Survey”. In: *Proceedings of the Survey Research Methods Section, American Statistical Association*, pp. 486–489.

Choper, Joshua, Daniel Schneider, and Kristen Harknett (2022). “Uncertain Time: Precarious Schedules and Job Turnover in the US Service Sector”. In: *ILR Review* 75.5, pp. 1099–1132.

Cortes, Guido Matias and Giovanni Gallipoli (2018). “The Costs of Occupational Mobility: An Aggregate Analysis”. In: *Journal of the European Economic Association* 16.2, pp. 275–315.

Costello, Anna B. and Jason Osborne (2005). “Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most from Your Analysis”. In: *Practical Assessment, Research, and Evaluation* 10.1, p. 7.

Dingel, Jonathan I. and Brent Neiman (2020). “How Many Jobs Can Be Done at Home?” In: *Journal of Public Economics* 189, p. 104235.

Fabrigar, Leandre R., Duane T. Wegener, Robert C. MacCallum, and Erin J. Strahan (1999). “Evaluating the Use of Exploratory Factor Analysis in Psychological Research”. In: *Psychological Methods* 4.3, p. 272.

Finnigan, Ryan (2018). “Varying Weekly Work Hours and Earnings Instability in the Great Recession”. In: *Social Science Research* 74, pp. 96–107.

Finnigan, Ryan and Jo Mhairi Hale (2018). “Working 9 to 5? Union Membership and Work Hours and Schedules”. In: *Social Forces* 96.4, pp. 1541–1568.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry (2022). *Integrated Public Use Microdata Series: Current Population Survey, Version 10.0 [Dataset]*. https://doi.org/10.18128/D030.V10.0. Minneapolis, MN: IPUMS.

Flood, Sarah M. and José D. Pacas (2017). “Using the Annual Social and Economic Supplement as Part of a Current Population Survey Panel”. In: *Journal of Economic and Social Measurement* 42.3–4, pp. 225–248.

Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay (2020). *Measuring Employer-to-Employer Reallocation*. Tech. rep. Working Paper 26883. National Bureau of Economic Research.

Gathmann, Christina and Uta Schönberg (2010). “How General is Human Capital? A Task-Based Approach”. In: *Journal of Labor Economics* 28.1, pp. 1–49.

Gonalons-Pons, Pilar and Markus Gangl (2021). “Marriage and masculinity: Male-breadwinner culture, unemployment, and separation risk in 29 countries”. In: *American Sociological Review* 86.3, pp. 465–502.

Gottschalk, Peter and Robert Moffitt (2009). “The rising instability of US earnings”. In: *Journal of Economic Perspectives* 23.4, pp. 3–24.

Groes, Fane, Philipp Kircher, and Iourii Manovskii (2015). “The U-shapes of occupational mobility”. In: *The Review of Economic Studies* 82.2, pp. 659–692.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer (2020). "Multidimensional skill mismatch". In: *American Economic Journal: Macroeconomics* 12.1, pp. 210–244.

Hahn, Eugene D and Refik Soyer (2005). "Probit and logit models: Differences in the multivariate realm". In: *The Journal of the Royal Statistical Society, Series B* 67, pp. 1–12.

Handel, Michael J (2016). "The O*NET content model: strengths and limitations". In: *Journal for Labour Market Research* 49.2, pp. 157–176.

Heckman, James J, Hidehiko Ichimura, and Petra E Todd (1997). "Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme". In: *The Review of Economic Studies* 64.4, pp. 605–654.

Ho, Daniel E, Kosuke Imai, Gary King, and Elizabeth A Stuart (2007). "Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference". In: *Political Analysis* 15.3, pp. 199–236.

Imbens, Guido W and Donald B Rubin (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Imbens, Guido W and Jeffrey M Wooldridge (2009). "Recent developments in the econometrics of program evaluation". In: *Journal of Economic Literature* 47.1, pp. 5–86.

