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Marta Lachowska
Alexandre Mas
Raffaele Saggio
Stephen A. Woodbury

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ABSTRACT

This paper uses a revealed preference approach applied to administrative data from Washington to document and characterize work-hour constraints. Workers have limited discretion over hours at a given employer, and there is substantial mismatch between workers who prefer long hours and employers that provide short hours. Voluntary job transitions suggest that the ratio of the marginal rate of substitution of earnings for hours (MRS) to the wage rate is on the order of 0.5-0.6 for prime-age workers. The average absolute deviation between observed hours and optimal hours is about 15%, and constraints on hours are particularly acute among low-wage workers. On average, observed hours tend to be less than preferred levels, and workers would require a 12% higher wage with their current employer to be as well off as they would be after moving to an employer offering ideal hours. These findings suggest that hours constraints are an equilibrium feature of the labor market because long-hour jobs are costly to employers, and that employers offer high-wage/long-hour packages to increase their overall value of employment.

Marta Lachowska
W.E. Upjohn Institute for
Employment Research
300 S. Westnedge Avenue
Kalamazoo, MI 49007
marta@upjohn.org

Alexandre Mas
Industrial Relations Section
Simpson International Building
Princeton University
Princeton, NJ 08544
and NBER
amas@princeton.edu

Raffaele Saggio
Department of Economics
University of British Columbia
6000 Iona Drive
Vancouver, BC V6T 1L4
and NBER
rsaggio@mail.ubc.ca

Stephen A. Woodbury
Department of Economics
Michigan State University
486 West Circle Drive, Room 110
East Lansing, MI 48824
and W.E. Upjohn Institute for Employment Research
woodbur2@msu.edu

1 Introduction

> *There is no place* [*within the framework of consumer demand theory*] *in which the interests of employers with respect to the hours of work of their employees enter as factors in the determination of employee hours of work.* Lewis (1967, pp. 1–2)

H. Gregg Lewis's dissatisfaction with the naive application of neoclassical consumer demand theory to individual labor supply decisions was based on the belief that employers have an evident interest in workers' hours, and the consequent implausibility of the assumption that workers could optimize their work hours at the margin. The model he developed in response (Lewis, 1967) differs from the canonical neoclassical model because the budget set is nonlinear, which implies that workers may be constrained—in equilibrium they may want to work longer or shorter hours at the current wage, but the market does not offer the option.[1] In theory, the payment needed to compensate a worker for a deviation from optimal hours may be large (Abowd and Ashenfelter, 1981), but we do not know of a full empirical accounting of the nature and magnitude of hour constraints and their quantitative importance for workers' welfare.

In this paper, we take a revealed preference approach to quantifying the gap between the marginal rate of substitution of earnings for hours (MRS) and the current wage; that is, to quantifying how far workers are off their supply curve. To do this, we construct a linked employer-employee panel from Washington administrative data, which is unusual because, in addition to earnings, they contain reliable information on paid hours of work (Lachowska, Mas and Woodbury, 2022). The data allow us to observe the extent of hour constraints in the labor market, to characterize worker sorting to employers with different hour requirements (and how that sorting depends on workers' skills), and to estimate the average worker's willingness to pay to relax hour constraints. The estimates then allow us to quantify the welfare loss from the gap between pre-

[1] The neoclassical-marginalist labor supply model can be traced to Robbins (1930) and Hicks (1946, chapter II). The Lewis model has remained obscure, probably because it was published in a Spanish-language journal and has only circulated as an unpublished manuscript in English. Rosen (1974) later expanded and generalized Lewis (1969) into what has become the standard reference for hedonic pricing. Rosen (1968, 1978) also developed a model of how employers choose the number of workers and hours per worker. See Pencavel (2016) for an interesting history of this topic.

ferred and actual hours, as well as to evaluate existing models of work-hour determination.

Our analysis builds on a two-way fixed effects model of work hours—an additively separable model in employer and worker effects on hours—that arises from workers and employers bargaining over hours. We interpret employer effects as reflecting employers' policies on hours, and worker effects as reflecting workers' preferences for hours. The data support this interpretation of the model.

Using the Kline, Saggio and Sølvsten (2020) (KSS) bias-corrected variance components from this statistical model, we begin with a descriptive analysis of employer hour policies and worker preferences that suggests mismatch and hour constraints. Heterogeneity among employers in hour policies is quantitatively important, accounting for roughly 56% of the variation in employer effects on earnings. Employer and worker effects on hours are only weakly positively correlated, implying an absence of sorting that is difficult to explain using benchmark frictional models like those of Dickens and Lundberg (1985) and Chetty et al. (2011). Extending the KSS method to derive an unbiased estimator of the covariance of worker and employer effects across the outcomes (hours and wages), we find that high-wage workers tend to work for employers with long hour requirements, even though those workers do not have strong preferences for long hours. Workers with less educational attainment are more likely to prefer long hours but to work for short-hour employers. These findings suggest that long-hour employers are more desirable to workers.

The heart of the analysis is to quantify and estimate the direction of hour constraints using a revealed preference PageRank measure of firm utility developed by Page et al. (1999) and Sorkin (2018). Employer effects on hours and employer utility remain strongly positively related after controlling for employer wage effects (and after adjusting for the relationship between work hours and the provision of fringe benefits). The estimates imply an average ratio of the MRS to the wage of 0.3, suggesting that workers place a very high value on additional hours and that most workers' hours are constrained from above. Constraints on hours follow a clear life-cycle pattern, with the MRS-to-wage ratio lowest for workers less than age 25, between 0.5 and 0.6 for prime-age workers, and close to 1 (i.e., optimality) for 56-60 year olds.

Based on this evidence, we devise an approach to estimating welfare loss due to hour constraints from both above and below. For a given employer wage policy, we identify the level of hours that leads to the highest PageRank utility. Comparing the estimated utility-maximizing hours with observed hours quantifies the change in the wage rate—or compensating variation—required to make workers indifferent between their optimal and constrained hours. The analysis shows that labor supply is inelastic, that there is a high degree of mismatch between preferred and actual hours, and that mismatch is costly to workers. We find that, on average, the absolute deviation between observed hours and optimal hours is about 15%, and that a 12% wage increase would be needed to make them as well off as at their optimal hours. Workers at low-wage employers and in the Retail and Food and Accommodation sectors are the most constrained.

These empirical findings can be explained by vertical differentiation among employers; that is, the existence of a hierarchical ranking of employers based on the desirability of their jobs, consistent with Sorkin (2018). In a Lewis (1969) hedonic equilibrium, when workers' hours are constrained from above, they can work more hours only by accepting a lower wage rate. But employers may choose to vertically differentiate to reduce recruiting costs or pay efficiency wages (among other motives). In this case, employers may accommodate workers, increasing their utility by increasing both hours and wage rates. If this vertical differentiation motive in wage and hour choice dominates, it can break both the traditional compensating differentials and labor supply links between hours and wages. It follows that vertical differentiation reconciles the existence of constraints on workers' hours and the positive correlation between employer effects on hours and wages. Vertical differentiation also helps explain the puzzling lack of sorting of long-hour workers to long-hour employers. This is because under an assignment mechanism where employers with above-market utility select on the productivity of queued applicants, sorting based on worker and employer preferences for hours will weaken.

Our work is closely related to the existing literature on hour constraints and adjustment costs. For example, Altonji and Paxson (1986) and Abowd and Card (1987) observed that changes in hours are much larger for job-movers than for job-stayers.[2] More recently, Chetty et al. (2011) examined the role of search costs that may limit worker mobility after changes in taxes, and Labanca and Pozzoli (2022*a*) have used linked employer-employee data from Denmark to measure hour constraints as the standard deviation of hours within the firm. Their findings show that workers in firms with less variability in hours respond less to changes in tax rates, suggesting that constraints shape labor supply decisions.

The work is also related to the voluminous literature on labor supply, which after early work using the canonical labor supply model, recognized demand-side factors as important in determining hours—for example, Ham (1985), Card (1991), Blundell, Ham and Meghir (1989), Valletta, Bengali and van der List (2020), Ham and Reilly (2002). In particular, these studies examined how changes in hours vary with industry and the unemployment rate, concluding industry and business cycle variables influence the supply of work hours, and that the wage rate is not a sufficient statistic for the demand side of the labor market. Our findings on the role of firms in shaping hours are in the same vein.

A growing literature has studied the provision of amenities by firms in imperfect labor markets (Hwang, Mortensen and Reed, 1998; Lang and Majumdar, 2004; Lavetti and Schmutte, 2016; Sorkin, 2018; Lamadon, Mogstad and Setzler, 2019; Morchio and Moser, 2021), and our findings offer further evidence on this topic by treating work hours as a key job attribute. They also support survey evidence suggesting underemployment, particularly in low-wage jobs. For example, in a survey experiment of Walmart workers, Dube, Naidu and Reich (2022) find that additional weekly hours are the most valued proposed amenity in a hypothetical job offer, including paid time off, control over hours, commute time, and measures of management respect and fairness. Similar findings have been reported in Kahn and Lang (2001), Watson and Swanberg (2013), Alexander and Haley-Lock (2015), and Schneider (2021).

[2]See also the large literature examining whether hour constraints push workers off of their supply curve—Lewis (1969); Abbott and Ashenfelter (1976); Abowd and Ashenfelter (1981); Altonji and Paxson (1986); Altonji and Paxson (1988); Kinoshita (1987); Kahn and Lang (1991); Kahn and Lang (1995); Lachowska et al. (2022); Chetty et al. (2011); Labanca and Pozzoli (2022*a*); Labanca and Pozzoli (2022*b*).

2 Econometric Framework

This section describes a framework for hours determination and the steps for estimating workers' willingness to pay to relax constraints on hours imposed by employers.

2.1 Hours Determination with Worker and Employer Heterogeneity

We fit and evaluate a model of hours determination that results from worker and employer bargaining over hours, as in Carry (2022). Each worker has a desired level of work hours A_i (where i indexes the worker), which depends on the worker's preferences and non-labor income. We assume A_i does not depend on the wage rate both because we estimate negligible uncompensated labor supply elasticities, mirroring the findings of a large prior literature (Kimball and Shapiro, 2008), and because the vast majority of the variation in hours is orthogonal to the wage rate.

Employers are also likely to have preferences for work schedules and work hours because of employer-specific technology or organization (see Section 6.1 for further discussion). The employer's preference for hours per worker is denoted by F_j, where j indexes the employer.

Bargaining results in a weighted geometric average of the employer and worker preferences for hours that depend on the bargaining weight δ:

$$h_{ij} = A_i^{\delta} F_j^{1-\delta} \rho_{ij}, \tag{1}$$

where the term ρ_{ij} is a multiplicative error term for a given pair (i, j). Taking logs gives:

$$\log h_{ij} = \alpha_i^h + \psi_j^h + \log \rho_{ij} \tag{2}$$

where $\alpha_i^h \equiv \delta \log A_i$ and $\psi_j^h \equiv (1-\delta) \log F_j$. The fixed effect α_i^h reflects the number of hours that individual i works irrespective of the identity of her current employer. The fixed effect ψ_j^h captures a given employer's hour policy that is uniformly applied to all its employees. In Section 6 we outline a model that illustrates how workers and firms formulate their targets in the presence of this bargaining.[3]

Three variance components result from this analysis: $\text{Var}(\psi_j^h), \text{Var}(\alpha_i^h),$ and $\text{Corr}(\psi_j^h, \alpha_i^h)$. $\text{Var}(\psi_j^h)$ reflects variability in hour policies across employers and quantifies the importance of employers in determining work hours. (Employers may play a minor role if they have little bargaining power [i.e., $\delta \approx 1$] or if all employers demand similar average hours per worker.) $\text{Var}(\alpha_i^h)$ reflects variability in workers' preferences for hours. (Workers will explain little of the overall variability of hours if they have little bargaining power [i.e., $\delta \approx 0$] or if the dispersion in workers' preferences for hours is small.) $\text{Corr}(\psi_j^h, \alpha_i^h) = \text{Corr}(F_j, A_i)$ reflects the degree of worker and employer sorting on hours and is independent of bargaining power δ.

2.2 Estimation of Variance Components

Because the data permit us to observe the level of hours worked by individual i employed by firm j in year t, it is possible to estimate the portion of hour variation attributable to worker-specific versus employer-specific differences. To do this, we estimate a two-way fixed effect specification (Abowd, Kramarz and Margolis, 1999, AKM)—using the logarithm of hours as the outcome variable:

$$\log h_{it} = \alpha_i^h + \psi_{j(i,t)}^h + x_t' \gamma^h + r_{it}^h \tag{3}$$

where, in addition to the terms in equation (2), $x_t' \gamma^h$ captures year effects, $j(i,t)$ denotes the identity of worker i's employer in year t, and the error term r_{it}^h combines unobserved components such as match effects for hours, drift in worker preferences for hours, and measurement error. We discuss the exogenous mobility assumption for identifying employer fixed effects in Section 3.3.[4]

The analysis also requires estimates of employer wage policies and worker fixed effects on

[3] As shown in Section 3.3, this parsimonious model of hours determination, which leads to an additively separable relationship in worker and employer preferences, does a good job of describing observed data on work hours despite its simplicity. In a robustness analysis, we also consider the version of this model fitted to levels of hours.

[4] Gallen, Lesner and Vejlin (2019) use a similar two-way fixed effects model to estimate establishment work-hour effects, which are then used in a Oaxaca-Blinder-Kitagawa decomposition of the gender gap.

wages. These are obtained by fitting a two-way fixed effect model of log wages given by:

$$\log w_{it} = \alpha_i^w + \psi_{j(i,t)}^w + x_t'\gamma^w + r_{it}^w \tag{4}$$

where $\log w_{it}$ is log of hourly wages, $\psi_{j(i,t)}^w$ is employer j's wage policy, and α_i^w is worker i's effect on wages. Except where mentioned, all worker and employer variance components are corrected for limited mobility bias (Andrews et al., 2008; Bonhomme et al., 2023) using the Kline, Saggio and Sølvsten (2020) (or KSS) estimator.

Correcting variance components in the presence of correlated errors A methodological contribution of this paper is to develop an extended KSS estimator that is unbiased for variance components between different outcomes with potentially correlated error terms, such as the error terms in equations (3) and (4). The method allows computation of the covariance between employer effects on hours and wages—$\text{Cov}(\psi^h, \psi^w)$—corrected for the correlation between error terms r^h and r^w. Details are described in Appendix B.2.

2.3 Quantifying Hour Constraints

If employer effects on hours reflect systematic differences in employers' hour policies and employer effects on wage rate measure employer wage premiums, we can quantify workers' willingness to pay to relax hour constraints.

Workers have utility functions that are increasing in earnings and decreasing in work hours: $U(e,h)$. To understand constraints on hours, consider the ratio of the marginal rate of substitution between hours and earnings to the wage. If workers are unconstrained and optimize, this ratio will be 1. If a worker's hours are less than optimal, it will be less than 1, and the worker would accept less than the current wage for a marginal increase in work hours.

Specifically, if $\text{MRS}_{e,h}(e,h) \equiv -\frac{\partial U(e,h)}{\partial h} / \frac{\partial U(e,h)}{\partial e}$, then for any well-behaved utility function we can write:

$$\frac{\text{MRS}_{e,h}(e^0,h^0)}{w} = -\frac{\partial U(e^0,h^0)/(\partial h/h^0)}{\partial U(e^0,h^0)/(\partial e/e^0)} = -\frac{\partial U(e^0,h^0)/\partial \log h^0}{\partial U(e^0,h^0)/\partial \log e^0}, \tag{5}$$

where e^0 and h^0 are the initial values of earnings and hours, and w is the wage rate. If $e^0 = e^*$ and $h^0 = h^*$, where h^* and $e^*(\equiv wh^*)$ are the utility-maximizing values of hours and earnings at the current wage, then it follows from utility maximization that $\frac{MRS_{e,h}(e^*,h^*)}{w} = 1$.

Equation (5) suggests a way to quantify the presence of hour constraints, provided a measure of utility from working is available. The latter can be obtained from a revealed preference ranking of employers derived from the PageRank algorithm (Page et al., 1999) and developed for the analysis of labor market flows by Sorkin (2018). Specifically, we assume that for worker i, the utility of being employed by employer j is given by $U_{ij} = v_j + e_{ij}$, where v_j represents the common value of being employed by firm j (this may depend on the employer's wage, hour policies, and other amenities) and e_{ij} is a match-specific component distributed according to a type 1 extreme value distribution. As shown by Sorkin (2018), v_j can be identified from the following recursive equation:

$$\exp(v_j) = \sum_{\ell \in \mathscr{B}_j} \omega_{\ell,j} \exp(v_\ell) \qquad j = 1, \ldots, J. \tag{6}$$

where $\omega_{\ell,j}$ is the number of workers who voluntarily move from employer ℓ to employer j scaled by the number of all workers who joined employer j as a result of an employer-to-employer transition, and $\mathscr{B}_j$ is the set of employers who lost a worker to employer j.

Equation (6) provides a measure or index of the desirability of an employer based on the employer-to-employer transitions. The premise of this recursive index is that a high-utility employer is one that recruits from other high-utility employers and that few workers voluntarily leave. The PageRank measure requires frictions—workers make systematic, voluntary moves to employers with higher rank only when an offer from such an employer materializes.[5] Therefore, workers in a given job may not be at their optimum. Equation (5) allows us to quantify how far workers are from their desired hours in their current job. If a worker has an employer with hour and wage policies that result in a MRS close to the offered wage, then the worker is close to the optimum. In contrast, if the ratio of the MRS to the wage is far from 1, the worker is constrained on hours and

[5] Sorkin (2018) provides a microfoundation for this measure based on the Burdett and Mortensen (1998) search-frictions model. We use a version of the PageRank index that adjusts for employer size and intensity of offer differences among employers, as proposed by Sorkin—see Appendix B.3 for details.

would be willing to pay for more or fewer hours.[6]

We fit the following model to estimate the average MRS at employer j:

$$v_j = \theta_0 + \theta_h \psi_j^h + \theta_w \psi_j^w + s'_j \gamma + \varepsilon_j \tag{7}$$

where v_j is the PageRank of firm j, the vector s_j captures sector fixed effects, and ψ_j^h and ψ_j^w represent the hour and wage policies associated with employer j. Because ψ_j^h and ψ_j^w are estimated from a model in logs, they map into equation (5). Specifically, given that $\frac{\partial U}{\partial \log h^0} = \theta_h - \theta_w$ and $\frac{\partial U}{\partial \log e^0} = \theta_w$, the ratio of the MRS between earnings and hours to the wage is:[7]

$$\frac{MRS_{e,h}}{w} = -\frac{\theta_h - \theta_w}{\theta_w}. \tag{8}$$

$MRS_{e,h}/w$ is estimated using a split-sample IV regression to account for measurement error in estimated employer effects. We first divide all worker-employer matches randomly into two subsamples—an estimation sample and a "hold-out" sample. For each subsample, we estimate separate AKM models for hours and wages and obtain the fitted employer effects. In estimating equation (7), the employer effects in the estimation sample are instrumented by employer effects from the hold-out sample; see Appendix B.4 for details.

Accounting for fringe benefits We expect that non-mandated fringe benefits, such as employer contributions to health and retirement plans, will be positively correlated with hours and make a positive contribution to utility independent of hours worked. One view is that incremental fringe benefits are part of the utility of extra hours and should not be controlled for. But we are ultimately interested in the trade-off between work hours and consumption, and the omission of fringe benefits from equation (7) could overstate the direct contribution of log hours to utility by the marginal valuation of additional fringe benefits. As discussed in Appendix D, we use external data

[6] An attractive feature of the PageRank measure is that it is choice-based. This property, as shown in Benjamin et al. (2014), results in more accurate MRS estimates than subjective measures of utility.

[7] To obtain this, note that $U = \beta_e \log e + \beta_h \log h \Rightarrow \beta_e \log w + (\beta_h + \beta_e) \log h$. Then, letting $\beta_e = \theta_w$ and $\theta_h = \beta_h + \beta_e \Rightarrow \beta_h = \theta_h - \theta_w$ gives $\frac{MRS}{w} = \frac{\beta_h}{\beta_e} = \frac{(\theta_h - \theta_w)}{\theta_w}$.

to quantify the elasticity of expenditures on non-mandated employer-provided fringe benefits with respect to their work hours. If workers value benefits at their cost to the employer, this elasticity (denoted ζ) is the bias in $MRS_{e,h}/w$ when not including fringe benefits in equation (7). In practice, we find that adjusting our estimates for these omitted factors does not fundamentally change our conclusions on the role of hour constraints.

2.4 Compensating Variation for Hour Constraints

The estimate of $MRS_{e,h}/w$ obtained from coefficients in equation (7) is only informative about the consequences of marginally relaxing hour constraints. Also, that equation measures the *average* constraint facing an employer's workers. If workers differ in whether they are above or below their optimal hours, then equation (7) will understate the effect on utility of easing constraints. Below, we describe an approach that quantifies the utility gains from relaxing both positive and negative hour constraints, across all jobs.

We first divide the data into bins of employer effects on wage rates $b_w \in \{1,\ldots,N_{b_w}\}$ and hours $b_h \in \{1,\ldots,N_{b_h}\}$. For a given wage-hour bundle offered by employers, the (smooth) estimate of utility is given by

$$\bar{v}_{b_w,b_h} = \frac{1}{N_{b_w,b_h}} \sum_{i,t} \mathbf{1}\{\psi^w_{j(i,t)} \in b_w, \psi^h_{j(i,t)} \in b_h\} v_{j(i,t)} \tag{9}$$

where $N_{b_w,b_h} \equiv \sum_{i,t} \mathbf{1}\{\psi^w_{j(i,t)} \in b_w, \psi^h_{j(i,t)} \in b_h\}$.[8] Let b_h^* denote the bin of employer hour effects where PageRank utility is the highest within a given employer wage effect bin, b_w. The compensating variation that employers with hour policy b_h would need to pay to make the worker indifferent between optimal hours and constrained hours is given by

$$CV_{b_w,b_h} = \frac{\bar{v}_{b_w,b_h^*} - \bar{v}_{b_w,b_h}}{\theta_w} \tag{10}$$

where θ_w is defined in equation (7). The average compensating variation across hours policies is

[8] To correct for correlated measurement errors in PageRank utility and employer effects, we compute the bins using the employer effects observed in the randomly-split hold-out sample. The utility averages in each bin are computed using the estimation sample.

then

$$\overline{CV} = \sum_{b_h, b_w} \frac{N_{b_w, b_h}}{N} CV_{b_w, b_h} \tag{11}$$

where N is the total number of worker-year observations in the data. In practice, we rescale CV_{b_w,b_h} by the observed employer wage effect in bin b_w, so that $\overline{CV}$ reports the percentage increase in employer wage effects required to equalize utilities within each observed wage bin.[9] We also adjust $\overline{CV}$ to account for omitted fringe benefits that may correlate with the hours change required to reach the optimum—see Appendix D for details.

