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ABSTRACT

Work Hours Mismatch*

Using a revealed preference approach applied to administrative data from Washington we document that workers have limited discretion over hours at a given employer, there is substantial mismatch between workers who prefer long hours and employers that provide short hours, and hour constraints are prevalent. Voluntary job transitions imply that a ratio of the marginal rate of substitution of earnings for hours to the wage rate is on the order of 0.5-0.6 for prime-age workers. The average absolute deviation between observed 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 hour constraints are an equilibrium feature of the labor market because long-hour jobs are costly to employers.

JEL Classification: J22, J23, J31, J40

Keywords: hour constraints, mismatch, sorting, labor supply, willingness to pay, wage premiums, hour policies

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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; elucidated by Rosen, 1974, 1986) 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 direction 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 between earnings and 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, in addition to earnings, 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 preferred and actual hours, as well as

[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 (Lewis, 1969) and has circulated in English only as an unpublished manuscript (Lewis, 1967). Rosen (1974, 1986) later expanded and generalized Lewis (1967, 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.

to evaluate existing models of work-hour determination.

Our analysis builds on a two-way fixed effects specification of work hours—an additively separable model in employer and worker effects on hours—that arises in a Lewis-Rosen model where workers and firms have heterogeneous preferences over work hours and bargain over a predetermined level of employer-specific surplus. In this framework, employer effects reflect employers' policies on hours, and worker effects reflect workers' preferences for hours. Because the data point to the existence of job ladders, we extend the model to allow for firm-specific wage markdowns due to imperfect competition.

A Kline, Saggio and Sølvsten (2020) (KSS) bias-corrected variance decomposition shows that heterogeneity among employers' hour policies accounts for roughly 56% of the variation in employer effects on earnings. We find that employer and worker effects on hours are only weakly positively correlated, implying an absence of sorting on workers' preferences and employers' requirements for hours that is inconsistent with the Lewis-Rosen model and is difficult to explain with benchmark frictional models (Dickens and Lundberg, 1985 and Chetty et al., 2011). Workers with less educational attainment are more likely to prefer long hours but to work for short-hour employers. Extending the KSS method to derive an unbiased estimator of the covariance of worker and employer effects across both hours and wages, we further find that employer-wage and employer-hours are positively correlated and high-wage workers tend to work for employers with long-hour requirements, even though those workers do not have strong preferences for long hours.

The heart of the analysis is to quantify and estimate the direction of hour constraints using a revealed preference PageRank measure of utility obtained from working for an employer (Page et al., 1999 and Sorkin, 2018). Employer effects on hours and utility remain strongly positively correlated 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 would willingly work more hours at their current wage rate and that most workers' hours are constrained from above. This result also holds when controlling for key employer-provided amenities, such as job stability, or when including interactions between firms' wage and hour policies. 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 (implying optimality) for 56-60 year-olds. These main empirical findings—constraints on work hours and imperfect sorting of workers and employers based on workers' preferences for hours and employers' requirements—imply what we refer to as work hours mismatch.

Based on the evidence, we devise an approach to estimating welfare loss due to hour constraints from both above and below. For each employer wage policy, we identify the work hours that would produce 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 hours mismatch is common and 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 the average worker as well off as at their optimal hours. Workers at low-wage employers and in the Retail and Food and Accommodation sectors are most constrained.

These empirical findings can be explained by a Lewis-Rosen compensating differentials model with imperfect competition that induces a job ladder; that is, 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. However, imperfect competition results in variation in firm desirability for a given worker, consistent with the evidence, and can account for the observed positive relationship between wages and hours across employers. In this way, imperfect competition reconciles the existence of constraints on workers' hours and the positive correlation between employer effects on hours and wages. It also helps explain the lack of sorting of long-hour workers to long-hour employers. It can be beneficial for a worker to move up the job ladder even when the available hours are sub-optimal.

Our work complements an 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, consistent with our findings that workers move up a wage-hours job ladder.[2] More recently, Chetty et al. (2011) examined the role of search costs that may limit worker mobility after tax changes, and Labanca and Pozzoli (2022*a*) 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 hours variability 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 employer-provided amenities 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. For example, in a survey experiment of Walmart workers, Dube, Naidu and Reich (2022) find that additional weekly hours are the most valued 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), Faberman et al. (2020), Schneider (2021) and D'Angelis (2022). Our estimates are consistent with this earlier evidence suggesting underemployment, particularly in low-wage jobs.

[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*); Beckmannshagen and Schröder (2022); Labanca and Pozzoli (2022*b*).

2 Theoretical Framework

Section 2.1 lays out a model of equilibrium hour constraints based on Lewis (1969), who first noted that workers may be forced off their labor supply curves whenever average hours per worker enter the firm's production function as an argument distinct from aggregate hours. These constraints arise even in a competitive model. To account for variation in hours within firms, we outline a variant of Lewis's model in which workers and firms bargain over hours and wages. Section 2.2 introduces imperfect competition and gives conditions for the existence and direction of hour constraints for a parameterized version of the model that draws on Carry (2022). We also show that this parametrization leads to a reduced form expression for log hours that is additively separable in worker and firm heterogeneity.

2.1 The Lewis-Rosen Model

In the Lewis-Rosen model (Lewis (1969), Rosen (1974)) workers, indexed by $i = 1, \ldots N$, have preferences over hours (h) and earnings (e) given by $u_i(e,h)$, where $u_i(\cdot,\cdot)$ is increasing in earnings (= hourly wage $\times$ work hours) and decreasing in hours. If workers can freely choose hours, then utility maximization implies that the marginal rate of substitution (MRS) between hours and earnings will equal the observed wage, w: $\text{MRS}_{e,h}(e,h) = -\frac{\partial u_i(e,h)}{\partial h} / \frac{\partial u_i(e,h)}{\partial e} = w$. Employers, indexed by $j = 1, \ldots J$, have heterogeneous technologies captured by a revenue function $R_j(h)$, which in turn yields a profit function $\Pi_j(w,h) = R_j(h) - wh$ representing the firm's surplus from employing a worker with hours h hours at the hourly wage w. If the firm's revenue function $R_j(h)$ is linear in hours, the firm's zero-profit isoprofit curve will be horizontal in wage-hour space because equilibrium wages do not depend on average hours per worker.

Once matched, the employer and the worker determine wages and hours via bargaining, similar to Carry (2022) and Del Rey, Naval and Silva (2022). We introduce bargaining to allow for the possibility that the distribution of technologies in hours utilization is coarse. As a result, workers with different preferences for leisure may work different hours for the same employer (as we see in the data). Bargaining occurs over a level of firm surplus that is predetermined by market conditions as in Farber (1986). With free entry of firms, bargained wages and hours satisfy utility maximization subject to a zero firm-surplus condition:[3]

$$(w_{ij}^b, h_{ij}^b) = \underset{w,h}{\operatorname{argmax}}\, u_i(e,h) \text{ s.t. } \Pi_j(w,h) = 0 \tag{1}$$

For a given job match, the tradeoff between wages and hours represents a compensating differential.

The properties of the revenue function determine whether there are equilibrium hour constraints. Recall that, for a given wage w, a worker's hours are optimal if the corresponding MRS equals the wage. When a worker bargains with an employer, the MRS is set equal to the marginal productivity of hours, $\frac{\partial R_j(h)}{\partial h}$, while the wage is set equal to the *average* hourly productivity, $\frac{R_j(h)}{h}$, given the zero firm surplus constraint.[4] As a result, unless $R_j(h)$ is linear in hours, the marginal productivity of hours generally does not equal the wage, leading to an equilibrium hour constraint for the worker. This point was also made by Kahn and Lang (2001).

Figure 1(a) illustrates equilibrium hour constraints. The worker's indifference curve is drawn in wage-hour space and is U-shaped because workers require a relatively high wage rate to work short or long hours. The firm's revenue function implies inverted U-shaped isoprofit curves in wage-hour space. Bargained hours and wages are given by the tangency (w_{ij}^b, h_{ij}^b) between the worker's indifference curve and firm's zero-surplus isoprofit curve. If workers could freely choose hours at the bargained wage, they would work $h_{ij}^{opt}(w_{ij}^b) > h_{ij}^b$. The figure thus shows a situation where worker's hours are constrained from above. When employed by firm j, individual i is off her supply curve and would accept less than the current wage to work an additional hour.[5]

If workers choose firms to maximize utility, the market equilibrium locus for wages and hours will be determined by the envelope of firms' isoprofit curves satisfying the zero-surplus condition

[3]Note that the hours' allocation based on equation (1) coincides with the hours' allocation that would emerge in the dynamic search and matching model of Carry (2022) as well as in the static bargaining model considered by Del Rey, Naval and Silva (2022). Both papers consider a standard Nash-bargaining problem where hours (and wages) are chosen to maximize the joint surplus of a match.

[4]See equation (19) in the Appendix.

[5]The framework also allows for hour constraints from below.

(Figure 1(b)—see also Kinoshita (1987). More productive firms may offer higher wages but for the market to be in a competitive equilibrium, those firms must offer unattractive hours to anyone they do not already employ. As is standard in compensating differential models, in equilibrium workers with preferences for long hours will sort to employers requiring long hours (and conversely)—sorting on hours will be perfect. Nevertheless, even with perfect sorting and no frictions, workers' hours may be constrained in equilibrium.

2.2 Imperfect Competition: Lewis-Rosen Extended

In a competitive equilibrium, no worker wishes to change firms; however, there is considerable evidence of job ladders; that is, a hierarchical ranking of firms based on the utility they offer workers (Moscarini and Postel-Vinay, 2018). To generate a job ladder, we extend the model described above to a setting of imperfect competition, which allows firms to have a positive surplus and hence to mark down wages.[6] Specifically, bargained wages and hours maximize worker utility subject to a firm-specific level of surplus, $k_j > 0$:

$$(w_{ij}^b, h_{ij}^b) = \underset{w,h}{\operatorname{argmax}}\, u_i(e,h) \text{ s.t. } \Pi_j(w,h) = k_j \tag{2}$$

To parameterize the model, we specify firms' technology as in Carry (2022). Firms have heterogeneous production technologies, T_j, and require tasks in which workers are productive up to a maximum number of hours per week z_j. (For hours greater than z_j, marginal product is zero.) The result is a firm-specific revenue function $R_j(h)$ given by:

$$R_j(h) = \begin{cases} h^{\alpha} T_j & \text{if } h \leq z_j \\ z_j^{\alpha} T_j & \text{if } h > z_j, \end{cases} \tag{3}$$

where α determines the return to an additional hour of work.

Worker utility is $u_i(w,h) = wh - \varepsilon_i h^{\mu}$, where ε_i captures preferences for leisure and μ measures disutility from working. It is reasonable to assume that the disutility from work hours is convex,

[6] Specifically, we relax the earlier assumption of zero firm surplus. Firms can now make positive surplus due to barriers to firm entry, search frictions, and costly mobility among other things.

i.e., $\mu > 1$. Solving the Lewis-Rosen objective function specified in equation (2) leads to the $MRS = \frac{\partial R_j(h)}{\partial h}$ condition, which implies that bargained hours between worker i and firm j can be written[7]

$$\log h_{ij}^b = \begin{cases} -\dfrac{\log\mu - \log(\alpha)}{\mu - \alpha} - \dfrac{\log\varepsilon_i}{\mu - \alpha} + \dfrac{\log T_j}{\mu - \alpha} & \text{if } h_{ij}^b \leq z_j \\ \log z_j \quad \text{otherwise,} \end{cases} \tag{4}$$

where $\dfrac{\log\varepsilon_i}{\mu - \alpha}$ denotes the number of hours an individual works irrespective of the employer; that is, the portable component of hours. $\dfrac{\log T_j}{\mu - \alpha}$ denotes the firm-level hours component, which depends on the firm's technology T_j.[8] In this model, individual preferences for hours are realized only when equation (2) has an interior solution, $h_{ij}^b < z_j$. For jobs where bargained hours equal the maximum productive level z_j, variation in hours will reflect only firms' heterogeneous technologies z_j.[9]

When a firm has a positive surplus, wages are set to average per-hour revenue $R_j(h)/h$ marked down by the profit margin p_j: $w_{ij}^b = \frac{R_j(h)}{h}[1 - p_j]$, where $p_j \equiv k_j/R_j(h)$. (We assume the profit margin scales linearly with hours.) For a given match, wages then satisfy:

$$\log w_{ij}^b = \begin{cases} \frac{(1-\alpha)(\log\mu - \log\alpha)}{\mu-\alpha} + \frac{1-\alpha}{\mu-\alpha}\log\varepsilon_i + \frac{\mu-1}{\mu-\alpha}\log T_j + \log(1-p_j) & \text{if } h_{ij}^b \leq z_j \\ \log T_j + (\alpha - 1)\log z_j + \log(1-p_j) \quad \text{otherwise,} \end{cases} \tag{5}$$

The extended Lewis-Rosen model just outlined gives rise to a job ladder, hour constraints, and imperfect sorting.

Job Ladder In the extended model, it is possible for one firm's hour-wage package to be strictly dominated by other firms' packages. The result is a job ladder, as illustrated in Figure 1(c). The dominated package offered by firm j exists in equilibrium because worker mobility is impeded

[7] See Appendix B for details on this and other derivations presented in this Section.

[8] A necessary condition for an interior solution is $\mu > \alpha$. This condition holds if the disutility in hours is convex, as we assume, and there are diminishing returns in hours to the firm. If there are increasing returns ($\alpha > 1$), then an interior solution requires that disutility from hours is sufficiently convex.

[9] If $u_i(w,h) = wh - \varepsilon_i h^\mu$, then it is possible to show that a log-additive expression for hours also emerges in the model of Carry (2022) and Del Rey, Naval and Silva (2022).

by queuing or other frictions. Figure 1(d) depicts a situation where two employers offer the same wage but different hours to worker i. As detailed in the next section, observing two firms offering the same wage but different hours allows us to calculate welfare losses due to hour constraints.

Sorting The job ladder that arises in the extended model leads to imperfect sorting on hours—such that workers with preferences for short hours are employed by firms with long hour requirements (and conversely). For example, wage markdown variations can lead workers with short hour preferences to accept jobs with long hour requirements because a high wage (due to a low markdown) more than compensates. Imperfect sorting can also occur if workers sort to employers via random search, as in Carry (2022), or more broadly when worker's utility depends on idiosyncratic job-match factors unrelated to wages or hours (Sorkin, 2018; Lamadon, Mogstad and Setzler, 2019).

Hour Constraints Equations (4) and (5) permit us to give a precise condition to characterize the existence and direction of hour constraints. When there is an interior solution ($h_{ij}^b < z_j$), the direction of hour constraints depends on the size of the markdown p_j relative to the returns of an extra hour of work α—see equation (27) in the Appendix. Recall that to be at their optimal hours, the MRS must be equal to the wage. However, when bargaining with the employer, the MRS does not equal the wage but rather the marginal increase in productivity given by an extra hour, $\frac{\partial R_j(h)}{\partial h}$. Therefore, hour constraints arise whenever the bargained hourly wage—which equals the *average* hourly productivity times a markdown—is different from the *marginal* product of labor. If the marginal increase in productivity due to an extra hour is below the bargained wage—i.e., when $\alpha < 1 - p_j$—then the firm finds it optimal to constrain hours. In the competitive case with no markdowns ($p_j = 0$), this condition implies that there are diminishing returns to average hours. Hours can be constrained from below—i.e., workers would like fewer hours—when the firm has increasing returns to scale in average hours. This case would arise if there are fixed costs of work.

Imperfect sorting on hours together with equilibrium hour constraints imply a work-hour *mismatch*.

3 Estimation Framework

If realized log hours in a given year t are given by the bargained hours in equation (4) plus an idiosyncratic match-specific shifter, we obtain:

$$\log h_{ijt} = \log h^{b}_{ij} + \rho_{ijt} \tag{6}$$

where ρ_{ijt} is a mean zero error that captures within-job hours volatility relative to the reference level of hours bargained by the worker and the firm at the time of job creation ($\log h^{b}_{ij}$). Equation (6) can be parametrized as a two-way fixed-effects regression model (Abowd, Kramarz and Margolis, 1999, AKM)—using the logarithm of hours as the outcome variable:

$$\log h_{it} = \alpha^{h}_{i} + \psi^{h}_{j(i,t)} + x'_{t}\gamma^{h} + r^{h}_{it} \tag{7}$$

where α^{h}_{i} and $\psi^{h}_{j(i,t)}$ are time-invariant worker and firm effects on hours with $j(i,t)$ denoting the identity of worker i's employer in year t, and $x'_{t}\gamma^{h}$ are year effects capturing hours variation common to all jobs in a given year, and r^{h}_{it} is a regression error term reflecting idiosyncratic within-job shocks to hours as well as drift in hours not captured by x_t.