Ingram, Beth F and George R Neumann (2006). "The returns to skill". In: *Labour Economics* 13.1, pp. 35–59.

Kaiser, Henry F (1960). "The application of electronic computers to factor analysis". In: *Educational and Psychological Measurement* 20.1, pp. 141–151.

Kambourov, Gueorgui and Iourii Manovskii (2008). "Rising occupational and industry mobility in the United States: 1968–97". In: *International Economic Review* 49.1, pp. 41–79.

— (2009). "Occupational specificity of human capital". In: *International Economic Review* 50.1, pp. 63–115.

— (2013). "A cautionary note on using (March) Current Population Survey and Panel Study of Income Dynamics data to study worker mobility". In: *Macroeconomic Dynamics* 17.1, pp. 172–194.

Kelly, Erin L, Phyllis Moen, J Michael Oakes, Wen Fan, Cassandra Okechukwu, Kelly D Davis, Leslie B Hammer, Ellen Ernst Kossek, Rosalind Berkowitz King, and Ginger C Hanson (2014). "Changing work and work-family conflict: Evidence from the work, family, and health network". In: *American Sociological Review* 79.3, pp. 485–516.

LaBriola, Joe and Daniel Schneider (2020). "Worker Power and Class Polarization in Intra-Year Work Hour Volatility". In: *Social Forces* 98.3, pp. 973–999.

Lambert, Susan J (2020). "Fair work schedules for the US economy and society: What's reasonable, feasible, and effective". In: *Vision 2020: Evidence for a Stronger Economy*, pp. 101–110.

Lise, Jeremy and Fabien Postel-Vinay (2020). "Multidimensional skills, sorting, and human capital accumulation". In: *American Economic Review* 110.8, pp. 2328–2376.

Madrian, Brigitte C and Lars John Lefgren (2000). "An approach to longitudinally matching Current Population Survey (CPS) respondents". In: *Journal of Economic and Social Measurement* 26.1, pp. 31–62.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger (2018). *The value of working conditions in the United States and implications for the structure of wages*. Tech. rep. National Bureau of Economic Research.

Mas, Alexandre and Amanda Pallais (2017). "Valuing alternative work arrangements". In: *American Economic Review* 107.12, pp. 3722–3729.

McCrate, Elaine, Susan J Lambert, and Julia R Henly (2019). "Competing for hours: unstable work schedules and underemployment among hourly workers in Canada". In: *Cambridge Journal of Economics* 43.5, pp. 1287–1314.

McFadden, Daniel (1973). "Conditional logit analysis of qualitative choice behavior". In: *Frontiers in Econometrics*. Ed. by Paul Zarembka. Academic Press, pp. 105–142.

Meyer, Peter B. and Anastasiya M. Osborne (2005). *Proposed category system for 1960–2000 census occupations*. Tech. rep. Working Paper 383. U.S. Department of Labor, Bureau of Labor Statistics.

Moen, Phyllis, Erin L Kelly, Wen Fan, Shi-Rong Lee, David Almeida, Ellen Ernst Kossek, and Orfeu M Buxton (2016). "Does a flexibility/support organizational initiative improve high-tech employees' well-being? Evidence from the work, family, and health network". In: *American Sociological Review* 81.1, pp. 134–164.

Moore, Jeffrey C (2008). "Seam bias in the 2004 SIPP panel: Much improved, but much bias still remains". In: *US Census Bureau Statistical Research Division Survey Methodology Research Report Series* 3, p. 2008.

Morduch, Jonathan and Julie Siwicki (2017). "In and out of poverty: Episodic poverty and income volatility in the US financial diaries". In: *Social Service Review* 91.3, pp. 390–421.

Moscarini, Giuseppe and Kaj Thomsson (2007). "Occupational and Job Mobility in the US". In: *The Scandinavian Journal of Economics* 109.4, pp. 807–836.