Illustration Figure 1 illustrates the quantities we seek to measure in a stylized depiction of the labor supply relationship. The labor supply curve is drawn as relatively elastic over low hours and inelastic at high hours because our estimates point to this functional form. At wage w^* the worker wishes to work h^* hours, but due to a constraint she is working fewer hours $\overline{h}$.[10] At the constrained hours, the MRS is between w^* and w^0. It will equal w^0 if there are no income effects. Equation (8) estimates the ratio of $\text{MRS}(e^0, \overline{h})$ to w observed at w^*. Area A shows the surplus a worker gains by moving from $\overline{h}$ to h^* at wage w^*. Absent income effects, the surplus gained equals the area between the wage and the labor supply curve moving from $\overline{h}$ to h^*. With income effects, it is smaller (shaded area A) because at wage w^* the MRS is larger than the MRS at a lower wage. The welfare quantity of interest CV_{b_w,b_h} from equation (10) is chosen to equate Area B to Area A. Area B represents the incremental surplus a worker gains from a higher wage at their constrained hours. This measure differs from the MRS in that it measures the benefit of fully closing the gap between constrained and optimal hours (rather than the benefit of the marginal hour), and because it is in terms of a wage rate that applies to all hours worked.

[9] Specifically, for each $b_w \times b_h$ cell, we divide the gap between optimal and observed utility (Δv) by the θ_w-estimate from equation (7) to obtain the change in employer wage effect that would equalize the utility gap, $\Delta\psi^w$. To express the compensating variation in proportional terms, we divide $\Delta\psi^w$ by the mean ψ^w in that cell.

[10] Setting constrained hours below optimum without loss of generality; the figure could be drawn with hours above optimum.

3 Data and Descriptive Evidence on Hours

In this section, we describe the Washington administrative data, construction of the analysis data set, and how workers' hours change following job transitions.

3.1 Matched Employer-Employee Data on Earnings and Work Hours

The data we use come from the records maintained by the Employment Security Department (ESD) of Washington State to administer Washington's unemployment insurance (UI) system; specifically, quarterly earnings records from all UI-covered employers in Washington for 2001:1 through 2014:4.[11] A record appears for each quarter-worker-employer combination that includes a year-quarter identifier, an individual worker identifier, an employer identifier, the NAICS industry code of the employer, and the worker's earnings and paid work hours during the quarter with that employer. The pairing of each worker with an employer in each quarter allows us to construct a linked employer-employee panel.[12]

Washington employers are required to report each worker's quarterly paid work hours because of Washington's practice, which is unique among the UI systems in the United States, of using work hours to determine eligibility for UI benefits. The availability of paid hours makes it possible to construct hourly wages for each quarter for most workers in Washington's formal labor market and allows us to track changes in hours as workers transition between employers. Because hours are collected to determine UI eligibility, there is reason to expect them to be of good quality, and Lachowska, Mas and Woodbury (2022) find evidence that employers do report hours reliably.

The measure of hours in the Washington data is best thought of as a measure of paid hours because the records do not indicate whether a worker is salaried or paid by the hour.[13] To check

[11] All employers are required to report quarterly earnings and hours except so-called reimbursable employers—government agencies, private non-profits, and federally recognized Indian tribes that elect to reimburse the UI agency for benefits paid to their laid off workers (see Washington Administrative Code Title 192, Chapter 300, Section 060). Workers who drop out of the labor force or move out of Washington will drop out of the panel.

[12] We observe demographic characteristics of workers who claimed UI benefits at some time during 2001–2014—about 30 percent of the panel. These demographics come from UI claim records, which are distinct from the wage records.

[13] For salaried, commissioned, and piecework employees, employers are instructed to report actual hours unless those hours are not tracked, in which case they are instructed to report 40 hours per week. Lachowska, Mas and

whether the estimates are sensitive to the inclusion of salaried workers, in Appendix C we describe a procedure that identifies jobs with a high probability of being on a salaried basis. The main conclusions of the paper are robust to dropping these salaried jobs. We keep the salaried jobs in the main estimation sample to retain the largest possible connected set.

3.2 Description of the Analysis Data Set

The main analysis data set is based on quarterly records that have been annualized as suggested by Sorkin (2018). We first construct employment spells where a worker had earnings from the same primary employer for at least five consecutive quarters.[14] We then drop the first quarter and the last two quarters of each spell and annualize earnings, hours, and wage rates within a calendar year, conditional on the calendar year including at least two consecutive quarters of earnings from the same primary employer.[15] As in Lachowska et al. (2023), we impose several restrictions on the estimation sample, dropping (a) workers with more than 9 employers in a year, (b) workers with annual earnings less than \$2,850 (in 2005 dollars), (c) workers with calculated hourly wage rates less than \$2.00 per hour (in 2005 dollars), and (d) workers who worked fewer than 400 hours in the calendar year.[16]

Table 1 shows means, variances, and counts for various cuts of the data. Column 1 comes from the "initial" sample subject to restrictions discussed in the previous paragraph, column 2 is based on the largest connected set (the set of employers connected by worker transitions), and column 3 is based on the leave-one-out sample (the largest connected set in which all employers remain connected after dropping any single worker). The means and variances of hourly wages, hours, and

Woodbury (2022) find that a larger proportion of workers report working more than 43 hours per week in the Current Population Survey (outgoing rotation groups) than employer reports show in the Washington administrative data. This suggests that a substantial percentage of salaried workers were paid to work 40 hours per week (as reported in the administrative data) but have actual work hours greater than 40 per week (as reported in the CPS.)

[14]The primary employer is the employer from whom the worker had the most earnings in the quarter.

[15]We drop the first and last quarters of each spell avoid making inferences based on a partial quarters of employment, and we drop the next-to-last quarter to remove changes in hours and earnings that occur in the quarter before a job loss. We show in Table A6 that the main conclusions about the role of worker and employer effects are similar if equation (3) is estimated using data restricted to full-quarter hours (quarters with a primary employer book-ended by quarters with the same primary employer).

[16]See Online Appendix Section B.1 of Lachowska, Mas and Woodbury (2020) and Lachowska et al. (2023) for further discussion of the data and working with administrative earnings records from a single state.

earnings (all in logs) are similar in all three. The leave-one-out connected set is the main analysis sample because it allows us to identify employer effects and variance components corrected for limited mobility bias. It includes about 3.7 million workers and 168,000 employers.

Figure 2 shows the distribution of work hours in the initial sample. The blue bars show the distribution of workers' weekly hours, computed as annualized work hours divided by 52 (weeks). Average hours are 35.2 hours per week with a standard deviation of 9.86, and about 20 percent of the observations cluster at 40 hours per week (the mode). This clustering at 40 hours per week is less than in survey data.[17] The red bars show the distribution of average weekly employer hours, weighted by the number of worker-year observations. Surprisingly, the dispersion of average employer hours is similar to the dispersion of workers' hours. This suggests large systematic differences among employers in hour policies.

3.3 Exogenous Mobility and the Limited Labor Supply Response

The employer effects in equation (3) are identified through job moves. Accordingly, job moves must be mean independent of the unobserved components of r_{it}^{h} after controlling for worker and employer effects; that is, they must satisfy the exogenous mobility assumption. To check the plausibility of this assumption, Figure 3 plots an event study along the lines of Card, Heining and Kline (2013). If workers' moves between employers are exogenous, conditional on worker and firm fixed effects, we expect changes in their hours to be symmetric and of opposite sign when moving to employers with longer and shorter average hours. Instead, if workers' moves are based on the error term, we expect these changes to be asymmetric.

Figure 3(a) shows changes in workers' hours following a job change, where the origin and destination employers are grouped by quartile of coworkers' mean hours. Before job moves, we see no systematic trends in worker hours, and after job moves, we see large differences that are approximately symmetric across types of moves (see also Table A1). This suggests that changes in hours following a move result from differences between the work-hour policies of the old and new

[17] Lachowska, Mas and Woodbury (2022) report that in the CPS, about 37 percent of workers report "actual" work hours of 40 per week, and about 52 percent report "usual" work hours of 40 per week.

employers. This symmetry, combined with the lack of systematic trends preceding a job move, suggests that the additive model with fixed worker and employer effects on hours, which results from the bargaining model in equation (1), is a reasonable description of the hour determination process.[18,19]

To examine whether changes in hours following job moves reflect labor supply responses to differences between the wage policies of the old and new employers (as opposed to differences in their hour policies), Figure 3(b) plots changes in workers' hours following job moves, holding constant employer effects on wages. (That is, we restrict job moves to those within the same quartile of coworkers' average wages.) The resulting worker responses are very similar to those in Figure 3(a), suggesting that changes in workers' hours following a job change reflect mainly different employer hour polices. This finding implies that the uncompensated labor supply elasticity is close to zero, as mentioned in Section 2.1.

4 Employer and Worker Effects on Hours and Wage Rates

Section 4.1 uses variance decomposition to quantify the importance of worker and employer effects on hours, and provides extensions and robustness checks. Section 4.2 examines the correlations among employer and worker effects on hours and wages. These moments are the basis for the findings described in Section 5 and will inform the model of hours determination presented in Section 6.

4.1 Variance Decomposition of Hours

Table 2 displays variance decompositions of hours and wages (based on equations (3) and (4)) and a variance decomposition of earnings (based on an analogous equation for log earnings). Four findings are evident. First, variation in employer effects explains about 27% of the overall variance

[18] The same conclusion has been reached when studying wages (e.g. Card, Heining and Kline, 2013) and earnings (e.g. Song et al., 2019). Given this, it is thus perhaps not surprising that the exogenous mobility assumption is supported in the case of log hours since log earnings vary (linearly) with log hours.

[19] Appendix B.1 provides further details on the event study in Figure 3 and its connection with the exogenous mobility assumption for identification of equation (3).

of log hours, so employers play a substantial though incomplete role in explaining the variation of work hours.[20] Second, variation in worker effects explains only 7% of the overall variance of log hours. Accordingly, workers have some, albeit limited, scope to vary their hours with an employer.[21] The low share of hour variation explained by worker effects does not necessarily imply that workers' preferences for hours are similar; rather, it implies that only a fraction of heterogeneity in preferences is realized in different hours, perhaps because workers have little power to negotiate hours (see Section 2.1).

Third, the correlation between worker and employer effects on hours is 0.05, and the associated covariance term explains about 1.3% of the overall variance in hours. Using a split-sample technique to account for measurement error, Figure 4(a) shows that the small estimated correlation between worker and employer effects on hours is not driven by a nonlinear relationship between these two effects. (Not accounting for sampling variation results in a relatively linear and negative relationship—see Figure 4(b).) Within sector, the correlation between worker and employer effects on hours is somewhat higher, 0.15 (see Table 3 and the discussion in the next subsection).[22] The lack of strong sorting between workers' preferences for hours and employers' requirements suggests the possibility of hours mismatch; that is, workers being unable to optimize their labor supply. We return to this point in Section 6.

Fourth, worker and employer effects together explain only 35% of the variation in hours, whereas worker and employer effects explain nearly 84% of the variation in wage rates. A model of hours that includes worker-employer match effects still explains only about 50% of the variation in hours (not shown in the table). Accordingly, much of the variation in hours appears to be within

[20] The importance of employer effects varies both among sectors and over time. About 44% of the variation in employer effects on hours occurs within sector—see Figure A1. Also, the variation in hours explained by employer effects increased to 40% during the Great Recession, suggesting that employer effects capture hours constraints, which are likely to increase during downturns—see Figure A2.

[21] The relatively low variability of worker effects on hours is apparent only with the KSS correction. Without correcting, the worker effects explain about 45% of the variance in hours (see Table A2), suggesting that the error term in equation (3) contains significant within-job heteroskedasticity and serial correlation. This contrasts with the situation for earnings, where the KSS correction leads only to a minor change in the share of variance explained by workers effects; see Lachowska et al. (2023).

[22] Figure A2 shows that the sorting of workers to employers based on hours decreases during recessions, suggesting workers have more difficulty matching with employers with similar preferences for hours during downturns.

a job over time, as opposed to resulting from fixed employer and worker effects.

Robustness The low correlation between worker and employer effects on hours is robust to restricting the sample to workers who are likely paid hourly (Table A3), using an indicator for part-time work (less than 35 hours per week) as the outcome (Table A4), using hours level as the outcome (Table A5), and estimating the model at quarterly rather than annual frequency (Table A6). The share of hour variation attributed to employer effects is similar across these different specifications, ranging from 19% to 30%. The share of hour variation attributable to worker effects is smaller when the sample is restricted to hourly workers (6%), but larger and close to the employer share when using a part-time indicator (25%) or the hours level (26%) as the outcome.

Mismatch by educational attainment To further examine the relationship between worker and employer preferences for hours, Figure 5 shows which educational groups are over- and under-represented to employers with respect to their preferences and their employers' requirements for hours. Light blue bars denote the relative proportion of short-hour workers in a group who are employed by long-hour employers ("long-short mismatched"), and dark bars denote the relative proportion of long-hour workers in a group who are employed by short-hour employers ("short-long mismatched"). The dashed horizontal line represents unity, so any bar above the line indicates that the educational group is overrepresented in that type of mismatch.

A disproportionately large number of workers with less education are "long-short mismatched" — that is, have preferences for long hours but are mismatched with a short-hour employer. Conversely, a disproportionately large number of workers with more education are "short-long mismatched." The results imply that workers with less educational attainment are more likely to be constrained from above in choosing their work hours.[23]

[23]Further analysis shows the rate of dual jobholding is higher among employers with low effects on hours (see Figure A3), and that workers who hold two jobs are "long-short mismatched," like workers with less education. These results parallel Lachowska et al. (2022), where we found that dual jobholding occurs when workers' hours on their primary job are constrained from above.

Validating worker effects on hours We have assumed that worker effects on hours reflect workers' preference for hours. One way to check this assumption is to examine whether the observed gender gap in work hours corresponds to a gender gap in worker effects on hours. In the 30% of the analysis sample that includes data on gender, the gender gap in hours is about 10 log points, whereas the gender gap in worker effects on hours is 7.5 log points.[24] That is, the worker effects explain about 75% of the gender gap in hours.[25]

Decomposing employer effects on earnings Because earnings are often the only available outcome in state UI wage records, employer effects on earnings are often interpreted as employer effects on hourly wage rates by assuming that employers do not affect workers' labor supply at the margin (Song et al., 2019). The estimates in Table 2 allow us to examine this assumption. The variance components for wages and earnings in Table 2 are similar to those found elsewhere (e.g., Card, Heining and Kline, 2013, Lachowska et al., 2023), with the worker component substantially larger than the employer component, and a significant positive correlation between the two. The estimates in Table 2 imply that 58% of the variance of employer effects on earnings comes from the hours margin.[26] In Section 5 we find that longer hours are highly valued by workers, on average. As a result, studies relying on earnings variation may still capture variation in worker welfare even if the variation results from differences in hour policies.

4.2 Correlations among Employer and Worker Effects on Hours and Wages

In Appendix B.2, we extend the KSS methodology to multiple equations, allowing estimation of the covariance between the worker and employer effects on hours with the worker and employer effects on wages. Table 3 displays two resulting correlation matrices of employer and worker

[24]The worker effects are calculated by fitting (3) separately for each gender, as in Card, Cardoso and Kline (2015) and Gallen, Lesner and Vejlin (2019).

[25]Evidence in Kahn and Lang (1995)) suggests that on average, women work fewer hours than men and are more likely to be satisfied with their hours than men, so it seems reasonable to infer that worker effects on hours reflect differences in tastes.

[26]Specifically, the decomposition is $\mathrm{Var}(\psi_j^e) = \mathrm{Var}(\psi_j^w) + \mathrm{Var}(\psi_j^h) + 2\,\mathrm{Cov}(\psi_j^h, \psi_j^w)$, where ψ_j^e is the employer effect on earnings. We use estimates from Tables 2 and A7. The variation of employer effects on earnings due to variation of employer effects on hours is $\mathrm{Var}(\psi_j^h) + 2\,\mathrm{Cov}(\psi_j^h, \psi_j^w)$.

effects within and across outcomes. Panel (a) shows correlations computed over the sample as a whole and panel (b) correlations within sector.[27]

Only two of the correlations in both panels (a) and (b) of Table 3 exceed 0.2. First, the correlation between worker and employer effects on wages is 0.30–0.38: high-wage workers tend to sort to employers who demand skills, consistent with evidence from existing studies. Second, the correlation between worker effects on wages and employer effects on hours is 0.21–0.30: high-wage workers tend to sort to employers with long hour requirements.[28] In Section 5, we show that long-hour employers tend to be more desirable, as measured by the PageRank index.

The correlation between high-wage employers and long-hour employers is moderately positive—the full-sample correlation between employer effects on hours and on wages is 0.32, but the within-sector correlation is 0.05. There is much variation in employer effects on hours among employers with a given wage policy—the KSS-R^2 from a regression of employer effects on hours on employer effects on wages equals 0.11.

The correlation between worker effects on wages and hours is somewhat negative (–0.15 to –0.06). As with employer effects, most of the variation in worker effects on hours occurs among workers within a given skill group—the KSS-R^2 from a regression of worker hour effects on worker wage effects equals 0.029. So little of the variation in worker preferences for hours can be explained by worker productivity, which is consistent with the findings in Abowd and Card (1989), but in the cross-section.

Finally, the sorting of workers who prefer long hours to employers with long-hour requirements is surprisingly limited: the correlation between employer and worker effects on hours is 0.05–0.15, which suggests a significant potential for mismatch.

[27] The within-sector correlations are computed using a two-step procedure. First, for each sector, we calculate mean worker and employer effects for each outcome along with the number of workers in each sector. We then calculate the covariance matrix for each outcome and effect, weighted by sector employment. This gives a matrix of between-sector covariances. Second, for each element of this matrix, we calculate the within-sector covariances as the difference between overall and between-sector covariances.

[28] This latter sorting persists after controlling for employer wage effects: a regression of worker wage effects on employer hour effects and employer wage effects—instrumented using a split-sample IV strategy—shows that employer hour effects explain 10% of the variation of worker wage effects (6% due to the variance of employer effects on hours alone and 4% due to the covariance between employer hours effects and employer wage effects).

5 The Role of Hour Constraints

This section links the existence of mismatch to the presence of hours constraints; that is, the condition of a worker preferring to work more (or less) at the current offered wage rate. To do this, we compute a hierarchical PageRank index of the desirability or utility of working for each employer, using the revealed preference approach developed by Sorkin (2018) and discussed in Section 2.3 and Appendix B.3. The index identifies "good" (or desirable) employers as those that poach many employees from other good employers and lose few workers to "bad" employers.

If workers were able to obtain their optimal hours at the current wage, we would expect no relationship between an employer's PageRank index and the employer's hour policy, conditional on the wage policy. The reason is that in equilibrium, workers and employers would be matched on their preferences for hours, so no employer would be able to systematically poach workers from other employers based solely on their hours policy.

Figure 6 displays the joint distribution of the PageRank index by employer effects on wages and hours. We divide the data into 100 cells based on vingtiles of the employer wage effect and quintiles of the employer hour effect. Cells with a higher value of the PageRank index are darker. The figure shows the hallmarks of constraints on hours. For a given employer wage effect, the PageRank varies substantially with the employer hour effect. Long-hour employers are generally ranked higher than short-hour employers within each wage-policy vingtile, although the relationship is not perfectly monotonic—the highest PageRank index is often observed at the fourth quintile of the employer hour effect. The existence of employers who offer longer hours and have a higher PageRank at a given wage rate suggests hours mismatch as we have defined it. In the next section, we further quantify this mismatch by estimating the ratio of the MRS to the wage rate.

5.1 Estimating the Ratio of the MRS to the Wage Rate

To test for hour constraints, we estimate equation (7). Table 4, column (1) reports estimates obtained by regressing the PageRank index on estimated employer effects for hours and wages. Hours and the PageRank index are strongly positively correlated, conditional on employer wage effects, which is consistent with the visual evidence in Figure 6. The coefficient on hours is essentially unchanged when controlling for sector effects (column (2)).[29]

Recall that under condition (8), if workers are unconstrained, then the marginal rate of substitution between hours and earnings equals the wage; that is, $\frac{MRS_{e,h}}{w} = -\frac{(\theta_h - \theta_w)}{\theta_w} = 1$. This hypothesis is rejected. Substituting Table 4's estimates into equation (8), the estimated $MRS_{e,h}/w$ is 0.21 $(-\frac{5.537-7.004}{7.004})$. Adjusting for the relationship between log hours and the value of fringe benefits as in Appendix D, we estimate $MRS_{e,h}/w$ to be 0.31. This value means that, on average, a worker is willing to work an extra hour for only 31 percent of their current wage.[30]

The estimated $MRS_{e,h}/w$ of 0.31 may seem surprisingly low; however, the PageRank index is derived from employer-to-employer transitions, which tend to be concentrated early in a worker's career, when workers are searching for stable—and more desirable—employment (Topel and Ward, 1992). These early-career transitions are likely to be among jobs that are further from the most preferred bundle of earnings and hours, resulting in a low $MRS_{e,h}/w$.

To assess how $MRS_{e,h}/w$ varies by age, we use the subsample of data for which we have demographics and re-estimate PageRank utility indexes separately for each of nine age groups. We then re-estimate equation (7) separately for each age group using the resulting age-specific rankings of employers. Figure 7 reports the estimates.[31] The lifecycle pattern in $MRS_{e,h}/w$ is clear. Young workers are furthest from the optimum with $MRS_{e,h}/w$ ratios less than 0.5. Prime-age workers appear somewhat less constrained, with $MRS_{e,h}/w$ ratios about 0.5–0.6. The ratio increases with age, and is close to 1 for workers older than 55. Only these older workers are transitioning among employers in a way that is consistent with the absence of hour constraints, possibly because older workers prefer shorter hours. The estimates in Table A12 also suggest that

[29] About 11% of the variation in PageRank is explained by employer effects on hours, 24% by employer effects on wages, and 12% by the covariance between the two (times 2).

[30] The low $MRS_{e,h}/w$ is robust to several alternative specifications, including controlling for the average variance of hours within employer (Table A9), excluding salaried workers (Table A10), and controlling for year effects (Table A11).

[31] A possible concern is that restricting the sample to employers with workers whose age is known may result in selection bias (that is, equation (7) is estimated using a subsample of employers that tend to be large). However, when equation (7) is estimated using the demographic subsample, the estimated benefit-adjusted $MRS_{e,h}/w$ is 0.27, similar to the 0.31 for the full sample. See Table A12.

the low $MRS_{e,h}/w$ in the pooled sample (0.31) is due at least partially to the disproportionately large number of transitions made by younger workers.