3.1 Quantifying Hour Constraints

To test for constraints, we estimate the ratio of the MRS between hours and earnings to the wage. Because in competitive equilibrium, $w = MRS$, this ratio will equal 1 if workers are unconstrained and optimize. 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.

To implement this test we use a revealed preference ranking of employers derived from the PageRank algorithm (Page et al., 1999) and developed for analyzing labor market flows by Sorkin (2018). Specifically, Sorkin (2018) assumes the utility of being employed by firm j can be written $U_{ij} = v_j + e_{ij}$, where e_{ij} is distributed according to a type-1 extreme value distribution. Then, the systematic component of utility v_j can be identified from the following recursive equation:

$$\exp(v_j) = \sum_{\ell \in \mathscr{B}_j} \omega_{j,\ell} \exp(v_\ell) \qquad j = 1, \ldots, J. \tag{8}$$

where $\omega_{j,\ell}$ is the number of workers who voluntarily move from employer ℓ to employer j, scaled by the number of workers who voluntarily left employer j for another employer, and $\mathscr{B}_j$ is the set of employers who received a worker from employer j following a voluntary separation (defined as an employer-to-employer transition).

Equation (8) provides a measure or index of the desirability of an employer j based on the employer-to-employer (voluntary) transitions. The premise of this index is that a high-utility employer is one that recruits from other high-utility employers and that few workers leave voluntarily. The PageRank measure supposes frictions—workers may not be at their optimal job, so they make systematic, voluntary moves to employers with higher rank when an offer from such an employer materializes.[10] 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. If the ratio of the MRS to the wage is far from 1, the worker is constrained on hours and would be willing to pay for more or fewer hours.[11]

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

$$v_j = \theta_0 + \theta_h \psi_j^h + \theta_w \psi_j^w + s_j' \gamma + \varepsilon_j \tag{9}$$

where v_j is the PageRank of firm j, ψ_j^h and ψ_j^w represent the hour and wage policies of employer j, and the vector s_j captures sector fixed effects.[12]

To interpret the estimates, note that for any well-behaved utility function we can write $\frac{\text{MRS}_{e,h}(e^0,h^0)}{w} = -\frac{\partial U(e^0,h^0)/(\partial h/h^0)}{\partial U(e^0,h^0)/(\partial e/e^0)} = -\frac{\partial U(e^0,h^0)/\partial \log h^0}{\partial U(e^0,h^0)/\partial \log e^0}$, where e^0 and h^0 are the initial values of earnings and hours,

[10] 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 C.3 for details.

[11] 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.

[12] This approach is similar to (Manning, 2013, Chapter 8), who obtains the marginal willingness to pay for hours by estimating a model that relates voluntary separations to 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 $\frac{MRS_{e,h}(e^*,h^*)}{w} = 1$. Because ψ_j^h and ψ_j^w are estimated from a model in logs, they map into this expression. 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:[13]

$$\frac{MRS_{e,h}}{w} = -\frac{\theta_h - \theta_w}{\theta_w}. \tag{10}$$

Estimating *MRS/w* We estimate $MRS_{e,h}/w$ using a split-sample IV 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 (9), the employer effects in the estimation sample are instrumented by employer effects from the hold-out sample—see Appendix C.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 contribute to utility independent of hours worked. Therefore, the omission of fringe benefits from equation (9) could overstate the direct contribution of log hours to utility by the marginal valuation of additional fringe benefits. As discussed in Appendix E, we use external data 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 (9). In practice, we find that adjusting our estimates for these omitted factors does not fundamentally change our conclusions on the role of hour constraints.

[13]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 $\frac{MRS}{w} = -\frac{\beta_h}{\beta_e} = -\frac{(\theta_h - \theta_w)}{\theta_w}$.

3.2 Compensating Variation for Hour Constraints

The estimate of $MRS_{e,h}/w$ based on equation (9) is only informative about the consequences of marginally relaxing hour constraints. Equation (9) measures the *average* constraint facing an employer's workers. If workers differ in whether they are above or below their optimal hours, then equation (9) will understate the effect on utility of easing constraints. To address this limitation, we develop an approach to quantifying 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

$$\bar{v}_{b_w,b_h} = \frac{1}{N_{b_w,b_h}} \sum_{i,t} \mathbf{1}\{\psi^w_{j(i,t)} \in b_w, \psi^h_{j(i,t)} \in b_h\} v_{j(i,t)} \tag{11}$$

where $N_{b_w,b_h} \equiv \sum_{i,t} \mathbf{1}\{\psi^w_{j(i,t)} \in b_w, \psi^h_{j(i,t)} \in b_h\}$.[14] 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.[15] 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

$$CV_{b_w,b_h} = \frac{\bar{v}_{b_w,b_h^*} - \bar{v}_{b_w,b_h}}{\theta_w} \tag{12}$$

where θ_w is defined in equation (9). The average compensating variation across hour policies is then

$$\overline{CV} = \sum_{b_h,b_w} \frac{N_{b_w,b_h}}{N} CV_{b_w,b_h} \tag{13}$$

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

[14] 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.

[15] Note that b_h^* does not necessarily represent "globally" optimal hours because even workers working b_h^* might still be facing hour constraints along the lines described in Figure 1(a). However, b_h^* represents the optimal hours among the observed set of hour policies offered by employers with wage policies belonging to bin b_w. See also the graphical representation in Figure 1(d).

employer wage effects required to equalize utilities within each observed wage bin.[16] We also adjust $\overline{CV}$ to account for omitted fringe benefits that may correlate with the hours' changes required to reach the optimum—see Appendix E for details.

Illustration Figure 2 illustrates the quantities we seek to measure by depicting the labor supply relationship. At wage w^* the worker wishes to work h^* hours, but due to a constraint she is working fewer hours $\overline{h}$, where the MRS is between w^* and w^0.[17] It will equal w^0 if there are no income effects. Equation (10) 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 less (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 (12) is chosen to equate Area B to Area A. Area B represents the incremental surplus a worker gains from a higher wage at constrained hours. This measure differs from the MRS in that it measures the benefit of fully closing the gap between constrained and optimal hours, and because it is in terms of a wage rate that applies to all hours worked.

4 Data

In this section, we describe the Washington administrative data and the construction of the analysis data set.

4.1 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

[16] 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 (9) 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.

[17] The figure can also be drawn with hours above optimum.

2014:4.[18] 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.

Washington employers are required to report each worker's quarterly paid work hours because of Washington's practice, 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.[19]

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.[20] To check whether the estimates are sensitive to the inclusion of salaried workers, in Appendix D.1 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.

The available data also include UI claim records, which include demographic information such as date of birth, gender, and level of education. Because demographic information is not included in the wage records, we observe demographics for the subset of workers who claimed UI at some point during 2005–2014, which is about one-third of the sample. We use this demographic subsample in sections 5.1, 6.2, and 6.5.[21]

[18] 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.

[19] 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.

[20] 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.

[21] For a discussion of the representativeness of the demographic sample, see Lachowska, Mas and Woodbury (2022).

4.2 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.[22] 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.[23] As in Lachowska et al. (2023), we impose several restrictions on the estimation sample, dropping workers with (a) more than 9 employers in a year, (b) annual earnings less than $2,850 (in 2005 dollars), (c) calculated hourly wage rates less than $2.00 per hour (in 2005 dollars), and (d) fewer than 400 hours in the calendar year.[24]

Table 1 shows means, variances, and counts for various cuts of the data. Column 1 comes from the "initial" sample subject to the 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 each employer remains connected after dropping any single worker). The means and variances of hourly wages, hours, and earnings (all in logs) are similar in all three samples. 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 3 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 similar to that in survey data.[25] The red bars show the distribution of average weekly

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

[23]We drop the first and last quarters of each spell to 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.

[24]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.

[25]Lachowska, Mas and Woodbury (2022) report that in the CPS, about 37 percent of workers report "actual" work

employer hours, weighted by the number of worker-year observations. Although the dispersion of individual worker hours is greater than that of average employer hours, there are still large systematic differences among employers in hour policies.

5 Sorting and Heterogeneity in Hours among Workers and Firms

The two-way fixed-effect specification for work hours in equation (7) allows us to quantify the relative importance of firm and worker heterogeneity in bargained hours—see Section 5.1. Section 5.2 discusses how these worker and firm component correlate with each other and in particular assesses the extent to which workers with preferences for long hours (low ε_i) sort to firms that demand long hours (high T_j and z_j)—see in particular Section 5.2.1.

5.1 Variance Components

Table 2 displays variance decompositions of hours, wages, and earnings based on equation (7) and the data described in Section 4. All variance components are corrected for limited mobility bias using the Kline, Saggio and Sølvsten (2020) (or KSS) estimator. $\mathrm{Var}(\psi_j^h)$ reflects variability in hour policies across employers and is therefore driven by variability in technologies (T_j) and/or the productive number of hours associated with a given job (z_j). $\mathrm{Var}(\alpha_i^h)$ reflects variability in workers' preferences for hours for jobs. $\mathrm{Corr}(\psi_j^h, \alpha_i^h)$ reflects the degree of worker and employer sorting on hours.[26]

hours of 40 per week, and about 52 percent report "usual" work hours of 40 per week.

[26]Unbiased estimation of variance components based on equation (7) requires "exogenous mobility"—i.e., workers must select employers according to their worker effects and observed firm effects, not based on r_{it}^h. (See Appendix C for a discussion.) Figure A1(a) shows an event study of the kind popularized by Card, Heining and Kline (2013) to assess the plausibility of exogenous mobility in the analysis sample. The evidence suggests that the log-additive specification with fixed worker and employer effects on hours is a reasonable description of hour-determination in these data. Similar conclusions were reached by Card, Heining and Kline (2013) for log daily wages using German data, by Song et al. (2019) for log earnings using US IRS data, and by Lachowska, Mas and Woodbury (2020) for wages and earnings using Washington data. 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 the employers' hour policies), Figure A1(b) plots changes in workers' hours following job moves in the subsample of transitions where the origin and destination employers belong to the same quartile of coworkers' average wages. The resulting worker responses are very similar to the unconditional responses plotted in Figure A1(a), suggesting that changes in workers' hours following a job change reflect mainly different employer hour policies rather than labor supply responses to employer wage policies.

Variation in employer effects explains about 27% of the overall variance of log hours, so employers play a substantial though imperfect role in explaining the variation of work hours.[27] Variation in worker effects explains only 7% of the overall variance of log hours. Accordingly, workers have limited scope for bargaining over hours with an employer;[28] that is, in the framework of Section 2, the cap in the productive number of hours (z_j) is a frequently binding constraint for workers.

Worker Effects as Proxies for Preferences To probe whether worker effects on hours can be interpreted as reflecting workers' preferences, we examine to what extent the observed gender gap in work hours is reflected in a gender gap in worker effects on hours. When we fit AKM equations for log hours separately for men and women as in Gallen, Lesner and Vejlin (2019), we find that the majority of the gender gap in hours ($\approx$ 65%) is explained by differences in average worker effects.[29] Given evidence in Kahn and Lang (1995) suggesting that on average, women work fewer hours than men and are more likely to be satisfied with their hours than men, it seems reasonable to infer that worker effects on hours reflect preferences for hours.

Decomposing Employer Effects on Earnings Because earnings are usually 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.,

[27] 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 A2. Also, the variation in hours explained by employer effects increased to 40% during the Great Recession, suggesting that employer effects capture hour constraints, which are likely to increase during downturns—see Figure A3.

[28] 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 (7) 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).

[29] See Table A3. The gender gap in hours is about 10 log points (whereas the gap in log earnings is about 30 log points). The average gender gap in firm effects on hours is about 3.5 log points, which is explained mainly by women sorting into employers offering shorter hours (Card, Cardoso and Kline, 2015), similar to what was found by Gallen, Lesner and Vejlin (2019) in Denmark.

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.[30,31] In Section 6 we find that longer hours are highly valued by workers on average; therefore, studies relying on earnings variation may still capture variation in worker welfare even if earnings variation results from differences in hour policies.

Within-Job Variability in Hours Table 2 also shows that hours have a large idiosyncratic component. 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).[32] Accordingly, much of the variation in hours appears to be within a job over time. To examine how much of the within-job variation in hours is employer-determined (reflecting scheduling instability) versus worker-determined (reflecting varying outside factors like childcare duties), we estimate an AKM model of within-job variability in hours.[33] The results in Table A6 show that firms, as opposed to workers, are the main source of within-job hours variation,

[30] 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^w and ψ_j^e represent the employer effect on wages and earnings, respectively. We use estimates from Tables 2 and A4. The variation of employer effects on earnings due to variation of employer effects on hours is computed as $\mathrm{Var}(\psi_j^h) + 2\,\mathrm{Cov}(\psi_j^h, \psi_j^w)$.

[31] Another way to assess the importance of firms' hours' policies for overall earnings inequality is by looking at the Oaxaca decomposition of Table A3 and noting that 16% of the raw gender gap in earnings is explained by women sorting into low-hours firms.

[32] We also consider a specification that allows for systematic interactions between the worker and firm effects in log hours which would arise if, for instance, the utility function of the worker was specified as $u_i(e,h) = e - h^{\varepsilon_i}$. We follow Bonhomme, Lamadon and Manresa (2019) and estimate an interacted fixed effects specification on log hours with 20 unobserved firm types and with worker latent types being drawn from a normal distribution with firm-type specific parameters. The resulting variance decomposition (Table A5) is very similar to the one observed in Table 2 with the log additive structure, with most of the variation being explained by firm heterogeneity and little assortative matching between worker and firm heterogeneity. The R^2 from going from a specification with no interaction with one with full interaction between worker unobserved heterogeneity increases very moderately (from 31% to 32%), consistent with what has been found by Bonhomme, Lamadon and Manresa (2019) for earnings in Sweden. This suggests that complementarities play a minor role in the analysis of log hours.

[33] Specifically, we compute the variability of hours within a job defined as $\omega_{ij} = \mathrm{Var}(\log h_{it}|i,j)$. We then fit an AKM model to ω_{ij}, after accounting for year effects, and where the variance components are weighted by the length of a given job spell. Note that, if the log addictive specification in equation (7) is correct, then within-job changes in log hours point-identify changes in the (true) error term r_{it}^h, which captures the variation in hours above/below the bargained level of hours described in Section 2. Therefore, the within-job variability of hours, i.e., $\mathrm{Var}(r_{it}^h|i,j)$ is point-identified by ω_{ij}.

similar to findings by Ganong et al. (2024) and baseline analysis of the variability of hours across jobs (Table 2).

5.2 Correlation of Worker and Firm Effects Within and Across Outcomes

Table 3 displays two resulting correlation matrices of employer and worker effects within and across outcomes. The across-outcomes correlations are computed by extending the KSS methodology to multiple outcomes—see Appendix C.2 for details. Panel (a) shows correlations computed over the sample as a whole and panel (b) correlations within sector.[34]

There is strong assortativeness on the wage dimension between workers and firms: the correlation between worker and employer effects on wages is 0.38: high-wage workers tend to sort to employers who demand skills, consistent with evidence from existing studies. There is also a moderately positive correlation between high-wage employers and long-hour employers. 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 considerable 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 fact that firms that offer similar wages have different hours policies suggests the presence of hours mismatches—a point that we develop further in the next section—and can be rationalized by the imperfect competition model described in Section 2.2 (See also the discussion in Section 7.)

5.2.1 Imperfect Sorting on Hours

A key finding in Table 3 is that sorting on worker and employer preferences for hours is limited. 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 (see Table 2).[35] Figure 4(a) shows

[34]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 of 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.

[35]The low correlation between worker and employer effects on hours is robust to restricting the sample to workers who are likely paid hourly (Table A7), using an indicator for part-time work (less than 35 hours per week) as the

that the small estimated correlation between worker and employer effects on hours is not driven by a nonlinear relationship between these two effects. (The results in the figure use a split-sample technique to account for measurement error. Not accounting for measurement error leads to 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.[36]

Figure 5 further examines the relationship between worker and employer preferences for hours. The figure shows that a disproportionately large number of workers with less education have preferences for long hours but have sorted to a short-hour employer, and conversely. This pattern of sorting also holds when proxying skill by worker effects on wages. Table 3 shows that high-wage workers tend to sort to employers with long hour requirements, as the correlation between worker effects on wages and employer effects on hours is 0.21–0.30.[37] However, higher-wage workers tend to prefer shorter-hour firms, as the correlation between worker effects on wages and hours is somewhat negative (–0.15 to –0.06).[38] The results suggest that workers with less education and lower wages tend to prefer longer hours but sort to short-hour employers. One conjecture is that these workers are likely to be constrained from above in choosing their work hours. The next section addresses this question directly.

outcome (Table A8), using hours level as the outcome (Table A10), and estimating the model at quarterly rather than annual frequency (Table A9).

[36]Figure A3 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.

[37]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).

[38]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.

