Work Hours Mismatch*

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PRELIMINARY. PLEASE DO NOT CIRCULATE

Abstract

Are workers on their labor supply curve? Using employer-employee matched data we document that firms explain approximately 27% of the variability in hours, while the worker component explains only 7%. Inconsistent with standard models of work hour determination, these components are only very weakly correlated. We use a SURE-AKM regression framework to relate the worker and firm components of hours to those on wages. The resulting covariances are then fit to a model where firms with heterogenous productivity set wages and hours while labor market frictions generate dispersion in utility across employers. The model suggests that 90% of the variation in hours is due to variation in utility provisions that is orthogonal to productivity. The evidence is thus consistent with imperfect competition creating a wedge between optimal and realized hours. We conclude by quantifying the welfare loss due to firm hour constraints. For a compensated labor supply elasticity of 0.2, the average worker requires 22% higher wages at observed hours to equalize utility relative to the situation where they can freely choose hours in a perfectly competitive labor market.

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1 Introduction

There is growing acceptance that imperfect competition is a relevant feature of the labor market, and that wage markdowns are pervasive (Manning, 2021). However, the implications of firm market power may extend beyond wages. One of the most salient features of a job, other than pay, is work hours. Work hours are an interesting attribute because they can be seen both as an amenity to workers, but also as an input into production. Consider as an example a firm with high training costs that, conditional on hiring a worker, prefers to have them work many hours. The firm may find that it could increase profits if its employees were to work more hours than they are willing to at the competitive wage. Because workers are always on their labor supply curve, this is not possible. But if the firm has market power, they can increase hours to achieve this outcome.

Since the monetary amount required to compensate a worker for a deviation of hours from their optimum is proportional to the square of this deviation (Abowd and Ashenfelter, 1981), distortions in hours can, in theory, have large deleterious impacts on worker welfare. Do firms set work hours such that they are distorted relative to a competitive situation? Our goal in this paper is to assess the theoretical and empirical relevance of this phenomenon.

To achieve this goal, we make use of high-quality employer-employee matched administrative data from Washington state. A distinctive feature of these data is that in addition to earnings, they contain high-quality information on hours (Lachowska, Mas and Woodbury, 2022). We estimate firm and worker variance components of earnings, wages and hours using an extension of the Kline, Saggio and Sølvsten (2020)— KSS henceforth—methodology which permits to derive an unbiased estimator of the covariance of worker and firm effects from different outcomes.

Applying a two-way fixed effects regression to hours, we find that firms explain approximately 27 percent of the overall variation of hours while individuals explain only 7 percent of hours variation. Numerous facts suggest that constraints are a defining feature of the firm component in hours and that there is a high degree of mismatch between preferred and actual hours: 1) Higher skill workers have a preference for fewer hours, but tend to work in firms with higher hour requirements; 2) There is close to a zero correlation between an individual's preference for hours and the hour requirement of their employer; 3) The variance of firm hour requirements are counter-cyclical; 4) Workers in low-hour firms are more likely to separate and have a second job.

These findings run counter to the predictions of competitive models of labor supply. In the canonical labor supply model, hours vary because of worker preferences and responses to wage changes (Lewis, 1957). The model requires that hours are divisible, an assumption that has long been deemed unrealistic. The relevance of firms in hours determination confirms this view. There is less agreement about whether the "menu" version of the neoclassical model holds. That is, the possibility that there is a continuum of wage-hours bundle that ensure workers are always on their supply curve (Pencavel, 1986). The facts described above also cast doubt on this interpretation as well since this model predicts a high degree of sorting between worker preferences and firm requirements. Moreover, the cyclicality of the firm-hours effect suggests that there is labor hoarding–a manifestation of work hours constraints–and the differential separation and dual job holding rates point to constraints being binding for some workers.[1] A variant of the menu model developed by Chetty et al. (2011) introduces search frictions, but preserves the perfectly competitive environment with free entry of firms. The zero-profit condition ensures that the distribution of hours offered by firms reflects the distribution of worker preferences at a given wage rate. This model also predicts a high degree of sorting in hour requirements and worker preferences.

A natural alternative to the competitive models described above is one where monopsonistic employers jointly set hours and wages while facing a firm-specific labor supply curve. The latter is shaped by worker preferences over consumption as well as the dispersion of idiosyncratic tastes over different workplaces as in (Card et al., 2018). This dispersion endows employers with market power to set *both* wages and hours. Specifically, labor market imperfections create a wedge between optimal and actual work hours that arises not just because there is a wage markdown but because it is profit maximizing for firms to demand a level of hours different from what would be demanded in a perfectly competitive labor market.

To estimate the empirical relevance of this phenomenon, we consider a partial equilibrium

[1] Lachowska et al. (2021) provide evidence that dual jobholding is related to the presence of hour constraints on the main job.

model of joint wage and hours determination by firms. The model has two sources of heterogeneity: firm-specific technology which translates work hours into profit (a neoclassical motive for hour variation), and job-utility that a firm targets (an imperfect competition motive). We fit the model to the observed variance-covariance matrix of the firm component in wages and hours. The fitted model implies that 90% of the variation in hours is due to variation employer-specific utility that is orthogonal to productivity. Thus, differences in target utility across firms (the imperfect competition motive) play a far more important role in explaining variation in work hours than heterogeneity in firm-specific productivity.

We conclude by quantifying the welfare loss due to estimated firm-hour constraints. We use the compensating differentials framework of Abowd and Ashenfelter (1981) to quantify the wage required to compensate a worker if the employer-component of hours deviates from an unconstrained benchmark. For a general utility function, an approximation of this quantity depends on the constrained labor supply elasticity. We find that for a compensated labor supply elasticity of 0.2, the average worker requires 22 percent higher wages at observed hours to equalize utility relative to the situation where they can freely choose hours. This analysis suggests that hours constraints are quantitatively important.

Our paper adds to a number of literatures. It addresses a new and potentially important dimension of how firms can exercise market power, and its welfare costs through distortions in work hours. It builds on the large literature on labor supply. After the early work on the canonical labor supply model, demand-side factors have been recognized as playing an important role in hours determination. Several studies, including Ham et al. (1985), Card (1991), Blundell, Ham and Meghir (1989); Ham and Reilly (2002) have looked at how changes in hours vary as a function of industry and the unemployment rate and concluded that the wage rate is not a sufficient statistic for the demand side of the labor market as industry and business cycle variables explain labor supply. Our findings on the role of firms in hours determination are in the spirit of this approach.

We also contribute to the literature on hour constraints and adjustment costs, including Altonji and Paxson (1986) and Abowd and Card (1987) who observed that the variability in the change of hours is much higher for workers changing jobs than workers in the same job. A related literature examines the implications of workers being off of their supply curves due to hours constraints (Lewis, 1969*a*; Abbott and Ashenfelter, 1976; Abowd and Ashenfelter, 1981; Altonji and Paxson, 1986; Kinoshita, 1987 Chetty et al., 2011). For example, Chetty et al. (2011) examine the role of search costs which may limit worker mobility after changes in taxes. In their model, the equilibrium distribution of offered hours matches the distribution of worker preferences. Our paper provides a new explanation for why hour requirements may not match worker preferences, and may survive in the labor market.

Our paper also contributes to the literature on wages and earnings decompositions from matched employer-employee data (Abowd, Kramarz and Margolis, 1999; Card, Heining and Kline, 2013). Having data on hours permits us to isolate how much of the variation in firm effects in earnings is coming from the hours margin. We find that 60% of the variance of firm effect in earnings is coming from work hours. This is informative because many papers, due to data limitations, were forced to estimate AKM regression on earnings while imposing various sample restrictions in an attempt to minimize the importance of the hours margin (Song et al., 2019). Relatedly, we also show that firm effects in hours matter to explain the overall gender gap. Around 17% of the raw gap in earnings between men and women can be explained by women sorting to employers with lower hours. This finding highlights how heterogeneity in hours requirements set by firms can further expand inequalities in the labor market thus contributing to the literature that has examined the role of firms driving pay inequalities in the labor market across groups (Card, Cardoso and Kline, 2015; Sorkin, 2017; Gerard et al., 2018; Palladino, Roulet and Stabile, 2021).

A methodological contribution of this work is an extension to the KSS methodology that permits to estimate the covariance between components estimated on two different outcomes. That is, with this extension, we can compute an estimate of the correlation in, say, the firm effect in hours and the firm effects in wages that is free of measurement error or "limited mobility bias" (Abowd et al., 2004; Andrews et al., 2008). We also extend the canonical AKM specification to allow for the firm effects in hours to vary over time as proposed by Lachowska et al. (2020) and Engbom and Moser (2020).

2 Data

2.1 Matched Employer-Employee Data from Washington State

The data we use originate from quarterly administrative earnings records maintained by the Employment Security Department of Washington State for the purpose of administering the Washington's unemployment insurance (UI) system. The data used in this paper are from 2002 through 2014.

The administrative earnings records include a quarterly record for each worker-employer pair that includes:[2] an individual worker identifier, a year-quarter identifier, an employer identifier, the North American Industry Classification System (NAICS) code of the employer, the worker's earnings from that employer in that quarter, and the worker's paid work hours from that employer in that quarter.