5.2 Hours and Other Workplace Amenities

One explanation for the low estimated $MRS_{e,h}/w$ is that long-hour employers have attractive attributes other than wages and fringe benefits that compensate for long hours. The recent literature on nonpecuniary job amenities provides a mixed picture on this possibility. Job amenities such as greater autonomy and recognition are positively correlated with hours (Sockin, 2021), but long-hour jobs are associated with more stress and worse work-life balance (Mas and Pallais, 2020). To investigate further the relationship between work hours and nonpecuniary amenities we examine data from the 2015 American Working Conditions Survey (Maestas et al., 2017), which asks a panel detailed questions about job and workplace characteristics. Specifically, for each of the 97 job and workplace characteristics in the survey that are not mechanically linked to work hours, we regress the characteristic on annual hours of work, the hourly wage, and indicators for employer-provided fringe benefits, industry, and employer size. In the vast majority of cases (81 of 97), the estimated relationship between a given characteristic and annual work hours is statistically insignificant.

Figure A4 reports the estimated coefficient on annual work hours from the 16 regressions in which the coefficient is statistically nonzero. Long-hour jobs are associated with a mix of desirable and undesirable attributes. Workers with long hours are more likely to report being able to apply their own ideas, to choose the order of tasks, to assess for themselves the quality of work, and to take breaks when wanted. However, long-hour jobs are also associated with significantly more stress, more reports of having to hide feelings, worry about work when not working, tight deadlines, not enough time to finish work, unclear expectations, feeling less motivated to do a good job, bosses who do not get people to work together, less trust between management and workers, and more bullying. Notably, there is no significant relationship between hours and prospects of career advancement (not shown in Figure A4). This is a complicated picture, but it does not point to a clear conclusion that attractive nonpecuniary amenities compensate for the negative aspects of working long hours.

5.3 Gaps between Optimal and Observed Hours

The estimates of $MRS_{e,h}/w$ in Section 5.1 suggest that, on average, workers would like to work more hours at the current wage. This section uses the methodology in Section 2.4 to quantify the gap between optimal and observed hours. To do this, we divide the employer hour and wage effects into deciles and compute the average value of the PageRank in a given wage-hour bin, as displayed in equation (9).[32] Next, for each employer wage effect bin, we identify the employer hour effect bin with the highest PageRank index. Plotting the PageRank-maximizing hours for each employer wage bin produces the average labor supply curve, free of hour constraints. We then compare the average observed hours to the optimal (PageRank-maximizing) hours to determine the direction of the constraint at a given wage.

Figure 8 shows that for most of the range of employer-wage policies, optimal hours exceed observed hours, implying that workers tend to be constrained from above. The optimal labor supply curve, denoted by blue triangles, is approximately horizontal, suggesting that aggregate labor supply is inelastic.[33] In contrast, the observed average labor supply curve, denoted by red squares, is concave. As a result, the largest gap between observed and optimal hours is among employers offering low wage premiums. (These also tend to be short-hour employers.) The large gap for workers at low-wage employers is related to the earlier finding that workers with less education tend to be more mismatched on hours.

Table 5 shows gaps between optimal and observed hours, by sector and aggregated. For all sectors aggregated the gap is about 11 log points. The average of the absolute gaps is similar, about 15 log points, suggesting that the majority of workers would prefer more hours—that is,

[32] Deciles of employer effects on wages and hours are the finest split of the data that ensures sufficient coverage in each cell. The variability of the average PageRank index computed over the resulting 100 cells is roughly 80% of the variability of the PageRank index in the micro-data. Increasing the number of bins to vingtiles increases the share of variation explained only modestly (to about 85%) and results in several bins with only a handful of employers.

[33] This is consistent with evidence on job transitions in Figure 3.

most workers are not on their supply curve. This is especially true in the Retail sector and in Food and Accommodation services. However, in two sectors—Transportation/Warehousing and Finance—workers systematically want fewer hours, on average.

5.4 Welfare Consequences of Hour Constraints

Column 3 of Table 5 shows the gaps between observed and optimal PageRank utility implied by the gaps between observed and optimal hours. The average gap in the PageRank index is –1.74, which corresponds to about 55% of its standard deviation. Equation (11) quantifies the increase in the employer wage premium needed to make workers indifferent between their current work hours and optimal hours at the current wage; that is, the compensating variation, CV. Column 4 of Table 5 shows the sample average CV to be about 12%.[34] The weighted average of sector-level CVs is similar (11%) suggesting that differences in preferences for hours among sectors are small.

How do we reconcile the low CV (about 12%) with the large difference between the MRS and the wage (i.e., $MRS_{e,h}/w = 0.31$)? One possible explanation is that individual labor supply is highly elastic at low hours and inelastic at high hours—see Figure 1.[35] Figure 1 illustrates that, with inelastic supply at the offered wage, even a small constraint can result in a very low $MRS_{e,h}/w$.

We can validate the estimates of $MRS_{e,h}/w$ and CV by conducting a simple calculation. Suppose workers supply labor inelastically at 40 hours and receive an hourly wage of \$20. Then the estimated $MRS_{e,h}/w$ of 0.3 in Table 4 results in a MRS of \$6 per hour. Assuming a 15% gap between optimal hours and observed hours—similar to the estimates presented in Table 5—the weekly value of increasing hours to the optimum would be $(40-(0.85\cdot 40))\cdot(20-6) = \$84$. This is 12.35% $(=\frac{84}{0.85\cdot 40\cdot 20})$ of constrained earnings, which is close to the 12.15% estimated average

[34] We also consider a parametric approach by estimating: $\mathbb{E}[v_j|\psi_j^w \in b_w, \psi_j^h] = b_w + \psi_j^h b_w + (\psi_j^h)^2 b_w$, where b_w are indicators for employer wage effect deciles, $\psi_j^h b_w$ interacts each wage decile indicator with employer hour effects, and $(\psi_j^h)^2 b_w$ interacts each decile indicator with the squared employer hour effects. This alternative approach suggests a somewhat larger $\overline{CV}$, of about 32% (see Table A13), suggesting that the estimate of $\overline{CV}$ shown in Table 5 may be conservative.

[35] Similarly, in a discrete choice experiment with job applicants Mas and Pallais (2019) estimate a labor supply relationship of this form, where marginal values of time are low relative to the wage until workers reach full-time hours.

compensating variation value.

6 Hedonic Model with Vertical Differentiation

A theory of work hours determination should account for the results described in Sections 4 and 5. These include the following:

1. Workers' discretion over their work hours at a given firm is limited; that is, the worker effects on hours explain about 7% of the variation in observed log hours (and about 26% of the level of hours, see Section 4.1);
2. Workers are on average constrained from above in supplying work hours—the average worker's observed hours are 11% below their optimum (Section 5.3);
3. Long-hour employers tend to be high-wage employers, but the relationship is not strong—the correlation between employer effect on hours and wages ranges from 0.05 (average of within-sector correlations) to 0.32 (in aggregate) (Section 4.2);
4. Employer hour policies vary greatly across employers paying similar wage premiums—the R^2 from a regression of employer effects on hours on employer effect on wages is 0.11 (Section 4.2);
5. The sorting of workers who prefer long hours to employers who require long hours is surprisingly limited; the correlation ranges from 0.05 (across all sectors) to 0.15 (averaged within sectors) (Section 4.2);
6. The covariance between worker effects on wages and employer effects on hours is positive; that is, high-wage workers tend to work for long-hour employers (Section 4.2).

6.1 The Lewis-Rosen Model

We first sketch the basic Lewis-Rosen model of hedonic hours and wages (Lewis (1969), Rosen (1974)) and describe which of our findings can be explained by it. We then extend the model to include bargaining and vertical differentiation of employers, in order to account for the empirical findings that do not fit within the basic model.

Employers Employers are heterogeneous with respect to technology and organization, and we assume they optimize sequentially, first determining their required labor input (total worker-hours), then optimizing on average hours per worker (and in doing so, on employment). Employers' reasons for having preferences over average hours include the relationship between work hours and productivity, worker setup costs, fixed (per worker) costs of employment, complementarities among workers in teams, and other considerations of scheduling and coordination (for example, it may be easier to fill shifts with many part-time workers than a smaller number of full-time workers).[36] We do not attempt to model this decision process; rather, our analysis starts after the employer has optimized total hours and focus on the choice of average hours per worker.[37]

We assume a loss function, $R(h-g_j) \geq 0$, translates the deviation of hours from their optimal level, g_j, into a monetary cost to the employer per work hour. When hours deviate from the optimum, it is as if the hourly wage per worker increases. In a model without vertical differentiation, firms choose F_j to minimize $R(F_j - g_j) + w^*(F_j)$, where $w^*(F_j)$ is the equilibrium market equalizing difference function that assigns a unique wage to a given choice of hours made by the employer. The resulting isoprofit curves $[\pi(F,w)]$ in Figure 9(a) are inverted U-shaped, reflecting the loss function; that is, when hours deviate from the optimum, the hourly wage must decrease to maintain constant profits.

Workers Workers are assumed to have a utility function over consumption (c) and work hours (h) of the form

$$U_i(c,h) = c \cdot \omega(T - b_i h) \tag{12}$$

where ω is a monotonic, quasi-concave function, T denotes the worker's time endowment, and b_i is a parameter indicating the distaste for work hours h of worker i, allowing for worker heterogeneity. (Leisure l equals $T-h$, and we assume for simplicity that all workers work a strictly positive number of hours.)

[36] Rosen (1978) has sketched a model of the hours-employment decision based on an earlier model (Rosen 1968).

[37] This setup differs from the standard compensating differentials framework (Rosen, 1968) because both workers' and employers' preferences for hours are nonmonotonic.

The indifference curves implied by U_i are defined over hourly wage rates and hours per pay period and are U-shaped, as shown in Figure 9(a). Workers require a relatively high wage rate to work short or long hours, and are willing to accept a lower wage rate to work conventional hours. Assuming that workers optimize consumption and leisure given the budget constraint $c \leq wh$, the optimal hours A_i for the worker satisfy

$$A_i = \frac{\omega(T - b_i A_i)}{\omega'(T - b_i A_i) b_i}. \tag{13}$$

Because of the functional form of U, workers' optimal hours do not depend on the wage rate.

Equilibrium The basic Lewis-Rosen model assumes a competitive labor market for workers with homogeneous skills. Employers have heterogeneous technologies, and workers have heterogeneous preferences for hours and wage rates. This setup results in a market-clearing equilibrium locus of hours and wage rates, which is an envelope of tangencies between employer isoprofit and worker indifference curves, shown as $w^*(F)$ in Figure 9(a). Although in general this function can be positively or negatively sloped, as drawn the equalizing difference function is downward-sloping, meaning that in equilibrium, the wage rate declines in hours.

For workers with preferences shown by indifference curve $U(w,F) = v_1$, and for employers with zero-profit isoprofit curve $\pi(w,F) = k_1$, the tangency at wage rate w_j and hours per worker h^* is an equilibrium. A key insight from the model is that, at w_j, workers' optimal hours are A_i (greater than h^*), and employers' profit-maximizing hours are F_j (less than h^*); in fact, whenever $w^*(F)$ is downward-sloping, workers' hours will be constrained from above (and employers' hours from below), as noted by Kahn and Lang (2001).

Accordingly, the basic Lewis-Rosen model can accommodate heterogeneous worker preferences for hours (point 1), and it can generate equilibrium hour constraints (point 2); however, it cannot account for some of the other findings. First, the data show a moderately positive correlation between employer effects on hours and wages (point 3), whereas the Lewis-Rosen model predicts a negative correlation when workers are constrained from above (as indicated by the downward-sloping equalizing difference function). Second, we observe variation in employer effects on hours, after holding employer effects on wages constant (point 4), whereas the Lewis-Rosen model predicts no such variation. (Relatedly, Figure 6 shows that, for a given employer effect on wages, some employers offer longer hours and are more attractive to workers, which does not occur in the basic Lewis-Rosen model.) Finally, the data show surprisingly little sorting of workers to employers based on hours (point 5); whereas the Lewis-Rosen model predicts sorting.

6.2 Extensions of the Lewis-Rosen Model

In what follows we sketch an extension of the Lewis-Rosen model (Lewis (1969); Rosen (1974)) to include bargaining between workers and employers and vertical differentiation among employers.

Bargaining over hours As before, we focus on a single labor market in which workers have heterogeneous preferences for work hours, and employers have heterogeneous production functions. However, in contrast to the perfect information setting of the basic Lewis-Rosen model, we assume that employers do not observe individual preferences for hours b_i—instead, they know only the distribution of preferences and that realized hours are given by equation (1). Accordingly, a given employer will be matched to workers with varying preferences for hours (rather than to workers with homogeneous hour preferences), and the employer's problem is to find the cost-minimizing wage and hours that meet the targeted expected utility of workers. Modeling hours determination through bargaining allows for dispersion in hours within employer, that is, a situation where two identical workers in the same employer may work different hours.

Figure 9(b) illustrates the problem. The blue curve represents an employer's expected isoprofit curve, and the solid red curve represents the indifference curve for workers who are matched to that employer based on expected utility. The employer offers the least-cost combination of wages and hours that meets the targeted expected utility of workers (where the solid expected indifference curve is tangent to the expected isoprofit). The dashed indifference curve depicts a representative worker who is matched to this employer and has a preference for working longer hours than the employer offers. With bargaining, this worker will have above-average hours with this employer.

Vertical differentiation The remaining recalcitrant findings can be explained by introducing vertical differentiation among employers in the total value of employment to workers, in the vein of Lang and Majumdar (2004). Sorkin (2018) refers to the underlying reasons for such differentiation as "Mortensen Motives," which include reducing recruiting costs, the need to pay efficiency wages, market power, and search frictions (as in Burdett and Mortensen (1998)). When differentiating themselves, employers will target a specific utility level v_j by choosing the least-cost wage-hour combination from an employer-specific wage-hour schedule.

Incorporating both bargaining and vertical differentiation formally, a risk-neutral employer j optimizes by choosing w_j and F_j to minimize the expected loss function and the expected realization of the hours bargain, subject to a targeted expected utility constraint:[38]

$$\min_{w_j,F_j} \mathbb{E}[R(h-g_j)|F_j,w_j]+w_j\cdot\mathbb{E}[A_i^{\delta}|F_j,w_j]F_j^{1-\delta}, \text{subject to } \mathbb{E}[U_i(c,h)|F_j,w_j]=v_j. \quad (14)$$

where h is given by the bargaining condition in equation (1).

Whereas in the basic Lewis-Rosen model, hours constraints from above are associated with a negative correlation between employer effects on wages and hours, with vertical differentiation, the model accommodates both hours constraints from above and a positive correlation. Consider an employer who minimizes costs subject to expected utility v_1. As in Figure 9(b), the worker's hours are constrained from above. If this employer (or another identical employer) chooses to cost-minimize subject to a higher utility level v_2, she may do so by choosing longer hours, higher wages, or both. If workers' hours are constrained from above, they have a low $MRS_{e,h}/w$ ratio (that is, they are willing to work an additional hour at less than the current hourly wage rate), and it will be cost-minimizing for the employer to increase hours.[39] Therefore, the observed wage-hour

[38]The employer expectation depends on worker preferences, $b_i \sim B$. $\mathbb{E}[A_i|F_j,w_j]$ is a function that determines the sorting of workers to employers; see the subsection on sorting below for an example of how employers might form that expectation in equilibrium.

[39]The pattern observed in Figure 6 showing that utility is increasing in hours at a fixed wage, implies that long-hour employers are likely employers with production functions requiring long hours.

combinations of different employers with identical production functions will follow an upward-sloping contract curve, as illustrated by the dark wavy line in Figure 9(c).[40]

Accordingly, the Lewis-Rosen model with bargaining and vertical differentiation accommodates worker heterogeneity (point 1) and explains the coexistence of hour constraints (point 2), the positive correlation of employer effects on hours and wages (point 3), and variation in employer effects on hours (and utility) among employers offering the same wage premium (point 4).

Sorting The basic Lewis-Rosen model predicts perfect sorting of workers and employers on hours, which we do not observe (point 5). However, allowing employers to post vertically-differentiated offers can substantially weaken this sorting. To say anything about sorting, however, we need to be specific about the assignment of workers to employers. We consider the following simple mechanism. Workers are ranked on skill, proxied by α^w, workers' portable component of the wage. The highest-skill worker gets first choice of employer, and we go down the list of workers ranked by α^w until all positions are filled.[41] Table 3 shows that high skill is not strongly correlated with a preference for long hours, so high-utility employers (who tend to be long-hour, high-wage employers) may hire skilled workers who have relatively weak preferences for more hours. It follows that the positive correlation between worker effects on wages and employer effects on hours (point 6) can coexist with little sorting on hours (point 5).

To illustrate, we consider three workers: worker 1 is the most skilled and has the weakest preferences for work hours, worker 2 is less skilled and has somewhat stronger preferences for hours, and worker 3 is the least skilled and has the strongest preferences for hours. The location of each worker on the Lewis-Rosen equalizing difference function is shown in Figure 9(d). The indifference curve of worker 1 is $U(w,F) = v_1$ (the solid red curve). If worker 1 has first choice of employers, and an employer targets a higher utility level v_2 for that worker by offering the wage-hour package (w_j, A_i), then worker 1 will accept that job and work longer hours than worker

[40] Kinoshita (1987) formally shows that a contract curve in the Lewis-Rosen model can be positively sloped while maintaining standard assumptions about worker preferences, namely that the utility function over earnings and hours is quasi-concave, and that leisure and earnings are both normal goods.

[41] See Holzer, Katz and Krueger (1991) and Manning (1993) for models of job queues and wage differences.

2 (who has stronger preferences for hours). But if worker 1 is offered the package (w'_j, A_i), she would accept only if her $MRS_{e,h}$ were lower at higher hours, as shown by the flatter, dashed red indifference curve. In neither of these cases does worker 1 work longer hours than worker 3 because the gap in preferred hours between workers 1 and 3 is greater than the gap between workers 1 and 2.

As this example shows, under this assignment mechanism, the extent to which sorting on hours will be undone with vertical differentiation depends on three factors. First, less dispersion in workers' preferred hours implies that sorting is undone more easily. Second, with lower $MRS_{e,h}$ at long hours, it is easier to undo sorting. Third, greater dispersion of utility targets implies that sorting is undone more easily. This last prediction is supported in Table 3 where we find more sorting on hours within sector, where the dispersion of utility among employers tends to be less (as can been seen in Table 5).

7 Conclusions

The empirical findings we have presented point to workers facing constraints from above in their choice of work hours, resulting in substantial mismatch between the hour preferences of workers and the hour requirements of employers. Using a ranking of employers derived from voluntary job transitions, we find that workers are off their supply curve, with a ratio of the marginal rate of substitution of earnings for hours (MRS) to the wage equal to 0.3, suggesting that longer hours are highly valued by workers. This high valuation of longer hours is especially pronounced for young workers. On average, the absolute deviation between optimal and observed hours is 15%, and in most sectors actual hours of work tend to be below the optimal. A welfare calculation suggests that employers would need to pay 12% higher wages to compensate workers for the hour constraints workers face.

An extension of the hedonic model of Lewis (1969) popularized by Rosen (1974) can explain these findings. The extension is the presence of vertical differentiation in the overall value of employment that employers can offer in equilibrium (Mortensen, 2003; Sorkin, 2018). The resulting dispersion of utility helps explain the positive relationship between employer effects on hours and wages despite a high willingness to pay for more hours, a relationship that cannot be rationalized as a compensating differential. If employers offering higher utilities are in excess demand—and these employers then select workers on the basis of their productivity—then this model can also explain why we see little sorting on hours and only high-productivity workers sort to longer-hour employers.

An important implication of the findings is that the value of estimating labor supply functions based on the canonical model of consumer demand is at best limited: If most workers are not on their labor supply curve, then wage-hour observations cannot be viewed as the outcome of a neoclassical constrained optimization problem that workers have solved. To reiterate Pencavel's admonition, "Economists should cease calling hours-wage regressions 'labor supply' research" (Pencavel, 2016, p. 22). Rather, employers play a clear role in determining hours, and labor economists face a more complicated problem, which Rosen (1986, p. 688) once characterized as "understanding ... how workers find their niche in the overall scheme of things and how all the pieces fit together in the labor market as a whole." Clear avenues for future research include understanding the frictions that give rise to equilibrium mismatch and hour constraints, and the reasons for differences among employers in offered utility.

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8 Tables

Table 1: Descriptive statistics for various samples

	(1) Initial annualized sample	(2) Largest connected set	(3) Leave-one-out connected set
Mean log hourly wage	3.02	3.02	3.03
Variance of log hourly wage	0.41	0.41	0.41
Mean log hours	7.46	7.46	7.47
Variance of log hours	0.13	0.13	0.12
Mean log earnings	10.48	10.48	10.50
Variance of log earnings	0.60	0.60	0.59
Number of worker-years	27,895,747	27,662,224	26,233,816
Number of workers	4,590,341	4,526,772	3,713,075
Number of employers	301,289	252,571	168,186

Notes : Column 1 shows the annualized sample. Column 2 shows the largest connected set of employers. Column 3 shows the leave-one-out connected set. See Section 3 for a description of the samples.

Table 2: Variance decomposition of hours, wages, and earnings

	(1) log hours		(2) log wages		(3) log earnings	
Standard deviation of outcome	0.35		0.64		0.76	
Variance components						
Std. of employer effects	0.18	26.81%	0.21	11.06%	0.31	16.63%
Std. of worker effects	0.09	7.19%	0.47	53.92%	0.45	34.46%
Covariance of worker, employer effects	0.00	1.27%	0.04	18.67%	0.06	21.75%
Correlation of worker, employer effects	0.05		0.38		0.45	
Share of variance explained	35.26%		83.65%		72.84%	

Notes: The table shows variance decompositions of log hours, log hourly wage, and log earnings into worker and employer components. Variance components are corrected using the Kline, Saggio and Sølvsten (2020 - KSS) leave-one-out method, using a "leave-match-out" approach; see the text for details. To the right of each variance component is the percentage of total variance explained by that component (this number is multiplied by two when looking at the covariance between worker and employer effects). All statistics are worker-year weighted. Year effects are omitted from the table.

Table 3: Correlations between worker and employer effects on wage rates and hours

Panel (a): Overall correlations

	log wages		log hours	
	Worker effect	Employer effect	Worker effect	Employer effect
log wages				
Worker effect	1.000	0.382	-0.148	0.297
Employer effect		1.000	-0.056	0.323
log hours				
Worker effect			1.000	0.046
Employer effect				1.000

Panel (b): Within-sector correlations

	log wages		log hours	
	Worker effect	Employer effect	Worker effect	Employer effect
log wages				
Worker effect	1.000	0.304	-0.063	0.209
Employer effect		1.000	-0.014	0.053
log hours				
Worker effect			1.000	0.151
Employer effect				1.000

Notes: This table shows the worker-year weighted correlations between the worker and employer effects after fitting an AKM model on log hourly wages and log hours. Sample size in both panels equals 26.2 million worker-year observations. The model controls for year effects. Panel (a) reports overall correlations and panel (b) reports within-sector correlations; see Section 4.2 for a description of the method. All correlations are computed using the KSS leave-match-out procedure.