6 Mismatch

This section tests for the presence of work-hours mismatches and quantifies their welfare costs. We follow the revealed preference approach developed by Sorkin (2018), and outlined in Section 3.1 and Appendix C.3, to compute a hierarchical PageRank index of the desirability or utility of working for each employer.

6.1 Constraints on Hours

As seen in condition (10), if workers obtain their optimal hours at the current wage we 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 sorted on their preferences and requirements for hours, so no employer would be able to systematically poach workers from other employers based solely on their hours policies.

Figure 6 displays the joint distribution of the PageRank index by employer effects on hours and wages. We divide the data into 100 cells based on vingtiles of the employer wage effects and quintiles of employer hour effects. 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 (or lower) quintile of the employer hour effect. In the next section, we further quantify hour constraints by estimating the ratio of the MRS to the wage rate.

6.2 Estimating the Ratio of the MRS to the Wage Rate

To test for hour constraints, we estimate equation (9). 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)).[39]

Under condition (10), 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 (10), 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 E, 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.

Job Security and Hours Variability We also consider how our estimates would change when including a firm-level proxy of job security. The latter represents a key unobserved amenity that might correlate with both the PageRank index as well as the hours policy of a given firm. To quantify a firm-level component in job security that is not contaminated by worker selection, we fit the following AKM specification to quarterly data

$$empl_{i,t+2} = \alpha_i^{empl} + \psi_{j(i,t)}^{empl} + x_t' \beta^{empl} + r_{it}^{empl} \tag{14}$$

where $empl_{i,t+2}$ is a dummy equal to one if the worker is employed in both quarter $t+1$ and $t+2$. In this specification, the firm effect $\psi_{j(i,t)}^{empl}$ captures the quarter t's employer propensity to provide a stable job (i.e., a job that does not end in non-employment in the short run).[40] We then estimate equation (9) adding these firm-level proxies of job security. Results are reported in Column 3 of Table 4. As expected, these firm-level proxies have a large positive effect on the PageRank index, suggesting that employers that provide stable jobs are more desirable. However, the inclusion of this amenity does not appear to significantly change our estimate of our hour constraints: the adjusted estimate of $MRS_{e,h}/w$ is now 0.36, very close to our baseline estimate of 0.31. This suggests that the inclusion of additional firm-level amenities potentially correlated with firm-hour policies does not significantly alter our conclusions on the presence of hour constraints—a point

[39] 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).

[40] This is close to the approach taken by Lachowska et al. (2023) who uses an AKM-specification for a binary outcome to quantify the employer's role in unemployment insurance (UI) take-up.

that we return to in Section 6.3. This conclusion remains valid also when augmenting equation (8) to include the firm-level component in hours variability analyzed in Table A6—see column 4 of Table 4.[41]

The Role of Age and Early Job Transitions 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 re-estimate PageRank utility indexes separately for different age groups. We then re-estimate equation (9) separately for each age group using the resulting age-specific rankings of employers. Figure 7 reports the estimates.[42] 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 A14 also suggest that 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.

6.3 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. To investigate the

[41] The low $MRS_{e,h}/w$ is robust to several alternative specifications, such as excluding salaried workers (Table A11), controlling for year effects (Table A12), and adding interactions between firm-hours and firm-wage effects (Table A13).

[42] A possible concern is that restricting the sample to employers with workers whose age is known may result in selection bias (that is, equation (9) is estimated using a subsample of employers that tend to be large). However, when equation (9) 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 A14.

relationship between work hours and nonpecuniary amenities we use the job attributes and estimated utility weights from the stated choice experiment from the 2015 American Working Conditions Survey, which was developed and analyzed by Maestas et al. (2017). In the experiment, respondents are asked to choose between jobs with different randomized attributes. Utility weights are estimated by fitting a logit to predict the chosen job as a function of 12 amenities.[43] Using the amenity values from respondents' actual jobs, we use the weights to create a composite index of the valuation of a job as a function of nonwage attributes. We regress this measure on log hours and the log wage. The results from this exercise are presented in Table A15. As reported in Maestas et al. (2017), there is a positive relationship between log wages and nonwage amenities.[44]

To expand the analysis beyond the 12 amenities used in the choice experiment, 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. Reinforcing the findings from the composite index, in the vast majority of cases (81 of 97), the estimated relationship between a given characteristic and annual work hours is statistically insignificant.[45]

6.4 Gaps between Optimal and Observed Hours

The estimates of $MRS_{e,h}/w$ in Section 6.2 suggest that, on average, workers would like to work more hours at the current wage. This section uses the methodology in Section 3.2 to quantify the gap between optimal and observed hours.[46] 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

[43]The amenities are: setting own schedule, telecommuting, moderate physical activity, sitting, choosing how to do work, days of paid time off, working on team or self, training opportunities, and frequent opportunities to serve.

[44]Adjusting the $MRS_{e,h}/w$ estimate for the positive correlation between wages and the (dollar-based) valuation of the 12 nonwage amenities of Maestas et al. (2017)—which can be done by applying the arguments developed in Appendix E for the coefficient θ_w as opposed to θ_h—leads to a slightly larger role of hour constraints as our preferred estimate of the $MRS_{e,h}/w$ goes from 0.31 to 0.28.

[45]Table A16 shows all of the point estimates and their standard errors. For the 16 of 97 attributes that are statistically significant,shown in Figure A5, long-hour jobs are associated with a mix of desirable and undesirable attributes. For example, workers with long hours are more likely to report being able to apply their own ideas, but also more stress at work.

[46]See footnote 15 for a discussion of local vs global optima.

displayed in equation (11).[47] 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.[48] 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.[49]) 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, 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.

[47] 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.

[48] This is consistent with evidence on job transitions in Figure A1.

[49] Further analysis shows the rate of dual jobholding is higher among employers with low effects on hours (see Figure A4), and that dual jobholder who are long-hour workers who have sorted to short-hour primary jobs. 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.

6.5 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 (13) 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%.[50] 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 2, which illustrates that, with inelastic supply at the offered wage, even a small constraint can result in a very low $MRS_{e,h}/w$.[51]

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 compensating variation value.

6.5.1 Heterogeneous PageRank

A key assumption of the analysis is that workers have a homogeneous ranking of firms up to an idiosyncratic utility draw. While heterogeneity in the rankings does not automatically lead to a

[50] 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 A17), suggesting that the estimate of $\overline{CV}$ shown in Table 5 may be conservative.

[51] Murphy and Topel (1997) develop such a labor supply curve from CPS annual demographic file data on prime-age males over 1967–1995.

biased estimate of CV, it is worthwhile to study whether allowing for heterogeneity in rankings affects the relationship between optimal and observed hours. We consider heterogeneity by gender and education.

To do this, we re-estimate the PageRank separately for each group (men vs. women; college vs. non-college) and compute a group-specific version of Figure 8. Figure A6(a) and (b) shows the results by gender. For men, the optimal hours are almost always uniformly above average hours and tend to vary little across employers with different wage policies, which is consistent with men having a close to zero uncompensated labor supply elasticity. For women there is some evidence that the most preferred employer is less likely to be the one offering more hours. Figure A6(c) and (d) shows a similar analysis but for no-college vs. college-educated individuals. For the latter group, there is some evidence that the gap between observed and ideal hours shrinks as these individuals sort into employers with higher wage policies. For individuals with no college degree, on the other hand, the gap between optimal and observed hours seems to shrink at a slower rate, possibly because these individuals are precluded from joining the highest-paid employers.

For both the gender and the education analysis, Figure A6 shows that the group-specific CV calculations lead to comparable estimates as when assuming a common ranking of employers (reported in Table 5). Based on this, we conclude that men and workers without a college degree are particularly likely to face hour constraints from above and that using a common ranking specification does not bias the estimation of the compensated variation required to close the gap between optimal and observed hours.[52]

7 Discussion

The Lewis-Rosen model described in Section 2.1 (and illustrated in Figures 1(a) and (b)) makes three testable predictions that bear directly on our analysis. First, hour constraints are an equilibrium feature of a competitive model where firms have requirements and workers have preferences

[52]Part of this is because the overall ranking of employers between men and women (or college and no-college workers) are highly correlated with each other. For instance, the correlation between the women vs. men estimate of V_j across firms is around 0.95, similar to what reported by Sorkin (2017).

for average hours. The evidence in Section 6.2 strongly supports this prediction. Second, the model predicts that in equilibrium, no worker would want to give up the current hours/wage bundle for a different one. This second prediction is clearly rejected in our data because we find evidence of a job ladder—systematic flows of workers to certain firms that tend to offer higher wages and hours—see Sections 6.1 and 6.4. Third, the model predicts perfect sorting of workers and employers based on their requirements and preferences for hours, which again we do not observe—see Section 5.2.1.

The extended Lewis-Rosen model described in Section 2.2 (illustrated in 1(c) and (d)) introduces imperfect competition and can reconcile these discrepant findings. With imperfect competition, firms with higher returns to hours (T_j) and lower wage markdowns (p_j) can offer more hours and higher wages. Variation in markdowns across firms leads to variation in wages at a fixed level of hours. The result is a job ladder that explains the positive correlation between firm effects on hours and wages—see Figure 1(c).[53,54] Consistent with a job ladder, we find a high degree of variation in employer effects on hours among employers with similar wage effects.

Imperfect competition and the resulting job ladder in the extended Lewis-Rosen model can also explain limited worker-employer sorting on hours. If workers sort to employers on the basis of hours and wages plus an idiosyncratic worker-firm component—as discussed in Section 3—then a large degree of variability in this idiosyncratic component will lower the probability that we observe a worker with a preference for long hours sort to an employer offering long hours. By a similar logic, variation in firm markdowns results in a job ladder whereby workers with preferences for short hours may accept a long-hour position if the wage premium is large enough. This is because workers are more likely to overrule their preferences for hours if the gains from doing so are sufficiently large. This last prediction is supported in Table 3 where we find more

[53]Given equations (4) and (5), a sufficient condition for positive correlation between the firm effects on wages and hours is that, as we assume, the disutility from hours is convex ($\mu > 1$) and that more productive firms have lower profit margins (i.e., $\text{Cov}(\log T_j, \log(1-p_j)) > 0$).

[54]The extended Lewis-Rosen model can also explain the negative correlation between worker effects on hours and wages—see Table 3. Note that within-firm variation in hours and wages, over which worker effects are identified, corresponds to situations where different workers bargain with the firm over a fixed level of firm surplus. As a result, the correlation in worker effects for hours and wages reflects compensating differentials. If hours are constrained from above—as we find in our results— then equations (4) and (5) imply that this correlation should be negative.

sorting on hours within sector, where the dispersion of utility among employers (which is driven by dispersion in markdowns) tends to be less—see Table 5.

In a job ladder we expect queuing by workers to join better firms. How workers and firms match in the presence of a queue when prices are not fully allocative is unknown, but our findings offer a clue. We find that workers with more education and a higher portable wage are more likely to work in long-hour firms, despite these workers not having relatively higher preferences for longer hours. It stands to reason that longer-hour firms are more attractive because of their high wages, and these firms select applicants based on skill rather than worker preferences for hours.

Finally, the evidence further points towards bargaining playing a fairly limited role in hours determination as seen by the limited variability in worker effects on hours. In terms of our model, this means that in many cases hours are at the corner solution of equation (4), where $h_{ij}^{b} > z_j$. This finding implies that hours tend to be capped at the productive ceiling and that in these jobs workers have no discretion over hours.

8 Conclusions

The empirical findings we have presented point to workers facing constraints from above in their choice of work hours, resulting in a 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) that allows for imperfect competition in the labor market can explain these findings. Heterogeneity in the level of firm surplus that different employers can obtain when bargaining over hours and wages with a given worker creates a job ladder in employer utility (Mortensen, 2003; Sorkin, 2018). The resulting utility dispersion stemming from imperfect competition 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. Imperfect competition can also explain the existence of hour mismatches. In particular, labor market frictions might prevent workers from obtaining jobs with more desirable hours. As a result, some workers might be stuck in low-hour jobs despite having a strong preference for more hours.

An important implication of the finding 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 work hour mismatch.

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9 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 : See Section 4.2 for a description of the samples. The leave-one-out connected set (column 3) is the main analysis sample.

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 AKM variance decompositions of log hours, log hourly wage, and log earnings into components attributable to worker and employer effects. The KSS leave-one-out correction of variances is computed at the match level; see Appendix C for details. To the right of each variance component is the percentage of the total variance explained by that component. (The covariance between worker and employer effects is multiplied by two). All statistics are weighted by the number of worker-year observations associated with each employer. 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 correlations between worker and employer effects from a model in which the covariance between worker and employer effects on hours is estimated jointly with the worker and employer effects on wages (see Appendix C.2). 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-one-out correction at the match level; see the Appendix C for details.

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

	(1)	(2)	(3)	(4)
Outcome: PageRank utility index				
Employer effect on hours (ψ^h)	5.224***	5.537***	5.132***	5.166***
	(0.713)	(0.538)	(0.537)	(0.555)
Employer effect on wages (ψ^w)	5.845***	7.005***	6.895***	6.890***
	(1.762)	(1.418)	(1.409)	(1.409)
Employer effect on job security			12.969***	12.973***
			(0.983)	(0.986)
Employer effect on within-job hours variability				0.423
				(1.239)
Number of employers	57,460	57,460	55,835	55,835
Controlling for sector effects	no	yes	yes	yes
% of variance explained by employer effect on hours	10.16%	11.42%	9.81%	9.94%
% of variance explained by employer effect on wages	16.83%	24.17%	23.42%	23.39%
% of variance explained by covariance between employer hours and wage effects	9.48%	12.05%	10.99%	11.06%
MRS/w ($[\theta_h - \theta_w]/\theta_w$)	0.11	0.21	0.26	0.25
p-value (MRS/w = 1)	0.00	0.00	0.00	0.00
MRS/w adjusted for fringe benefits	0.21	0.31	0.36	0.35
p-value (Adjusted MRS/w = 1)	0.00	0.00	0.00	0.00

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 (ψ^h) and on wages (ψ^w) obtained from AKM two-way fixed effects models of hours and wages. The coefficient associated with employer effects on hours is θ_h and the coefficient associated with employer effects on wages is θ_w. To implement the split-sample IV, we divide worker-employer pairs randomly into two subsamples. We then estimate a two-way fixed effects model and the PageRank algorithm separately over 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). In column 3, we add a proxy for job security, calculated by fitting an AKM model to the probability of having a job in the next two quarters (see section 6.2). Column 4 adds the firm effect computed from estimating an AKM specification on within-job variability of hours (see section 6.2). 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 are omitted from the analysis.
The bottom rows of the table report the ratio of the implied marginal rate of substitution between earnings and hours (MRS) to the wage, along with the p-value from a test of this quantity being equal to 1 (standard error calculated using the delta method). "MRS/w adjusted for fringe benefits" adjusts to account for fringe benefits that could be correlated with hours (see Appendix E).

All coefficients and variance components are weighted by the number of worker-year observations associated with each employer. Robust standard errors are in parenthesis.