The data include quarterly records of all UI-covered employers and workers in the state. The availability of pairing each worker with an employer in a given quarter allows us to construct a panel of linked employer-employee records. The only employers missing from this panel are employers exempt from reporting quarterly earnings and hours. These are the so-called reimbursable employers: government agencies, private non-profits, and federally recognized Indian tribes who elect to reimburse the UI agency for benefits paid to their laid off workers.[3] The workers missing from this panel are the self-employed (who do not file quarterly earnings reports) and workers in the underground economy (whose earnings are not reported). Workers who drop out of the labor force or move out of Washington state will also not appear in the records.

The availability of work hours in the administrative earnings records is a distinctive advantage of Washington State records, making it possible to construct hourly earnings in quarter t for most workers in Washington's formal labor market and the allowing to track changes in hours as workers

[2] We observe limited demographic characteristics for workers who separated from their employer, claimed UI benefits, and received it. These beneficiaries represent only about 30 percent of the panel.

[3] See Washington Administrative Code Title 192, Chapter 300, Section 060.

transition between employers. The next subsection briefly describes what the data on hours is collected, its strengths, and limitations.[4]

2.2 Paid Work Hours and Their Reliability

The administrative earnings records of most states UI systems comprise of records that typically includes a worker identifier, an employer identifier, and the worker's earnings from that employer in that quarter. However, employers in Washington State are additionally required to report each worker's quarterly paid work hours. This requirement results from Washington's practice, which is unique among the UI systems in the United States, of using work hours to determine eligibility for UI benefits. Because hours are collected for the administrative purpose of determining UI eligibility, there is reason to expect them to be of good quality. Below, we describe further what hours data are collected and from whom, and discuss evidence supporting that they are of high quality.

Employers are specifically asked to report paid hours, including regular hours, overtime hours, and hours of paid leave. 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; see Unemployment Insurance Tax Information, Employment Security Department, Washington State, October 2014 (Revised). Accordingly, the measure of hours available in Washington State administrative records reflects the total number of hours worked for which a worker was *paid*.

In many cases, employers correctly report that a worker had positive earnings and zero paid hours in the same quarter. In general, we take these reports to be accurate because the Washington Employment Security Department instructs employers to report back pay, bonuses, commissions, cafeteria and 401k plan payments, royalties and residuals, severance and separation pay, settlements, sick leave, and tips and gratuities as quarter t earnings if they were paid in quarter t, even if the worker no longer worked for the employer in that quarter (see https://esd.wa.gov/employer-

[4]For further discussion of these aspects; see Lachowska, Mas and Woodbury (2022).

taxes/zero-hour-reports, last accessed February 24, 2022).

Previous examination of employers' reporting of hours in the Washington data suggests that the reliability of hours reporting in the Washington administrative records is high; see Lachowska, Mas and Woodbury (2022). Specifically, the distributions of hours in the administrative records and Current Population Survey outgoing rotation groups (CPS) both suggest that about half of workers work approximately 40 hours per week. Furthermore, the quarter-to-quarter changes in the log of earnings are highly correlated with quarter-to-quarter changes in the log of paid hours, suggesting that the hours data are measured with little error. Finally, annual changes in Washingtonâs minimum wage rate (which is indexed) are clearly reflected in year-to-year changes in the distribution of paid hours in the administrative data.

2.3 Construction of the Analysis Data Set

In keeping with prior literature, the main analysis data set is based on annualized quarterly records tracking a worker's employment with her highest-paying employer (primary employer) in that quarter. These annualized data set are subject to the "Sorkin cut" (Sorkin 2018), which requires a series of at least five consecutive quarters during which a worker has earnings from the same primary employer. For each of these employment spells, the first quarter and the last two quarters are dropped, then the remaining quarters are annualized within a calendar year, conditional on the calendar year including at least two consecutive quarters of earnings from the same primary employer.[5]

We implment this cut because, as mentioned above, it is relatively common that employers report that a worker had positive earnings and zero paid hours in the same quarter, especially at the end of an employment spell. By dropping the last two quarters of an employment spell, we omit such cases. Furthermore, if a worker starts new employment mid-quarter, the resulting earnings and hours reported in that first quarter will be artificially low and potentially create bias when

[5]Specifically, after dropping the first quarter and the two last quarters of each employment spell, we compute the mean quarterly earnings (and hours) within each calendar year and multiply them by four. See Online Appendix Section B.1 of Lachowska, Mas and Woodbury (2019) for a discussion of other aspects of the data.

estimating firm effects. By dropping the first quarter of an employment spell, we alleviate this concern.[6]

3 Descriptive Evidence on the Role of Firms in Hours Determination

This section is intended to serve as a preview of results motivating our inquiry into understanding why employers matter in setting work hours. First, subsection 3.1 begins by estimating a standard labor supply model with coworker changes in hours as additional controls. In this regression, the elasticity of labor supply—the response of an individual's change in work hours to a change in her wage rate—is economically small, while the coworker change in work hours predicts nearly perfectly the change in individual's work hours. This is contrary to what traditional labor supply models predict. Next, subsection 3.2 shows that job-to-job transitions are associated with systematic changes in work hours explained by the labor supply of coworkers. Subsection 3.3 concludes by discussing theories that rationalize the existence of a firm-level component in hours.

3.1 The Influence of Employers in a Model of Labor Supply

The traditional tool used to analyze individual data on hours is the labor supply structural equation (e.g. Abowd and Card, 1989):

$$\Delta \log h_{it} = \eta \Delta \log w_{it} + \Delta e_{it}, \tag{1}$$

where $\Delta \log h_{it}$ represents changes in log hours from period $t-1$ to t by individual i; similarly $\Delta \log w_{it}$ captures changes in log wage base rates. Equation (1) can be obtained from neo-classical life-cycle models as in MaCurdy (1981). In these models, Δe_{it} typically captures a combination of changes in preferences, prediction error in forecasting marginal utility of consumption, and

[6]Furthermore, as in Lachowska et al. (2020), we impose several restrictions on the estimation sample, dropping the following: (a) workers with more than 9 employers in a year, (b) workers with annual earnings less than $2,850 (in 2005 dollars) and workers with calculated hourly wage rates $2.00/hour (in 2005 dollars) (following Card, Heining and Kline (2013); Sorkin (2018)), and (c) workers who worked fewer than 400 hours in the calendar year.

measurement error (Ashenfelter and Ham, 1979; MaCurdy, 1983). The parameter η represents the inter-temporal labor supply elasticity.

Estimation of equation (1) has been typically confined to either repeated cross-section or panel-data where information on employers is not available. This, however, does not necessarily represent a limitation because in a neo-classical framework employers have no role in setting hours of work (nor wages). In other words, where you work should not predict how much you work.

The matched employer-employee data permits us to test this prediction. A simple test is one where equation (1) is augmented with information on changes of hours from the *coworkers* of individual i:

$$\Delta \log h_{it} = \beta \Delta \log w_{it} + \delta \Delta \log \bar{h}_{-i,t} + \Delta v_{it}, \tag{2}$$

where $\bar{h}_{-i,t} = \frac{1}{n_{j(i,t)t} - 1} \sum_{\ell : j(\ell,t) = j(i,t)} h_{\ell t}$; $j(i,t)$ indexes the identity of worker i's employer in period t and n_{jt} is the size of employer j in period t. The neo-classical labor supply model with random sorting of workers to employers predicts that $\beta = \eta$ and $\delta = 0$. In other words, once we control for changes in the wage rate faced by individual i in period t, the average change in labor supply made by her coworkers has no predictive power on her own changes in hours.

A test of this prediction is displayed in Figure 1. There, we represent the relationship between changes in individual log hours and changes in individual log wages as well as changes in coworkers hours. These graphs are obtained by estimating equation (1) using quarterly data on job stayers, i.e. individuals who remain with their primary employer. The analysis is constrained to "full-employment" quarters[7] To account for division bias in equation (1), we instrument Δw_{it} with $\Delta \bar{w}_{-i,t}$. We also restrict estimation to employers with at least 50 workers to minimize the role of measurement error in both $\Delta \bar{w}_{-i,t}$ and $\Delta \bar{h}_{-i,t}$.

Figure 1, Panel (a) shows that δ is far from zero. In fact, δ is approximately equal to 1 and precisely estimated. Interestingly, Figure 1, Panel (b), shows that the relationship between changes

[7]A quarter q is considered a full-employment quarter if a worker is employed with the same primary employer in quarters q-1 and q+1.

in hours and changes in wages—after controlling for changes in coworkers hours— is virtually flat, returning a labor supply elasticity of -0.004.

Taken at face value, this evidence seems to contradict the neo-classical prediction that variation in worker wage rates should predict variation in worker hours while employer-level information should not matter. A simple alternative model to interpret Figure 1 is one where the employer does play a key role in setting hours. The change of hours of my coworker predicts my own change of hours since it is the employer that unilaterally decides hours of work for all its employees.

Yet, we caution against such simplistic interpretation. The discussion so far has assumed random sorting of workers to employers. It is well know that a regression of an outcome on its leave-out group-average can return a significant coefficient in the presence of non-random sorting of individuals to groups (Deaton, 1990; Angrist, 2014).[8] As a first attempt to disentangle the role of employers vs. sorting in explaining variability in hours in the WA data, we next use the event-study pioneered by Card, Heining and Kline (2013) and follow the same worker as she switches between different employers.