Table 4: Relationship between the PageRank index and employer effects on hours and wages

	(1)	(2)
Outcome: PageRank utility index		
Employer effect on hours	5.224***	5.537***
	(0.713)	(0.538)
Employer effect on wages	5.845***	7.005***
	(1.762)	(1.418)
Number of employers	57,460	57,460
Controlling for sector effects	no	yes
% of variance explained by employer effect on hours	10.16%	11.42%
% of variance explained by employer effect on wages	16.83%	24.17%
% of variance explained by covariance between employer hours and wage effects	9.48%	12.05%
MRS/w ($[\theta_h - \theta_w]/\theta_w$)	0.11	0.21
p-value (MRS/w = 1)	0.00	0.00
MRS/w adjusted for fringe benefits	0.21	0.31
p-value (Adjusted MRS/w = 1)	0.00	0.00
Mean outcome variable (standard deviation)	-4.600 (3.333)	

Notes : This table reports the results from a split-sample IV regression where the outcome is the PageRank utility (Sorkin, 2018) and the two key regressors are the fitted employer effects on hours and on wages obtained from fitting two-way fixed effects models. The coefficient associated with employer effects on hours is θ_h and the coefficient associated with employer effects on wages is θ_w. To construct the split-sample IV, we divide the worker-employer pairs randomly into two subsamples. We then estimate a two-way fixed effects model and the PageRank algorithm separately within each subsample. We instrument the employer effects (on wages and hours) with the corresponding effect calculated from the hold-out sample. The PageRank utility index is calculated using quarterly employer-to-employer transitions and corrects for differences in firm size and intensity of offers as described in Sorkin (2018). Below the table, we report the variance decomposition of the PageRank utility, where each variance component has been corrected to account for sampling noise using the split-sample approach. Public administration and the education sector were omitted from the analysis. The last rows of the table report the ratio of the implied marginal rate of substitution (MRS) between earnings and hours relative to the wage and the p-value from a test of this quantity being equal to 1 (the standard error is calculated using the delta method). Adjusted MRS adjusts from the omission of fringe benefits that might correlate with hours; see Appendix D for details. All coefficients and variance components are weighted by the number of worker-year observations associated with a given employer. Robust standard errors are in parenthesis.

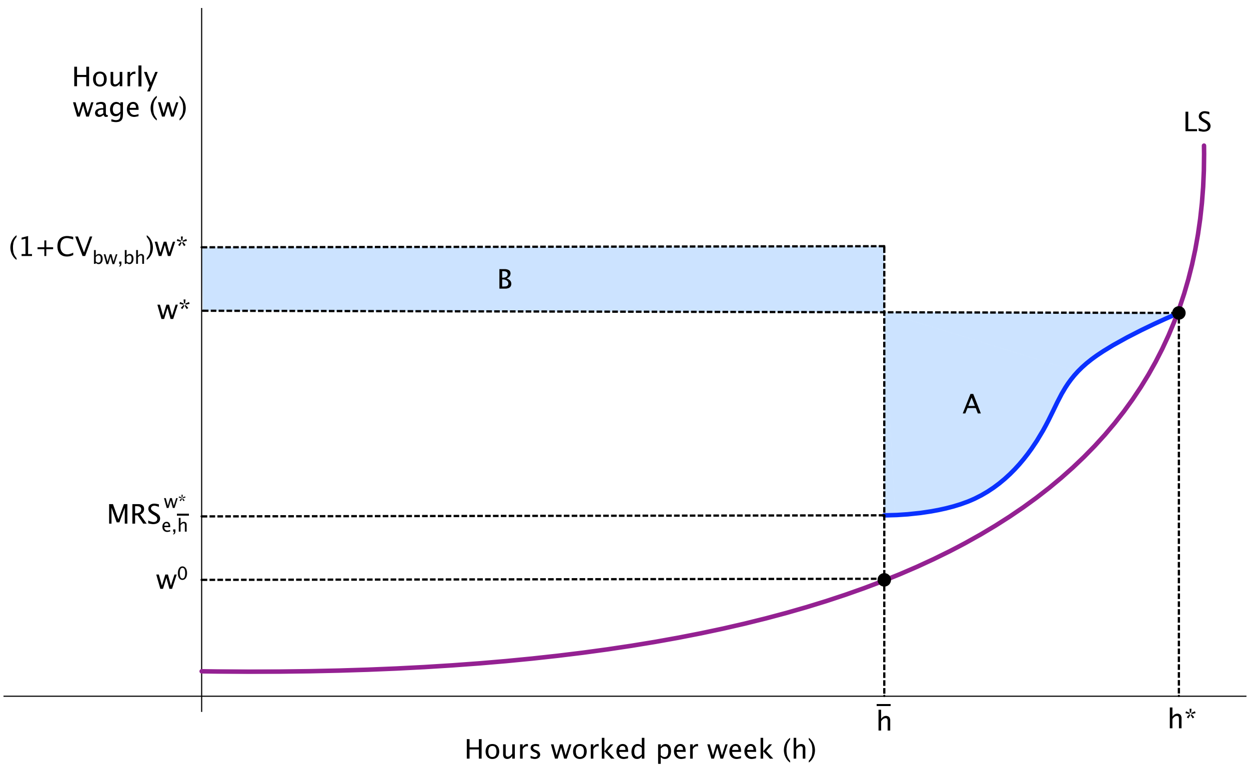
Table 5: Gaps between optimal and observed hours and compensating variation, in aggregate and by sector

	(1) Gap between observed and optimal hours	(2) Gap between observed and optimal hours (in absolute value)	(3) Gap between observed and optimal PageRank	(4) Compensating variation (in %)
All sectors	-0.11	0.15	-1.74	12.15
Estimates by sector				
Agriculture, fishing, etc.	-0.06	0.10	-1.23	9.81
Mining, quarrying, gas Extraction	0.00	0.05	-1.05	7.50
Utilities	-0.01	0.01	-0.62	4.40
Construction	-0.08	0.09	-1.45	9.85
Manufacturing	-0.06	0.07	-1.37	9.03
Wholesale trade	-0.04	0.07	-1.25	9.31
Retail trade	-0.04	0.15	-1.67	13.80
Transportation and warehousing	0.04	0.15	-1.41	10.82
Information	-0.05	0.06	-1.00	4.45
Finance and insurance	0.01	0.05	-1.23	9.03
Real estate and rental and leasing	-0.07	0.11	-1.56	12.03
Professional, scientific, and technical services	-0.04	0.06	-1.45	10.07
Mgt of companies	-0.06	0.14	-0.73	2.77
Admin support and waste mgt	-0.14	0.15	-1.77	12.85
Health care and social assistance	-0.06	0.12	-1.69	12.72
Arts and entertaintment	-0.12	0.18	-1.33	10.60
Food and accomodation	-0.11	0.16	-1.70	13.80
Other services	-0.08	0.13	-1.60	12.04
Weighted average compensating variation across sectors				10.96

Notes : The table shows compensating variation (CV) described in Section 2.4 in aggregate and by sector. The first row shows the baseline results pooling all the sectors. To compute the sector-specific estimate, we divide the data into 10 x 10 cells defined by deciles of employer wage effects and employer hours effects in each sector. For each decile of employer wage effects, we identify the decile of hours that leads to the highest PageRank utility. Column 1 reports the weighted average difference between an observed employer hours effect and the optimal hours effect---the employer hours effect associated with the highest utility across the deciles of employer wage effects, weighted by the number of worker-year observations in each cell. Column 2 computes the absolute value of the difference between observed and optimal hours, while column 3 reports the gap in the PageRank. Column 4 reports CV: the average percentage increase in employer wage effects that would make a worker indifferent between working their observed hours and optimal hours. For each row this is calculated using the point estimate (θ_w) on employer wage effects reported in column 2, Table 4. The CV calculations are adjusted to control for variation in fringe benefits stemming from working more hours using auxiliary sector-specific information from the CPS; see Appendix D for details. The last row reports the weighted average of sector-specific CVs in column 4 where the weights are the number of worker-year observations in each sector.

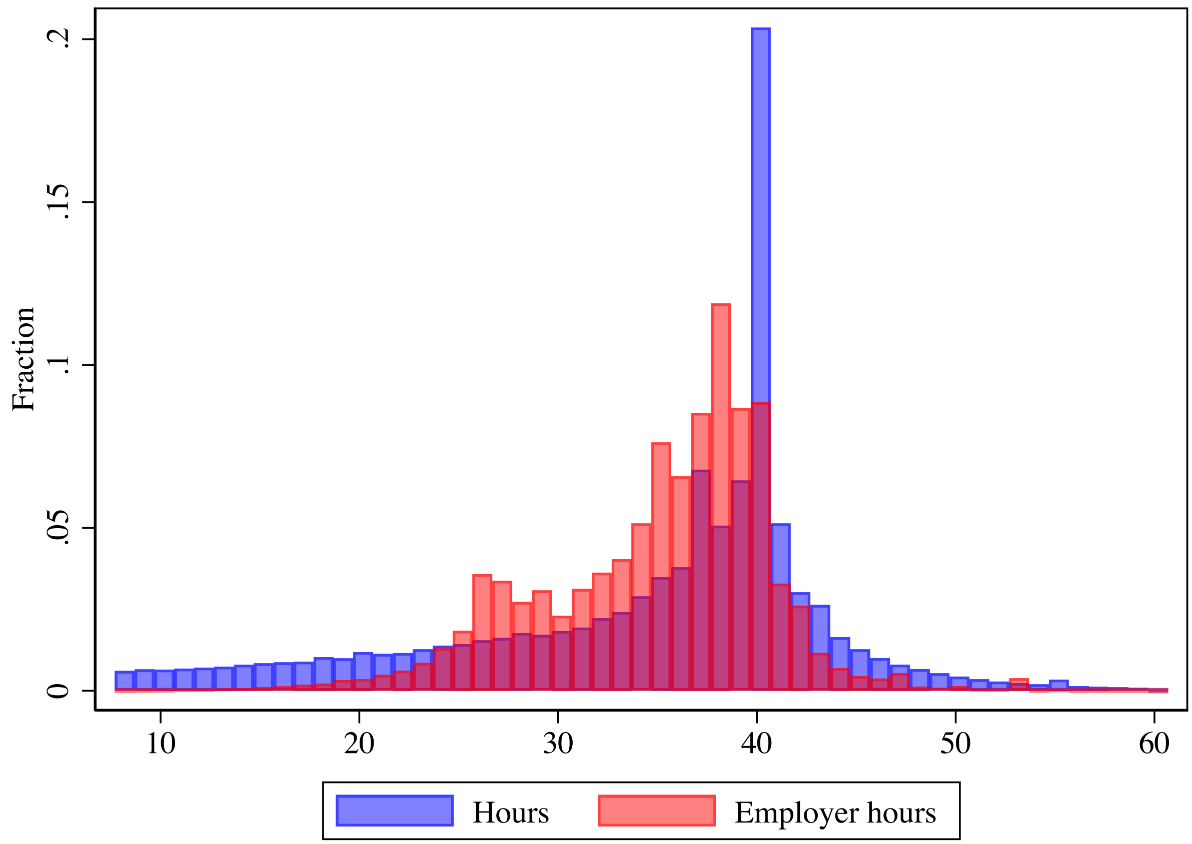
9 Figures

Figure 1: Willingness to pay to eliminate hour constraints



Notes: The figure traces a labor supply curve that is relatively elastic at low hours and inelastic at high hours. At the wage w^* the worker wishes to work h^* but is constrained to work $\bar{h}$ hours. At $\bar{h}$, the MRS is between w^* and w^0 (exactly at w^0 without income effects). Area A shows the surplus the worker gains from moving from $\bar{h}$ to h^* at wage w^*. (Without income effects, the surplus gained is equal to the area between the wage and the labor supply curve moving from $\bar{h}$ to h^*.) The welfare quantity of interest CV_{b_w,b_h} from equation (10) equates Area B to Area A. Area B represents the incremental surplus a worker gains from a higher wage at constrained hours. See last paragraph of Section 2.4 for discussion.

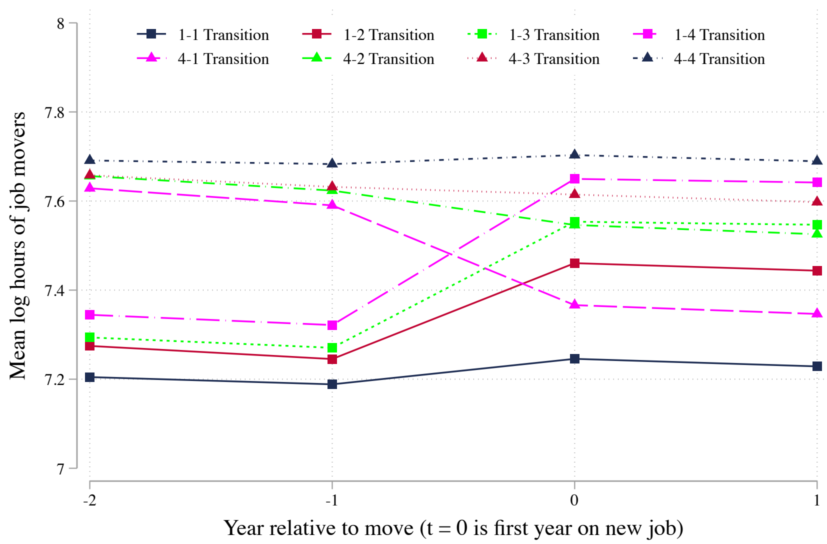
Figure 2: Distribution of work hours



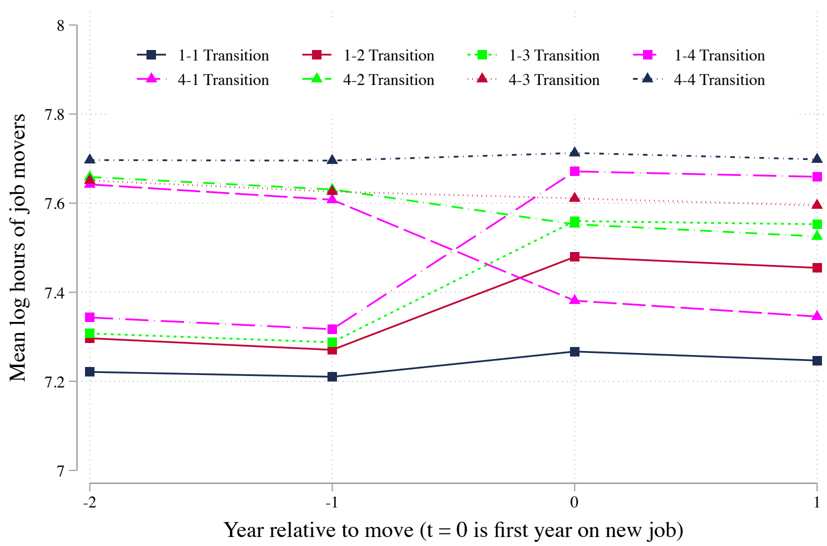
Notes: The initial annualized sample described in Section 3.2. Weekly hours are computed as annualized hours divided by 52 (weeks). Employer hours are computed as employer-level averages of hours. The distribution of employer hours is weighted by worker-years. Values with more than 60 hours per week are not displayed.

Figure 3: Mean hours of job movers, by quartile of mean hours of coworkers at origin and destination jobs

(a) Baseline event study



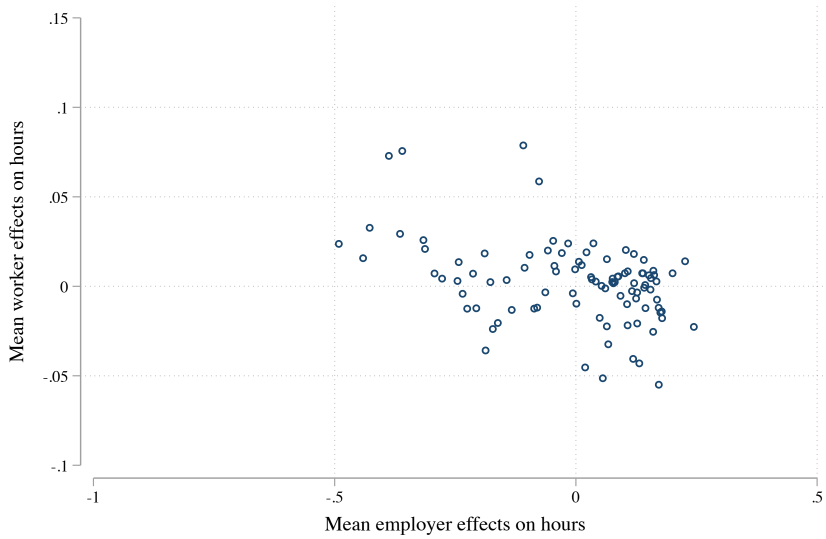
(b) Same quartiles of coworkers' wages in origin and destination job



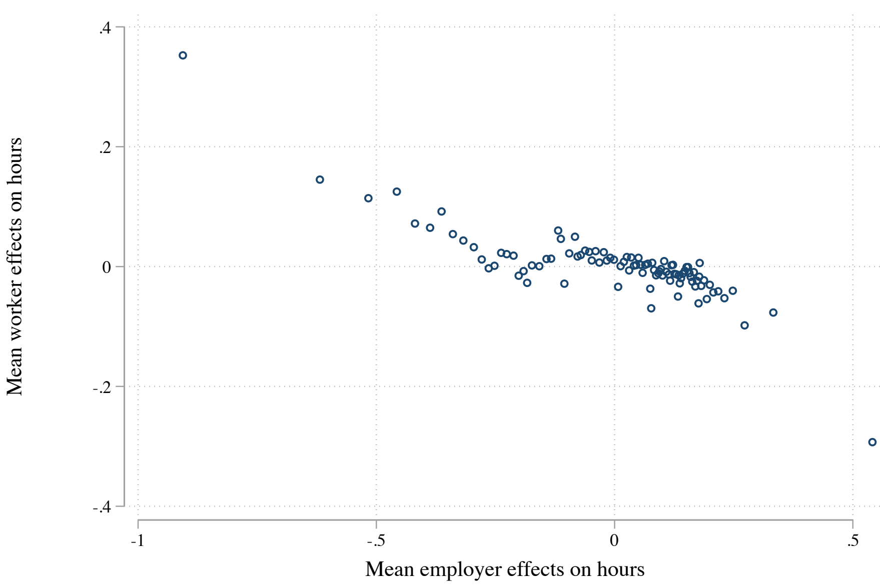
Notes: The figure shows employer-to-employer transitions where a worker held a job for at least two consecutive years prior to the transition and remained with the new employer for at least two years. For each transition, we calculate quartiles of the leave-one-out average of coworkers' log hours in the last year in the origin job and in the first year of the destination job. Figure 3(a) shows transitions where the origin employer is either in the bottom or in the top quartile of average coworker hours. 3(b) further restricts the transitions to occur between employers in the same quartile of average coworkers' log wages. Table A1 reports the numbers for all possible transitions.

Figure 4: Lack of positive worker-employer sorting on hours

(a) Sorting corrected using split samples

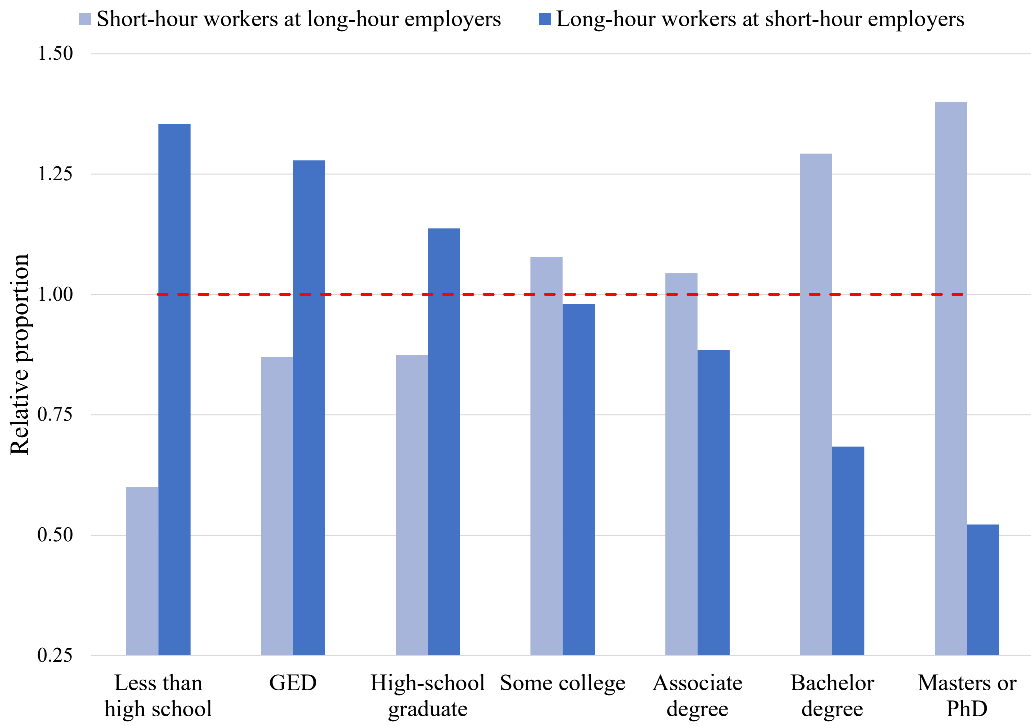


(b) Sorting measured with error



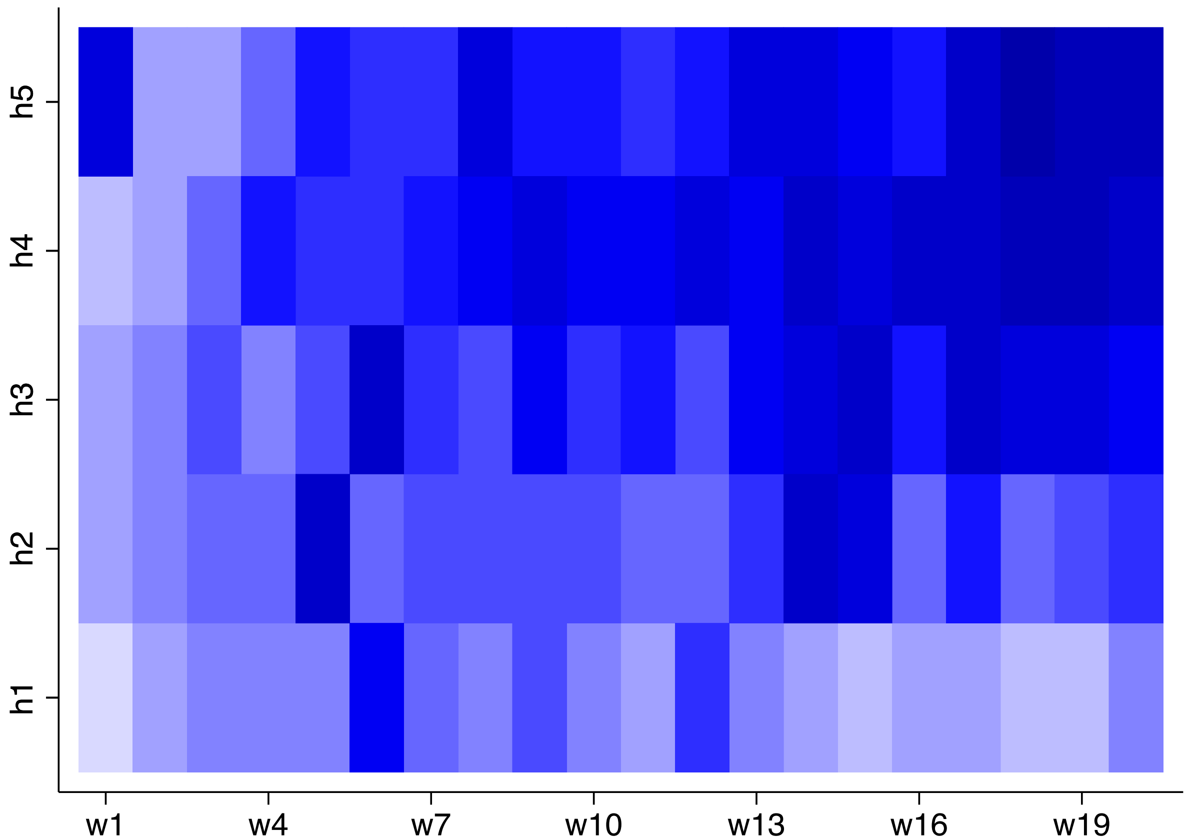
Notes: Figure 4(a) plots mean estimated employer and worker effects on hours using a split-sample approach to account for measurement error. Specifically, we divide all jobs in the the leave-one-out sample in Section 3.2 randomly in two subsamples (the hold-out sample and the estimation sample) and fit equation (3) separately in each subsample. The centiles of employer hour effects are calculated in the hold-out sample and the mean worker and employer effects in each such centile are calculated in the estimation sample. Figure 4(b) plots mean estimated employer and worker effects by centiles of employer hour effects in the estimation sample (that is, without correcting for measurement error).