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

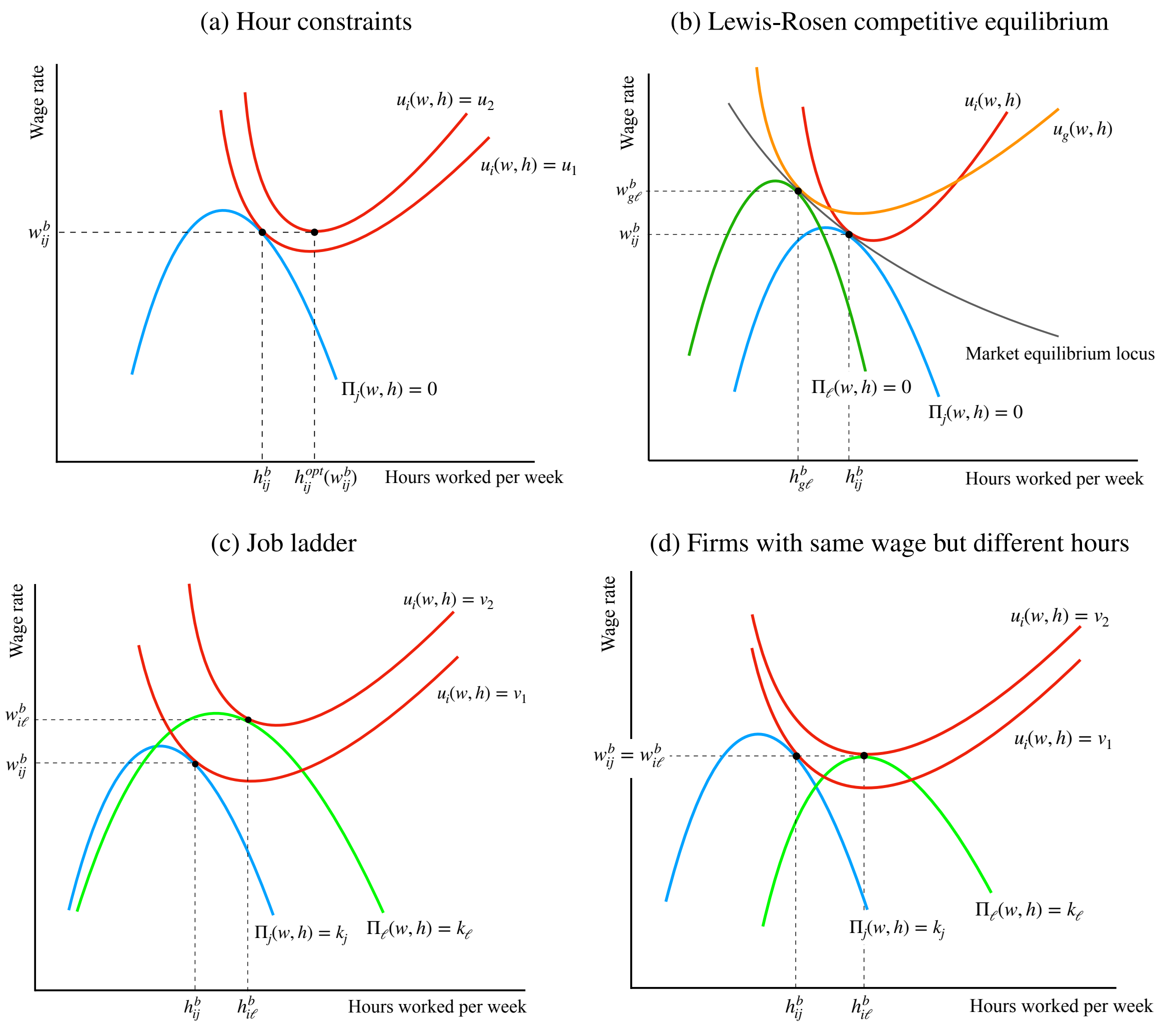
	(1) Gap between observed and optimal hours	(2) Gap between observed and optimal hours (absolute value)	(3) Gap between observed and optimal PageRanks	(4) Compensating variation (%)
All sectors	-0.11	0.15	-1.74	12.15
Estimates by sector				
Agriculture, fishing, etc.	-0.06	0.10	-1.23	9.81
Mining, quarrying, 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 estimated compensating variations (CVs) described in section 3.2, in aggregate and by sector. The first row shows baseline results pooling all sectors. To compute sector-specific estimates, we divide the data into 10 x 10 cells defined by deciles of employer effects on wages and hours in each sector. For each decile of employer effects on wages, we identify the decile of employer effects on hours that gives the highest PageRank utility. This is the optimal employer effect for that wage-effect decile (the figures are weighted by the number of worker-year observations in each cell).

Column 1 reports weighted average differences between observed employer effects on hours and optimal employer effects on hours. Column 2 reports absolute values of the differences between observed and optimal hours, and column 3 reports the gap between observed and optimal PageRanks. Column 4 reports estimated CVs: the average percentage increases in the employer effect on wages that would make a worker indifferent between working their observed hours and optimal hours. For each row, this is calculated using the estimated employer effect on wages (θ_w) reported in Table 4, column 2. The CV calculations are adjusted to account for the correlation between fringe benefits and work hours (see Appendix E). The figure at the bottom row is the weighted average of sector-specific CVs in column 4, where the weights are the number of worker-year observations in each sector.

10 Figures

Figure 1: Theoretical framework



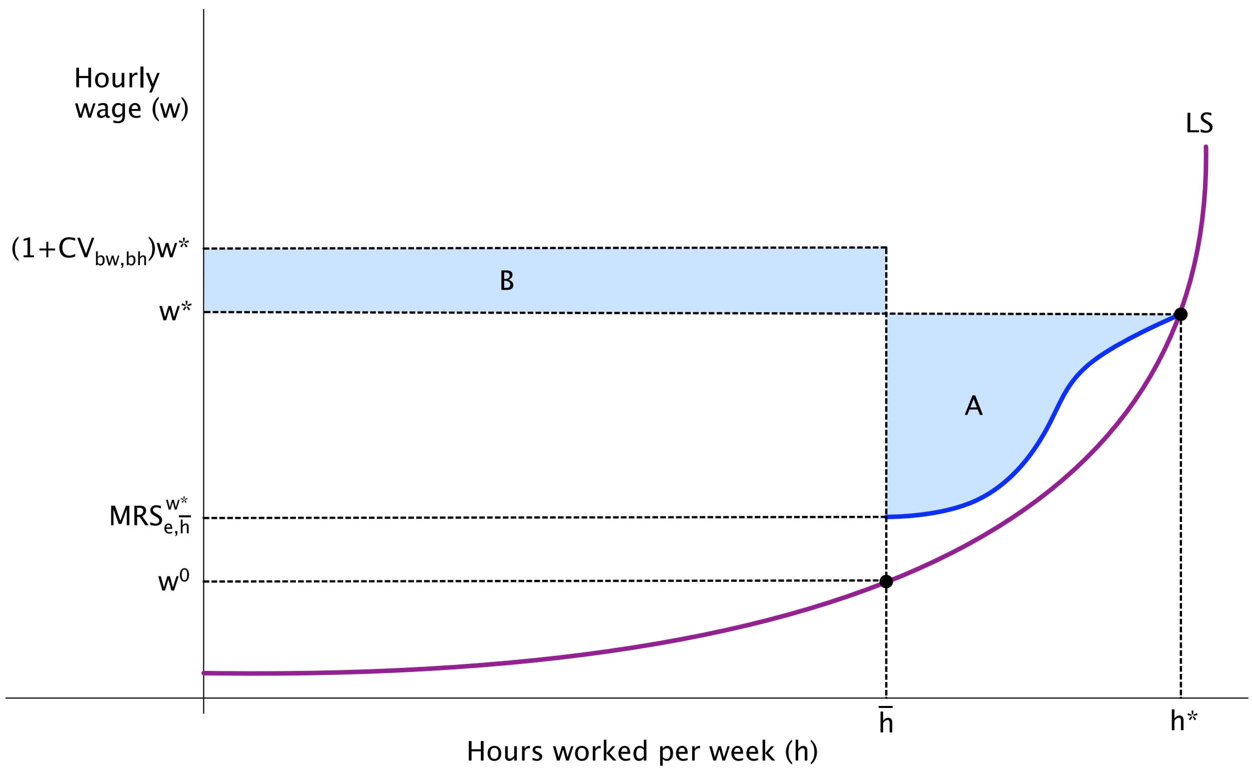
Notes: Panel (a) shows a worker's indifference curves and a firm's zero-profit isoprofit curve in wage-hour space. The indifference curves are U-shaped assuming workers require a high wage rate to work short or long hours, and the isoprofit curve has an inverted U-shape because a firm is willing to employ the worker at very short or very long hours only at a low wage. Bargained hours and wages are given by the tangency (w_{ij}^b, h_{ij}^b) between the worker's indifference curve and the firm's zero-surplus isoprofit function. The worker is constrained to h_{ij}^b work hours, but if she could freely choose hours at the bargained wage, she would work $h_{ij}^{opt}(w^b) > h_{ij}^b(w^b)$.

Panel (b) shows the negatively-sloped market equilibrium locus for wages and hours that would arise in a perfectly competitive labor market. Each worker chooses the firm offering the highest utility, so perfect sorting results–see the discussion at the end of Section 2.1.

Panel (c) illustrates the job ladder that arises under imperfect competition (Section 2.2). Employers j and ℓ have different production functions (T) and markdowns (p) allowing some firms to offer higher-valued jobs than others–worker i prefers hour-wage package $(h_{i\ell}^b, w_{i\ell}^b)$ to (h_{ij}^b, w_{ij}^b). Because of frictions, not all workers can obtain higher-valued packages.

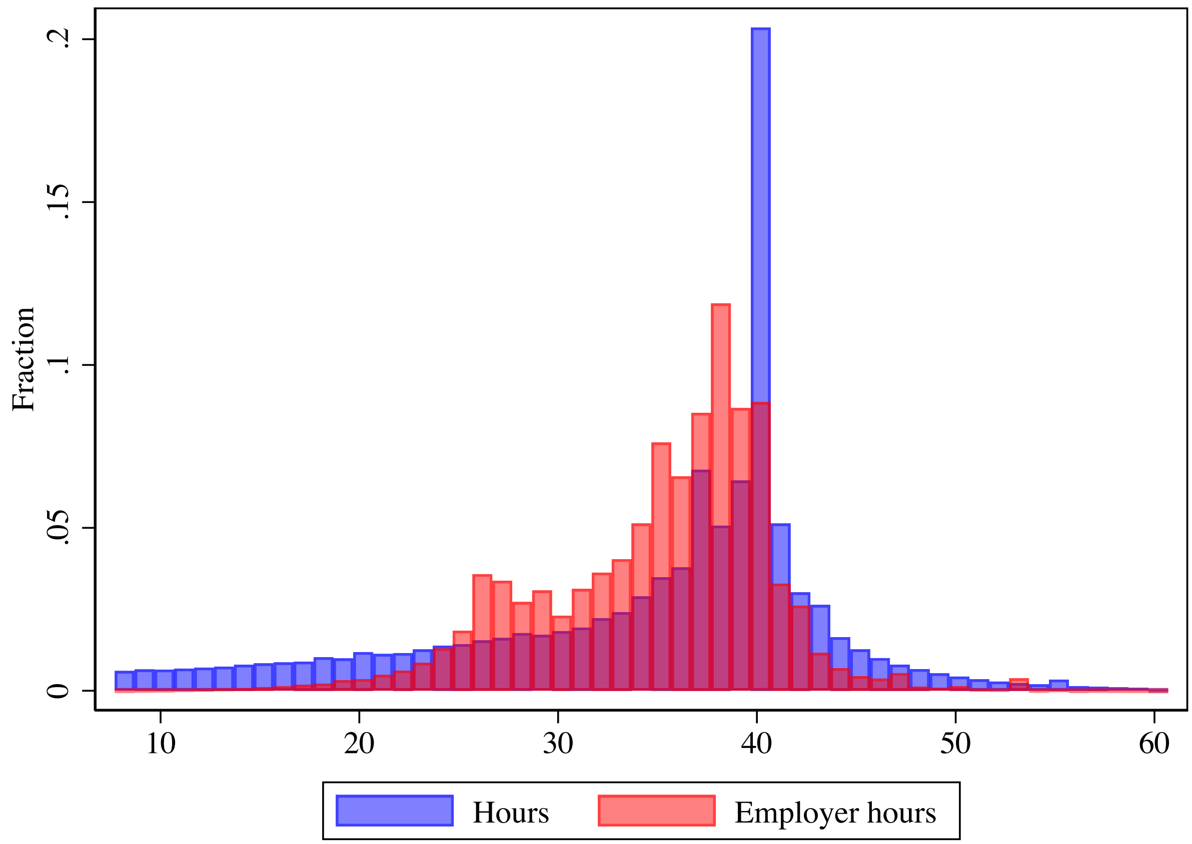
Similarly, Panel (d) shows a situation with two employers, j and ℓ. The two employers offer worker i the same bargained wage, but ℓ can offer more hours, leading to higher utility given worker i's preferences.

Figure 2: 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 (12) 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 3.2 for discussion.

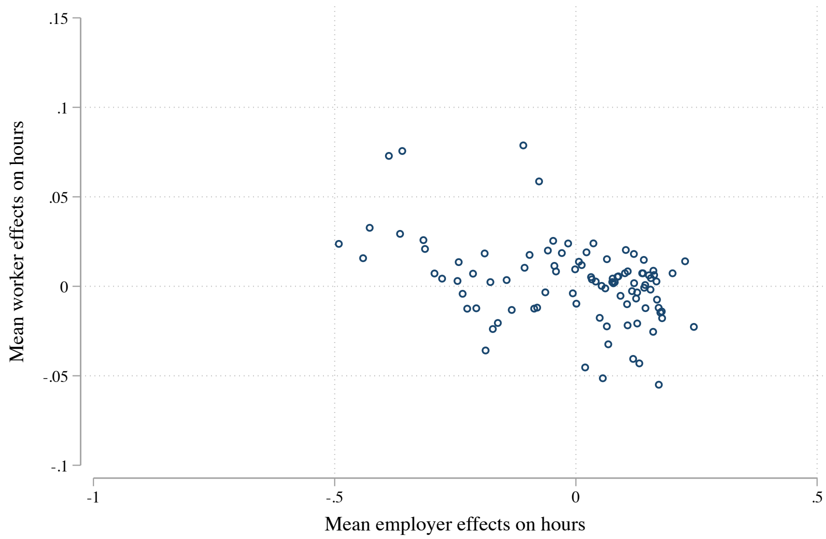
Figure 3: Work hour distributions



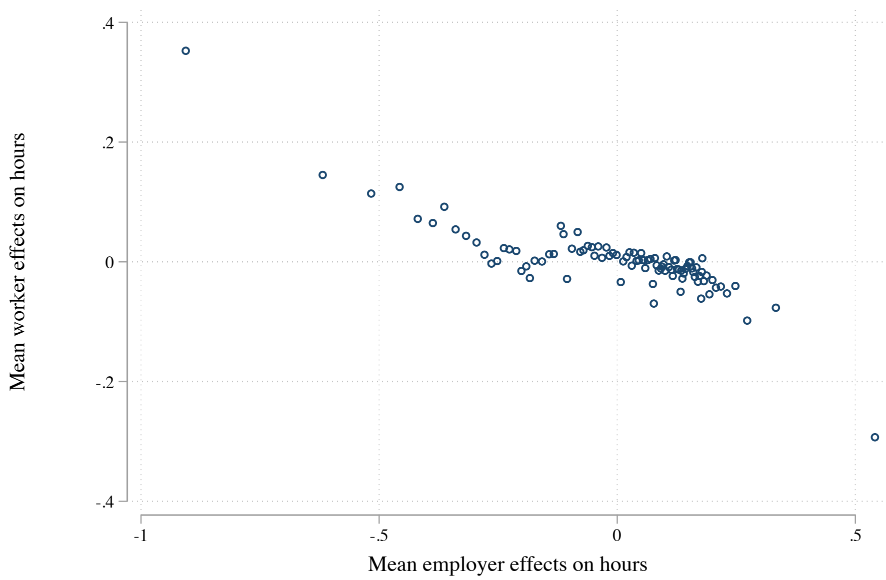
Notes: The blue histogram shows the distribution of weekly paid work hours for individual workers in the initial annualized sample (described in Section 4.2). The red histogram shows the distribution of employer average hours (employer-level averages weighted by worker-years). Values with more than 60 hours per week are not displayed.Weekly hours are computed as annualized hours divided by 52 (weeks).