Moscarini, Giuseppe and Francis G Vella (2008). *Occupational mobility and the business cycle*. Tech. rep. National Bureau of Economic Research.

Neal, Derek (1999). "The complexity of job mobility among young men". In: *Journal of Labor Economics* 17.2, pp. 237–261.

Olson, Ryan, Tori L Crain, Todd E Bodner, Rosalind King, Leslie B Hammer, Laura Cousino Klein, Leslie Erickson, Phyllis Moen, Lisa F Berkman, and Orfeu M Buxton (2015). "A workplace intervention improves sleep: Results from the randomized controlled Work, Family, and Health Study". In: *Sleep Health* 1.1, pp. 55–65.

Petrucci, Larissa, Lola Loustaunau, Ellen Scott, and Lina Stepick (2022). "Persistent Unpredictability: Analyzing Experiences with the First Statewide Scheduling Legislation in Oregon". In: *ILR Review* 75.5, pp. 1133–1158.

Poletaev, Maxim and Chris Robinson (2008). “Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000”. In: *Journal of Labor Economics* 26.3, pp. 387–420.

Polivka, Anne E and Jennifer M Rothgeb (1993). “Redesigning the CPS questionnaire”. In: *Monthly Labor Review* 116.9, pp. 10–28.

Rio-Chanona, R. Maria del, Penny Mealy, Anton Pichler, Francois Lafond, and J. Doyne Farmer (2020). “Supply and Demand Shocks in the COVID-19 Pandemic: An Industry and Occupation Perspective”. In: *Oxford Review of Economic Policy* 36.Supplement_1, S94–S137.

Rivera Drew, Julia A, Sarah Flood, and John Robert Warren (2014). “Making full use of the longitudinal design of the Current Population Survey: Methods for linking records across 16 months\m {1}”. In: *Journal of Economic and Social Measurement* 39.3, pp. 121–144.

Robinson, Chris (2018). “Occupational mobility, occupation distance, and specific human capital”. In: *Journal of Human Resources* 53.2, pp. 513–551.

Rosen, Sherwin (1986). “The theory of equalizing differences”. In: *Handbook of Labor Economics.* Vol. 1. Elsevier, pp. 641–692.

Rosenbaum, Paul R and Donald B Rubin (1985). “Constructing a control group using multivariate matched sampling methods that incorporate the propensity score”. In: *The American Statistician* 39.1, pp. 33–38.

Rubin, Donald B (1973). “Matching to remove bias in observational studies”. In: *Biometrics*, pp. 159–183.

Schmitt, John (2003). *Creating a consistent hourly wage series from the Current Population Survey's Outgoing Rotation Group, 1979–2002.* Tech. rep. Center for Economic and Policy Research.

Schneider, Daniel and Kristen Harknett (2019). “Consequences of routine work-schedule instability for worker health and well-being”. In: *American Sociological Review* 84.1, pp. 82–114.

Spiegelhalter, DJ, NG Best, BP Carlin, and A Van der Linde (2003). “Bayesian measures of model complexity and fit”. In: *Quality Control and Applied Statistics* 48.4, pp. 431–432.

Sullivan, Paul (2010). “Empirical evidence on occupation and industry-specific human capital”. In: *Labour Economics* 17.3, pp. 567–580.

Villa, Juan M (2016). “diff: Simplifying the estimation of difference-in-differences treatment effects”. In: *The Stata Journal* 16.1, pp. 52–71.

Wiswall, Matthew and Basit Zafar (2018). “Preference for the workplace, investment in human capital, and gender”. In: *The Quarterly Journal of Economics* 133.1, pp. 457–507.