3.2 Job Changes and Systematic Hours Responses

If the variation in hours across firms is simply due to non-random sorting of workers to firms, then an individual who switches employers should not experience systematic changes in hours.[9] If, on the other hand, we find that hours systematically change when an individual joins a different workplace, then this suggests a firm-level component in hours variability that is potentially unrelated to sorting patterns.

Figure 2, panel(a) presents a simple event-study analysis along the lines of the one initially proposed by Card, Heining and Kline (2013) but for log hours (as opposed to log wages). Job transitions of individuals are classified according to the mean hours of other workers at origin and destination employer of a given job move. Specifically, we take all the job transitions occurred

[8]Moreover, large group size can mechanically return a coefficient of 1 when regressing an outcome on its group leave-out-average and thus cannot be used to assess the importance of group-level heterogeneity.

[9]Implicit in this argument is the assumption that wages simply reflect supply and demand factor and thus employers have no market power in setting wages (as well as hours).

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-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 based on the quartiles of coworker hours at the origin and destination employers.[10] 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.

Similarly to what has been found when looking at wages in several different countries (e.g Card, Heining and Kline, 2013; Card, Cardoso and Kline, 2015; Macis and Schivardi, 2016), Figure 2 shows that when 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. These systematic changes occur in both directions. When moving from an employer where coworkers work relatively more to a new employer where coworkers hours are systematically lower, we observe a significant reduction in hours worked by the individual. Consistent with that, Figure 2(a) shows that the levels of hours of work are significantly different according to whether the origin employer is in the first or last quartile of coworkers hours distribution, suggesting an important role in employer heterogeneity in determining hours of work.

Two other important observations are in order. First, Figure 2(a) suggests that the increase in hours worked when moving from a bottom to a top employer (1-4 transition) in terms of hours worked are roughly symmetric to the losses in hours experienced when moving in the opposite direction (4-1 transition). Table A1 confirms that this symmetry is observed across all transitions. The (approximately) symmetric changes in hours following a job move suggest that the logarithm of hours can be decomposed into the sum of a worker and firm-level component.

Second, Figure 2(a) does not show systematic and quantitatively large adjustments in hours in the year leading up to the job move. Table A1 shows that the same holds when also looking

[10]For clarity, in Figure 2, 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 all the remaining transitions. Importantly, there are not systematic adjustment in hours worked depending on the type of transitions made by the individual.

Taken together, the flat profile in the years leading to the job move, combined with the symmetric changes in hours worked mentioned before, suggest that a reasonable statistical model is one that decomposes the logarithm of hours into a worker, a firm-level component plus a time-varying residual that is uncorrelated with mobility decisions, similarly to what many have advocated to study sources of variation in log wages (Card, Heining and Kline, 2013).

3.3 Why Would There Be a Firm Component in a Worker's Labor Supply?

Before introducing the econometric framework quantifying the importance of worker- and firm-level components as well as sorting in explaining the variability of hours, we briefly discuss three theories that can predict the existence of a firm-level component in an individual's labor supply.

The first explanation is that an individual's labor supply responds to firm-specific wage premia. Hence, although in a neo-classical model, a worker's labor supply is determined by her preferences and the market wage, if the offered wage for the same individual is different across employers, (Card, Heining and Kline, 2013; Card et al., 2018; Bonhomme et al., 2020), the systematic hours response depicted in Figure 2 panel (a), could represent the systematic difference in firm-wage premia offered by the origin and destination employer times a labor supply coefficient.

According to this explanation, if we were to restrict the analysis in Figure 2, panel (a), to transitions where there are no systematic wage differences between origin and destination employers, hours responses within this subset of transitions should be close to zero. Figure 2, panel (b) tests this by plotting an event study akin to the one shown in Panel (a) but where we focus on a subset of transitions where the quartile of average of coworker log *wages* is the same between origin and destination employers. Remarkably, this event study is very similar to the one represented in Panel (a). For instance, moving from a bottom-quartile employer to a top-quartile employer in panel (a) returns a 27 log point increase in hours; whereas in panel (b), we observe a 29 log point increase. Table A1 further shows that this similarity is observed also when looking at all 4×4 types of transitions.

Interestingly, Table A1 shows that observing transitions where two employers share the same quartile of leave-out average wage but remarkably different leave-out averages in terms of hours is fairly common. For instance, there are around 11,000 job transitions where workers moved from the top to a bottom employer in terms of hours worked. For around 34% of these transitions, origin and destination employers have an identical quartile of leave-out average wages. This evidence therefore suggests that labor supply adjustments to heterogeneous firm wage premiums are potentially second-order in generating a firm-level component in hours.

A second, potentially more compelling, theory that can predict the existence of a firm-level component in hours is due Lewis (1969*b*). In this paper, Gregg Lewis, unsatisfied with the neoclassical theory that assumes that employers have no saying in determining hours of work (a theory that he himself helped developed, see Lewis, 1957), postulates the idea that employers set hours according to their technology and pay a compensating wage differential defined according to a market wage hedonic curve shaped by workers and employers preferences.[11] This model thus predicts the existence of a firm-level component in hours of work as well as a firm-level component in wages. Crucially, however, this model assumes a perfectly competitive labor market. As a result, utilities of workers across workplaces must be equalized (at the margin). This implies that the firm level component in both wages and hours need to be perfectly correlated as a result of market or "compensating" forces. Finally, as noted by Rosen (1986), the theory of equalizing differences predicts sorting of workers to firms. Firms that face the higher costs in adjusting their hours requirements tend to employ workers that have the weakest preferences for leisure.

A third, and final, theory builds from Lewis (1969*b*) but assumes that labor markets are imperfect, possibly because of workplace differentiation as in Card et al. (2018). Instead of setting hours and wages according to a market-based hedonic function mapping hours to wages, each firm sets hours and wages according to its own labor supply curve. In this model, utilities are no longer equalized across workplaces. Moreover, firms have latitude to set both wages and hours which im-

[11] Rosen (1974) later expanded and generalized Lewis (1969*b*) into what has now become the standard reference for hedonic pricing.

plies the presence of a firm-level component in both outcomes. However, the two components are no longer necessarily perfectly correlated as in standard compensating differential models (Sorkin, 2018). Understanding how much of the covariability in wages and hours is due to compensating differentials as opposed to labor market imperfections is at the center of the discussion of Section 6.

Having discussed why economic theory might predict the existence of a firm-level component in hours determination, the next section presents a two-way fixed effects model designed to capture the importance of worker and employer heterogeneity as well as sorting in determining hours of work.

4 Econometric Framework

Section 4.1 introduces the two-way fixed effect model used to disentangle worker and employer heterogeneity in work hours. Section 4.2 then introduces a seemingly unrelated regression equations (SURE) model designed to estimate the covariability in worker- and firm-level components in hours, wages, and earnings. Section 4.3 presents the estimation strategy which extends the leave-out methodology of Kline, Saggio and Sølvsten (2020)—KSS henceforth—to derive unbiased estimates in measures of covariability in worker- and firm-level components from different outcomes (e.g. the correlation between the firm level component in hours and wages).

4.1 Two-Way Regression Equation for Hours

To decompose the variability of hours into a firm- and a worker-level component, we implement the Abowd, Kramarz and Margolis (1999) (AKM) two-way fixed effects regression using the log of hours as the dependent variable.

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

where $\log h_{it}$ is the log of hours worked by worker i in year t; $j(i,t)$ indexes the identity of worker i's primary employer in year t; and x_{it} captures year effects. Equation (3) is estimated by pooling all the available years from the WA data (2002-2014).[12]

The term α_i^h captures worker's portable component of hours worked. That is, the amount of hours that individual i works irrespective of the identity of her current employer. The term $\psi_{j(i,t)}^h$ captures the systematic firm-level component in hours. It is interpreted as a proportional premium (or discount) of hours that employer j offers to all its employees. Sources that can give rise to a firm-level component in hours includes common labor supply responses to different firm wage premiums as well as heterogeneous hours requirements across firms, see the discussion in Section 3.3.

We assume that r_{it}^h can be decomposed into three components:

$$r_{it}^h = m_{j(i,t),t}^h + \lambda_{it}^h + e_{it}^h \tag{4}$$

where $m_{j(i,t),t}^h$ represents a match component in hours worked: any idiosyncratic change in hours worked 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 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., 2021). 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: Identification of 3 rests on an assumption of exogenous mobility. As detailed in Card, Heining and Kline (2013), the assumption of exogenous mobility does not rule out the possibility that workers sort to employers on the basis of $(\alpha_i^h, \{\psi_j\}_{j=1}^J)$ as well as other characteristics of the employer unrelated to hours. The assumption of exogenous mobility would be violated if

[12] We also presents results from an extension to (3) where we allow firm effects to vary over time, see also Lachowska et al. (2020).

individuals systematically sort to employers on the basis of a match effect $m^h_{j(i,t),t}$ in hours worked. This would change the interpretation of the firm effects in hours as they would no longer capture systematic differences in hours policies across employers. Following Card, Heining and Kline (2013), we note however that if workers sort to employers on the basis of $m^h_{j(i,t),t}$, we should not expect symmetric responses of the type observed in Figure 2 and Table A1. Note also that models that predicts sorting to firms on the basis of a match component in hours would also naturally predict a strong degree of assortativeness in hours between worker- and firm-level components. One of our most important results, however, is the almost complete lack of assortative matching in hours. This casts further doubts on the importance of sorting on the basis of a match component when it comes to hours worked.