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

(a) Sorting corrected using split samples

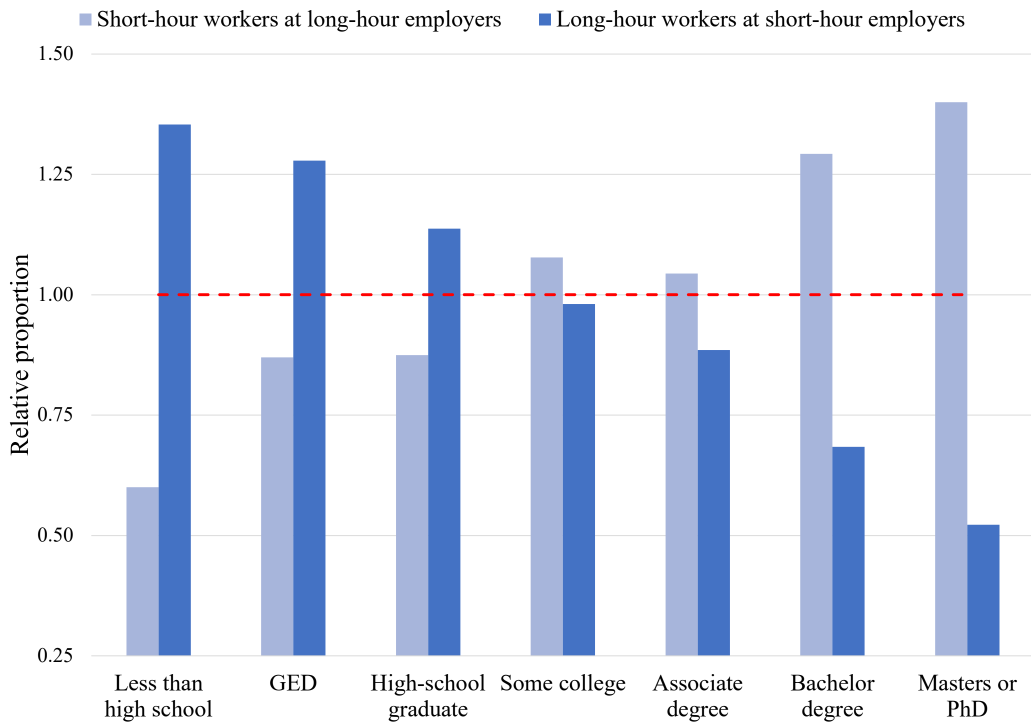


(b) Sorting measured with error



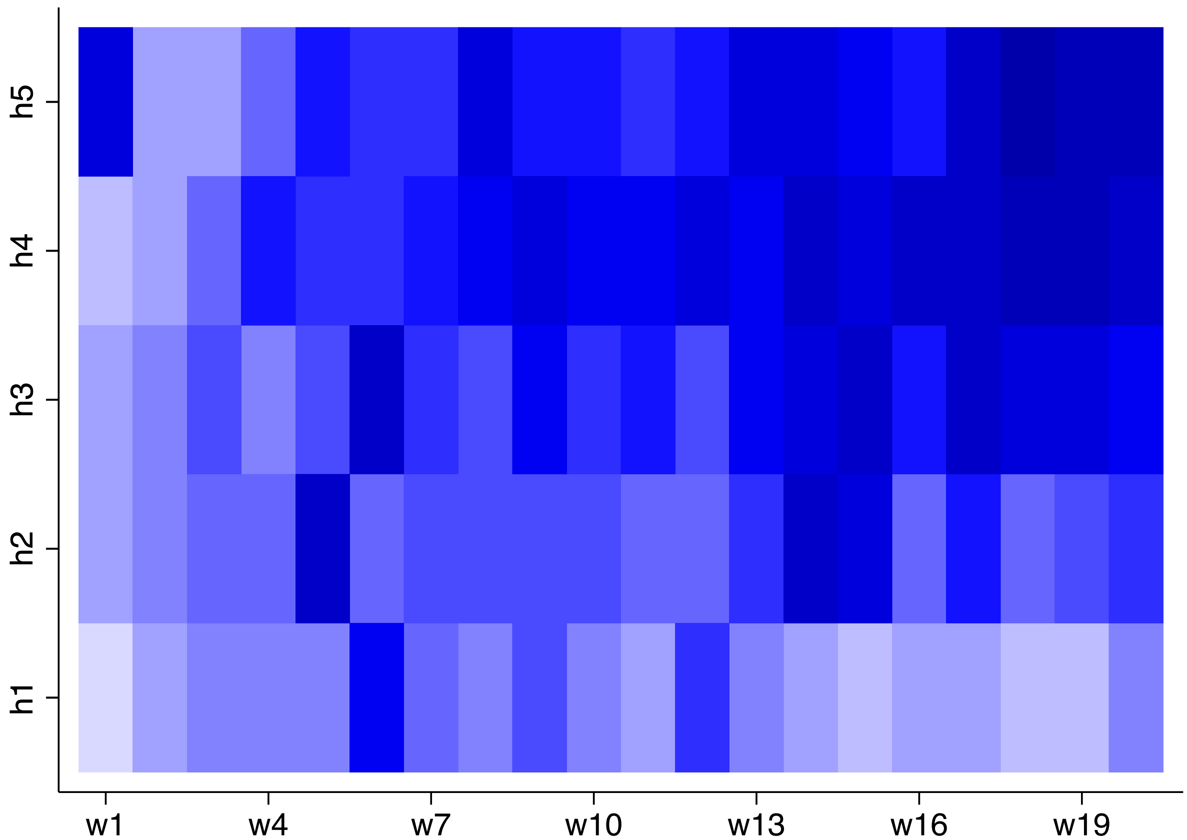
Notes: Figure 4(a) plots mean estimated employer and worker effects on hours using a split-sample approach to account for measurement error. Specifically, we divide all jobs in the the leave-one-out sample in Section 4.2 randomly in two subsamples (the hold-out sample and the estimation sample) and fit equation (7) 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



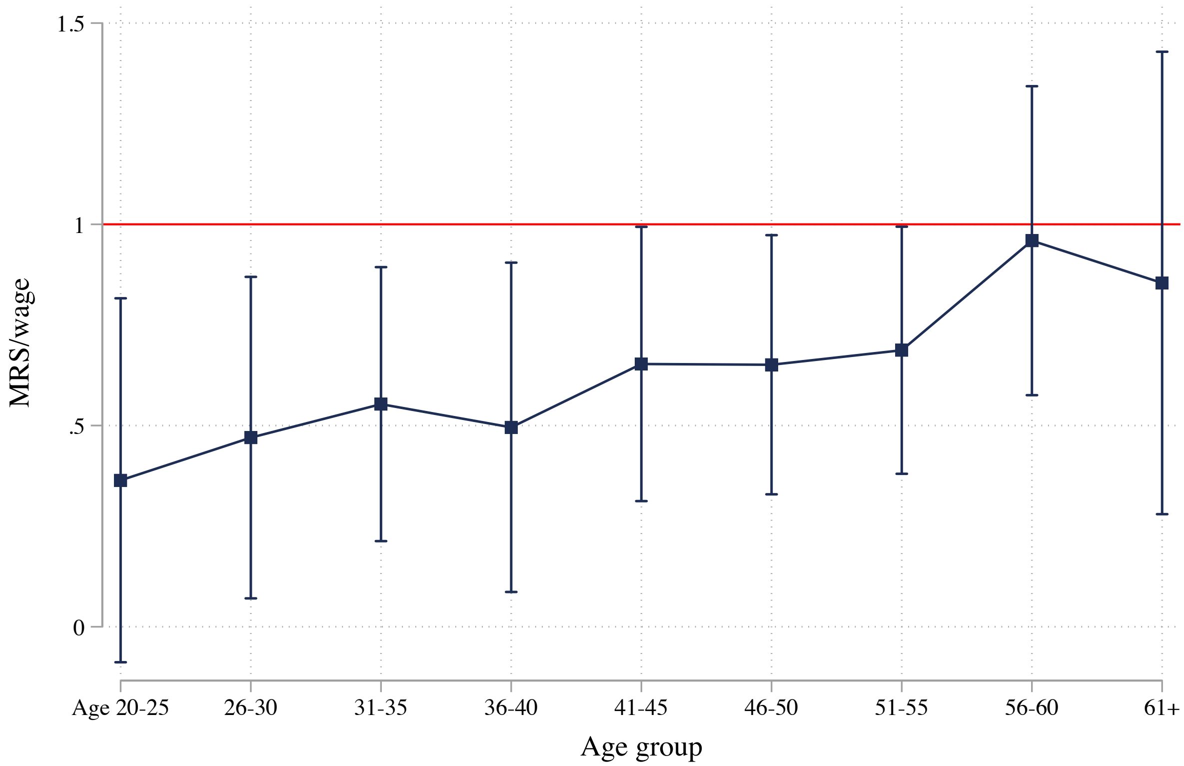
Notes: A short-hour (long-hour) worker is defined as a worker whose hour effect is in the first (fourth) quartile of worker hour effects. A short-hour (long-hour) employer is defined as an employer whose hour effect is in the first (fourth) quartile of employer hour effects. For each educational group, 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



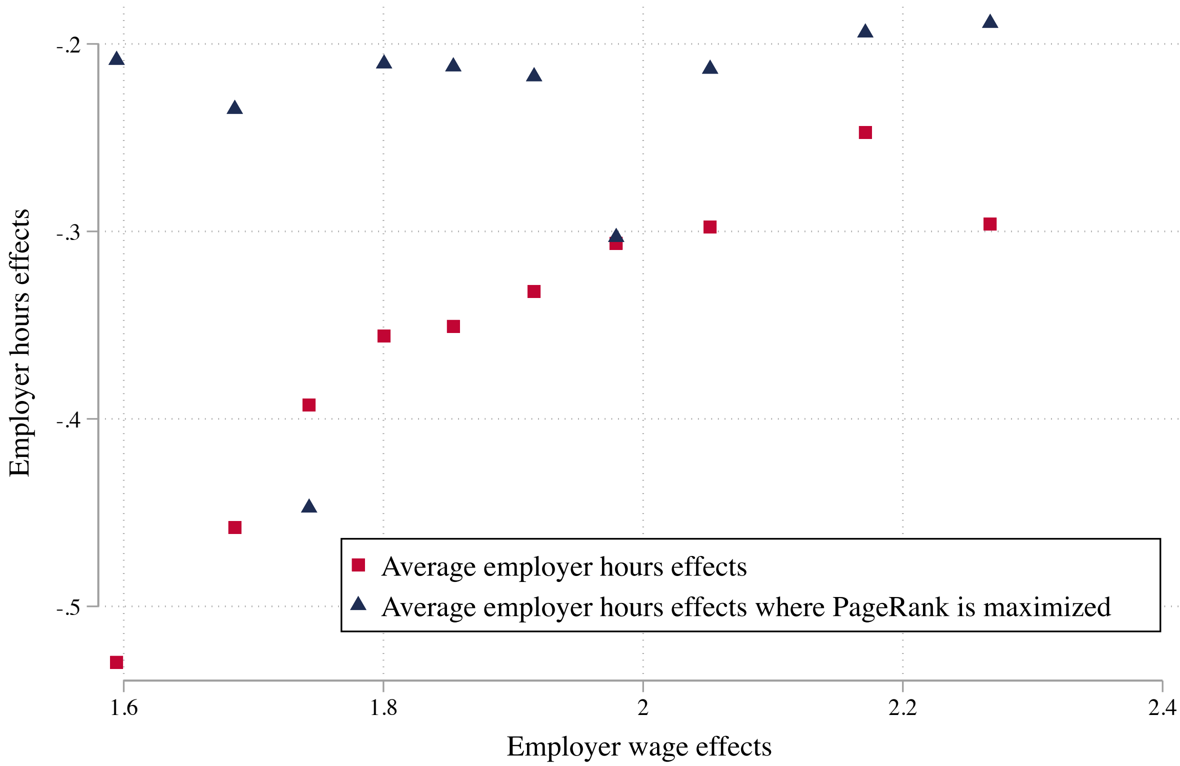
Notes: This figure shows the average PageRank index by each vingtile of employer wage effects and by each quintile of employer hour effects. The PageRank index is a measure of a given employer's utility, calculated as in Sorkin (2018). Darker shade of a cell implies a higher value of the PageRank index. Public administration and the education sector are omitted. See Section 6 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 (9). 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 (10) and Section 3.1 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



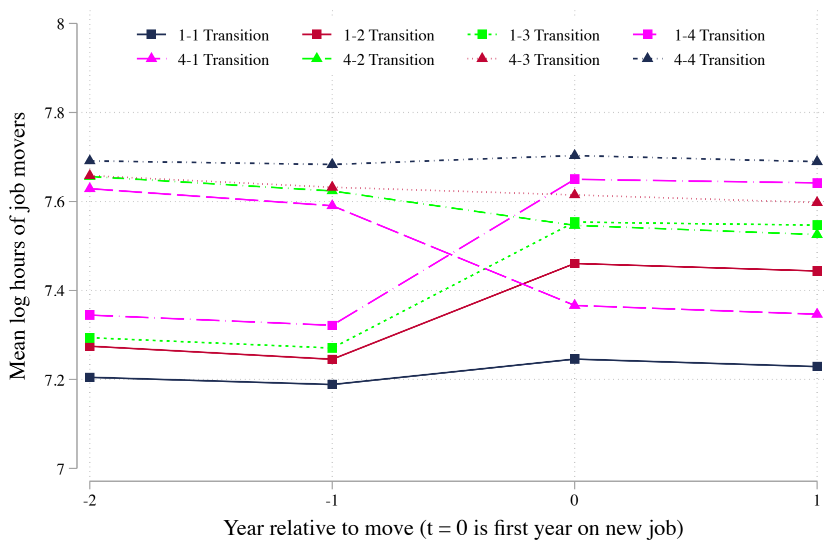
Notes: The data are divided into 10×10 cells defined by deciles of employer wage effects and employer hour effects. For each decile of employer wage effects, we identify the employer hours decile with the highest PageRank index (Sorkin, 2018). The navy triangles represent the weighted average of employer hour effects in the PageRank-maximizing ("optimal") hours decile, where the weight is the number of worker-year observations in the corresponding wage decile $\times$ "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 6.4 for further details.

Online Appendix

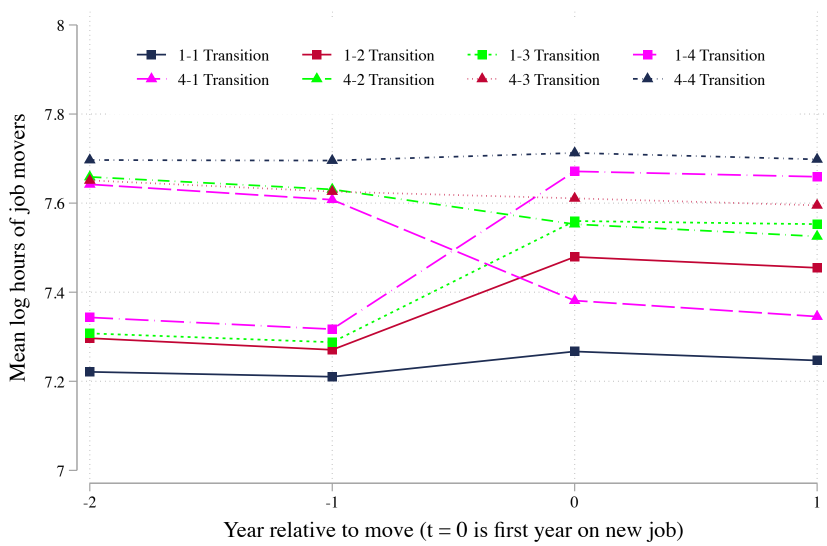
A Additional Tables and Figures

Figure A1: Mean hours of job movers, by quartile of mean hours of coworkers at origin and destination jobs

(a) Baseline event study



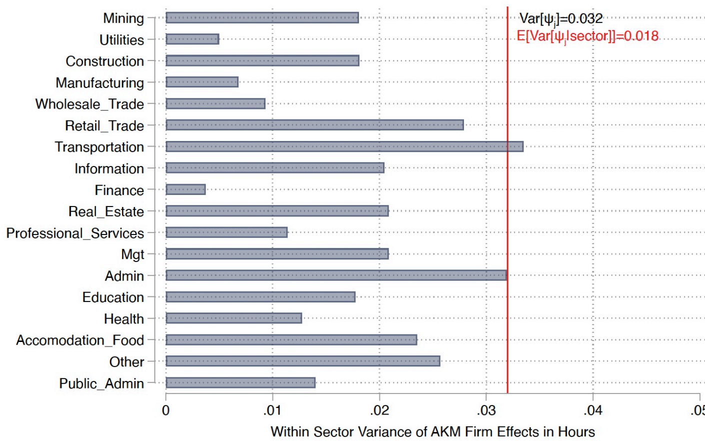
(b) Restricted to coworkers' wages in origin and destination jobs being in the same quartile



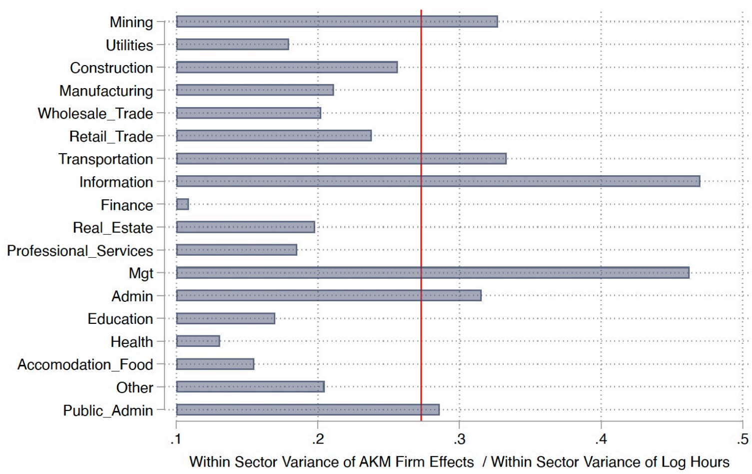
Notes: The figure shows employer-to-employer transitions where a worker held a job for at least two consecutive years prior to the transition and remained with the new employer for at least two years. For each transition, we calculate quartiles of the leave-one-out average of coworkers' log hours in the last year in the origin job and in the first year of the destination job. Figure A1(a) shows transitions where the origin employer is either in the bottom or in the top quartile of average coworker hours. A1(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 A2: Within-sector variation in employer effects