Wolfe, Julia, Janelle Jones, and David Cooper (2018). “‘Fair workweek’laws help more than 1.8 million workers: Laws promote workplace flexibility and protect against unfair scheduling practices”. In: *Economic Policy Institute.*

Appendices

A 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 and 4, I use the CPS individual basic weight WTFINL, and for Section 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 and 4. For the analysis in Section 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:

$$w_i^2 = \frac{LNKFW8WT_i * EARNWTi}{WTFINLi} \tag{10}$$

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 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:

$$w_i^3 = w_i^{1,2} \prod_{n=1}^{N} \frac{Pr(x_t^n = x_{i,t}^n \mid \text{In labour force})}{Pr(x_t^n = x_{i,t}^n \mid \text{Under sample restrictions})} \tag{11}$$

where $x_{i,t}^n$ 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.[31]. This procedure is repeated for each monthly CPS survey separately denoted by the

[31] 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

time subscript t. The calculated relative probabilities are multiplied by w_i^1 and w_i^2.

In the next step, w_i^3 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_i^3) 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 11 to predict the probability of self-reporting:

$$Pr(SR_i = 1) = \Phi(X_i \beta) \tag{12}$$

Finally, I amend the weights by dividing w_i^3 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:

$$w_i^4 = \frac{w_i^3}{Pr(SR_i = 1)} \tag{13}$$

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

B 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

(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).

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).[32]

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.[33] 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.

C Probit Model Variables

C.1 Work-Hour Instability

To systematically use the coefficient of variation (CV) measure, which is constructed for each individual as described in Section 2.2, I first divide the sample by gender. Next, I split all female and male workers into 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.[34] The categorization of individuals within occupations

[32]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.

[33]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.

[34]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-).

accounts for the possibility that workers are more likely to compare their working conditions with colleagues or workers in similar occupations. For example, comparing bricklayers and insurance clerks is not very useful because they work in completely 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.

C.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 standardising the average work hours of individuals within year-gender cells. In the second approach, average work hours are standardised within year-gender-occupation cells.

C.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 2009; 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 standardised based on employment shares in the January 2012 CPS. Next, I combine the five standardised task distance measures of each occupation to construct their 'mean task distance' based on the following Euclidean distance formula:

$$\mu_j(edist5) = \sqrt{dist_{1j}^2 w_1 + dist_{2j}^2 w_2 + dist_{3j}^2 w_3 + dist_{4j}^2 w_4 + dist_{5j}^2 w_5} \tag{14}$$

where $dist_{kj} = \frac{task_{kj} - \mu(task_k)}{\sigma(task_k)}$ is the standardised 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.[35] The mean task distance $\mu_j(edist5)$ of occupation j is equal to λ when there is a

[35] 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). 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.

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. 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 14 shows the category system, including some example occupations for each category.[36]

Table 14: 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.

C.4 Occupation Characteristics

I add three additional occupation characteristics to the model: expected wages, job loss probabilities, and occupations' ability to work remotely. To construct the expected occupation wages, I use hourly wage data from the earner study of the monthly outgoing rotation groups in the CPS.[37] 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 US 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 standardised within year-gender cells. Consequently, the marginal effects shown in Table 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

[36] 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.

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

"temporarily laid off". Next, I calculate the proportion of involuntarily unemployed relative to the total workforce within each occupation in a given year. Next, 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 standardised 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 has the 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.[38] The binary measure suggests that 112 out of 430 occupations in my panel can be done entirely from home.

C.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.

[38] I classify occupations in my panel as 'remote work occupations' only if all assigned O*NET occupations are also classified as such. As a robustness check, I also use a more granular measure provided by Rio-Chanona et al. (2020). 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.