Another source of potential violation of the exogenous mobility assumption is that firm-to-firm transitions are predicted by innovations to the individual portable component of hours, λ^h_{it}. These innovations change how a worker values the consumption-leisure tradeoff and as a result of these changes the worker decides to move to a different employer. This can lead to an overstatement of the importance of employer effects in hours. Importantly, this theory also predicts some systematic changes in hours worked leading up to a job transition. However, Figure 2 shows that there are no systematic trends prior to a job transition. Moreover, Table A1 shows that hours trends similarly in the original employer across all types of job transitions, casting further doubts on the importance of this source of bias.[13]

In conclusion, despite the known limitations of AKM specifications, the evidence supports the idea that a simple model that decomposes log hours into the sum of worker and firm fixed effect represents an useful empirical to tool to quantify the importance of firm heterogeneity in driving of hours of work, similarly to what many have advocated when analyzing matched employer-employee data on wages (e.g. Card, Heining and Kline, 2013) as well as earnings (e.g. Song et al., 2019).

[13]Clearly, this type of analysis does to permit to rule out cases of instantaneous changes to preferences that leads 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.

4.2 SURE-AKM for Hours, Wages, and Earnings

The AKM specification is a standard tool to assess the importance of firm heterogeneity to explain variability in wages (e.g Card, Heining and Kline, 2013; Card, Cardoso and Kline, 2015; Lachowska et al., 2020) as well as earnings (e.g. Bonhomme, Lamadon and Manresa, 2019; Song et al., 2019; Sorkin, 2018). Yet, other than in Lachowska, Mas and Woodbury (2019), the AKM specification has not been applied to decompose the variability in hours into firm- and worker-specific components nor has it been used to understand whether the firm-specific variation in hours stems from variation in earnings or hourly wage rates.

Being able to properly quantify the importance of firm heterogeneity in driving hours variability is important for a correct interpretation of AKM equations fitted to earnings. These type of regressions are often observed in the literature as many matched employer-employee datasets do not provide a measure of either days or hours worked.[14] As a result, when interpreting these AKM regressions on earnings, the underlying assumption is that the variability in ψ_j^h across firms can be ignored (Song et al., 2019). Estimation of equation (3) permits to directly test the validity of this assumption.

Relatedly, a systematic assessment of the covariability between the firm level component in wages and hours can also provide new evidence for the interpretation of firm effects in wages. The latter is typically rationalized as a combination of firm market power in wage settings and compensating differentials (Sorkin, 2018). As highlighted in Section 3.3, a potential source of compensating differentials (and therefore firm effects in wages) is due to firms requiring different hours of work. Thus, an assessment on the importance of firm-effects in hours can inform in principle how important compensating differentials for different hours requirements are in generating firm-effects in wages.

The discussion above highlights the importance of being able to estimate reliably the *covariability* between firm-level components from different outcomes (wages, earnings). Accordingly,

[14] Examples include most of the matched employer-employee data available for the US such as IRS tax data as well as data from the LEHD.

we fit a model with several AKM equations, each having its own dependent variable (log hours, log wages, and log earnings) but the same set of regressors

$$\begin{aligned}
\log h_{it} &= \alpha_i^h + \psi_{j(i,t)}^h + x_{it}'\beta^h + r_{it}^h \\
\log w_{it} &= \alpha_i^w + \psi_{j(i,t)}^w + x_{it}'\beta^w + r_{it}^w \\
\log e_{it} &= \alpha_i^e + \psi_{j(i,t)}^e + x_{it}'\beta^e + r_{it}^e
\end{aligned} \tag{5}$$

where h_{it} is log hours, w_{it} is log wages, and e_{it} is log earnings. We refer to the system of equations in (5) as the seemingly unrelated regression equations AKM (SURE-AKM). In doing so, we allow the error terms in each AKM regression to be correlated across outcomes. As detailed in the next section, this poses challenges in deriving unbiased estimates of variance components such as $Cov(\psi_{j(i,t)}^h, \psi_{j(i,t)}^w)$. We therefore introduce an extension to the leave-out methodology to estimate variance components developed by KSS in a SURE-AKM context.

4.3 Estimation of Variance Components

We seek to estimate the variance-covariance matrix of $\{(\alpha_i^h, \psi_{j(i,t)}^h), (\alpha_i^w, \psi_{j(i,t)}^w), (\alpha_i^e, \psi_{j(i,t)}^e)\}$. It is well known that estimates of these variance components obtained by replacing each firm-level and worker-level component with its OLS estimate counterpart obtained after fitting equation (5) leads to biases (Krueger and Summers, 1988; Andrews et al., 2008).

The leave-out methodology of KSS permits to derive unbiased estimates of variance components from a single AKM equation, e.g $(Var(\psi_{j(i,t)}^h), Cov(\psi_{j(i,t)}^h, \alpha_i^h), Var(\alpha_i^h))$. However, as explained at the beginning of Section 4.2, our interest also lies in variance components from different outcomes such as $Cov(\psi_{j(i,t)}^h, \psi_{j(i,t)}^w)$. However, computing this covariance using OLS estimates $(\hat{\psi}_{j(i,t)}^h, \hat{\psi}_{j(i,t)}^w)$ also leads to biases because estimation error in $\hat{\psi}_{j(i,t)}^h$ is assumed to be correlated with estimation error in $\hat{\psi}_{j(i,t)}^w$.[15] In other words, $Cov(r_{it}^h, r_{it}^w) \neq 0$ as typically assumed in SURE models.[16]

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

[16]Note that in our context a reason why error terms might be correlated across outcomes is division bias.

To derive estimates of cross-equations variance components, we extend the leave-out methodology of KSS to a SUR context. This permits to compute correlation in firm-level components obtained from different outcomes which we believe can be of great of interest also outside of labor economics (e.g. education, health).[17]

Implementation: To derive unbiased estimate of the variance components of interest, we estimate equation (5) on the leave-out connected set as defined in KSS. This 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.[18] Table A2 shows summary statistics across different samples. The leave-out connected set retains around 95% of the person-year observations observed in the largest connected set and around 67% of the firms. Summary statistics on hourly wages, hours and earnings are extremely similar between the leave-out connected set, connected set and original sample. To estimate the KSS leave-out correction on these data, we allow each error term to be serially correlated within match, consistent with the representation given in equation (4). Appendix D provides further details on the computation of the KSS correction within a SURE framework.

5 Results

5.1 Variance Decomposition of Hours

Table 1 presents results from a variance decomposition of log hours obtained after estimating (3) on the leave-out sample described in Section 4.3 and Table A2. The table reports the standard

[17]The leave-out approach is close in spirit to a split-sample approach. An unbiased estimate of $Cov(\psi^h_{j(i,t)}, \psi^w_{j(i,t)})$ can be obtained by randomly dividing the data in two samples (A and B) and estimate an AKM regression on hours from sample A and an AKM regression on wages using sample B. Taking the covariance of firm-level components from the two split samples delivers an unbiased estimate of $Cov(\psi^h_{j(i,t)}, \psi^w_{j(i,t)})$. A caveat however of the split-sample approach is that by randomly dividing the sample, one might "break" connectivity. That is, a particular firm might only be present in sample A or sample B and it is therefore excluded from computation of $Cov(\psi^h_{j(i,t)}, \psi^w_{j(i,t)})$. The leave-out methodology, and in particular the notion of the leave-out connected set derived in KSS, does not suffer from this limitation, as all firms from which it is possible to construct an unbiased estimate are included in estimation, see also Lemma 1 of KSS.

[18]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-out connected set.

deviation of person effects, standard deviation of firm effects and covariance/correlation of these two components. All variance components are estimated using the leave-out methodology of KSS to account for so-called "limited mobility biases" (Andrews et al., 2008).

Table 1 presents three interesting and novel findings. First, the worker component seems to explain little of the overall variability of hours. The standard deviation of the worker fixed effects in hours amounts to around 0.09 which implies that the variance of person effects explains around 7% of the overall observed variance of log hours. This finding casts doubts on the importance of workers' preferences in determining hours of work as predicted by an entire class of neo-classical models of labor supply (Pencavel, 2016).

The second key finding is that the employers play a substantial role in determining hours. The standard deviation of the firm effects for hours is twice as large as the one found for the worker fixed effects. Variability in firm effects explains around 27% of the overall variance in log hours. Thus, it seems that firms, as opposed to workers, play the predominant role in explaining the overall variability of hours observed across jobs.

The third and final key takeaway is the lack of assortative matching in hours. We find a correlation between the worker and firm component in hours of only 0.05. The associated covariance term (multiplied by 2) explains around 1.2% of the overall variance of log hours. As discussed in more detail in Section 6, the lack of strong correlation between the worker and firm component in hours casts doubts on the importance of compensating differential models in explaining the covariability of firm-wage and firm-hour fixed effects (Lewis, 1969*b*; Rosen, 1986).