(a) Levels



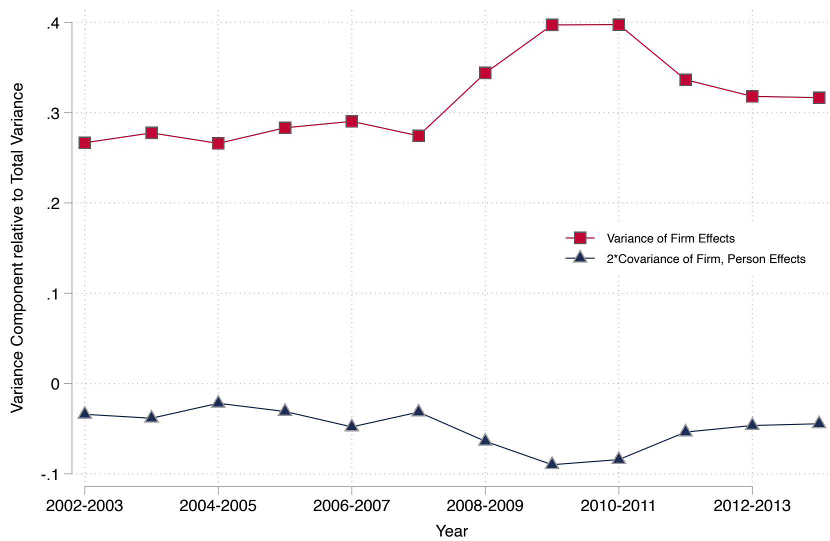
(b) Shares



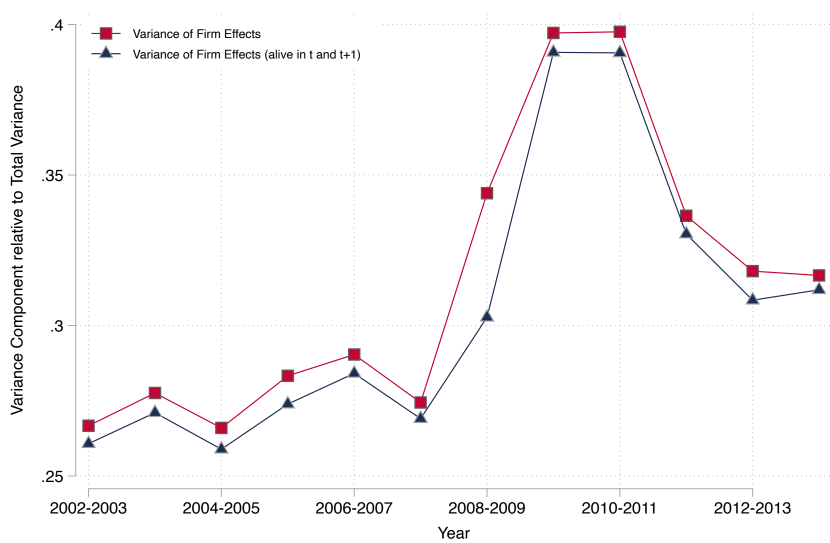
Notes: Panel (a) displays the variation of firm effects within each sector. All variances are KSS corrected. Panel (b) re-scales these within-sector variances of firm effects by the corresponding overall variance of hours observed in a given sector. The vertical red line in panel (a) denotes the overall 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 A3: Role of employers in determining hours over the business cycle

(a) R-AKM estimates

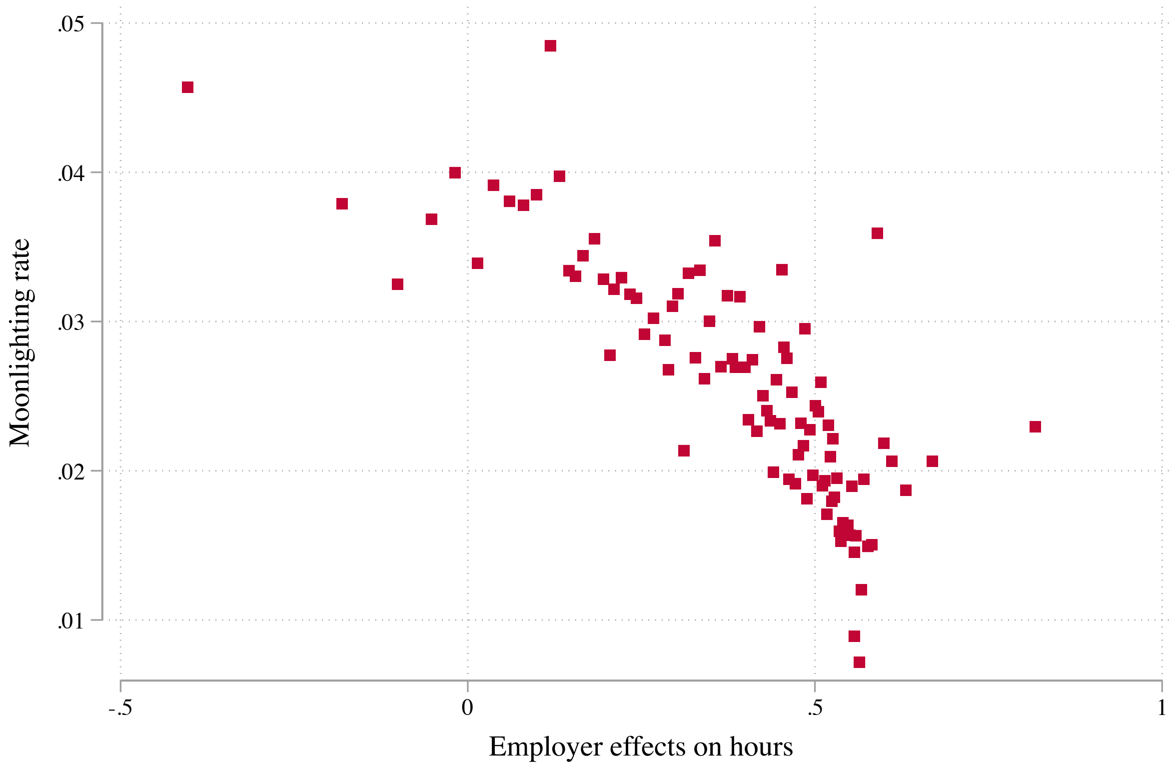


(b) Balanced version



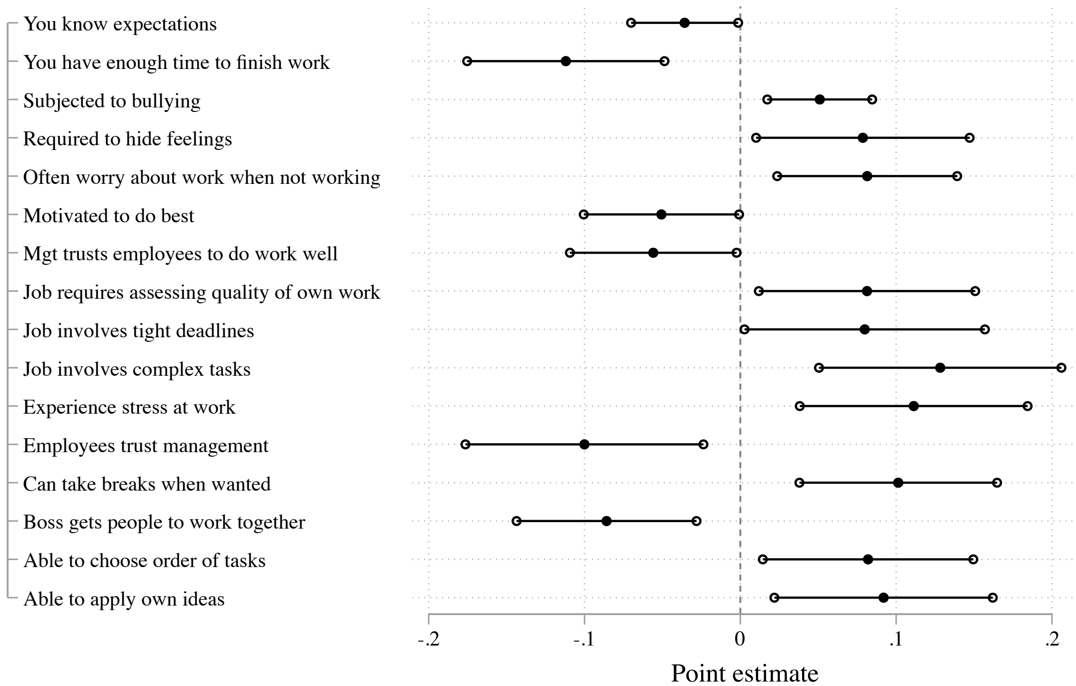
Notes: To construct this figure, we estimate equation (7) separately to successive overlapping two-year intervals (2002–2003, 2003–2004, etc.) and corrects the interval-specific variance of employer effects using the Rolling-AKM (R-AKM) methodology from Lachowska et al. (2023). Both variance components 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 A4: 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 (7). 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.

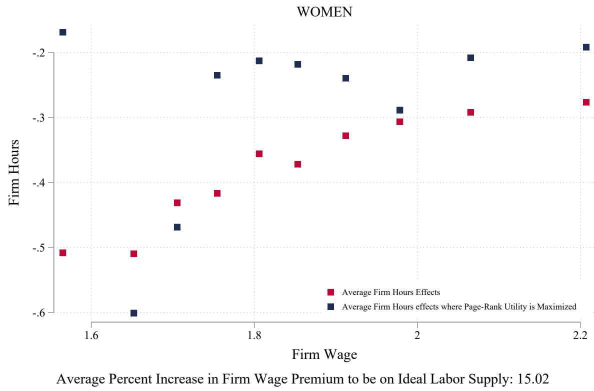
Figure A5: Statistically significant associations between workplace characteristics and hours



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.

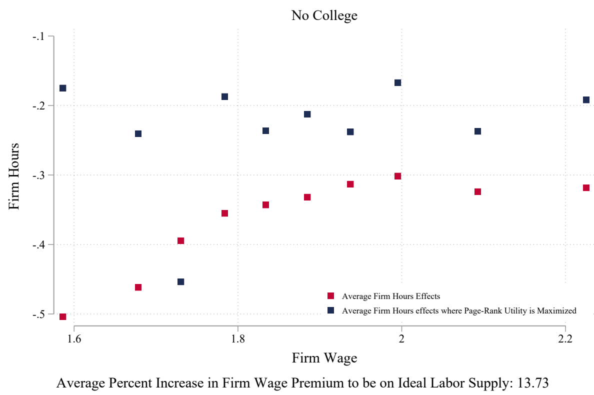
Figure A6: Gap between Optimal and Observed Hours with Heterogenous PageRank Valuations

(a)



(b)

(c)



(d)

Notes: Each panel presents a plot similar to the one described in Figure 8 done separately for the group of workers highlighted at the top of each figure. Each panel also uses a group-specific valuation of firms, V_j. That is, we estimate the ranking of firms of Sorkin (2018) using only the voluntary moves made by a particular group of workers. Below each panel, we report the estimate of the compensating variation required to equalize the gap between observe and ideal hours within each group as described in equation 13. See also the footnote to Figure 8 for further details on the construction of each panel.

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: Oaxaca Decomposition of Firm Effects in Log Hours

	Raw Gender Gaps		Firm Effects in Log Hours		Oaxaca Decomposition of Firm Effects in Hours	
	Log Earnings	Log Hours	Men	Women	Sorting	Bargaining
	[1]	[2]	[3]	[4]	[5]	[6]
All Sample	0.2989	0.0994	0.2982	0.2625	0.0466	-0.0110
Age<=30	0.2235	0.1074	0.2658	0.2303	0.0493	-0.0138
Age>30 & Age<=40	0.3013	0.1055	0.3078	0.2770	0.0418	-0.0110
Age>40	0.3418	0.0925	0.3106	0.2722	0.0478	-0.0094
Years: 2003-2006	0.2976	0.1004	0.2855	0.2555	0.0444	-0.0143
Years: 2007-2010	0.3007	0.0917	0.2978	0.2621	0.0469	-0.0112
Years: 2011-2014	0.2984	0.1068	0.3138	0.2720	0.0486	-0.0068

Note: Column 1 and Column 2 of this table report the gender gap in average log earnings and log hours for the dual connected sample, i.e. the sample where we can identify for the same firm both a firm effect for women as well as men when estimating an AKM equation for hours separately for men and women as in Card, Cardoso and Kline (2015). Columns 3 and 4 report the average firm effects in hours for men and women. Columns 4 and 5 report the Oaxaca decomposition of the gap in firm effects in hours. The sorting component corresponds to the difference in the average value of firm effects of women computed across the jobs held by men versus women. The bargaining component captures differences in the firm effects of men vs. women across the jobs held by women. Each row of the table corresponds to a different sample. Row 1 is the dual-connected sample defined above. Row 2-4 considers person-year observations associated with a given age range. Rows 5-7 consider different time intervals. Firms' effects in hours for both men and women have been normalized relative to the average firm effect in hours found in the Restaurant and Accommodation sector as in Card, Cardoso and Kline (2015).

Table A4: 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 A5: Variance Decomposition of Log Hours from interacted fixed effects specification estimated via BLM

Std. of Log Hours	0.31	
Variance Decomposition		
Std. of Firm Effects	0.17	28.12%
Std. of Worker Effects	0.05	2.13%
Covariance of Worker, Firm Effs	0.00	0.42%
Correlation of Worker, Firm Effs	0.03	
R2 no interaction	0.31	
R2 with interaction	0.32	

Note: This table reports estimates a variance decomposition of log hours using the interacted fixed effects specification of Bonhomme, Lamadon and Manresa (2019)---BLM henceforth--- with 20 unobserved firm types. Each variance component is computed using the simulation method discussed in BLM with 1,000,000 simulations. "R2 no interaction" computes the fraction of the variance of the outcome explained when projecting the outcome on a model that has no interaction between the worker and the firm effect. "R2 with interaction" reports the R2 after accounting for the interaction between the worker and the firm effect in the regression. The estimates are computed using the BLM package for R available at https://github.com/tlamadon/rblm on the period 2013-2014.

Table A6: Decomposition of Within-Job Variability in Log Hours

Average within-job variance in Log Hours	0.03	
Std. Deviation of Average within-job variability in Log Hours	0.07	
<u>Variance Decomposition</u>		
Std. of Firm Effects	0.04	30.38%
Std. of Worker Effects	0.02	8.61%
Covariance of Worker, Firm Effs	-0.0003	-11.58%
Correlation of Worker, Firm Effs	-0.36	

<u>Note:</u> This table reports the variance decomposition based on fitting an AKM specification to the within-job variability of log hours. Specifically, we compute the within-job variability of log hours and fit the latter onto firm and worker dummies, after netting out unrestricted interactions based on when the job started and when the job ended. Variance decomposition parameters are estimated using the leave-out procedure of Kline, Saggio and Sølvsten (2020 - KSS). Right next to each variance component, we report the percentage of the total variance explained by the corresponding component (this number is multiplied by 2 when looking at the covariance between worker, and firm effects). Leave-out correction based on a "leave-match-out" approach, see text for details. All statistics are person-year weighted.

Table A7: 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 D. 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 A8: 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 A9: 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 A10: 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 A11: Page Rank Utility and Firm Effects in Hours, Firm Effects in Wages, excluding Salar

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

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 appr 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 w are computed excluding from the estimation sample jobs that are on a salaried basis, as explained in Appendix D. To construct the split-sample IV, we start by 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 algorith 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- 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 variance decomposition of the page rank utility, where each variance component has been corrected to account for sampling noise using again a split-sam Administration and Education sector were excluded from the analysis. All reported regressions and variance components are weighted by the total number of observations associated with a given employer. Robust standard errors are displayed in parenthesis.