Figure 5: Mismatch between worker-hour preferences and employer-hour requirements by educational attainment



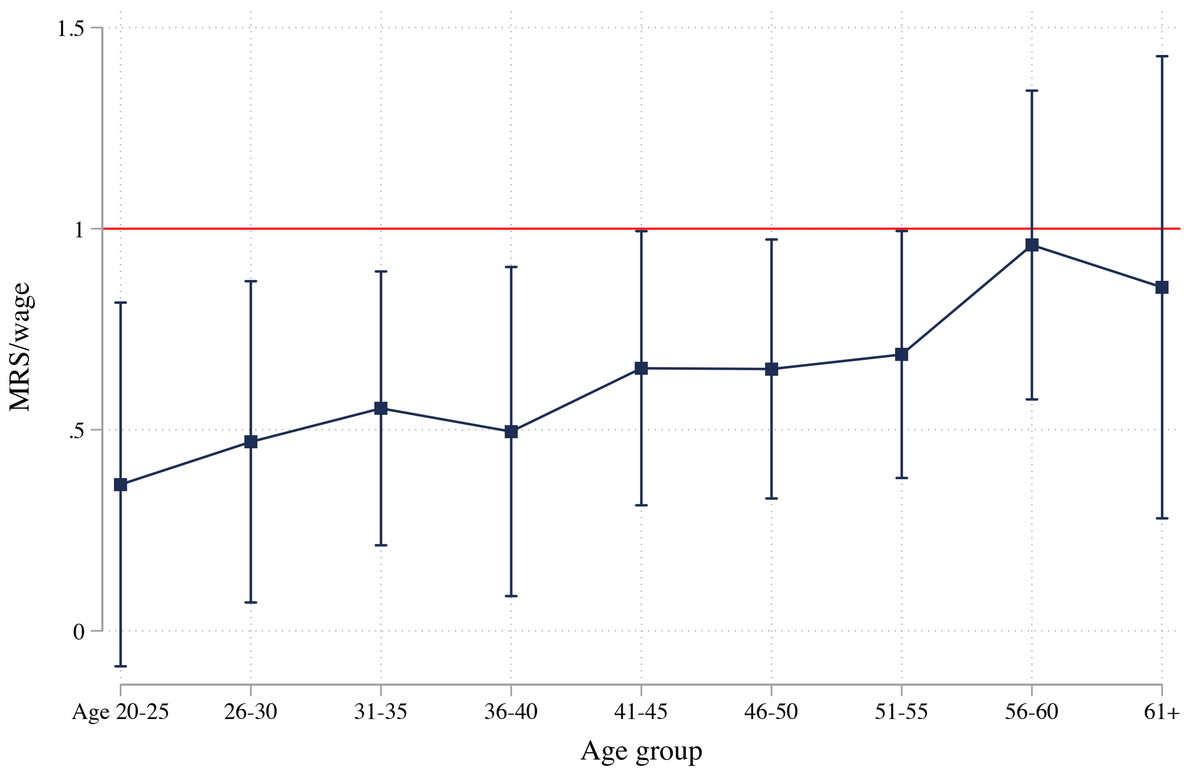
Notes: A short-hour (long-hour) worker is defined as a worker whose hour effect is in the first (fourth) quartile of worker hour effects. A short-hour (long-hour) employer is defined as an employer whose hour effect is in the first (fourth) quartile of employer hour effects. For each educational group, we calculate the ratio of the proportion of that educational attainment for short/long-hours workers in long/short-hours employers relative to the overall mean. Long-hour workers at short-hour employers tend to be less educated than the average worker. Short-hour workers at long-hour employers tend to be more educated than the average worker. The calculation is done for the subset of observations with demographic information.

Figure 6: PageRank index, by quantiles of employer hours and wage effects



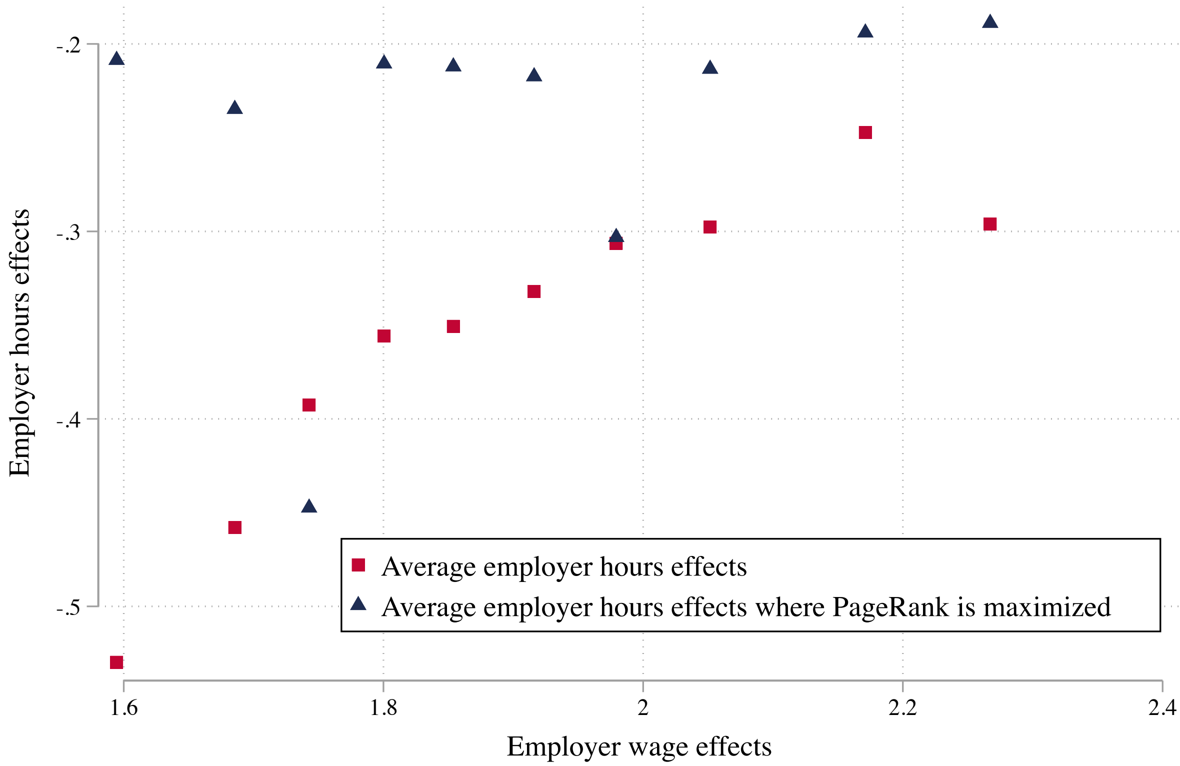
Notes: This figure shows the average PageRank index by each vingtile of employer wage effects and by each quintile of employer hour effects. The PageRank index is a measure of a given employer's utility, calculated as in Sorkin (2018). Darker shade of a cell implies a higher value of the PageRank index. Public administration and the education sector are omitted. See Section 5 for further details.

Figure 7: Ratio between marginal rate of substitution and observed wage over the life cycle



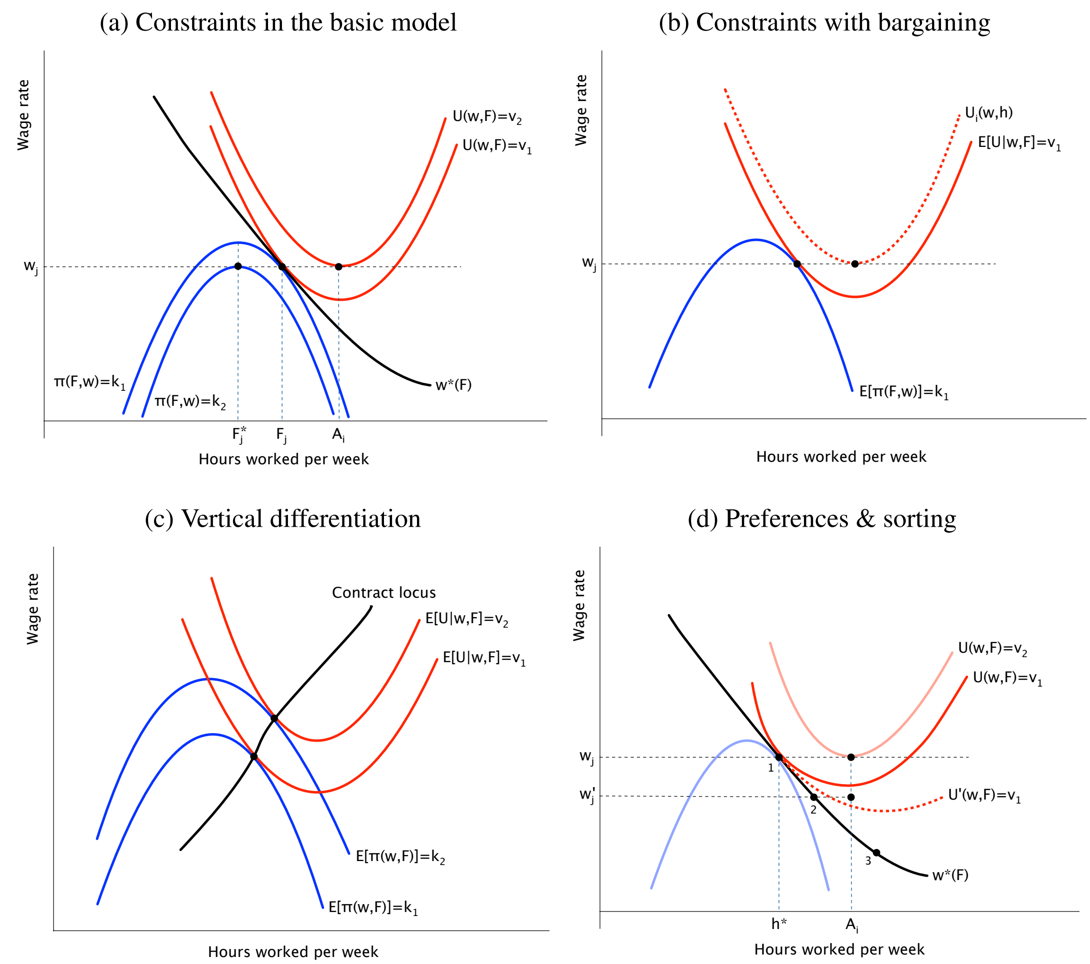
Notes: The figure displays the ratio between the marginal rate of substitution between earnings and hours and the observed wage ($MRS/wage$) across age groups. The PageRank utility index of Page et al. (1999); Sorkin (2018) is calculated separately for each age group and regressed on employer wage effects and employer hour effects as described in equation (7). The regression is estimated using a split-sample IV to account for measurement error. The graph shows $MRS/wage$ for each age group, see equation (8) and Section 2.3 for further details. The vertical bars represent 95% confidence intervals calculated using the delta method. Each regression controls for sector fixed effects.

Figure 8: Gap between observed and optimal hours



Notes: The data are divided into 10× 10 cells defined by deciles of employer wage effects and employer hour effects. For each decile of employer wage effects, we identify the employer hours decile with the highest PageRank index (Sorkin, 2018). The navy triangles represent the weighted average of employer hour effects in the PageRank-maximizing ("optimal") hours decile, where the weight is the number of worker-year observations in the corresponding wage decile × "optimal hours" decile cell. The red squares represent the overall weighted average of employer hours effects for a given decile of employer wage effects. To avoid contamination due to correlated measurement errors between employer wage effects, employer hour effects, and the PageRank utility index, we follow a split-sample IV strategy. That is, the deciles of employer wage effects and of employer hour effects are calculated from the hold-out sample and the corresponding within-cell weighted averages are computed using the estimation sample. Public administration and the education sectors are omitted from these calculations. See Section 5.3 for further details.

Figure 9: Hour constraints and vertical differentiation in the Lewis-Rosen model



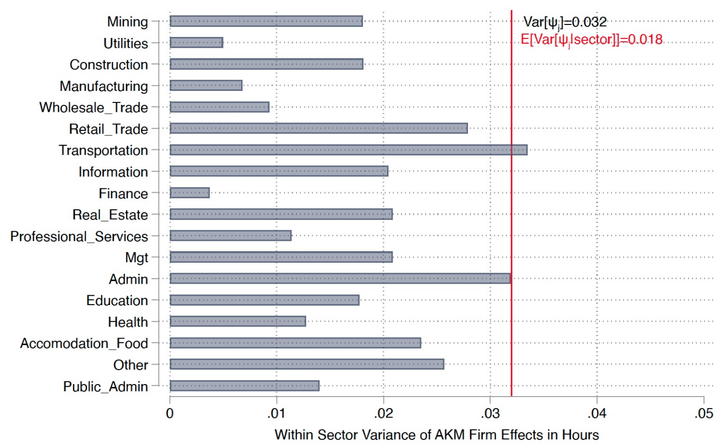
Notes: Figure 9(a) shows a negatively-sloped market equalizing difference function $w^*(F)$ constraining the worker from working more, as the equilibrium hours are at (w_j, h^*), but the worker prefers (w_j, A_i). Figure 9(b) shows hour constraints in a model with bargaining over hours. Figure 9(c) shows how vertical differentiation results in a positively-sloped contract curve connecting different employer wage-hour packages. Figure 9(d) shows three workers, 1, 2, and 3. Worker 1, whose indifference curve is the solid red line, prefers to work the fewest hours. Worker 1 is the most skilled and is the first be offered a job. If she is offered wage-hour package (w_j, A_i), she will take that job but not the package (w'_j, A_i). If worker 1's MRS were lower at high hours—denoted by the flatter, dashed red curve—then she would accept package (w'_j, A_i). In both cases, worker 1 works longer hours than worker 2, resulting in a short-hour worker working for a long-hour employer. In neither case does worker 1 work more than worker 3 because the gap in their preferences for hours is too large. See Section 6 for discussion.

Appendix

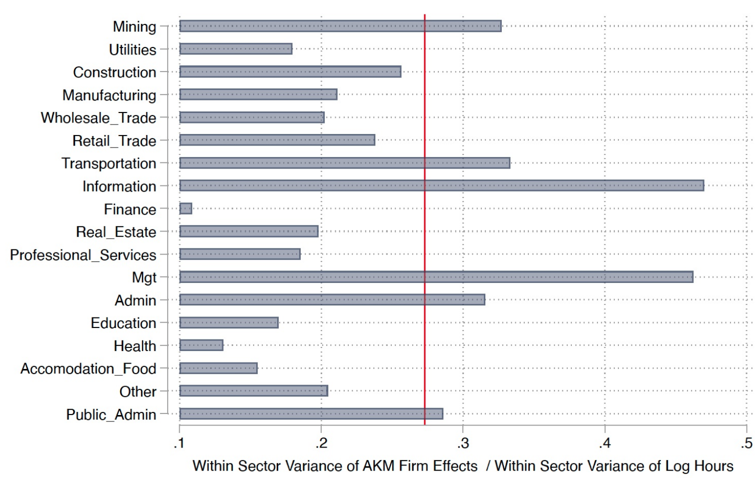
A Additional Tables and Figures

Figure A1: Within-sector variation in employer effects

(a) Levels



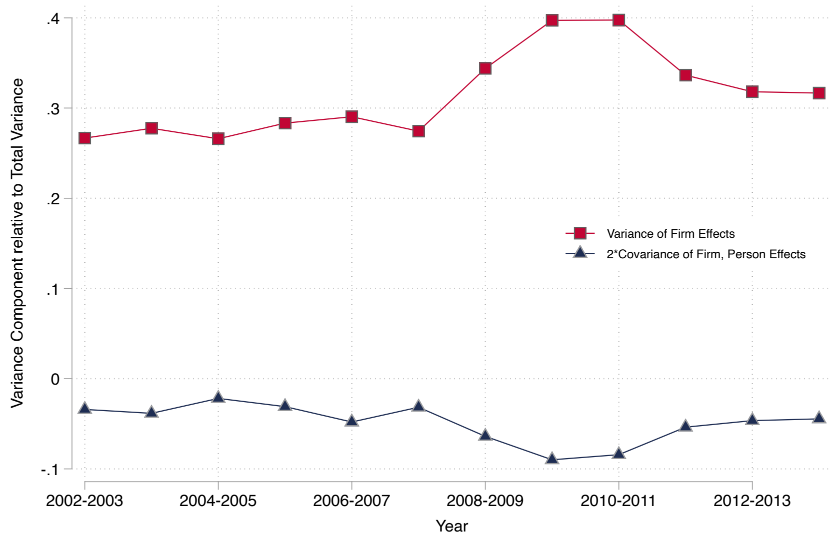
(b) Shares



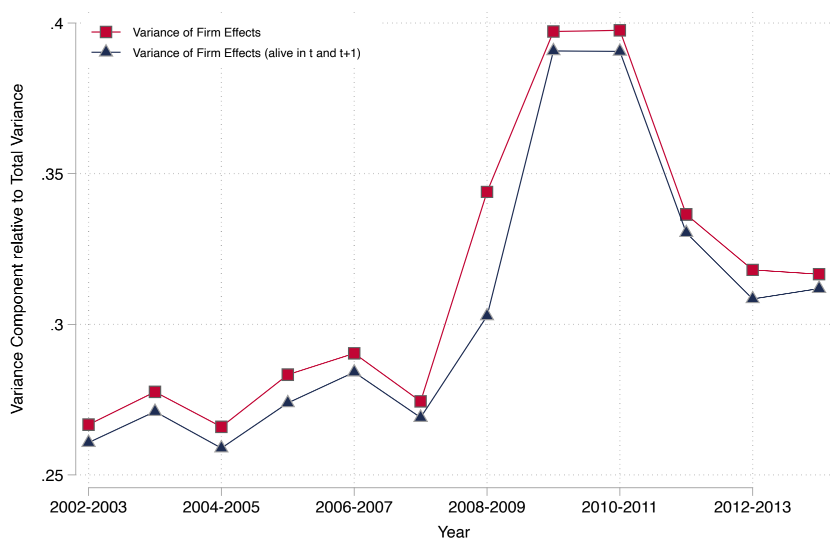
Notes: Panel (a) displays the variation of firm effects within each sector. All variances are KSS corrected. Panel (b) re-scales these within-sector variances of firm effects by the corresponding overall variance of hours observed in a given sector. The vertical red line in panel (a) denotes the overall variance of firm effects displayed in Table 2; that is, $0.35^2 = 0.032$. Similarly, the vertical line in panel (b) captures the overall share of the variance of log hours that is explained by firm effects in the pooled samples. We display in panel (a) in red also the corresponding "within component", i.e., how much of the overall variation in firm effects for hours is explained by average within-sector variation in the firm-effects for log hours. All variances are worker-year weighted.