It is useful to contrast our results on hours to what others have found when applying two-way fixed effects methods but looking at wages (e.g. Card, Heining and Kline, 2013, Lachowska et al., 2020). The typical finding is that firms explain around 10-15% of the corresponding variance of log wages while the share assigned to worker fixed effects is often of the order of 50-70%. Moreover, the implied correlation between worker and firm fixed effects tends to be larger than what found on the hours dimension and increasing overtime (Song et al., 2019). When looking at log hours, all these results are almost completely flipped: firms, not workers, are the most important factors in explaining the variability of hours and there is virtually no assortativeness between the two components.

We conclude this section with two final remarks. Table A3 stresses the importance of the KSS correction. A naive plug-in decomposition of log hours, thus without applying the KSS leave-out correction, finds that the worker effects would explain almost 45% of the overall variability of hours. Evidently, this result underlies the importance of decoupling statistical noise from the true signal present in each worker fixed effect for hours.

Related to this observation, an important takeaway from Table 1 is that the overall fit of the two-way decomposition to log hours, after properly adjusting all the resulting variance components is around 0.35. This again stand in contrast with two-way decomposition applied to wages that tend to return adjusted R^2 (which are robust only to homeskedastic error terms) and KSS-adjusted R^2 (which are robust to unrestricted heteroskedasticity and serial correlation within match) in the order of 0.85-0.90. Interestingly, estimating a one-way model with unrestricted worker-firm match effects returns an higher KSS-adjusted R^2 of the order of 0.5. Thus, around half of the variation of hours remains unexplained even after adding match effects, suggesting that a large degree of variability of hours occurs within jobs.

5.1.1 Within/Between Sector Decomposition

A simple reason for why there exists a firm-level component in log hours is heterogeneity across sectors. Hours of work of an employee working in a restaurant sector might be very different from the ones worked in the financial sector. This leads to the question: how much of the variability in the firm-component for hours reflect differences across sectors?[19]

To answer this question, we note that the variability of firm effects in log hours can be decom-

[19] Interestingly, estimating the within-sector variability in firm-effects was among one of the key research questions pursued by Abowd, Kramarz and Margolis (1999) inspired by the literature on inter-industry wage differentials (Krueger and Summers, 1988; Gibbons and Katz, 1992). Econometric and computational challenges, however, limited the possibility to answer this question in a reliable way.

posed as

$$Var[\hat{\psi}_j^h] = \underbrace{Var_s(E[\hat{\psi}_j^h|sector = s])}_{\text{Between Component}} + \underbrace{E_s(Var[\hat{\psi}_j^h|sector = s])}_{\text{Within Component}}, \tag{6}$$

where the "within component" captures how much of the overall variability in firm effects for hours is explained by the average within-sector variability in firm-effects. If the within component is relatively small relative to $Var[\hat{\psi}_j^h]$, then this means that the bulk of the variation of the firm effects is due to fixed heterogeneity across sectors, i.e. the "between" component.

Figure 3, panel(a) displays the variability of firm effects within each NAICS sector, after applying the KSS to each within-sector variance. Interestingly, we find considerable variation in firm effects within each sector. As displayed in Panel (b), which rescales each within-sector variance of firm effects by the overall within-sector variance of log hours, in some sectors (e.g Mining, Transportation or Information) firms are able to explain beyond 30% of the observed variance of hours. Averaging all the within-sector variance of firm effects, we find that the within-component highlighted in equation (6) explains 56% of the total variance of firm effects. Thus, we conclude that firm effects in hours do not simple capture fixed differences in hours requirements across sectors but even within each sector, there exists considerable heterogeneity in the firm component. [20]

5.2 Covariability in Hours, Wages and Earnings

We now turn to examine the importance of worker and firm components in hours, wages and earnings and variance-covariance structure both within and between outcomes as described by the SURE-AKM framework of equation (3). Table 2 provides the within-outcome variance decomposition. When focusing on hourly wages, firms explain a relatively small share (11%) of the total variance also in the State of Washington. It is the worker component that explains the lion share (54%) and there is a significant amount of assortativity between the two components; the

[20] Similarly, Figure B1 shows results from a projection of firm effects onto sector dummies and log firm size. Average firm effects appear larger in blue-collar sectors such Manufacturing, Utilities, etc and smaller in sectors such as retail trade and accommodation/food. Yet, the standard errors surrounding these within-sector *averages* are large, highlighting once more the importance of the within-sector component in driving the overall variability in firm effects. Figure B1 also displays that larger firms tend to have larger firm-hour effects, after controlling for differences across sectors.

correlation of worker and firm effects is approximately 0.4 and the covariance term multiplies by 2 explains 18% of the variance. Moving into earnings, here we see a variance decomposition where the firm component is again the component that explains the least (17%) of the variance. The worker component explains 34% of the variance and we find a large degree of assortativeness between the worker and firm component (correlation = 0.45).

Table 2 shows clearly that the margin where firms appear to play the most important role is hours, not wages. This leads to the question of how much of the firm effect in earnings is coming from the intensive margin and in particular by heterogeneous hours policies implemented by firms. Specifically, we can decompose

$$\underbrace{Var(\psi^{e}_{J(i,t)})}_{0.097} = \underbrace{Var(\psi^{h}_{J(i,t)})}_{0.032} + \underbrace{Var(\psi^{w}_{J(i,t)})}_{0.045} + \underbrace{2Cov(\psi^{w}_{J(i,t)}, \psi^{h}_{J(i,t)})}_{0.024} \tag{7}$$

where unbiased estimates of each component shown in (7) are also displayed in Table A4. Based on this decomposition, we conclude that 0.032+0.024 = 0.056, i.e. around 58% of the variance of firm effects in earnings is coming from the hours margin. This finding is important because often in many administrative datasets earnings from a primary employer is the only available outcome. Yet, often firm effects in earnings are interpreted as if they were in fact firm effects in wages by implicitly assuming that employers do not affect *directly* the hours margin. An assumption that seems implausible at best given the evidence presented thus far.

Variance Components Between Outcomes: Table 3 displays the correlation of firm and worker effects both within and across outcomes. Focusing on across-outcomes correlation, there exists a positive correlation—of around 0.32— between the firm component in wages and hours [21]. To what extent this correlation could represent compensating differentials, common labor supply responses to different firm-wage premiums vs. other factors is discussed in Section 6. Focusing on the person-effect dimension, we find that the correlation between the person effect in hours and

[21] This finding echoes the findings in Labanca and Pozzoli (2022), who find a positive correlation between the AKM firm effects in wages and the standard deviation of mean coworker hours–their measure of firm-hour constraints.

person effect in wages is negative. That is, individuals with an higher portable component of hours tend to receive a lower hourly wage. Interestingly, however, there exists positive assortivness between the firm component in hours and the worker level component in wages. In other words, higher skilled individuals tend to be employed by firms demanding higher hours requirements.

5.3 Firm Effects in Hours and Hours Constraints

This section discusses to what extent the presence of firm-hour fixed effects reflects that employers constrain the work hours (Altonji and Paxson, 1986; Chetty et al., 2011). To do so, we consider three corroborating pieces of evidence. The first piece documents the presence of labor hoarding. The second piece shows that separation rates are positively correlated with firm effects in hours. The third piece of evidence shows that firm effects in hours are positively correlated with dual jobholding rates.

Labor Hoarding: Firms have strong incentives to constraint hours of work when facing downturns (and are subject to potentially high turnover costs). To the extent that our firm-effects in hours relate to constraints on labor supply imposed by employers, we would then expect to see the importance of firms in determining hours of work to increase during recessions.

To test this prediction, we need a time-varying measure of firm heterogeneity. We thus estimate equation (3) separately to successive overlapping two-year intervals (2002-2003, 2003-2004, etc) and correct the interval-specific variance of firm effects via the KSS methodology, an approach labelled as Rolling-AKM (R-AKM) by Lachowska et al. (2020).

Results are displayed in Figure 4, panel (a). The variance of firm effects spikes during the Great Recession. In 2008-2009, the firm level component in hours explains around 40% of the total variance. Thus, heterogeneity in hours requirements set by firms become more important during downturns, consistent with the labor hoarding hypothesis just described. Panel (b) of Figure 4 shows that the rising importance of firms during the Great Recession is not driven by firms exiting the sample as the importance of the firm component displays a similar trend when focusing on a balanced sample of firms.

Interestingly, the degree of assortativness in hours worked between workers and firms instead *decreases* during recessions. This is consistent again with a view of the world where firms are the primary actors in determining hours and might then constraint hours of work during downturns. Workers' difficulties in substituting between different employers during recessions can then generate negative assortativness patterns, consistent with the evidence displayed in Figure 4.

Separation and Dual Jobholding Rates: If employers set hours in a perfectly competitive labor market and pay a compensating differential for their hours requirements, we would not expect firm effects in hours to significantly predict separation rates. Conversely, if these firm effects are related to hours constraints set by firms (and do not necessarily pay a compensating differential for their hours requirements), then one can expect to find a negative correlation between firm effects in hours and separation rates.

Similarly, firm-hour effects can also predict the probability that a worker has two jobs. Workers whose primary employer constraints their hours below what they want have an incentive to take on a second job; as shown in Lachowska et al. (2021). [22] Accordingly, if firm effects in hours represent employer-level hours constraints, we expect dual jobholding rates to vary negatively with firm effects in hours.