Table A12: 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 (9) 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 A13: Page Rank Utility and Firm Effects in Hours, Firm Effects in Wages and their interaction

	[1]	[2]
Outcome: Page Rank Utility (Sorkin, 2018)		
Firm Effect in Hours	5.9314***	5.8885***
	(0.6529)	(0.6508)
Firm Effect in Wages	7.1909***	7.8790***
	(1.3755)	(1.6087)
Interaction	10.5507***	10.5507***
	(3.9852)	(3.9852)
# of Firms	57,460	57,460
Interaction term centered at the mean or median?	Mean	Median
Controlling for Sector Fixed Effects	yes	yes
% of Variance Explained by Firm Effects in Hours	13.1	12.91
% of Variance Explained by Firm Effects in Wages	25.47	30.58
% of Variance Explained by Covariance	13.25	14.41
MRS/w	0.18	0.25
p-value (MRS/w=1)	0.00	0.00
Adjusted MRS/w	0.28	0.35
p-value (Adjusted MRS/w=1)	0.00	0.00

Note: This table reports the results from equation (9) after adding an interaction term between hours and wage policies. In column 1, the interaction term is represented by demeaned firm-hour and firm-wage effects, so that the resulting MRS/w ratio is calculated for the worker employed at the average firm in terms of hours and wage policies. Column 2 is similar but the interaction is now centered relative to the median firm-hour and firm-wage effect.. The regression uses as outcome is the page rank utility calculated using the revealed preference approach of Sorkin (2018) and all the key regressors are instrumented using a split-sample IV approach, see Table 4 for further details. 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 A14: 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 C.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 A15: Relationship between the composite amenity index and log wages and hours

	[1]	[2]
Outcome: Composite amenity index		
Log weekly hours	0.006	
	(0.0058)	
Log annual hours		0.0011
		(0.0020)
Log wages	0.0135***	0.0133***
	(0.0043)	(0.0044)
Constant	0.9085***	0.9237***
	(0.0216)	(0.0169)
# of Observations	1,738	1,704
R2	0.04	0.04

Note: The composite amenity index is obtained using the Maestas et al. (2017) approach that employs a series of stated-preference experiments to gather data on workers' willingness-to-pay for various randomized job characteristics, such as autonomy and pace of work. Using the data from Maestas et al. (2017), utility weights are estimated by fitting a logit model to predict the chosen job as a function of 12 amenities. We then apply the utility weights to characteristics of respondents' actual jobs to create a composite index of the valuation of a job as a function of nonwage attributes. We regress this composite index on log weekly hours (or log annual hours) and log hourly wage. The table reports the coeffecients and standard errors (bootstrapped 500 times, reported in parantheses) from this regression.

Table A16: Relationship Between Hours and Workplace Characteristics

Outcome variable	(1) Coefficient on log annual hours	(2) Standard error	(3) Number of observations
Can choose where to work (Yes = 1)	-0.014	0.033	1,369
Often worry about work when not working (Yes = 1)	0.081	0.029	1,391
Not difficult to take an hour off to take care of personal or family matters (Yes = 1)	0.000	0.038	1,393
Does job require assessing for yourself quality of own work? (Yes = 1)	0.081	0.035	1,393
Solving unforseen problems on own? (Yes = 1)	0.046	0.031	1,393
Monotonous work (Yes = 1)	0.037	0.035	1,393
Job involves complex tasks (Yes = 1)	0.128	0.040	1,393
Job involves learning new things (Yes = 1)	0.057	0.031	1,393
Able to choose order of tasks (Yes = 1)	0.082	0.034	1,393
Able to choose methods of work (Yes = 1)	0.036	0.035	1,393
Able to choose speed of work (Yes = 1)	-0.001	0.030	1,393
Consulted before work objectives are set (Yes = 1)	0.054	0.037	1,393
Involved in improving work organization/processes (Yes = 1)	0.031	0.039	1,393
Have say in choice of working partners (Yes = 1)	-0.016	0.032	1,392
Can take breaks when wanted (Yes = 1)	0.101	0.032	1,393
Influence decisions important for your work (Yes = 1)	0.035	0.036	1,393
Able to apply your own ideas (Yes = 1)	0.092	0.036	1,393
Job involves tight deadlines (Yes = 1)	0.080	0.039	1,393
Is your pace of work dependent on work done by colleagues (Yes = 1)	0.026	0.039	1,393
Is your pace of work dependent on direct demands from people (Yes = 1)	0.023	0.033	1,393
Is your pace of work dependent on automatic speed of machine/product movement (Yes = 1)	-0.023	0.040	1,393
Is your pace of work dependent on direct control of boss/client (Yes = 1)	-0.049	0.038	1,393
Do you have on-the-job-training (Yes = 1)	-0.025	0.039	1,393
Work tiring painful majority of time (Yes = 1)	-0.026	0.034	1,392
Work requires lifting majority of time (Yes = 1)	-0.015	0.019	1,292
Work requires lifting heavy loads majority of time (Yes = 1)	-0.036	0.034	1,257
Work requires sitting majority of time (Yes = 1)	0.020	0.036	619
Work requires repetitive movement majority of time (Yes = 1)	-0.032	0.038	716
Work requires dealing directly with customers majority of time (Yes = 1)	-0.043	0.048	614
Works with portable computer devices majority of time (Yes = 1)	-0.017	0.026	953
Work requires standing majority of time (Yes = 1)	-0.035	0.028	977
Works with computer majority of time (Yes = 1)	-0.021	0.049	449
Exposed to vibrations (Yes = 1)	-0.014	0.028	1,393
Exposed to loud noises (Yes = 1)	-0.022	0.027	1,392
Exposed to high temperatures (Yes = 1)	-0.066	0.035	1,392
Exposed to low temperatures (Yes = 1)	-0.057	0.034	1,393
Exposed to smoke/fumes (Yes = 1)	-0.008	0.019	1,392
Exposed to vapors (Yes = 1)	0.002	0.020	1,392
Exposed to chemicals (Yes = 1)	-0.008	0.021	1,392
Exposed to tobacco smoke (Yes = 1)	-0.038	0.023	1,393
Exposed to infectious materials (Yes = 1)	-0.032	0.028	1,393
Are you bothered by background noise (Yes = 1)	-0.018	0.039	1,223
Are you bothered by noise from coworkers (Yes = 1)	0.026	0.042	1,289
Are you bothered by crowded workspace (Yes = 1)	-0.025	0.040	1,257
Are you bothered by cramped workspace (Yes = 1)	-0.050	0.040	1,262
Are you bothered by lack of cleanliness (Yes = 1)	-0.041	0.039	1,278
Are you bothered by poor lighting (Yes = 1)	-0.017	0.030	1,283
Are you bothered by lack of natural light (Yes = 1)	-0.006	0.031	1,283
Are you bothered by heat/humidity (Yes = 1)	-0.022	0.035	1,286
Are you bothered by cold (Yes = 1)	0.023	0.037	1,285
Are you bothered by exposure to weather (Yes = 1)	0.023	0.025	1,230

Outcome variable	(1) Coefficient on log annual hours	(2) Standard error	(3) Number of observations
Are you bothered by unpleasant scents (Yes = 1)	-0.053	0.029	1,271
Are you bothered by poor ventilation (Yes = 1)	0.024	0.025	1,251
Are you bothered by lack of operabkle windows (Yes = 1)	0.035	0.033	1,178
Are you bothered by inadequate furniture (Yes = 1)	0.069	0.036	1,233
Are you bothered by inadequate equipment (Yes = 1)	-0.018	0.039	1,261
Are you bothered by inadequate toilet facilities (Yes = 1)	-0.045	0.039	1,271
Are you bothered by inadequate eating facilities (Yes = 1)	0.021	0.040	1,258
Are you bothered by unpleasant décor (Yes = 1)	0.006	0.030	1,244
Are you bothered by inadequate parking (Yes = 1)	-0.026	0.037	1,250
Are you bothered by unsafe surrounding area (Yes = 1)	-0.032	0.035	1,251
Are you bothered by lack of public transit (Yes = 1)	-0.011	0.029	1,148
How many people under your supervision (Number)	-0.808	1.267	1,390
Boss trusts you (Yes = 1)	-0.014	0.024	1,369
Boss respects you (Yes = 1)	-0.012	0.024	1,369
Boss gives praise (Yes = 1)	0.004	0.038	1,369
Boss gets people to work together (Yes = 1)	-0.086	0.029	1,369
Boss is helpful (Yes = 1)	0.001	0.041	1,369
Boss provides useful feedback (Yes = 1)	-0.016	0.037	1,369
Boss encourages & supports your development (Yes = 1)	-0.042	0.027	1,369
Employees are appreciated when done a good job (Yes = 1)	-0.058	0.039	1,369
Management trusts employees to do work well (Yes = 1)	-0.056	0.027	1,369
Conflicts are resolved fairly (Yes = 1)	-0.042	0.038	1,369
Work is distributed fairly (Yes = 1)	-0.029	0.042	1,369
There is good cooperation between you and colleagues (Yes = 1)	-0.025	0.029	1,369
Generally, employees trust management (Yes = 1)	-0.100	0.039	1,368
You like & respect your colleagues (Yes = 1)	-0.042	0.032	1,368
You have enough time to finish work (Yes = 1)	-0.112	0.032	1,393
You know expectations (Yes = 1)	-0.036	0.018	1,393
Motivated to do best (Yes = 1)	-0.051	0.025	1,393
Treated fairly (Yes = 1)	-0.034	0.036	1,393
Receive contradictory instructions (Yes = 1)	-0.016	0.029	1,393
Experience stress at work (Yes = 1)	0.111	0.037	1,393
Required to hide feelings (Yes = 1)	0.079	0.035	1,393
Treated less favorably on grounds of age/race/nationality/sex/religion/disability/sexual orientation (Yes = 1)	-0.032	0.032	1,393
Offers prospects for career advancement (Yes = 1)	-0.021	0.038	1,393
Subjected to verbal abuse (Yes = 1)	-0.012	0.035	1,393
Subjected to threats (Yes = 1)	0.002	0.013	1,393
Subjected to humilating behaviors (Yes = 1)	0.038	0.020	1,393
Subjected to bullying (Yes = 1)	0.051	0.017	1,392
Subjected to physical violence (Yes = 1)	-0.003	0.011	1,393
Work provides opportunity to use talents (Yes = 1)	-0.032	0.038	1,387
Work provides opportunity to make positive impact on community (Yes = 1)	-0.057	0.039	1,373
Work provides sense of accomplishment (Yes = 1)	0.014	0.038	1,385
Work provides goals to aspire (Yes = 1)	-0.027	0.041	1,376
Work provies satisfsaction of work well done (Yes = 1)	-0.009	0.038	1,387
Work provides feeling of doing useful work (Yes = 1)	0.015	0.037	1,386

Note: Estimates from the 2015 American Working Conditions Survey (Maestas et al., 2017). The table shows coefficients and associated standard errors 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.

Table A17: 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 Bargained Hours and Wages

Here we provide the derivations for the expression of bargained hours and wages under the parametrization introduced in Section 2. With imperfect competition, bargained hours and wages solve the following maximization problem

$$(w_{ij}^b, h_{ij}^b) = \underset{w,h}{\operatorname{argmax}}\, u_i(e,h) \text{ s.t. } R_j(h) - wh = k_j \tag{15}$$

This problem has the following first order conditions

$$\frac{\partial u_i(e_{ij}^b, h_{ij}^b)}{\partial e} = -\lambda. \tag{16}$$

$$\frac{\partial u_i(e_{ij}^b, h_{ij}^b)}{\partial e} w + \frac{\partial u_i(e_{ij}^b, h_{ij}^b)}{\partial h} = \lambda \left[\frac{\partial R_j(h_{ij}^b)}{\partial h} - w \right]. \tag{17}$$

$$R_j(h_{ij}^b) - w_{ij}^b h_{ij}^b = k_j. \tag{18}$$

Bargained hours and wages therefore must satisfy the following conditions:

$$-\frac{\frac{\partial u_i(e_{ij}^b, h_{ij}^b)}{\partial h}}{\frac{\partial u_i(e_{ij}^b, h_{ij}^b)}{\partial e}} = \frac{\partial R_j(h_{ij}^b)}{\partial h} \tag{19}$$

$$w_{ij}^b = \frac{R_j(h_{ij}^b) - k_j}{h_{ij}^b} \tag{20}$$

Note that the first equation states the MRS must equal to the marginal revenue of hours. Evaluating these two equations under the parametrization of the revenue function $R_j(h)$ proposed in Carry (2022), i.e.,

$$R_j(h) = \begin{cases} h^{\alpha} T_j & \text{if } h \leq z_j \\ z_j^{\alpha} T_j & \text{if } h > z_j. \end{cases} \tag{21}$$

and assuming that worker's utility is $u_i(w,h) = wh - \varepsilon_i h^{\mu}$ implies that, if $h_{ij}^b < z_j$,

$$\mu(h_{ij}^b)^{\mu-1}\varepsilon_i = T_j(h_{ij}^b)^{\alpha-1}\alpha. \tag{22}$$

Note that this equation coincides with equation (31) of Carry (2022). The (interior) solution for bargained logarithm of hours is therefore given by

$$\log h_{ij}^b = -\frac{\log\mu - \log(\alpha)}{\mu-\alpha} - \frac{\log\varepsilon_i}{\mu-\alpha} + \frac{\log T_j}{\mu-\alpha} \tag{23}$$

Turning to wages, letting p_j capture the firm-specific profit margin then we have that

$$w_{ij}^b = \frac{R_j(h_{ij}^b)}{h_{ij}^b}[1-p_j], \tag{24}$$

that is, the hourly wage is given by the per-hour revenue generated by the worker times a markdown that depends on the rents available to firm j, captured by firm-specific profit margin p_j. Using equation (23) we can express the wage for jobs where $h_{ij}^b < z_j$ as

$$\log w_{ij}^b = \frac{(1-\alpha)(\log u - \log\alpha)}{\mu-\alpha} + \frac{1-\alpha}{\mu-\alpha}\log\varepsilon_i + \frac{\mu-1}{\mu-\alpha}\log T_j + \log(1-p_j) \tag{25}$$

which follows a log additive formulation as the one found for hours.

B.1 Hour Constraints

If workers can freely choose hours given the wage, then hours worked are such that

$$\Gamma(w,h) \equiv \varepsilon_i\mu h^{\mu-1} - w = 0. \tag{26}$$

If a worker's hours are less then optimal, we have $\Gamma(w,h) < 0$. Conversely, if a worker's hours are more than optimal, then $\Gamma(w,h) > 0$. Let us now sign the function $\Gamma(w,h)$ when evaluated at the bargained hours and wages (h_{ij}^b, w_{ij}^b) assuming that $h_{ij}^b < z_j$.

$$
\begin{aligned}
sgn(\Gamma(w_{ij}^b, h_{ij}^b) &= sgn\{\log \varepsilon_i + \log \mu + (\mu - 1)\log(h_{ij}^b) - \log(w_{ij}^b)\} \\
\text{[using equation (24)]} &= sgn\{\log \varepsilon_i + \log \mu + (\mu - 1)\log(h_{ij}^b) - \log(T_j) - (\alpha - 1)\log(h_{ij}^b) - \log(1 - p_j)\} \\
\text{[using equation (23)]} &= sgn\{\alpha - (1 - p_j)\}
\end{aligned}
\tag{27}
$$

Intuition When workers can choose hours freely, the disutility of working an extra hour (times –1) is equal to the hourly wage. When bargaining with the employer, the disutility of working an extra hour is set equal to the marginal productivity of that extra hour—see equation (22). This implies that hour constraints arise whenever the bargained hourly wage differs from the marginal product of labor, i.e., $\frac{\partial R_j(h)}{\partial h}$. Recall that the hourly wage is set equal to the *average* productivity of labor times a wedge that is driven by the rents available to firm j, $w_{ij}^b = \frac{R_j(h)}{h}[1 - p_j]$. If the marginal increase in revenue from an extra hour is below the bargained wage—i.e., when $\alpha < 1 - p_j$—then the firm finds it optimal to constrain hours. Note that if firms make extreme markdowns ($p_j \approx 1$), then they will require their employees to work longer than their optimal hours (because the hourly wage is so low). Similarly, if the production function exhibits increasing returns to scale to hours (which is consistent with firms facing large fixed costs in hiring) then $\alpha > 1 > (1 - p_j)$, and workers will be required to work longer than their optimal hours.

For cases where $h_{ij}^b \geq z_j$, then the direction of hours constraints will depend on all the parameters of the model including z_j, T_j, and ε_i.

C Identification, Estimation, and Computation

This appendix describes provides additional details on the identification, estimation and computation of our analysis. Appendix C.1 discusses the assumption of exogenous mobility when using log hours as an outcome in an AKM specification. Appendix C.2 describes the extension of the KSS methodology that permits to derive an unbiased estimate of the variance components from different outcomes. Appendix C.3 provides details on how to compute the ranking of employers following the revealed preference approach of Sorkin (2018). Appendix C.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.

C.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 (7) as follows

$$r_{it}^h = m_{j(i,t),t}^h + \lambda_{it}^h + e_{it}^h \tag{28}$$

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 (28). 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.[55] 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 A1(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, similar to what has been found when looking

[55] For clarity, in Figure A1, 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.

at 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 A1(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 A1(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 A1(a) is lack of systematic and quantitatively large adjustments in hours in the years leading up to the job move.[56] 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.[57]

Limited Labor Supply Responses: To examine whether changes in hours following job moves reflect labor supply responses to differences between the wage policies of the old and new employ-

[56] 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 A1.

[57] 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.

ers (as opposed to differences in their hour policies), Figure A1(b) plots changes in workers' hours following job moves restricting job moves to those within the same quartile of coworkers' average wages. The resulting worker responses are very similar to those in Figure A1(a), suggesting that changes in workers' hours following a job change reflect mainly different employer hour polices.