Figure A2: Role of employers in determining hours over the business cycle

(a) R-AKM estimates

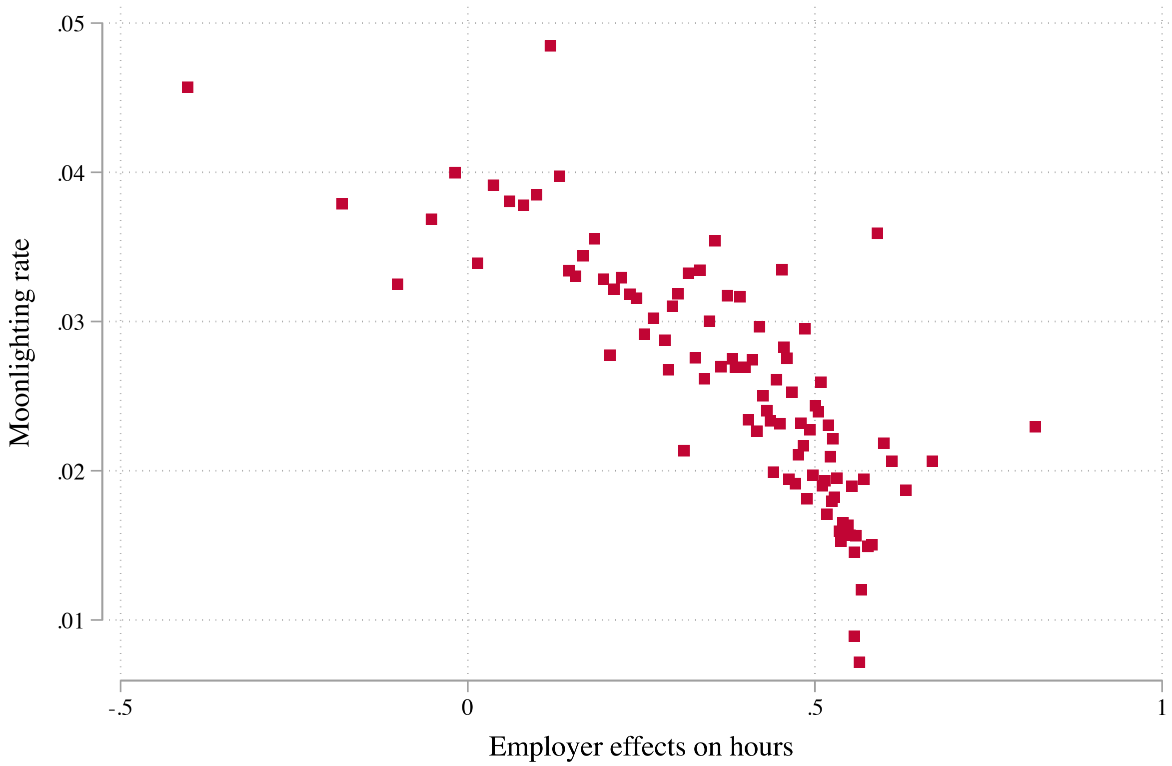


(b) Balanced version



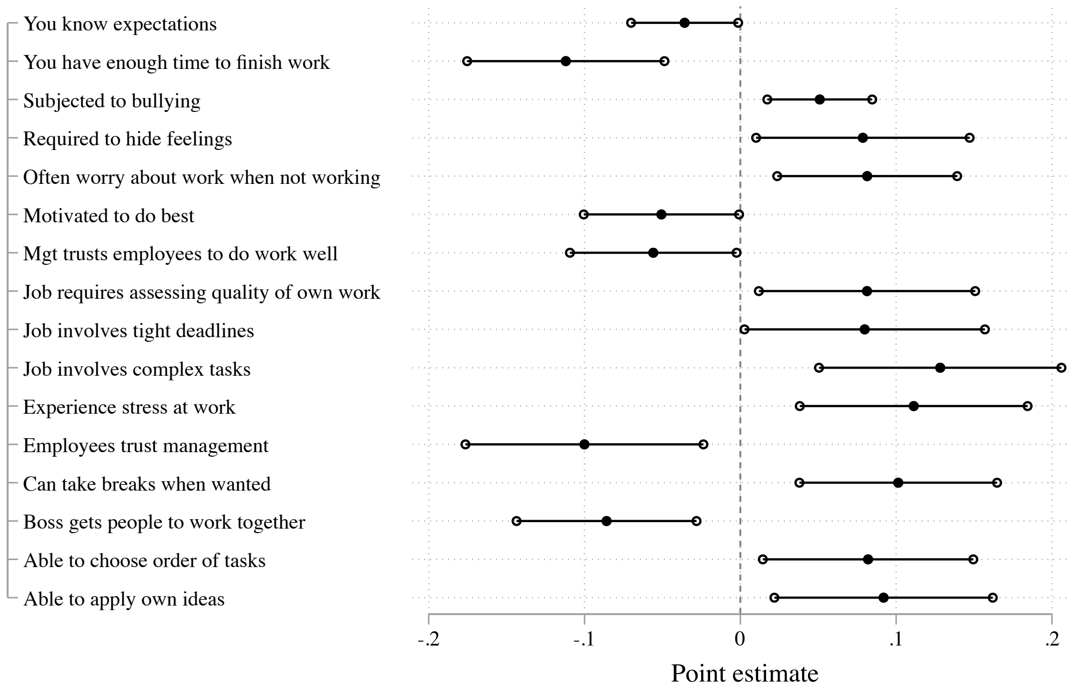
Notes: To construct this figure, we estimate equation (3) separately to successive overlapping two-year intervals (2002–2003, 2003–2004, etc.) and corrects the interval-specific variance of employer effects using the Rolling-AKM (R-AKM) methodology from Lachowska et al. (2023). Both variance components are rescaled by the observed overall variability of hours present in a given interval. Panel (b) presents the share of the variance explained by firm effects displayed in panel (a) along with the variance of firm effects obtained after imposing that each firm is alive in both years within an interval.

Figure A3: Moonlighting and employer hour effects



Note: The figure displays a binscatter between the fraction of workers who moonlight (that is, simultaneously hold two jobs, as defined in Lachowska et al., 2022) and the firm-hour fixed effect (from the primary job) estimated from equation (3). The average moonlighting rate equals 0.028. The associated KSS-adjusted slope between moonlighting and employer effects equals –0.042. Employer effects on hours are normalized relative the average employer effect among employers that belong in the 100th centile of the within-firm standard deviation of log hours.

Figure A4: Statistically significant associations between workplace characteristics and hours



Notes: Estimates from the 2015 American Working Conditions Survey (Maestas et al., 2017). The figure shows coefficients (black dots) and associated robust 95-percent confidence intervals (CI) (bars with hollow dots) from separate regressions of a given job characteristic on annual hours of work. The model also controls for hourly wage, and indicators for employer-provided fringe benefits, industry, and employer size. The number of observations in each regression ranges from 1,368 to 1,393.

Table A1: Change of Employer and Change of Hours Worked

Origin/Destination Quartile	Number of Observations	Average Log Hours Before/After Job Transition				Change from 2 Years Before to 1 Year After Job Transition	
		t*=-2	t*=-1	t*=0	t*=1	Raw	Adjusted
Panel (a): All Transitions							
1 to 1	94,396	7.20	7.19	7.25	7.23	0.02	0.00
1 to 2	49,278	7.27	7.25	7.46	7.44	0.17	0.14
1 to 3	27,123	7.29	7.27	7.55	7.55	0.25	0.23
1 to 4	21,308	7.34	7.32	7.65	7.64	0.30	0.27
2 to 1	41,091	7.42	7.39	7.31	7.31	-0.12	-0.11
2 to 2	91,735	7.48	7.45	7.50	7.48	0.00	0.00
2 to 3	59,460	7.50	7.47	7.58	7.57	0.07	0.07
2 to 4	35,680	7.52	7.50	7.66	7.65	0.13	0.13
3 to 1	15,507	7.52	7.49	7.34	7.32	-0.21	-0.21
3 to 2	41,135	7.57	7.54	7.53	7.51	-0.05	-0.05
3 to 3	70,050	7.58	7.56	7.59	7.58	0.00	0.00
3 to 4	59,342	7.60	7.58	7.66	7.66	0.06	0.06
4 to 1	10,949	7.63	7.59	7.37	7.35	-0.28	-0.28
4 to 2	25,242	7.66	7.62	7.55	7.53	-0.13	-0.13
4 to 3	52,949	7.66	7.63	7.61	7.60	-0.06	-0.06
4 to 4	130,592	7.69	7.68	7.70	7.69	0.00	0.00
Panel (b): Same Quartile of Co-workers Wage Distribution							
1 to 1	61,945	7.22	7.21	7.27	7.25	0.03	0.00
1 to 2	24,663	7.30	7.27	7.48	7.45	0.16	0.13
1 to 3	7,912	7.31	7.29	7.56	7.55	0.25	0.22
1 to 4	6,009	7.34	7.32	7.67	7.66	0.32	0.29
2 to 1	21,047	7.44	7.42	7.32	7.32	-0.12	-0.11
2 to 2	49,934	7.49	7.46	7.50	7.48	-0.01	0.00
2 to 3	31,948	7.50	7.48	7.57	7.56	0.06	0.07
2 to 4	14,955	7.52	7.50	7.66	7.65	0.13	0.14
3 to 1	5,716	7.54	7.50	7.36	7.34	-0.20	-0.20
3 to 2	18,814	7.57	7.54	7.53	7.51	-0.06	-0.05
3 to 3	41,613	7.58	7.56	7.59	7.58	0.00	0.00
3 to 4	34,360	7.60	7.58	7.66	7.65	0.05	0.06
4 to 1	3,703	7.64	7.61	7.38	7.35	-0.30	-0.30
4 to 2	10,113	7.66	7.63	7.55	7.53	-0.13	-0.13
4 to 3	28,125	7.65	7.63	7.61	7.60	-0.06	-0.06
4 to 4	90,940	7.70	7.70	7.71	7.70	0.00	0.00

Note: This table is constructed by looking at job transitions observed in the WA data where the worker held the job for at least two years and then moved in t*=0 to a different employer and remained with this new employer also for at least two years. For each job transition, we calculate quartiles of the leave-out average of co-workers log hours in the last year in the old origin job and in the first year of the new destination job. Job transitions are then classified according to the 4x4 types of transitions based on the quartiles of coworker hours at the origin and destination employers. Panel (a) reports average log hours in the two years prior to the job move, and in the two years in the new destination job for the transitions. Panel (b) is similar but we restrict attention to transitions where origin and destination employers share the same quartile in average co-workers wage distribution. The last two columns report the "long" change in log hours by contrasting log hours in t*=-2 and t*=1. The last column adjusts that "long" change by substracting off mean change for job movers from the same origin quartile who remain in same quartile.

Table A2: Unadjusted Variance Decomposition of Log Hours

		Share of Total Variance (%)
Info on Leave Out Connected Set:		
Number of Movers	1,884,040	
Number of Firms	168,186	
Number of Person-Year Observations	26,233,816	
Mean Log Hours	7.47	
Std. Log Hours	0.35	
Variance Decomposition (Unadjusted Estimated)		
Std. of Firm Effects	0.20	34.27%
Std. of Worker Effects	0.23	44.91%
Covariance of Worker, Firm Effects	-0.01	-4.49%
Correlation of Worker, Firm Effects	-0.11	

Note: This table reports the variance decomposition based on an AKM model fitted on log hours using the WA data over the periods 2002-2014. The model controls for year fixed effects. Variance decomposition parameters estimated using a "plug-in" approach and thus are unadjusted for sampling noise in the estimates. Summary statistics on the leave-out connected set defined in KSS are reported on top. Leave-out correction based on a "leave-match-out" approach, see text for details.

Table A3: Variance Decomposition of Hours, Wages and Earnings --- Excluding Salaried Workers

	Log Hours		Log Wages		Log Earnings	
Std. of Outcome	0.35		0.56		0.69	
Variance Decomposition						
Std. of Firm Effects	0.19	29.03%	0.21	13.54%	0.31	20.71%
Std. of Worker Effects	0.08	5.58%	0.39	48.75%	0.35	26.02%
Covariance of Worker, Firm Effs	0.00	0.46%	0.03	19.68%	0.05	22.38%
Correlation of Worker, Firm Effs	0.02		0.38		0.48	

Note: This table reports the variance decomposition based after fitting an AKM decomposition on log hours, log hourly wage and log earnings using the WA data over the perioods 2002-2014 after excluding salaried jobs using the procedure detailed in Appendix C. The model controls for year fixed effects. Variance decomposition parameters estimated using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Leave-out correction based on a "leave-match-out" approach, see text for details. All statistics are person-year weighted.

Table A4: Variance Decomposition after fitting AKM to an indicator equal to 1 for part-time jobs

		Share of Total Variance (%)
Info on Leave Out Connected Set:		
Number of Movers	1,884,040	
Number of Firms	168,186	
Number of Person-Year Observations	26,233,816	
Share of Part-Time Workers	0.35	
Std of Part-Time Indicator	0.48	
Variance Decomposition		
Std. of Firm Effects	0.23	23.99%
Std. of Worker Effects	0.24	25.13%
Covariance of Worker, Firm Effects	0.00	3.39%
Correlation of Worker, Firm Effects	0.07	
Additional Correlations		
Correlation Firm Effects Part-Time, Firm Effects Log Hours	-0.90	
Correlation Person Effects Part-Time, Person Effects Log Hours	-0.49	

Note: This table reports the variance decomposition based on an AKM model fitted after fitting AKM to an indicator equal to 1 for part-time jobs using the WA data over the periods 2002-2014. A part-time job is defined as a job where the annualized level of hours divided by 52 is less than 35 hours. The model controls for year fixed effects. Variance decomposition parameters estimated using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Summary statistics on the leave-out connected set defined in KSS are reported on top. Leave-out correction based on a "leave-match-out" approach, see text for details. All statistics are person-year weighted.

Table A5: Variance Decomposition of Annual Hours in Levels

		Share of Total Variance (%)
Info on Leave Out Connected Set:		
Number of Movers	1,884,040	
Number of Firms	168,186	
Number of Person-Year Observations	26,233,816	
Mean Log Hours	1840.53	
Std. Log Hours	502.51	
Variance Decomposition		
Std. of Firm Effects	279.47	30.93%
Std. of Worker Effects	256.94	26.14%
Covariance of Worker, Firm Effects	-1003.60	-0.79%
Correlation of Worker, Firm Effects	-0.01	

Note: This table reports the variance decomposition based on an AKM model fitted on the (annualized) level of hours (i.e. without taking the logarithm) worked by individuals with their primary employer using the WA data over the periods 2002-2014. The model controls for year fixed effects. Variance decomposition parameters estimated using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Summary statistics on the leave-out connected set defined in KSS are reported on top. Leave-out correction based on a "leave-match-out" approach, see text for details. All statistics are person-year weighted.

Table A6: Variance Decomposition of Log Hours (Quarterly Frequency)

		Share of Total Variance (%)
Info on Leave Out Connected Set:		
Number of Movers	2,550,654	
Number of Firms	213,248	
Number of Person-Quarter Observations	103,852,269	
Mean Log Hours	6.01	
Std. Log Hours	0.58	
Variance Decomposition		
Std. of Firm Effects	0.25	18.55%
Std. of Worker Effects	0.19	10.28%
Covariance of Worker, Firm Effects	0.00	0.94%
Correlation of Worker, Firm Effects	0.03	

Note: This table reports the variance decomposition based on an AKM model fitted on log hours using the WA data over the periods 2002-2014, at the quartely frequency. The model controls for quarter-year fixed effects and only considers quarters of "full-employment", see text for definition. Variance decomposition parameters estimated using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Summary statistics on the leave-out connected set defined in KSS are reported on top. Leave-out correction based on a "leave-match-out" approach, see text for details. All statistics are person-quarter weighted.

Table A7: Covariance Matrix in Firm/Person Effects in Log Wages, Log Hours

	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.2185	0.0378	-0.0064	0.0248
Firm Effect		0.0448	-0.0011	0.0122
Log Hours				
Person Effect			0.0086	0.0008
Firm Effect				0.0320

Note: This table reports the correlation matrix between the worker and firm component obtained after fitting an AKM specification to log hours and log wages. The model controls for year fixed effects. All correlations are computed using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Leave-out correction based on a "leave-match-out" approach, see text for details.

Table A8: Within/Between Sector Decomposition of Variance Components

Panel (a): Variance Components	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.2185	0.0378	-0.0064	0.0248
Firm Effect		0.0448	-0.0011	0.0122
Log Hours				
Person Effect			0.0086	0.0008
Firm Effect				0.0320
Panel (b): Between-Sector Components	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.0317	0.0156	-0.0041	0.0129
Firm Effect		0.0161	-0.0009	0.0111
Log Hours				
Person Effect			0.0016	-0.0009
Firm Effect				0.0146
Panel (c): Within-Sector Components	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.1868	0.0222	-0.0023	0.0119
Firm Effect		0.0287	-0.0002	0.0012
Log Hours				
Person Effect			0.0070	0.0017
Firm Effect				0.0173

Note: Panel (a) reports the person-year weighted variances and covariances between person and firm effects across different outcomes, all corrected using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). We then apply a law of total variance decomposition to each variance component by reporting in Panel (b) the between sector component and in Panel (c) the within-sector component. The within-component is calculated as the difference between the KSS-adjusted covariance component reported in Panel (a) and the between component displayed in Panel (b).

Table A9: Page Rank Utility and Firm Effects in Hours, Firm Effects in Wages, controlling for average deviation in hours

	[1]	[2]	[3]
Outcome: Page Rank Utility (Sorkin, 2018)			
Firm Effect in Hours	7.8712***	5.5546***	6.2085***
	(2.3679)	(1.4155)	(0.8087)
Average Within-Job Variability in Hours at the Firm	-0.1254	1.9544	3.9937
	(5.2174)	(4.7200)	(2.8426)
Firm Effect in Wages		5.9053***	7.0757***
		(1.7908)	(1.4115)
# of Firms	56,323	56,323	56,323
Controlling for Sector Fixed Effects	no	no	yes
% of Variance Explained by Firm Effects in Hours	23.06	11.48	14.35
% of Variance Explained by Firm Effects in Wages		17.18	24.66
% of Variance Explained by Covariance in Firm Effects		10.2	13.66
MRS/w		.06	.12
p-value (MRS/w=1)		0	0
Adjusted MRS/w		.16	.22
p-value (Adjusted MRS/w=1)		0	0

Note: This table reports the results from a split-sample IV regression where the outcome is the page rank utility calculated using the revealed preference approach of Sorkin (2018) and the key regressors corresponds to the firm effects in hours and wages calculated after fitting a two-way fixed effects decomposition on log hours and log wages. To construct the split-sample IV, we start by dividing the worker-firm pairs observed in the WA data randomly into two subsamples. We then estimate a two-way fixed effects decomposition as well as the page-rank algorithm of Sorkin (2018) separately within each subsample. This permits us to instrument a given firm-effects (in either wages or hours) with the same quantify calculated from the left-out sample. The regression also controls for the average within-job variability in hours at a given firm, that is the average standard deviation in hours across jobs present in a given firm. The page rank utility measure is calculated using job-to-job transitions and corrects for differences in firm-size and intensity of offers as described in Sorkin (2018). Below the table, we report the variance decomposition of the page rank utility, where each variance component has been corrected to account for sampling noise using again a split-sample approach. Public Administration and Education sector were excluded from the analysis. The last rows of the table report the ratio of the implied marginal rate of substitution (MRS) between earnings and hours relative to the wage and the p-value from a test of this quantity being equal to 1 (where the associated standard error is calculated using the delta method). Adjusted MRS is the adjusted MRS that accounts from the omission of fringe benefits that might correlate with hours and utility from employment in the regression, see Appendix D for details. All coefficients and variance components are weighted by the total number of person-year observations associated with a given employer. Robust standard errors are displayed in parenthesis.

Table A10: Page Rank Utility and Firm Effects in Hours, Firm Effects in Wages, excluding Salaried Jobs

	[1]	[2]	[3]
Outcome: Page Rank Utility (Sorkin, 2018)			
Firm Effect in Hours	7.3202***	5.1672***	5.2976***
	(1.6346)	(0.7406)	(0.5542)
Firm Effect in Wages		5.3610***	6.7263***
		(1.7211)	(1.4147)
# of Firms	52,275	52,275	52,275
Controlling for Sector Fixed Effects	no	no	yes
% of Variance Explained by Firm Effects in Hours	24.09	12.01	12.62
% of Variance Explained by Firm Effects in Wages		12.92	20.34
% of Variance Explained by Covariance in Firm Effects Hours/Wages		7.92	10.19

Note: This table reports the results from a split-sample IV regression where the outcome is the page rank utility calculated using the revealed preference approach of Sorkin (2018) and the key regressors corresponds to the firm effects in hours and wages calculated after fitting a two-way fixed effects decomposition on log hours and log wages where the latter are computed excluding from the estimation sample jobs that are on a salaried basis, as explained in Appendix C. To construct the split-sample IV, we start by dividing the worker-firm pairs observed in the WA data randomly into two subsamples. We then estimate a two-way fixed effects decomposition as well as the page-rank algorithm of Sorkin (2018) separately within each subsample. This permits us to instrument a given firm-effects (in either wages or hours) with the same quantify calculated from the left-out sample. The page rank utility measure is calculated using job-to-job transitions and corrects for differences in firm-size and intensity of offers as described in Sorkin (2018). Below the table, we report the variance decomposition of the page rank utility, where each variance component has been corrected to account for sampling noise using again a split-sample approach. Public Administration and Education sector were excluded from the analysis. All reported regressions and variance components are weighted by the total number of person-year observations associated with a given employer. Robust standard errors are displayed in parenthesis.

Table A11: Page Rank Utility and Firm Effects in Hours, Firm Effects in Wages

	[1]	[2]
Outcome: Page Rank Utility (Sorkin, 2018)		
Firm Effect in Hours	5.1678***	5.4330***
	(0.7187)	(0.5517)
Firm Effect in Wages	5.8574***	6.9980***
	(1.7590)	(1.4122)
# of Person-Year-Obs	8,746,690	8,746,690
Controlling for Year Fixed Effects	yes	yes
Controlling for Sector Fixed Effects	no	yes
% of Variance Explained by Firm Effects in Hours	9.94	10.99
% of Variance Explained by Firm Effects in Wages	16.9	24.12
% of Variance Explained by Covariance in Firm Effects	9.4	11.81
MRS/w	0.12	0.22
p-value (MRS/w=1)	0.00	0.00
Adjusted MRS/w	0.22	0.32
p-value (Adjusted MRS/w=1)	0.00	0.00

Note: This table reports the results from equation (7) estimated at the person-year level and adding year fixed effects as controls. The regression uses as outcome is the page rank utility calculated using the revealed preference approach of Sorkin (2018) and the key regressors (instrumented using a split-sample IV) corresponds to the firm effects in hours and wages calculated after fitting a two-way fixed effects decomposition on log hours and log wages. To construct the split-sample IV, we start by dividing the worker-firm pairs observed in the WA data randomly into two subsamples. We then estimate a two-way fixed effects decomposition as well as the page-rank algorithm of Sorkin (2018) separately within each subsample. This permits us to instrument a given firm-effects (in either wages or hours) with the same quantify calculated from the left-out sample. The page rank utility measure is calculated using job-to-job transitions and corrects for differences in firm-size and intensity of offers as described in Sorkin (2018). Below the table, we report the variance decomposition of the page rank utility, where each variance component has been corrected to account for sampling noise using again a split-sample approach. Public Administration and Education sector were excluded from the analysis. The last rows of the table report the implied marginal rate of substitution (MRS) between earnings and hours and the p-value from a test of this quantity being equal to 1. Adjusted MRS is the adjusted MRS aftering from the omission of fringe benefits that might correlate with hours in the regression. Cluster standard errors at the firm level are displayed in parenthesis.