Figure 5, panel (a) displays average separation rates and firm effects in hours for a given centile of the firm-hour effects distribution. There is a robust negative correlation between these two variables. Adjusting for classical measurement in the explanatory variable, returns a slope coefficient of around -0.22. This means that a 1 standard deviation (sd) increase in firm effects for hours maps into a 4 percentage point increase in separation rates, an increase of around 20% relative to average separation rates observed in this sample.

Figure 5, panel (b) shows that firm effects in hours also predict dual jobholding rates. Firms with lower hours requirements are associated with a significant higher fraction of employees moonlighting. Around 5% of workers employed by firms in the bottom of the distribution of firm-hour

[22] Our definitions of dual jobholders and primary employer follows Lachowska et al. (2021).

effects have a secondary job. This is double the share of dual jobholders observed in the overall sample see Lachowska et al. (2021) for details. A 1 sd increase in firm effects for hours leads to a 0.7 percentage point increase in the probability to have a secondary job, an increase of around 30% relative to the observed average share of dual jobholders observed in the data.

Table 4 prints the results displayed in Figure 5 and provides further results. Column 1 prints the plug-in coefficient obtained by regressing firm separation rates on estimated firm-effects for hours. To correct for both classical and non-classical measurement error associated with this regression, we estimate this relationship using a split-sample IV strategy (Goldschmidt and Schmieder, 2017; Sorkin, 2018). Specifically, we divide all worker-firm matches randomly into two subsamples (sample A and B). We then estimate an AKM regression separately within each subsample. The subset of person-year observations from sample A where the associated employer fixed effect is identified in both subsample A and B corresponds to the sample used in Columns 2 to 4 of Table Table 4. Even after adjusting for non-classical measurement error, we still find a robust negative relationship between separation rates and firm effects in hours. The same holds when looking at the probability to hold two jobs. Controlling for firm-wage effects in Column 3 returns very similar coefficients. The same conclusion holds also when adding sector fixed effects, suggesting that the negative correlation between separation rates and firm-hour effects is not driven by unobserved differences across sectors but holds within each industry as well.

To sum up, the estimated firm-hour fixed effects ψ_j^h appear to predict well both separation rates and the probability to hold a secondary job. Together with the evidence on labor hoarding documented previously, this further suggests that these firm fixed effects in hours are potentially related to hours constraints set by employers. The fact that, even after controlling for sector fixed and wage premia, we still observe a negative relationship between separation rates and the firm component in hours further suggests that firms might not be paying a compensating differential for these hours constraints with potential large welfare costs for workers. We return to this point in Section 6.

5.4 Gender Gap in Earnings and Employer Heterogeneity in Hours

We now establish the importance of employers heterogeneity in hours determination in explaining the observed gap in (conditional) earnings between men and women. Card, Cardoso and Kline (2015) document that women are more likely to sort into employers that pay a lower wage premium. This explains a significant portion of the gender wage gap in Portugal.

The availability of earnings, hours and wages combined with associated measures of the importance of firms for each of three outcomes permits us to extend the analysis of Card, Cardoso and Kline (2015). How much of the difference in total pay between men and women is coming from the intensive labor supply margin? Are the latter explained by the fact that women sort to firms with different hours policies relative to men? Or are these differences in hours instead explained by women sorting to the same type of employers as men but then bargaining a different amount of hours?

To answer this question, we augment the SURE framework of (5) and allow the firm effects to be gender specific in each equation

$$\begin{aligned}\log h_{it} &= \alpha_i^h + \psi^h_{j(i,t),G(i)} + x'_{it}\beta^h_{G(i)} + r_{it}^{h,G(i)} \\ \log w_{it} &= \alpha_i^w + \psi^w_{j(i,t),G(i)} + x'_{it}\beta^w_{G(i)} + r_{it}^{w,G(i)} \\ \log e_{it} &= \alpha_i^e + \psi^e_{j(i,t),G(i)} + x'_{it}\beta^e_{G(i)} + r_{it}^{e,G(i)}\end{aligned} \tag{8}$$

where $G(i)$ takes value $\{F,M\}$ and thus denote the gender of worker i. Estimation of (8) permits us to run an Oaxaca decomposition (Oaxaca, 1973; Fortin, Lemieux and Firpo, 2011) on the difference between the average firm premium in earnings received by men $E[\psi^e_{j,M}|male]$ and the average firm premium in earnings received by women $E[\psi^e_{j,F}|female]$

$$\begin{aligned}E[\psi^e_{j,M}|male] - E[\psi^e_{j,F}|female] = {} & \underbrace{E[\psi^w_{j,M} - \psi^w_{j,F}|female]}_{\text{Diff. in Bargaining (Wages)}} + \underbrace{E[\psi^w_{j,M}|male] - E[\psi^w_{j,M}|female]}_{\text{Diff. in Sorting (Wages)}} + \\ & + \underbrace{E[\psi^h_{j,M} - \psi^h_{j,F}|female]}_{\text{Diff. in Bargaining (Hours)}} + \underbrace{E[\psi^h_{j,M}|male] - E[\psi^h_{j,M}|female]}_{\text{Diff. in Sorting (Hours)}}.\end{aligned} \tag{9}$$

The first two components isolate the importance of firm heterogeneity in setting hourly wages. The first component is what Card, Cardoso and Kline (2015) defines as the "bargaining component". This term captures the average differences in bargaining power obtained by computing the average difference between the firm premia in wages $\psi^w_{j,M} - \psi^w_{j,F}$ using the distribution of jobs held by women. The second term is the "sorting" component as it captures the difference in the average value of $\psi^w_{j,M}$ across jobs held by men vs. women.[23]

The last two terms isolate the importance of firm heterogeneity on the intensive margin. Just like for wages, we have bargaining component which captures the within-firm difference in hours of work between men and women across jobs held by men (do women work less hours because they bargain lower hours with their employer relative to men?). The sorting component captures the difference in the average value of $\psi^h_{j,F}$ across jobs held by men vs. women (do women work less hours because they sort to employers offering lower hours premiums?).

Implementation: Two caveats apply to this analysis. First, the importance of the bargaining component varies with the type of normalization used (the same does not apply to the sorting component). We follow Card, Cardoso and Kline (2015) and normalize the firm effects relative to the Accommodation/Restaurant sector for the purpose of this exercise. Second, we can only estimate equation (8) within the subset of workers that received at least one UI payment as information on gender is only available for this particular population. This subsample is described in Table A2. We can measure demographic characteristics for about a third of the WA data. Being a sample of UI recipients, average wage and earnings are lower compared to what we observe at baseline. Interestingly, hours are instead slightly higher. These summary stats remain fairly constant when pruning the data to arrive at the leave-out connected set.

Results: Table A5 displays results after fitting equation 8 separately by gender. Within each sample, we find that firms, similarly to what shown when estimating the pooled model, explain the

[23] We will also report results from the equivalent decomposition that weights the bargaining component using the distribution of jobs held by men and uses $\psi^w_{j,F}$ and $\psi^h_{j,M}$ to compute the sorting component for both hours and wages.

larger share of the variance (28% for men, 22% for women) while the importance of covariance term remains very limited.

Table 5 displays the Oaxaca decomposition highlighted in equation (9). The latter is computed within the sample where we have demographic information and we have identified, for a given employer, both its male- and female-specific firm effect. We observe a gender gap in earnings of around 30 log points. This gender gap is thus close to the 33 log points difference analyzed by Sorkin (2017) using US data available from the Longitudinal Employer Household Dynamics (LEHD) database. Differences in average firm wage premiums explains roughly 50% of the raw gap while differences in firm hours premiums explain an additional 13%. Evidently, firms and in particular firm-wage policies play a key role in explaining gender differences within UI recipients in the WA state.

How important are the sorting and bargaining channel? When focusing on hours, we find that the importance of firms comes from the sorting margin, i.e. 17% of the raw gap in earnings can be explained by men sorting to firms with higher hours requirements.[24] The bargaining component enters with a negative sign in the decomposition albeit its overall contribution appears quantitatively small. The analysis thus rejects the idea of women bargaining lower hours relative to men from a given employer.

The relative importance of the sorting and bargaining channel is different when looking at wages. Here we find the bargaining component playing a much more important role. Almost 50% of the difference in the firm wage premium between men and women is explained by the bargaining channel.[25] This contrasts with Card, Cardoso and Kline (2015) who find a share of around 30% within Portugal when decomposing differences in average (daily) firm wage premiums. We do not have the data to investigate whether this result extends beyond a sample of UI recipients which might therefore highlight interesting differences between the European and American wage

[24] Sorkin (2017) finds that the sorting component associated to firm premiums in earnings explain around 25% of the overall gender gap in earnings while we find to be around 33%.

[25] Table A6 shows the decomposition when using the alternative Oaxaca decomposition (i.e. weighting the bargaining coefficient by the distribution of jobs held by men and using $\psi^{h}_{j,F}$ and $\psi^{w}_{j,F}$ to compute the sorting component) and we find an even larger bargaining component.

structures. Nevertheless, we view this as an interesting finding that has the potential to stimulate further research.

Finally we note that the decomposition appears relatively stable over time. When applying the decomposition across different age groups, we find a gender gap increasing overtime consistent with what the literature has typically found with a rising importance of the sorting coefficient (e.g. Palladino, Roulet and Stabile, 2021).