C.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 obtained after fitting equation (7) and its counterpart for log wage rates 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 $\hat{\psi}_{j(i,t)}^w$.[58] 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

$$\begin{aligned} \log h_{it} &= X_{it}' \beta^h + r_{it}^h \\ \log w_{it} &= X_{it}' \beta^w + r_{it}^w \end{aligned} \tag{29}$$

where X_{it} stacks all the worker and firm indicators as well as the controls x_{it}; similarly $\beta^h \equiv (\alpha^{h'}, \psi^{h'}, \gamma^{h'})'$, 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,

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

let $\beta = (\beta^h, \beta^w)$.

All our estimands are variance components of the form

$$\theta = \beta' A \beta \tag{30}$$

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

$$\theta_{\psi^h, \psi^w} = \beta'(A_h' A_w)\beta \tag{31}$$

where

$$A_h = \begin{pmatrix} A_\psi \\ 0 \end{pmatrix}; \qquad A_w = \begin{pmatrix} 0 \\ A_\psi \end{pmatrix}, \tag{32}$$

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

$$A_\psi = \frac{1}{\sqrt{n}} \begin{pmatrix} 0_{1\times N} & f_{11} & 0_{1\times P} \\ 0_{1\times N} & f_{12} & 0_{1\times P} \\ \vdots & \dots & \vdots \\ 0_{1\times N} & f_{NT} & 0_{1\times P} \end{pmatrix} \tag{33}$$

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 $\sigma_{it}^{h,w} \equiv \mathrm{Cov}(r_{it}^h, r_{it}^w)$, 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 $\sigma_{it}^{h,h} \equiv \mathrm{Var}(r_{it}^h)$ 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).

$$\hat{\sigma}_{-it}^{h,h} = \log h_{it} (\log h_{it} - X_{it}' \hat{\beta}_{-it}^h) \tag{34}$$

where $\hat{\beta}^h_{-it}$ 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 :

$$\hat{\sigma}^{h,w}_{-it} = \log h_{it}(\log w_{it} - X'_{it}\hat{\beta}^w_{-it}) \tag{35}$$

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 (29) 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.[59] 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 (28).

C.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,

[59] 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.

then the latter can be identified from the following recursive equation

$$\exp(v_j) = \sum_{\ell \in \mathscr{B}_j} \omega_{\ell,j} \exp(v_\ell) \qquad j = 1, \ldots, J. \tag{36}$$

where $\omega_{\ell,j}$ is the number of workers who voluntarily move from employer ℓ to employer j (as a result of a voluntary employer-to-employer (EE) transition) divided the number of all workers who left employer j as a result of an EE transition; $\mathscr{B}_j$ is the set of employers who received a worker from employer j as a result of an employer-to-employer transition. Equation (36) 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 (36) 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 (36) 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 (36), $\{v_j\}_{j=1}^{J}$, 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 nonemployment). Under the assumption that all workers search from the same offer distribution, the resulting adjusted ranks capture the systematic component utility across different employers.

C.4 Split-Sample IV

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

$$v_j = \theta_0 + \theta_h \psi_j^h + \theta_w \psi_j^w + s'_j \gamma + \varepsilon_j. \tag{37}$$

Plugging in OLS estimates of $\{\psi_j^w, \psi_j^h\}$ in order to estimate this equation can create biases, however, because 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 (9).

D Supplementary materials, not for publication

D.1 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.[60]

Figure D7 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.[61] We then

[60]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.

[61]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.

merge the CPS information on the share of hourly workers in each sector-specific quartile to the Washington administrative data.

Figure D8(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 D8(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).

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 administrative data

$$salaried_{cq} = \alpha_c + \lambda_q + \beta \overline{bunching}_{cq} + \bar{X}_{cq}^{'}\gamma + r_{cq} \tag{38}$$

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.[62]

[62]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).

Estimating equation (38) 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 D.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 D9 shows a bar chart of average residuals by each sector and each earnings quartile. The residuals are obtained from fitting equation (38) controlling for $\overline{bunching}_{qc}$ and the sector and earnings-quartile fixed effects (corresponding to the model in column 2 in Table D.1). 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 Management).

Estimates from regression (38) 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

$$\widehat{salaried}_{ij} = \hat{\alpha}_{c(i,j)} + \hat{\lambda}_{q(i,j)} + \hat{\beta} bunching_{ij} + X_{ij}^{'} \hat{\gamma} \tag{39}$$

where $\{\hat{\alpha}, \hat{\lambda}, \hat{\beta}, \hat{\gamma}\}$ are the OLS estimates from (38) 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 (7) by dropping jobs whose associated $\widehat{salaried}_{ij}$ is in the 70th percentile of the corresponding worker-year distribution.[63] The 70th percentile is chosen to match the fact that in the CPS approximately 70% of workers are hourly workers. Table D2 presents summary statistics on the sample that excludes jobs presumed to be on a salaried basis.

[63] 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.

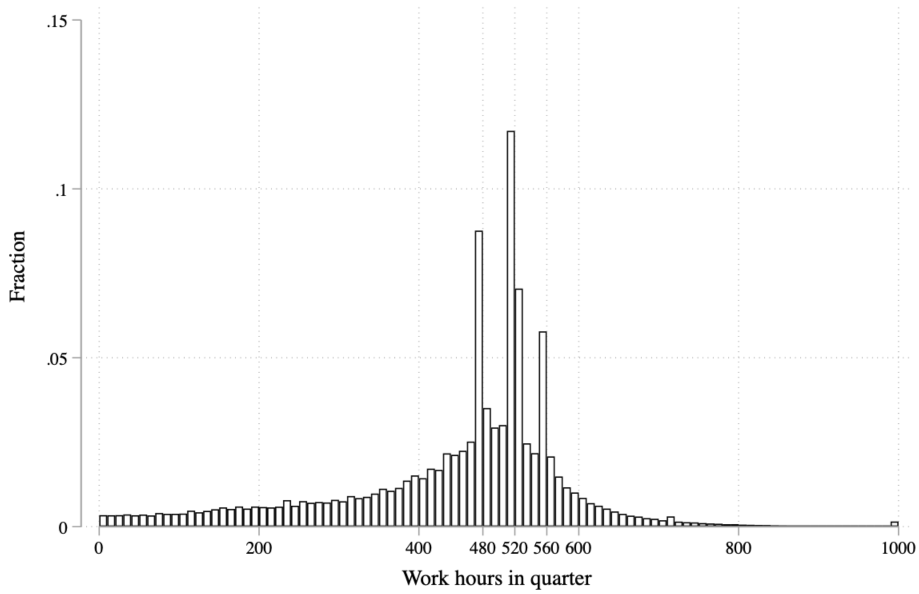
As expected, the average log wage is approximately 16 log points smaller in this sample compared to what we observe in the WA data shown in Table 1. This makes sense as salaried jobs tend to be high-paying and concentrated in high-paying sectors, such as finance. Interestingly, however, the observed 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 A7 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 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 D3. 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 5 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.

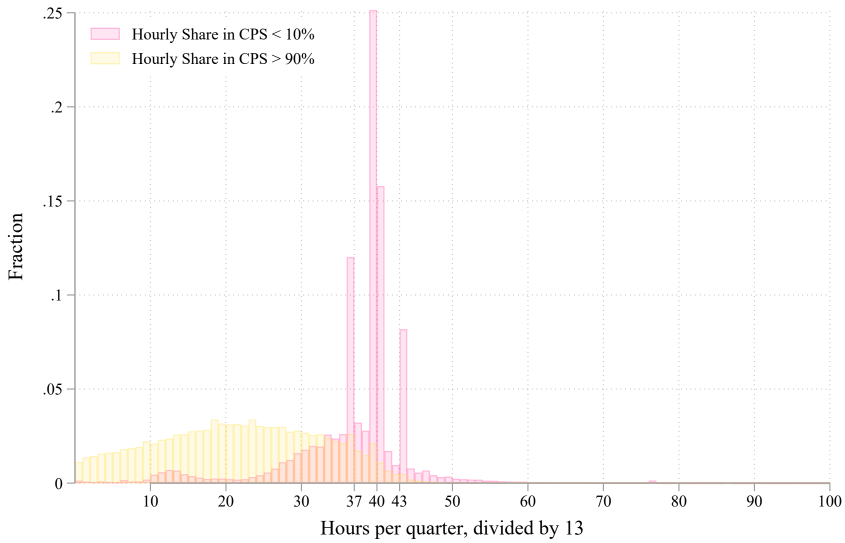
Figure D7: Distribution of quarterly work hours in full quarters and primary employment, Washington administrative records



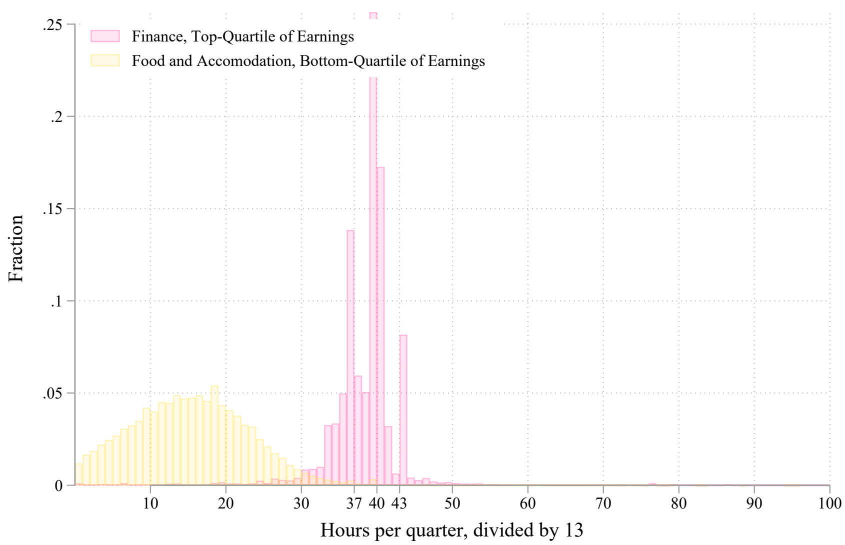
Note: The sample is restricted to worker-quarter observations representing full quarters and primary employment. Values with more than 1,000 hours per quarter are not displayed.

Figure D8: Distribution of hours worked in Washington administrative records by implied share of hourly workers according to the CPS

(a) By Corresponding Share of Hourly



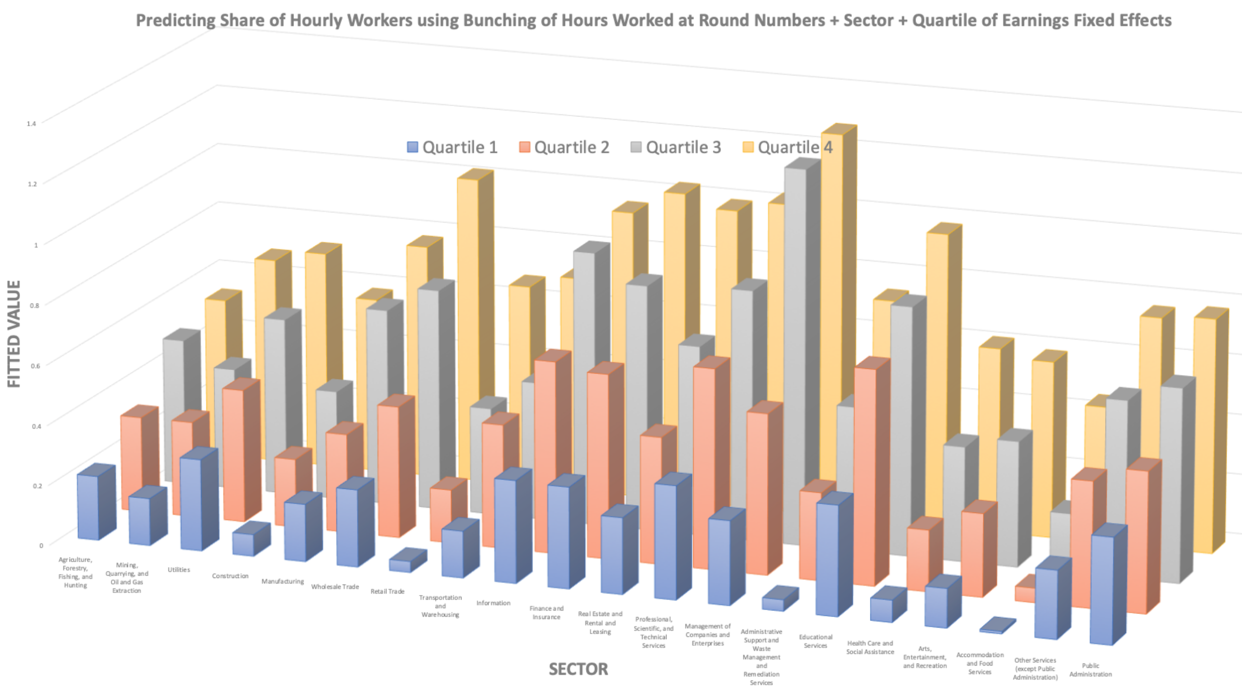
(b) By Sector



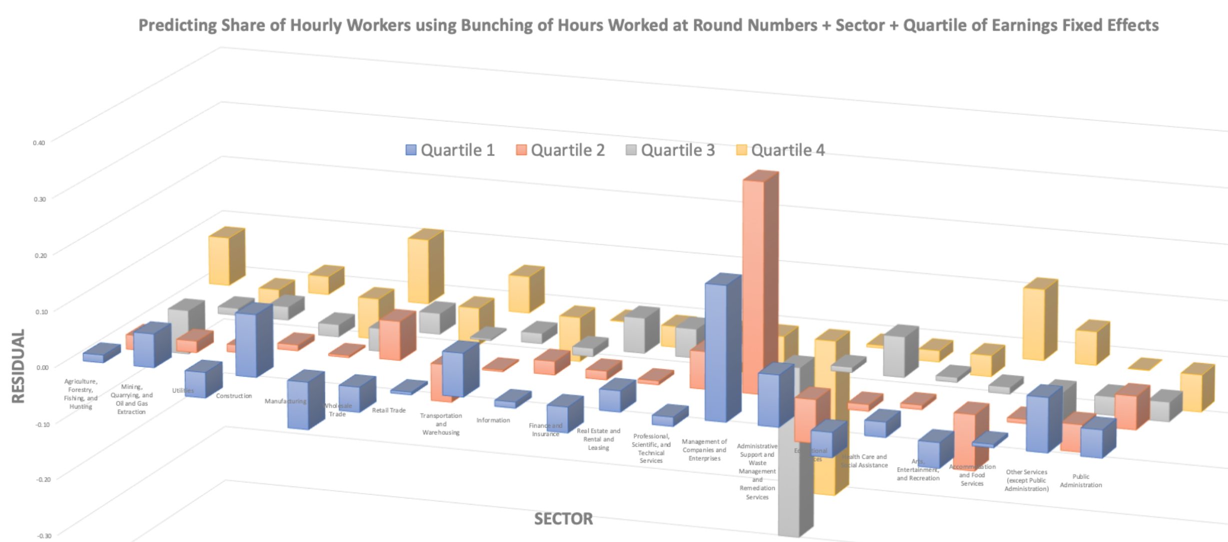
Note: We calculate the sector-by-earnings quartile share of hourly workers in the CPS and merge the shares to the Washington administrative records. We then calculate the histogram of weekly work hours worked (quarterly hours divided by 13) by whether the share of hourly workers is above 90% or below 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 D9: 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 (38) across 20 industries and 4 sector-specific quartiles of earnings.

Table D1: 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 D2: 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 D 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 D3: 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 periods 2002-2014 after excluding salaried jobs using the procedure detailed in Appendix D. 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 D4: 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

E Estimating the Relationship Between Fringe Benefits and Hours

Consider the long version of equation (9) that includes fringe benefits:

$$v_j = \theta_0 + \theta_h^L \psi_j^h + \theta_w \psi_j^w + s_j' \gamma + \sum_l \kappa_l b_{jl} + \varepsilon_j, \tag{40}$$

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:

$$\frac{\theta_h^L}{\theta_w} = \frac{\theta_h}{\theta_w} - \zeta, \tag{41}$$

where θ_h is the population parameter on ψ_j^h in the short regression version in equation (9) 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:

$$\zeta = \sum_l \frac{\kappa_l}{\theta_w} \beta_{\psi^h, b_l | \psi^w} \tag{42}$$

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:

$$\log(C_i) = B_1 \log(\text{annual income}_i) + B_2 \log(\text{annual hours}_i) + s_i'\gamma + e_i, \tag{43}$$

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 (42). 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 3.2. Specifically, the compensating variation in (12) adjusts for increases in utility that might arise for changes to fringe benefits by computing

$$CV_{b_w,b_h} = \frac{\bar{v}_{b_w,b_h^*} - \bar{v}_{b_w,b_h}}{\theta_w} - \zeta(\bar{\psi}_{b_w,b_h^*} - \bar{\psi}_{b_w,b_h^*}) \tag{44}$$

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.