D Robustness Checks of the Probit Model Results

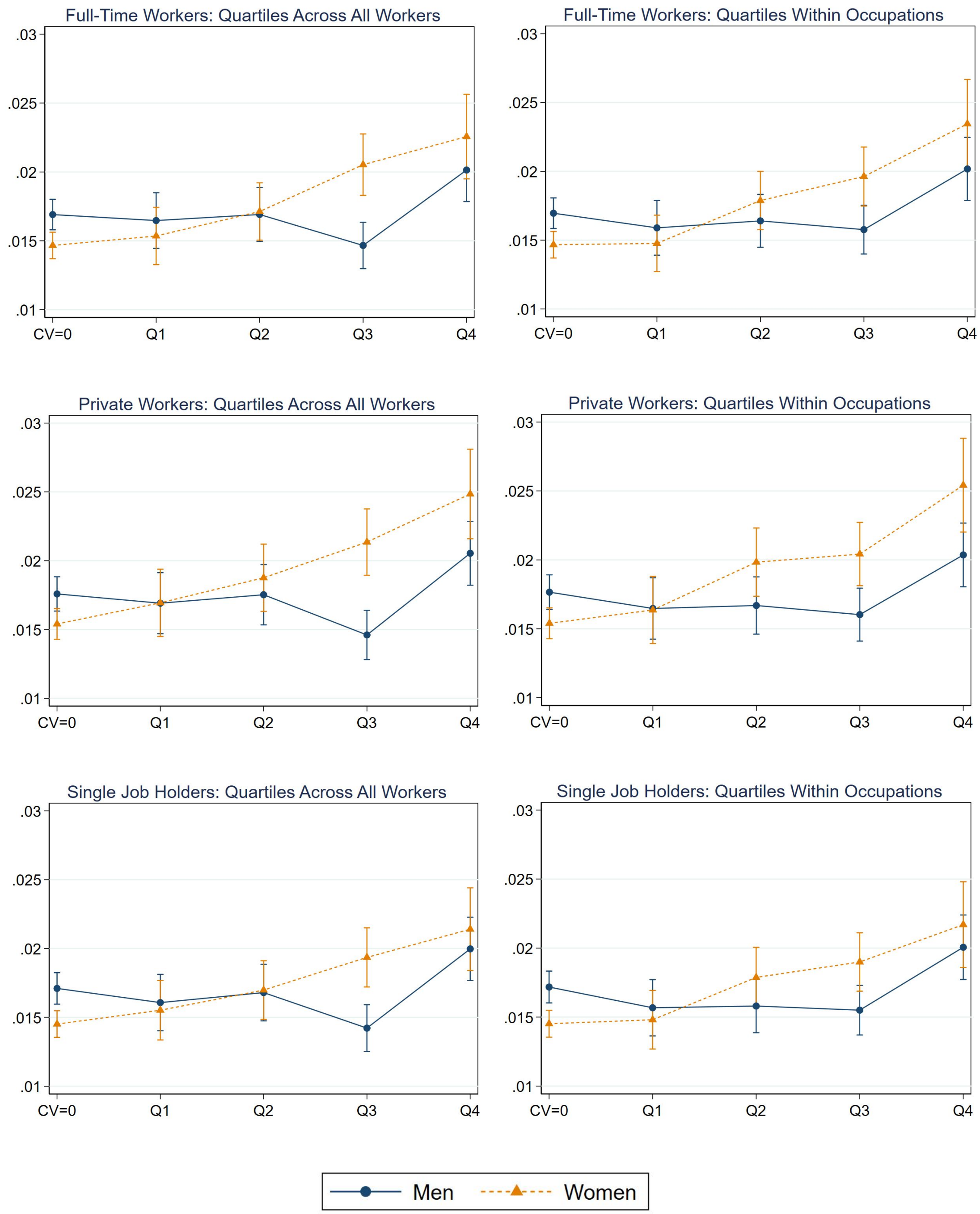

Figure 10: Predicted Occupational Mobility Rates for Different Types of Workers

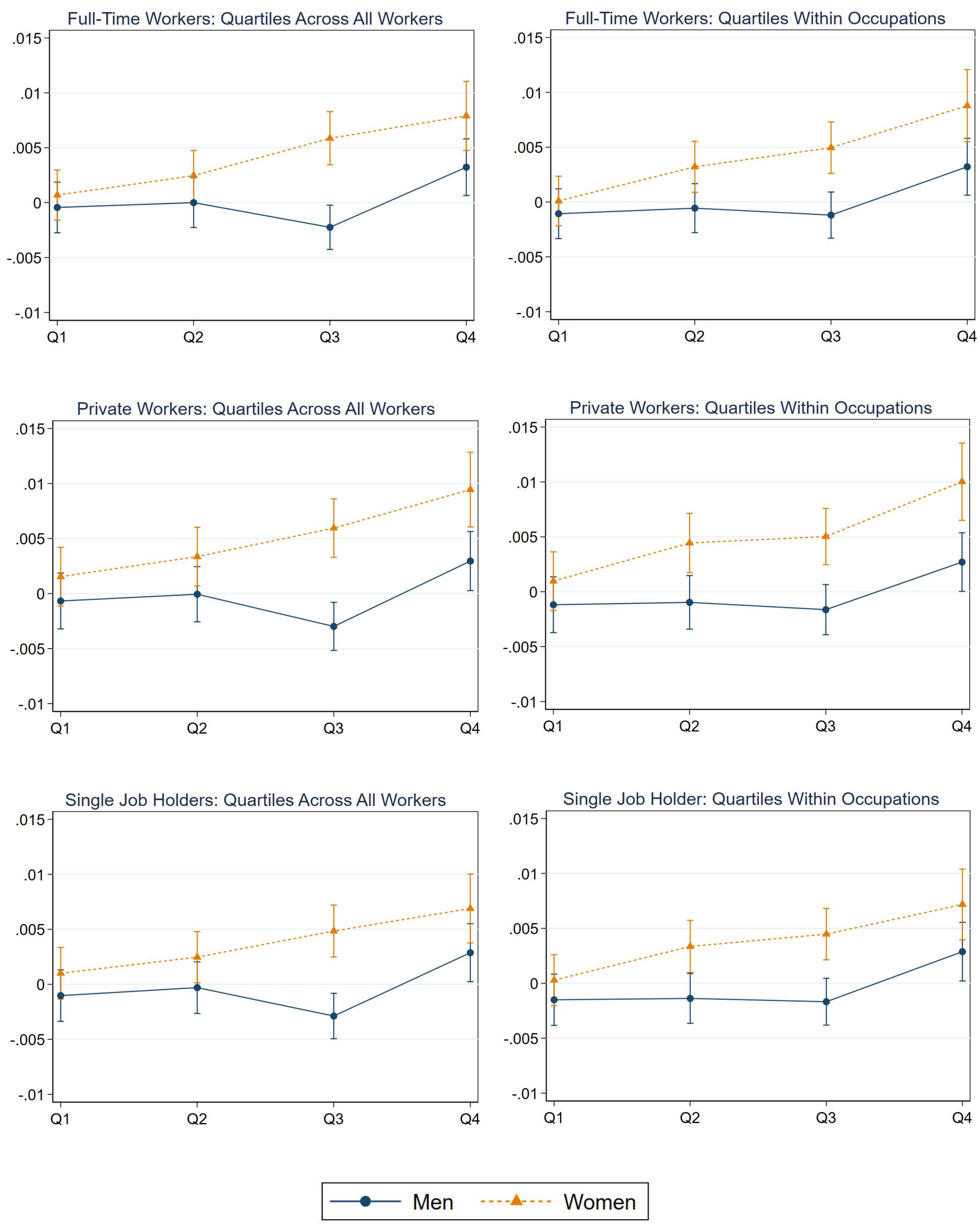

Figure 11: Marginal Effects of Work-Hour Instability for Different Types of Workers

Table 15: 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 16: 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.

Alma Mater Studiorum - Università di Bologna

DEPARTMENT OF ECONOMICS

Strada Maggiore 45
40125 Bologna - Italy
Tel. +39 051 2092604
Fax +39 051 2092664
http://www.dse.unibo.it