6 Hours Determination in Imperfect Labor Markets

As discussed in Section 3.3, a possible reason why the analysis detects the presence of a firm component is because employers set hours of work and then pay a compensating differential for their hours requirements. This idea traces back to Lewis (1969*b*) market hedonic wage curve and it has been further expanded in several dimensions (e.g. Rosen, 1974; Abowd and Ashenfelter, 1981; Rosen, 1986).

Traditionally, the theory of compensating differentials is presented under an assumption of perfectly competitive labor markets so that utilities are equalized (on the margin) across workplaces. This leads to the prediction that the firm component in hours and the firm component in wages should be perfectly correlated. Clearly, this prediction is rejected by the data. The correlation between the firm component in hours and the one in wages is around 0.3.

This result therefore suggests that firms might set hours without necessarily paying the corresponding wage that would require workers to be on their labor supply curve. However, quantifying how much rents or labor market imperfections matter in the determination of hours is challenging without a model that can rationalize how firms set hours and wages.

We thus present a simple partial equilibrium framework where firms are heterogeneous in their technology, θ_j, and level of utility provided to workers, V_j. We then show that knowledge of (ψ_j^w, ψ_j^h) permits to isolate the importance of "Residualized Rents" which we define as the component of V_j, and thus of labor market imperfections, that is orthogonal to a firm's technology.

This result (and framework) complements the one analyzed by Sorkin (2018). He considers a setup where the researcher has data on total pay, ψ_j^e, and V_j (but not on the specific amenity offered by the firm, a_j) and showed that it was possible to derive the importance of (residualized) compensating differentials in total pay. We have data on the firm component on wages and hours but not on V_j. Yet, since hours can be in fact treated as an amenity, this permits us to identify the importance of labor market imperfections in setting hours of work.

The argument is presented in Section 6.1. Appendix F extends the analysis presented here by considering a more general model of an imperfect labor market where workers hold idiosyncratic preferences over workplaces, as in Card et al. (2018), which give firms latitude to set up not only wages but also hours of work.

6.1 Identifying the Importance of Rents in Setting Hours of Work

Assume that workers derive utility from working for employer j given by

$$U_j = \psi_j^w + (1-\gamma)\psi_j^h \tag{10}$$

where $\gamma \neq 1$ is a parameter that captures disutility from work. Employers set wages and hours to maximize profits according to

$$\pi_j = \tilde{\theta}_j \exp(\psi_j^h) - \exp(\psi_j^h + \psi_j^w) \tag{11}$$

subject to $U_j = V_j$, where V_j is the desired level of utility provision set by employer j (Hwang, Mortensen and Reed, 1998); the parameter $\tilde{\theta}_j > 0$ captures how a specified level of hours worked set by the firm, $\exp(\psi_j^h)$, maps into revenues (Pencavel, 2018). We allow for an arbitrary correlation between V_j and $\theta_j \equiv \log(\tilde{\theta}_j)$.

Profit maximization leads to the following data generating processes (DGP) for wages and hours

$$\psi_j^w = \theta_j - \log(\gamma) \tag{12}$$

$$\psi_j^h = \frac{1}{1-\gamma}[V_j - \theta_j + \log(\gamma)] \tag{13}$$

Now consider the best linear projection of V_j onto θ_j (after normalizing both latent factors to have mean zero)

$$V_j = \beta\theta_j + v_j$$

The term v_j is by construction uncorrelated with θ_j and represents the component of the variance of V_j that is not explained by θ_j. In words: the term v_j isolates the component of rents that is unrelated to technology. We can then rewrite equation (13) as

$$\psi_j^h = \frac{\beta-1}{1-\gamma}\theta_j + \frac{1}{1-\gamma}v_j + \frac{\log(\gamma)}{1-\gamma} \tag{14}$$

which leads to the following decomposition of $\text{Var}(\psi_j^h)$

$$\text{Var}(\psi_j^h) = \left(\frac{\beta-1}{1-\gamma}\right)^2 \text{Var}(\theta_j) + \frac{1}{(1-\gamma)^2}\text{Var}(v_j). \tag{15}$$

Thus, $\frac{1}{(1-\gamma)^2}\text{Var}(v_j)$ captures the importance of labor market rents—not generated by technological differences across firms—in explaining the overall variation in hours requirements set by firms. Our key result is that we can identify this term as the variance of the residual obtained after projecting firm hours effects onto firm wage effects. That is

$$Var(\psi_j^h) - \eta^2 Var(\psi_j^w) = \frac{1}{(1-\gamma)^2}Var(v_j)$$

where $\eta \equiv \frac{Cov(\psi_j^w, \psi_j^h)}{Var(\psi_j^w)} = \frac{\beta-1}{1-\gamma}$. The proof of this result is shown in Appendix E. The intuition is as follows: given the DGP in equation (12), we know that technological differences are identified, up to a constant, by ψ_j^w. Given the latter, once can treat equation (14) as a regression where the unobserved error, $\frac{1}{1-\gamma}v_j$, is uncorrelated with the regressor, ψ_j^w. Therefore, running a regression of ψ_j^h onto ψ_j^w permits to identify the variance component $\frac{1}{(1-\gamma)^2}\text{Var}(v_j)$.

6.2 Quantifying the Role of Rents

The discussion above highlights that deviations of realized firm hours premiums/discounts from the linear fit obtained using firm wage premiums/discounts isolates the importance of rents. This concept is visualized in Figure 6. The figure presents a binscatter plot of $\hat{\psi}_j^h$ onto $\hat{\psi}_j^w$. The regression slope identifies $\frac{\beta-1}{1-\gamma}$. Correlation between technology, θ_j and rents, V_j, prevents this regression to identify the rate at which differences in technology map into wages while holding constant V_j, i.e. the compensating differential channel.[26]

Nevertheless, deviations of $\hat{\psi}_j^h$ from its best linear fit identifies the importance of (residualized) rents, $\dfrac{1}{1-\gamma}v_j$. The magnitude of these deviations are represented by the lines which plots $\hat{\psi}_j^h \pm$ the standard deviation of $\hat{\psi}_j^h$ within a particular bin of $\hat{\psi}_j^w$. This captures the variability of hours requirements across firms that share the same level firm-wage premium and thus technology.[27] According to the model described above, this variability represents dispersion in utility across these employers, and thus the importance of rents in generating hours variability.

Using the leave-out adjusted variance components from Table A4, we have that $Var(\psi_j^h) = 0.032$, $Var(\psi_j^w) = 0.0448$ and $Cov(\psi_j^w, \psi_j^h) = 0.0122$. This implies that $\eta = 0.2729$ and therefore $\dfrac{1}{(1-\gamma)^2}Var(v_j) = 0.0286$ or that 90% of the overall variability in firm-hour effects is reflected in variation in rents while holding technology constant.

7 Discussion on Welfare

The previous section establishes that most of the variation in hours requirements set by firms is not driven by "market" or compensating differential motives. But how d. This section tries to provide an estimate of the welfare loss induced by workers by quantifying the distance between the observed wage premium paid by firms and the one that employees would receive in a perfectly competitive labor market. This distance is computed by providing a mapping between the

[26]This is what Sorkin (2018) defines as "Rosen Motives".

[27]We used the same intuition back when proving descriptive facts on the importance of firms in determining hours, see Figure 2, Panel(b).

AKM firm wage and hours premiums with the compensating differential wage equation derived by Abowd and Ashenfelter (1981).

Suppose there are $J+1$ employers indexed by $j = \{0,1,\ldots J\}$ and workers indexed by $i = \{1,\ldots,N\}$. There exists one competitive sector, indexed by $j = 0$, where each worker i freely chooses hours at a competitive wage w_{i0}. Let the optimal amount of hours worked in this sector by worker i be h_{i0}. All remaining J employers set hours, h_{ij}, based on their own technology/preferences and pay a compensating wage given by w_{ij}.

The utility function of the worker is given by $u(c, T-h)$ where c is a consumption good (with price p) and T is total available time.[28] Notice that utility is not indexed by j. This implies that employers are all perfectly substitutable in the eyes of workers. The equilibrium wage w_{ij} therefore must be set such that

$$\underbrace{V(w_{ij}, p, w_{ij}h_{ij} + y_i)}_{\text{Utility from job where hours are set by employer } j} = \underbrace{V(w_{i0}, p, w_{i0}h_{i0} + y_i)}_{\text{Utility from job where hours are chosen by the worker}} \tag{16}$$

where $V(w, p, y)$ represents the indirect utility function, and y_i is non-labor income. Abowd and Ashenfelter (1981) showed that, given the equilibrium condition (16), and applying a second-order Taylor expansion around h_{i0}, the compensating wage paid by employer j is proportional to the squared difference between the hours required by employer j, h_{ij}, and the hours worked by the employee in the competitive sector where she can freely choose hours, h_{i0}. Specifically,

$$\frac{w_{ij} - w_{i0}}{w_{i0}} \approx \frac{1}{2\varepsilon^c} \left(\frac{h_{ij} - h_{i0}}{h_{i0}} \right)^2 \frac{h_{i0}}{h_{ij}}, \tag{17}$$

where ε^c is the compensated (Hicksian) labor supply elasticity. Notice that a low capability of substituting leisure with consumption (low ε^c) implies a large sensitivity of wage differentials to deviations in hours. For instance, suppose that employer j requires worker i to work 20% more compared to what she would work in the competitive sector. Assuming a compensated labor

[28] The utility function is assumed to be strictly quasi-concave and two times continuously differentiable.

supply of $\varepsilon^c = 0.2$, then this implies that, under perfect competition, employer j must pay worker i's $2.5 \times 0.20^2 \times (1+0.20)^{-1} = 8\%$ more than her market wage to compensate her for being off her labor supply curve.