Table A12: Page Rank Utility and Firm Effects in Hours, Firm Effects in Wages in sample with Demographic Data

	Sample with Demographic Info	Age b/w 30 and 50	Age <30	Age > 50
Outcome: Page Rank Utility (Sorkin, 2018)				
Firm Effect in Hours	4.8844***	4.4583***	4.7036***	3.5455***
	(0.5330)	(0.6021)	(0.6738)	(0.7859)
Firm Effect in Wages	5.8930***	6.0594***	5.6974***	7.0279***
	(1.4124)	(1.5495)	(0.9581)	(1.6588)
# of Firms	40,011	22,072	19,605	6,638
Controlling for Sector Fixed Effects	yes	yes	yes	yes
% of Variance Explained by Firm Effects in Hours	10.84	8.39	14.68	5.26
% of Variance Explained by Firm Effects in Wages	20.27	22.17	20.91	28
% of Variance Explained by Covariance in Firm Effects Hours/Wages	8.77	7.15	10.79	9.35 9.35
MRS/w	.17	.26	.17	.5
pvalue MRS/w=1	0	0	0	0
adj MRS/w	.27	.36	.27	.6
pvalue adj MRS/w=1	0	0	0	.02

Note: This table reports the results from a split-sample IV regression where the outcome is the page rank utility calculated using the revealed preference approach of Sorkin (2018)---estimated separately for each of the columns listed on the table---and the key regressors corresponds to the firm effects in hours and wages calculated after fitting a two-way fixed effects decomposition on log hours and log wages. All reported coefficients are computed using a split-sample IV strategy to account for measurement error, as described in the main text and Appendix B.4. Column 1 estimates the relationship between page-rank utility and firm-wage and firm-hour effects where the page-rank utility has been re-estimated using only the job to job transitions made by individuals for whom we have demographic information. Columns 2-4 are similar in that the page-rank utility index has been estimated separately for each of the age groups listed in the table. Below the table, we report the variance decomposition of the page rank utility, where each variance component has been corrected to account for sampling noise using again a split-sample approach. Public Administration and Education sector were excluded from the analysis. The last rows of the table report the implied marginal rate of substitution (MRS) between earnings and hours relative to the wage and the p-value from a test of this ratio being equal to 1. Adjusted MRS is the adjusted MRS aftering from the omission of fringe benefits that might correlate with hours in the regression. All coefficients and variance components are weighted by the total number of person-year observations associated with a given employer. Robust standard errors are displayed in parenthesis

Table A13: Deviations from Optimal Hours and Resulting Compensating Variation using Quadratic Specification

	Gap b/w Observed and Optimal Hours	Gap b/w Observed and Optimal Hours (Absolute Value)	Gap b/w Observed and Optimal Utility	Compensating Variation (Expressed in % terms)
Decile of Firm-Wage Effects				
1	-1.30	1.30	-15.11	0.95
2	-1.69	1.69	-11.41	0.74
3	-0.30	0.30	-3.93	0.27
4	-0.06	0.11	-1.91	0.14
5	-0.41	0.41	-2.53	0.19
6	-0.20	0.20	-1.97	0.15
7	-0.41	0.41	-2.10	0.16
8	-0.17	0.19	-2.68	0.22
9	-0.10	0.18	-1.28	0.11
10	-0.45	0.45	-2.82	0.25
Weighted Average WTP 31.82				

Note: This table presents the willingness to pay calculations described in the text but under the assumption that utility is quadratic in firm-hours with coefficients that depend upon a particular bin of the firm-wage effects. To estimate this parametric specification, we regress, separately for each decile of firm-wage effects, PageRank utility on a quadratic in firm-hours effects via split-sample IV. We then use the fitted values from this regression to find the employer offering the highest utility within a bin of firm-wage and calculate the gaps in firm-hours (first column) between a given employer and the employer offering the highest utility. Column 2 is similar but reports this gap in absolute value while Column 3 reports the gaps in terms of PageRank utility. Finally, Column 4 presents the average WTP in a given bin that would equalize utility between the current employer and the employer offering the highest utility. The weighted average of this quantify is reported in the last row, where the weights are given by the number of person-year observations.

B Identification, Estimation, and Computation

This appendix describes provides additional details on the identification, estimation and computation of our analysis. Appendix B.1 discusses the assumption of exogenous mobility when using log hours as an outcome in an AKM specification. Appendix B.2 describes the extension of the KSS methodology that permits to derive an unbiased estimate of the variance components from different outcomes. Appendix B.3 provides details on how to compute the ranking of employers following the revealed preference approach of Sorkin (2018). Appendix B.4 provides details on the split-sample IV strategy used to estimate the importance of firm-wage and firm-hour policies in determining the PageRank utility index.

B.1 Exogenous Mobility

In order to discuss identification surrounding an AKM equation on hours, it is useful to start by decomposing the unobserved error r_{it}^h in equation (3) as follows

$$r_{it}^h = m_{j(i,t),t}^h + \lambda_{it}^h + e_{it}^h \tag{15}$$

where $m_{j(i,t),t}^h$ represents a match component in hours worked: any idiosyncratic change in hours worked associated with a given match relative to $\alpha_i^h + \psi_{j(i,t)}^h$ is captured by this term. The term λ_{it}^h captures changes to the portable component of hours of an individual. Such innovations might represent changes in preferences, changes to non-labor income, and the arrival of outside offers that could affect current labor supply as predicted by sequential auction models (Postel-Vinay and Robin, 2002; Di Addario et al., 2023). Finally, e_{it}^h represents measurement error which is assumed to be independent and identically distributed across worker years. All three components are assumed to have (unconditional) mean zero (and thus implicitly define α_i^h).

Identification of the AKM equation for hours relies on the so-called exogenous mobility assumption. The latter rules out the possibility that job moves are systematically related to any of the components described in equation (15). As detailed in Card, Heining and Kline (2013), exogenous mobility does not rule out the possibility that workers sort to employers on the basis of $(\alpha_i^h, \{\psi_j^h\}_{j=1}^J)$ as well as other characteristics of the employer other than hours. Exogenous mobility is violated if, for instance, individuals systematically sort to employers on the basis of a match effect in hours worked. This type of sorting would arise in models of comparative advantage (Roy, 1951). Sorting on a match component would ultimately contaminate the interpretation of the firm effects capturing systematic hours requirements imposed by firms because this type of endogenous mobility implies that each worker obtains a different hour requirement that depends upon the corresponding match component.

Do workers sort to firms on the basis of a match component? As noted by Card, Heining and Kline (2013), lack of sorting on a match component implies a symmetric condition on hours changes following a job transition. That is, the change in hours following a transition from a bottom to a top-hours employer should be symmetric and opposite to the hours' changes observed when looking at transitions from top-to-bottom employers.

To check for such symmetric patterns, we implement the event study analysis on job moves of Card, Heining and Kline (2013) on hours. Job transitions are classified according to the mean hours of co-workers at origin and destination employer. Specifically, we take all the job transitions that occurred in the WA data where an individual held a job for at least two consecutive years prior to the job transition and remained with the new employer also for at least two years. We then calculate quartiles of the leave-one-out average of coworkers log hours in the last year in the old origin job and in the first year of the new destination job. Job transitions are then classified according to the 4×4 types of transitions that result from other quartiles of coworker hours at the origin and destination employers.[42] Finally, we calculate mean log hours in the two years prior to the job move, and in the two years in the new destination job.

Figure 3(a) shows that moving from a workplace where coworkers work less on average to a workplace where coworkers work relatively more (i.e. a 1-4 type of transition) maps into a systematic increase of an individual's hours of work, similarly to what has been found when looking at

[42]For clarity, in Figure 3, we restrict attention to cases where the origin employer is either in the first or fourth quartile of the coworkers hours distribution. Table A1 prints all the associated transitions.

wages (e.g Card, Heining and Kline, 2013; Card, Cardoso and Kline, 2015; Macis and Schivardi, 2016). These systematic changes occur in both directions. When moving from an employer where coworkers work relatively more to an employer where coworkers work less (i.e. a 4-1 transition), we observe a significant reduction in hours worked by the individual. Consistent with that, Figure 3(a) shows that work hours differ significantly according to whether the origin employer is in the bottom or top quartile of the coworker hours distribution.

Figure 3(a) also suggests that the increase in hours worked when moving from a bottom-quartile to a top-quartile employer are roughly symmetric to the losses in hours experienced when moving in the opposite direction. Table A1 confirms that this symmetry is observed across multiple types of transitions. The approximate symmetry of hours gains and losses following a job move supports the exogenous mobility assumption described above.

Another interesting aspect that emerges from inspection of Figure 3(a) is lack of systematic and quantitatively large adjustments in hours in the years leading up to the job move.[43] Table A1 shows that the same holds when also looking at all the remaining transitions. There is no systematic adjustment in hours worked depending on the type of transitions made by the individual (e.g., an upward trend in hours before moving to a long-hour employer).

This is important because another source of endogenous mobility is that firm-to-firm transitions are predicted by innovations to the individual portable component of hours, λ_{it}^{h}. This type of sorting could lead to an overstatement of the importance of employer effects in hours and thus bias our analysis. As mentioned, the lack of systematic trends prior to a job transition and the very similar trends displayed across different types of job transitions cast doubts on the importance of this source of endogenous mobility.[44]

[43]Recall that our analysis is on "full-employment" quarters, so partial quarters that occur close to a job transition will not be captured by the event study analysis of Figure 3.

[44]Clearly, this type of analysis does not permit to rule out cases of instantaneous changes to preferences that lead to instantaneous changes of employers. As for several classes of models, being able to distinguish between instantaneous changes in preferences and other factors is typically very hard.

B.2 Estimation and Computation of Variance Components

We seek to estimate the variance-covariance matrix of $\{(\alpha_i^h, \psi_{j(i,t)}^h), (\alpha_i^w, \psi_{j(i,t)}^w)\}$. It is well known that estimates of these variance components obtained by replacing each firm-level and worker-level component with its OLS estimate counterpart obtained after fitting equation (3) and (4) leads to biases (Krueger and Summers, 1988; Andrews et al., 2008).

The leave-one-out methodology of KSS permits to derive unbiased estimates of variance components from a single AKM equation, e.g $(\mathrm{Var}(\psi_{j(i,t)}^h), \mathrm{Cov}(\psi_{j(i,t)}^h, \alpha_i^h), \mathrm{Var}(\alpha_i^h))$. However, our interest also lies in variance components from different outcomes such as $\mathrm{Cov}(\psi_{j(i,t)}^h, \psi_{j(i,t)}^w)$. Computing this covariance using OLS estimates or so-called "plug-in" approaches $(\hat{\psi}_{j(i,t)}^h, \hat{\psi}_{j(i,t)}^w)$ also leads to biases because estimation error in $\hat{\psi}_{j(i,t)}^h$ is assumed to be correlated with estimation error in $\hat{\psi}_{j(i,t)}^w$.[45] In this context, one reason why the error terms from the hours and wage equations might be correlated – $\mathrm{Cov}(r_{it}^h, r_{it}^w) \neq 0$ – is due to division bias resulting from hourly wages rates being defined as earnings divided by hours (Borjas, 1980).

To show this—and how to correct for this bias using a leave-one-out approach—we start by writing the equations for hours-wages-earnings as follows

$$\begin{aligned} \log h_{it} &= X_{it}^\top \beta^h + r_{it}^h \\ \log w_{it} &= X_{it}^\top \beta^w + r_{it}^w \end{aligned} \tag{16}$$

where X_{it} stacks all the worker and firm indicators as well as the controls x_{it}; similarly $\beta^h \equiv (\alpha^{h\top}, \psi^{h\top}, \gamma^{h\top})'$, i.e. β^h is a vector that stacks together the N workers fixed effects, the J firm fixed effects, and the P effects of controls when using hours as outcome (and similarly for β^w). Finally, let $\beta = (\beta^h, \beta^w)$.

All our estimands are variance components of the form

$$\theta = \beta' A \beta \tag{17}$$

[45]Moreover, this correlation does not vanish asymptotically as firm effects are typically estimated from a handful of movers.

where A is a known matrix that depends upon the variance component of interest. For instance, if one is interested in the covariance of firm effects in hours and firm effects in wages, the estimand can be written as

$$\theta_{\psi^h,\psi^w} = \beta'(A_h'A_w)\beta \tag{18}$$

where

$$A_h = \begin{pmatrix} A_\psi \\ 0 \end{pmatrix}; \qquad A_w = \begin{pmatrix} 0 \\ A_\psi \end{pmatrix}, \tag{19}$$

where A_ψ is a $n \times K$ matrix (with $K = N + J + P$) given by

$$A_\psi = \frac{1}{\sqrt{n}} \begin{pmatrix} 0_{1\times N} & f_{11} & 0_{1\times P} \\ 0_{1\times N} & f_{12} & 0_{1\times P} \\ \vdots & \dots & \vdots \\ 0_{1\times N} & f_{NT} & 0_{1\times P} \end{pmatrix} \tag{20}$$

with f_{it} representing a $J \times 1$ vector of firm indicators, i.e. $f_{it} = (\mathbf{1}\{j(i,t) = 1\}, \mathbf{1}\{j(i,t) = 2\}, \dots, \mathbf{1}\{j(i,t) = J\})$ and n is the total number of person-year observations.

Correlation between r_{it}^h and r_{it}^w prevents the plug-in estimator $\tilde{\theta}_{\psi^h,\psi^w} = \hat{\beta}'(A_h'A_w)\hat{\beta}$ to be unbiased. However, as shown by KSS, if one has available an unbiased estimator of the heteroskedatic covariance $\sigma_{it}^{h,w} \equiv \text{Cov}(r_{it}^h, r_{it}^w)$, then the latter can used to derive an unbiased estimator of θ_{ψ^h,ψ^w} in the same way as an unbiased estimator of $\sigma_{it}^{h,h} \equiv \text{Var}(r_{it}^h)$ can be used to derive an unbiased estimator of a "within-outcome" variance components such as θ_{ψ^h,ψ^h}. KSS propose the following unbiased leave-one-out estimator of the heteroskedatic variance from a given outcome (say, hours).

$$\hat{\sigma}_{-it}^{h,h} = \log h_{it}(\log h_{it} - X_{it}'\hat{\beta}_{-it}^h) \tag{21}$$

where $\hat{\beta}_{-it}^h$ is the OLS estimator of β^h leaving out observation (i,t). The latter can be easily extended for cross-equations variance components as follows :

$$\hat{\sigma}_{-it}^{h,w} = \log h_{it}(\log w_{it} - X_{it}'\hat{\beta}_{-it}^w) \tag{22}$$

We thus use these cross-fit, leave-one-out, estimates to correct for cross-equation variance components between worker and firm effects thus extending the original, single-equation, approach considered by KSS.

Implementation: To derive unbiased estimate of the variance components of interest, we estimate equation (16) on the leave-one-out connected set as defined in KSS using the WA data from 2002-2014. The latter represents the largest set of firms that are connected to each other by worker mobility patterns even after leaving a single worker out from the computation of the connected set.[46] Table 1 shows summary statistics across different samples. The leave-one-out connected set retains about 95% of the person-year observations observed in the largest connected set and about 67% of the firms. Summary statistics on hourly wages, hours and earnings are extremely similar between the leave-one-out connected set, connected set and original sample. To estimate the KSS leave-one-out correction on these data, we allow each error term to be serially correlated within match, consistent with the representation given in equation (15).

B.3 Computation of PageRank Utility

Sorkin (2018) show that, when workers receive a common utility when being employed by a particular employer plus an idiosyncractic utility term drawn from a type 1 extreme value distribution, it is possible to use employer-to-employer transitions made by workers to identify the common/systematic component utility and thus provide a ranking of different employers. Specifically, letting v_j denote the common value of working for employer j net of idiosyncratic utility draws, then the latter can be identified from the following recursive equation

$$\exp(v_j) = \sum_{\ell \in \mathscr{B}_j} \omega_{\ell,j} \exp(v_\ell) \qquad j = 1, \ldots, J. \tag{23}$$

where $\omega_{\ell,j}$ is the number of workers that moved from employer ℓ to employer j (as a result of a employer-to-employer transitions) scaled by the number of all workers that joined employer j as

[46] Thus, any firm associated with a single mover—defined as a worker who transitioned between different employers in a given year—are not going to be part of the leave-one-out connected set.

a result of a employer-to-employer (EE) transitions; $\mathscr{B}_j$ is the set of employers that were left by an employee in order to join employer j. Equation (23) underlies a recursive formulation of good employers as those that poach many employees from other good employers and lose few workers from "bad" employers. This concept is used by Google to rank webpages (Page et al., 1999) and is why we refer to v_j as "PageRank utility." The solution to equation (23) corresponds to an employer rank under various on-the-job search models (Burdett and Mortensen, 1998; Sorkin, 2018; Morchio and Moser, 2021).

To calculate the PageRank, we begin with the quarterly version of the employer-employee matched dataset. We restrict the sample to primary employers (the employer with whom a worker had the highest earnings in that quarter) and drop observations with zero hours worked in a quarter. We then restrict the dataset only to employer-to-employer transitions where the worker does not have any intermittent quarter with zero earnings (by doing so, we drop observations where a worker was hired by an employer out on nonemployment). This leads to a dataset consisting of about 4.9 million EE transitions from about 316,000 distinct employers in quarter t to about 329,000 distinct employers in quarter $t+1$.

Equation (23) is estimated via power iterations on the strongly connected set, i.e. the largest set of connected firms where each employer has at least one leaver as well as one joiner. The resulting strongly connected set comprises of about 206,000 distinct employers.

The solution to equation (23), $\{v_j\}_{j=1}^J$, can be interpreted as a measure of common utility only under the unrealistic assumptions that all firms are the same size and make the same number of offers. Following Sorkin (2018), we thus adjust the resulting employer ranks by differences in firm size and offers intensity (where the latter is proxied by the share of hires that come from non-employment). Under the assumption that all workers search from the same offer distribution, the resulting adjusted ranks capture the systematic component utility across different employers.

B.4 Split-Sample IV

To understand how the PageRank utility index vary with different firm-wage, firm-hours, policies we estimate the following equation

$$v_j = \theta_0 + \theta_h \psi_j^h + \theta_w \psi_j^w + s_j' \gamma + \varepsilon_j. \tag{24}$$

Plugging-in OLS estimates of $\{\psi_j^w, \psi_j^h\}$ in order to estimate this equation can create biases, however, since both estimates are measured with error that can also correlate with measurement error in v_j. We use a split-sample IV approach to account for these issues. We start by randomly dividing all the jobs observed in our full sample into two split-samples (say, sample A and sample B). We then fit the AKM specification within each subsample's largest connected set. Each subsample is also used to derive the associated employer rank v_j. The set of of firms from which we can identify a firm effect in both sample A and sample B as well as its employer ranking is the sample used in this analysis. This permits to use the firm-wage and firm-hour effects obtained from the hold-out sample as instruments when fitting equation (7).

C Salaried Workers in Washington State Administrative Data

Employers in Washington State report paid hours worked in a quarter for their UI-covered employees. These hours include regular hours, overtime hours, and hours of vacation and paid leave. If employers track the hours of their salaried employees, then the employers must report the corresponding hours of work. If the hours of salaried employees — which include also commissioned, and piecework employees — are not tracked, then employers are instructed to report 40 hours per week (Lachowska, Mas and Woodbury, 2022).

The administrative earnings records do not identify which jobs are on a salaried vs. hourly basis or, to be more precise, whether the employer tracks the actual hours of work of its salaried employees. The description above suggests, however, that full-time salaried employees whose work hours are not tracked are expected to have hours that tend to bunch at 40 hours per week.

Because we do not know if workers are paid once a month or every second week and because the number of weeks in a quarter varies from 12 to 14, 40 hours of work per week may correspond to 480, 520, or 560 hours per quarter (Lachowska, Mas and Woodbury, 2022). Accordingly, we expect the distribution of work hours for such workers to exhibit spikes at these three values.[47]

Figure C5 shows the distribution of quarterly work hours. There are clear spikes at 480, 520, and 560 work hours per quarter. We use this pattern to predict whether a worker is likely to be salaried. To do so, we proceed in two steps. First, using the Washington State administrative earnings records, we compute the sector-specific quartile of earnings. Second, we apply these sector-specific earnings quartile values to the 2002–2014 Current Population Survey (CPS). Using the CPS, we compute the share of hourly workers in each sector-specific quartile.[48] We then merge the CPS information on the share of hourly workers in each sector-specific quartile to the Washington administrative data.

Figure C6, panel(a), shows the distribution of quarterly work hours divided by 13 — a proxy for "weekly" work hours — in the Washington data for cells where the share of hourly workers according to the CPS is either below 10% and or above 90%. In cells where the share of hourly workers is below 10%, we observe a large degree of bunching of work hours at 40, 37, or 43. Conversely, the distribution of hours in cells where the fraction of hourly workers is above 90% does not exhibit any particular spikes and appears relatively smooth. Figure C6, panel (b) captures the same idea conveyed in panel (a) by plotting the distribution of work hours for workers employed in the Accommodation and Food Services sector and who belong to the bottom quartile of the earnings distribution (and thus are very likely to be hourly workers) and for workers in the Finance industry, who belong to the top quartile of the earnings distribution (and thus are likely to be salaried workers whose hours might not be tracked by employers explicitly).

[47] Assuming 13 weeks per quarter and five-day workweeks, 520 work hours per quarter equals 40 work hours per week. However, because the number of workdays per quarter varies, a 40-hour workweek may sometimes translate into quarterly hours slightly greater or less than 520. Other spikes may result from many employers' practice of using two-week pay periods, which result in either 12 paid weeks in a quarter (and 6 paychecks) or 14 paid weeks in a quarter (and 7 paychecks). The result is that workers with 40 paid hours every two weeks will be reported as having either 480 or 560 hours in a quarter.

[48] The crosswalk from the NAICS-based sectors to a CICS-based equivalent in the CPS is outlined in the table accompanying this appendix, see Table C4.

The bunching of "weekly" hours at 40, 37, or 43 thus appears to be a strong predictor for whether the employer tracks the hours of its employee which in turn is highly correlated with the probability to observe salaried employees. To illustrate this point more formally, we estimate the following regression using the adminsitrative data

$$salaried_{cq} = \alpha_c + \lambda_q + \beta \overline{bunching}_{cq} + \bar{X}'_{cq}\gamma + r_{cq} \tag{25}$$

where $salaried_{cq}$ is the share salaried workers in sector c and earnings quartile q (based on the information from the CPS described above); α_c are sector fixed effects; λ_q are earnings-quartile fixed effects; $\bar{X}_{cq}$ represents a fourth-order polynomial of within-job moments based on the variance-covariance matrix of earnings and hours observed within a job; $\overline{bunching}_{qc}$ denotes the share of workers in a given cell whose job reported either 480, 520 or 560 hours for at least 75% of the quarters in which we observe the job.[49]

Estimating equation (25) using only $\overline{bunching}_{qc}$ as a predictor returns an R^2 of 0.40, suggesting that bunching of hours is an important predictor of the observed share of salaried workers; see Table C.1. Augmenting the regression with sector and earnings-quartile fixed effects returns an adjusted R^2 of 0.91. Adding a fourth-order polynomial of moments based on the variance-covariance matrix of earnings and hours observed within a job increases the adjusted R^2 modestly from 0.91 to 0.93.

Figure C7 shows a bar chart of average residuals by each sector and each earnings quartile. The residuals are obtained from fitting equation (25) controlling for $\overline{bunching}_{qc}$ and the sector and earnings-quartile fixed effects (corresponding to the model in column 2 in the Appendix C.1 table). The model performs overall well, with generally small absolute deviations of the residuals from zero. However, the model tends to over-predict the share of salaried workers among lower-level managers and under-predict the share of salaried among high-earning waste and remedial service workers (see the positive residual for quartiles 1 and 2 in Management of Companies and Enterprises and the negative residuals in quartiles 3 and 4 in Administrative Services and Waste

[49]To calculate this number, we work with a worker-quarter panel where we only retain full-employment quarters and drop jobs that are observed for 5 or less quarters (approximately 10% of the original full sample).

Management).

C.1 Sensitivity of Baseline Results to Presence of Salaried Workers

Estimates from regression (25) can be used to construct a *job-level* score for the administrative data that captures the likelihood that a given job is on a salaried basis (and thus significantly less likely that the employer tracks hours of work). Specifically, we compute

$$\widehat{salaried}_{ij} = \hat{\alpha}_{c(i,j)} + \hat{\lambda}_{q(i,j)} + \hat{\beta} bunching_{ij} + X_{ij}^{'}\hat{\gamma} \tag{26}$$

where $\{\hat{\alpha}, \hat{\lambda}, \hat{\beta}, \hat{\gamma}\}$ are the OLS estimates from (25) and $c(\cdot,\cdot)$ and $q(\cdot,\cdot)$ identify the sector and the earnings-quartile for a given job (i, j), where i denotes the worker and j denotes the firm. We then re-estimate the AKM specification (3) by dropping jobs whose associated $\widehat{salaried}_{ij}$ is in the 70th percentile of the corresponding worker-year distribution.[50] The 70th percentile is chosen to match the fact that in the CPS approximately 70% of workers are hourly workers. Table C2 presents summary statistics on the sample that excludes jobs presumed to be on a salaried basis. As expected, the average log wage is approximately 16 log points smaller in this sample compared to what we observe in the WA data shown in Table 1. This makes sense as salaried jobs tend to be high-paying and concentrated in high-paying sectors, such as finance. Interestingly, however, the observed mean and variance of log hours is very similar to what we report in Table 1. The same conclusions are obtained when focusing on a comparison between leave-one-out connected samples.

Table A3 provides the variance decomposition of hours, wages and salaried within the sample that excludes salaried jobs. Reassuringly, we find numbers that are very similar to what displayed in Table 2. For instance, firm effects explain 29% of the overall variation in hours (it was 27% in the full sample) while person effects continue to explain a small fraction ($\approx$ 6% while it is 7% in the full sample) of the overall variability of hours and there is a small degree of assortativeness

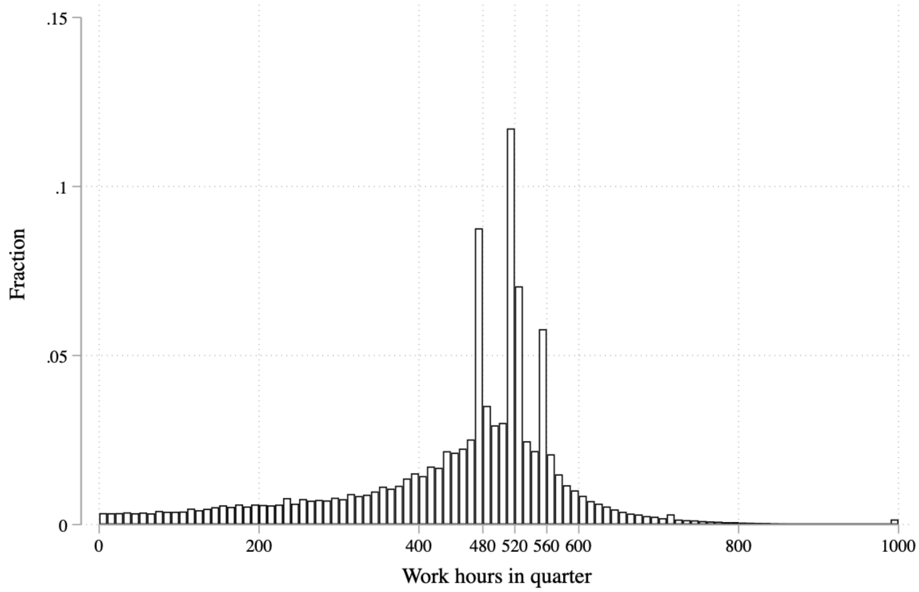
[50] We further retain in the sample jobs observed for fewer than 5 quarters ($\approx$ 10% of the original person-year observations) for which the bunching indicator was not constructed. We retain these jobs to minimize the trimming imposed by the leave-one-out procedure.

between the worker and firm component in hours (implied correlation is 0.02 while it is 0.05 in the full sample).

The analysis of covariance of firm and worker components in hours with the same components estimated on hours and wages also display very similar results compared to what we obtain in the full sample, as shown in Table C3. The correlation in the firm component in hours with the firm component in wages is 0.27 while it is 0.32 in the full sample that retains also salaried jobs. The other key conclusions drawn in Section 4.2 are also maintained when excluding salaried jobs: there is a negative correlation in the person effect for hours and the person effect for wages while there is a positive correlation between the person effect in wages and firm effect in hours.

Based on this evidence, we conclude that the presence of jobs that are likely to be on a salaried basis does not affect our results and that concerns due to the fact our data might capture only paid hours as opposed to actual hours worked for a subset of workers for whom employers do not directly track hours is likely to have second-order effects for our key conclusions.

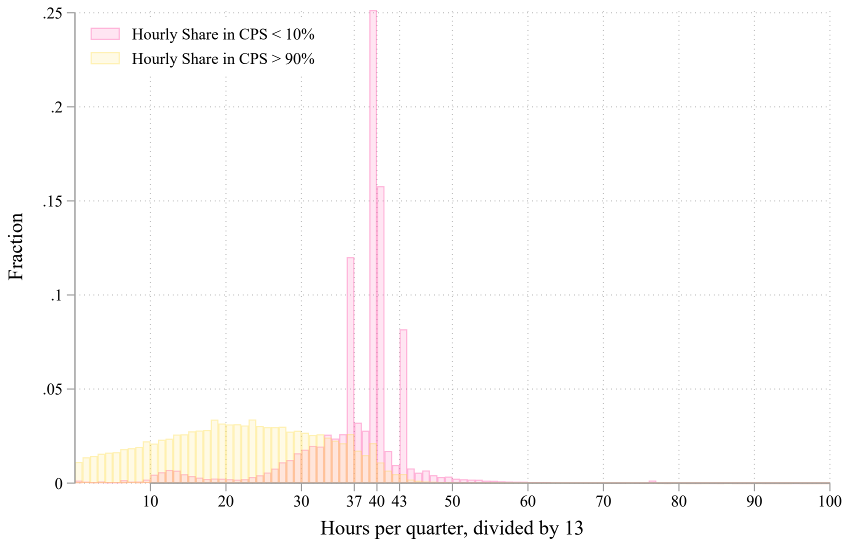
Figure C5: Distribution of quarterly work hours in full quarters and primary employment, Washington administrative records



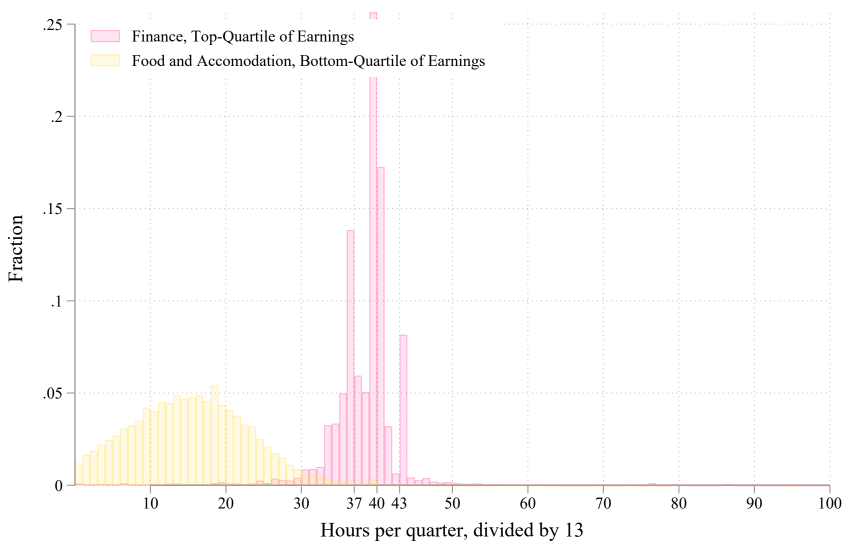
Note: The sample is restricted to worker-quarter observations representing full quarters and primary employment. Values with more than 1,000 hours per quarter are not displayed.

Figure C6: Distribution of hours worked in Washington administrative records by implied share of hourly workers according to the CPS

(a) By Corresponding Share of Hourly



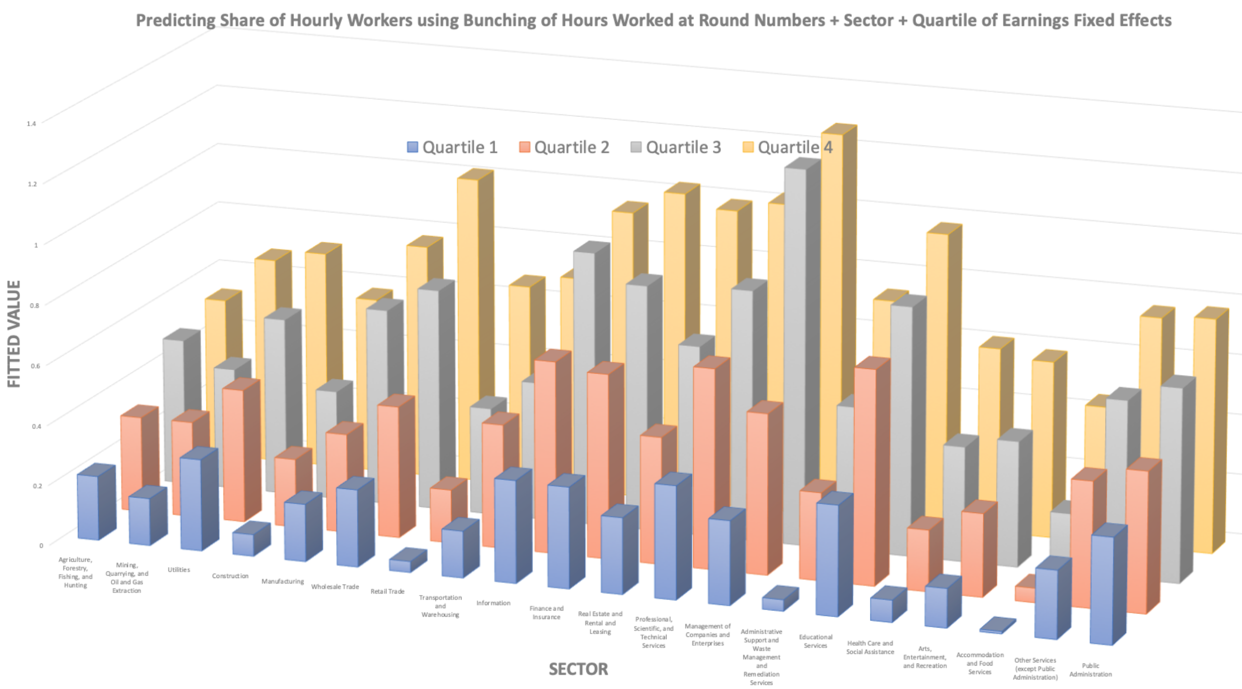
(b) By Sector



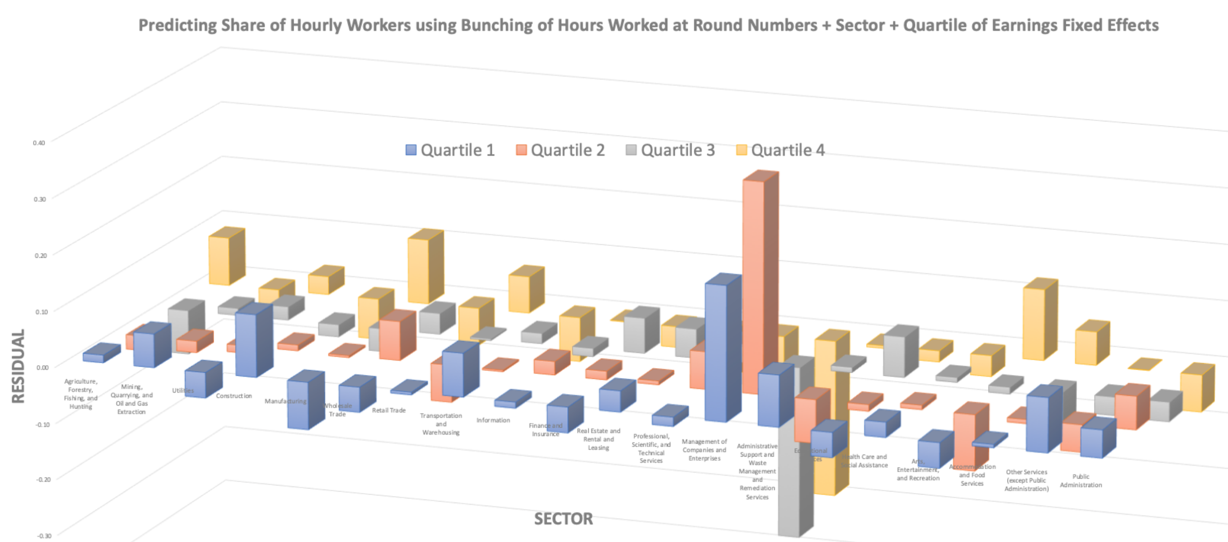
Note: We calculate the sector-by-earnings quartile share of hourly workers in the CPS and merge the shares to the Washington administrative records. We then calculate the histogram of weekly work hours worked (quarterly hours divided by 13) by whether the share of hourly workers is above 90% or below 10% (panel a). Panel (b) is shows the histogram for observations in the accommodation and food sector and bottom earnings quartile and for observations in the finance sector and top earnings quartile. Values of hours above 100 are not displayed.

Figure C7: Distribution of hours worked in Washington administrative records by implied share of hourly workers according to the CPS

(a) Fitted Values



(b) Residuals



Note: This figure displays the fitted values and residuals obtained from equation (25) across 20 industries and 4 sector-specific quartiles of earnings.

Table C1: Predicting Hourly Shares Calculated from the CPS

Outcome: Share of Hourly Workers from the CPS			
	[1]	[2]	[3]
Fraction of Jobs whose Hours Bunch at round Numbers	1.911	0.6917	0.9941
	(0.2550)	(0.2135)	(0.3141)
Adj R2	0.3992	0.9110	0.9326
Quartile FE	No	Yes	Yes
Industry FE	No	Yes	Yes
Additional Controls	No	No	Yes
Number of Observations	84	84	84

Note: Using the CPS in the years 2002-2014, we calculate the share of hourly workers in a 2-digits NAICS code and industry-specific quartile of earnings. Within each cell, we then calculate the fraction of jobs whose corresponding quarterly hours of work bunch at round numbers (480, 520, or 560) for at least 75% of the quarters in which we observe such job. This fraction is calculated only among jobs that have at least 6 full-employment quarters, see Section 3 for a definition of full-employment quarters. We then project the CPS-based share of hourly workers on the fraction of jobs bunching at round numbers. In Column 3, we add to the regression averages of the within-job variance of hours, earnings, and covariance between hours and earnings (and take a fourth-order polynomial for each of these three measures). All regressions are weighted by the number of worker-quarter observations observed in a given cell.

Table C.2: Summary Statistics after Excluding Salaried Jobs

	Initial Sample	*Largest Connected Set*	*Leave-Out Connected Set*
Number of Person-Year Obs	20,023,715	19,815,521	18,409,421
Number of Workers	3,939,139	3,868,559	2,958,658
Number of Firms	283,696	230,357	151,387
Summary Statistics on Outcomes			
Mean Log Hourly Wage	2.86	2.86	2.87
Variance of Log Hourly Wages	0.32	0.32	0.31
Mean Log Hours	7.45	7.45	7.47
Variance of Log Hours	0.13	0.13	0.12
Mean Log Earnings	10.31	10.31	10.33
Variance of Log Earnings	0.50	0.50	0.48

Note: This table provides summary statistics on the Washington state administrative data (WA data), after excluding from the sample jobs that are flagged as having a high-chance of being on a salaried basis, see Appendix C for details. Column 1 displays statistics on the universe of worker-firm matches described in Section 2. Column 2 focuses on the largest connected set of firms linked by patterns of worker mobility so that both worker and firm effects are identified (up to a normalizing constant). The leave-out connected set represents the largest connected set of firms where each firm remains connected to the main network after removing a worker from the graph, see Kline, Saggio and Sølvsten (2020) for details.

Table C3: Correlation Matrix in Firm/Person Effects, Excluding Salaried Jobs

	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	1.0000	0.3829	-0.3615	0.3186
Firm Effect		1.0000	-0.1081	0.2745
Log Hours				
Person Effect			1.0000	0.0182
Firm Effect				1.0000

Note: This table reports the correlation matrix between the worker and firm component obtained after fitting an AKM equation on log hours and log hourly wage using the WA data over the perioods 2002-2014 after excluding salaried jobs using the procedure detailed in Appendix C. The model controls for year fixed effects. All correlations are computed using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Leave-out correction based on a "leave-match-out" approach, see text for details.

Table C4: Crosswalk from IND1990 (the 3-digit harmonized industry code used in the IPUMS CPS, based on Census Industry Classification System codes) and the 2-digit NAICS code (used in the Washington administration data)

3-digit Census industry code	2-digit NAICS code	Label
010, 011, 031, 032	11	Agriculture, Forestry, Fishing and Hunting
040, 041, 042, 050	21	Mining, Quarrying, and Oil and Gas Extraction
450-470, 472	22	Utilities
060	23	Construction
100-162, 172-392	31	Manufacturing
500-571	42	Wholesale Trade
580-640, 642-691	44	Retail Trade
400-432	48	Transportation and Warehousing
171, 440-442, 732, 852	51	Information
700-710	52	Finance and Insurance
711, 712, 742	53	Real Estate and Rental and Leasing
012, 721, 730, 741, 841, 882-891, 893	54	Professional, Scientific, and Technical Services
892	55	Management of Companies and Enterprises
020, 471, 722, 731, 740, 760	56	Administrative and Support and Waste Management and Remediation Services
842, 850, 851, 860	61	Educational Services
812-840, 861-871	62	Health Care and Social Assistance
800-810, 872	71	Arts, Entertainment, and Recreation
641, 762, 770	72	Accommodation and Food Services
750-752, 761, 771-791, 873-881	81	Other Services (except Public Administration)
900-960	92	Public Administration

D Estimating the Relationship Between Fringe Benefits and Hours

Consider the long version of equation (7) that includes fringe benefits:

$$v_j = \theta_0 + \theta_h^L \psi_j^h + \theta_w \psi_j^w + s_j' \gamma + \sum_l \kappa_l b_{jl} + \varepsilon_j, \tag{27}$$

where κ_l is the regression coefficients on the quantity of the lth fringe benefit offered by firm j, b_{jl}. The ratio of the coefficient on log hours and log wages can be written as:

$$\frac{\theta_h^L}{\theta_w} = \frac{\theta_h}{\theta_w} - \zeta, \tag{28}$$

where θ_h is the population parameter on ψ_j^h in the short regression version in equation (7) that does not include fringe benefits. The ζ term is the bias in the population parameter θ_h, rescaled by θ_w, when estimating this short regression. This bias term can be expressed as:

$$\zeta = \sum_l \frac{\kappa_l}{\theta_w} \beta_{\psi^h, b_l | \psi^w} \tag{29}$$

where $\beta_{\psi^h, b_l | \psi^w}$ is the coefficient of the regression of ψ_j^h on b_{jl} controlling for ψ_j^w. Since ψ_j^w is in log units, ζ represents the marginal value to the worker in log dollar scale due to the incremental provision of fringe benefits stemming from a marginal increase in log hours. If we assume that workers value benefits equal to what they cost the firm to provide, then $\zeta = \frac{dlog(C)}{dlog(h)}$ where C is the cost of benefit provision for firms. Thus, it is necessary to estimate the elasticity of fringe benefit expenditures with respect to work hours.

We use two methods to calculate ζ, and both give virtually the same adjustment factor. In the first approach we linearly interpolate the value of an average full-time benefit package such that it has no value at 0 hours of work and full value at or above 40 hours. For benefits we consider all non-mandated benefits, namely insurance, retirement and savings plans, supplemental pay, and paid leave. The value of full-time benefits is assumed to be 22.4% of the total compensation of the worker, corresponding to the share of these non-mandated benefits to total employer cost per worker (the breakdown is: insurance 8%, retirement 3.9%, paid leave 7.3%, supplemental pay 3.2%). These shares are taken from the BLS Employer Costs for Employee Compensation Survey, in 2007 which is roughly in the middle of our sample.

The second approach is data-driven. The Current Population Survey (CPS) has information on the dollar value of the employer contribution to health insurance. We then multiply these contributions by 6 so that in our sample the ratio of imputed benefits to total compensation is 22.4%.

Under both methods we assume that workers value fringe benefits at cost so that we can compute the total value of worker compensation by adding annual income to the imputed per-worker cost of fringe benefits. This total compensation measure is denoted C_i. We then estimate model:

$$\log(C_i) = B_1 \log(\text{annual income}_i) + B_2 \log(\text{annual hours}_i) + s_i'\gamma + e_i, \tag{30}$$

where s_i are industry dummies. Because we are controlling for the log of annual income, B_2 reflects the incremental log monetary value of additional fringe benefits to workers due to an increase in log hours, the same as ζ in equation (29). We therefore use B_2 as the empirical analog to ζ to adjust for the contribution of fringe benefits to the CV for hours. In the interpolation method we estimate $\hat{B_2} = 0.106$ and in the data-driven approach $\hat{B_2} = 0.095$. We therefore settle on $\zeta = 0.1$.

We use this adjustment also for the CV calculations described in Section 2.4. Specifically, the compensating variation in (10) adjusts for increases in utility that might arise for changes to fringe benefits by computing

$$CV_{b_w,b_h} = \frac{\bar{v}_{b_w,b_h^*} - \bar{v}_{b_w,b_h}}{\theta_w} - \zeta(\bar{\psi}_{b_w,b_h^*} - \bar{\psi}_{b_w,b_h^*}) \tag{31}$$

where $\bar{\psi}_{b_w,b_h}$ are the average firm-hours effects observed in the cell indexed by b_w and b_h. For analyses where we estimate willingness to pay measures by sector we use the estimated $\hat{B}_2$ from the data-driven approach estimated separately by industry.