Mapping to Firm Wage, Hours Premiums: Equation (17) relates the proportional increase/decrease in hours required by employer j to an employer specific wage premium. Under a log-additive DGP where $\log h_{ij} = \alpha_i^h + \psi_j^h$ where $\psi_0^h = 0$and $\log w_{ij} = \alpha_i^w + \psi_j^w$, equation (17) can be then approximated by

$$\psi_j^w \approx \frac{1}{2\varepsilon^c} \frac{(\psi_j^h)^2}{1+\psi_j^h}. \tag{18}$$

Normalization: The mapping of equation (17) to the data requires us to correctly identify a firm or set of firms where workers freely choose hours. Our preferred normalization imposes that the firm-hour fixed effects are on average equal to zero in firms that display the highest degree of variability in hours across its employees. That is, we compute for each firm the within-firm dispersion of hours across workers and derive centiles of this measure. We then normalize the firm effects for hours relative to the average firm effect found in the 100th centile of the within-firm dispersion of hours (Labanca and Pozzoli, 2022). Note that firms belonging to this centile correspond to firms with the highest within-firm variability of hours across workers and thus may be thought as employers where workers can choose more freely hours based on their preferences and wages rates. As an alternative, we normalize the firm effects relative to the average firm effect found in firms that have 90% of more of its employees working for them as a secondary job. The idea is that these employers, as they tend to represent the employer from a secondary job, are used by workers for moonlighting purposes and are chosen precisely because workers in these jobs can choose hours more freely and get closer to their preferred hours-leisure tradeoff.

Estimation: Estimation of (18) presents the challenge that $\phi_j \equiv \dfrac{(\psi_j^h)^2}{1+\psi_j^h}$ is a non-linear transformation of ψ_j^h. We have an unbiased but noisy measure of ψ_j^w given from its OLS counterpart.

To mitigate potential issues due to measurement error in driving the relationship between the firm wage premium and ϕ_j, we divide the data in 100 equally size bins based from the estimated normalized firm effects and compute this relationship in the binned data. This gives us an estimate of the rate at which normalized squared deviations in hours requirements made by firms map into firm-wage premiums. To quantify whether firm under/over pay for their hours requirements, we then contrast the estimated relationship between ψ_j^w and ϕ_j to what a researcher would predict with prior knowledge of ε_c, the compensated labor supply elasticity. An enormous literature has tried to estimate this parameter Bargain, Orsini and Peichl (2014). We use two benchmarks. One based from the meta analysis of (Bargain, Orsini and Peichl, 2014) who find a compensated elasticity of around 0.2. The second is based from the experimental evidence of Mas and Pallais (2019) who find $\varepsilon^c = 0.5$.

Results: Figure 7 presents the results. Regressing ψ_j^w on ϕ_j calculated from the binned data returns a coefficient of 0.75. To interpret this coefficient, take a firm requiring a 20% deviation in hours. According to the slope just described, this firm pays on average a premium of $0.75 \times 0.2^2(1+0.2)^{-1}$=2.5%. However, in a perfectly competitive model with $\varepsilon^c = 0.2$, the firm would need to pay a 8% wage premium. The difference between the red line and two locues thus captures the degree of underpay observed in the data. Averaging the difference between the red line and two hypothetical locus displayed in Figure 7 returns an average degree of underpayment equal to 22% in the case where workers have a small elasticity ($\varepsilon^c = 0.2$). The same number shirnks to 3% if workers are assumed to be fairly elastic, $\varepsilon^c = 0.5$.

8 Conclusions

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9 Tables

Table 1: 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		
Std. of Firm Effects	0.18	26.81%
Std. of Worker Effects	0.09	7.19%
Covariance of Worker, Firm Effects	0.00	1.27%
Correlation of Worker, Firm Effects	0.05	

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 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 2: Variance Decomposition of Hours, Wages and Earnings

	Log Hours		Log Wages		Log Earnings	
Std. of Outcome	0.35		0.64		0.76	
Variance Decomposition						
Std. of Firm 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, Firm Effs	0.00	1.27%	0.04	18.67%	0.06	21.75%
Correlation of Worker, Firm Effs	0.05		0.38		0.45	

Note: This table reports the variance decomposition based on a SURE-AKM model on log hours, log hourly wage and log earnings using the WA data over the perioods 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). Leave-out correction based on a "leave-match-out" approach, see text for details. All statistics are person-year weighted.

Table 3: Correlation Matrix in Firm/Person Effects, Between/Within Outcomes

	Log Wages		Log Hours		Log Earnings	
	Person Effect	Firm Effect	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages						
Person Effect	1.0000	0.3823	-0.1484	0.2971	1.0000	0.4224
Firm Effect		1.0000	-0.0559	0.3232	0.3929	0.8541
Log Hours						
Person Effect			1.0000	0.0456	-0.3526	0.0305
Firm Effect				1.0000	0.3375	0.7553
Log Earnings						
Person Effect					1.0000	0.4543
Firm Effect						1.0000

Note: This table reports the correlation matrix between the worker and firm component based from an AKM-SURE fit on log hours, log hourly wage and log earnings using the WA data over the perioods 2002-2014. 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 4: Relantionship between Firm Effects in Hours and Separation/Dual Job Holding Rates

	Leave Out Sample	Split-Sample	Split-Sample	Split-Sample
	[1]	[2]	[3]	[4]
Outcome: Separation Rates				
Firm Effect in Hours	-0.1743***	-0.2058***	-0.1685***	-0.1404***
	(0.0223)	(0.0293)	(0.0243)	(0.0279)
Outcome: Dual Job Holding Rates				
Firm Effect in Hours	-0.0334***	-0.0374***	-0.0333***	-0.0260***
	(0.0029)	(0.0032)	(0.0027)	(0.0029)
Number of Person-Year Observations	22369110	10369037	10369037	10369037
Controlling for Firm Effects in Wages	no	no	yes	yes
Controlling for Sector Fixed Effects	no	no	no	yes
Method	Plug-in	Split-Sample IV	Split-Sample IV	Split-Sample IV

Note: This table shows the relationship between separation and dual job holding rates with respect to the firm-hours fixed effects. In Column 1, the sample is the leave-out sample described in Table A.2 (omitting the last year for which we have data as we cannot measure separation there). The sample in Columns 2 to 4 represents a connected split-sample. That is, we start by dividing all worker-firm matches randomly into two subsamples (sample A and B). We then estimate an AKM model separately within each subsample. The subset of person-year observations from sample A where the associated employer fixed effect is identified in both subsample A and B corresponds to the sample used in Columns 2 to 4. We use this sample to run a split-sample IV/2SLS strategy. That is, when projecting separation or dual job holding onto firm-hour effects, we instrument the latter with the quantity estimated from the leave-out subsample. This permits to adjusts for non-classical measurement error in the firm-hours fixed effects. When the regression controls for firm-wage fixed effects, we include as an additional instrument also the firm-wage effect estimated from the leave-out sample. Separation is a dummy equal to 1 if a worker has a different dominant employer in t+1. Dual job holding is a dummy equal to 1 if the worker is holding two contemporaneous jobs (the firm-hour effects is the one associated with the employer that pays the most the individual in that year). All standard errors are clustered at the firm level.

Table 5: Oaxaca Decomposition of the Gender Gap in Earnings according to Firm Effects in Wages and Hours

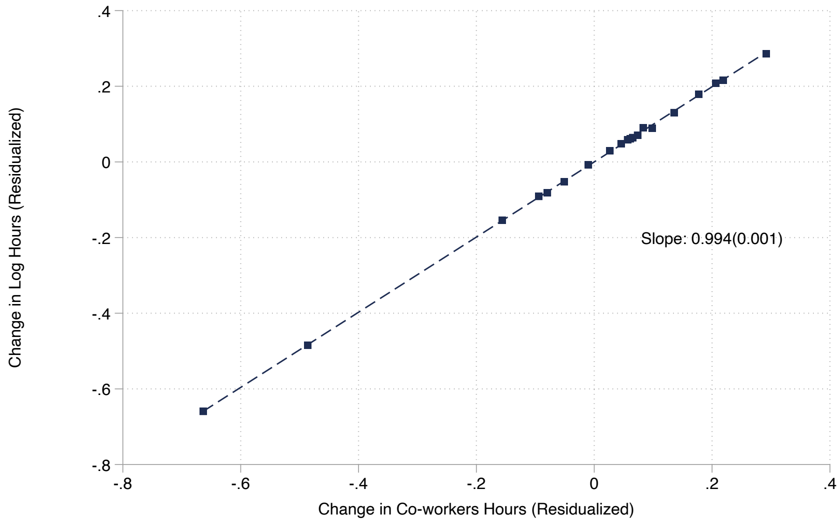
		Mean Firm Wage		Mean Firm Hours		Oaxaca Decomposition: Wages		Oaxaca Decomposition: Hours	
	Gender Gap in Earnings	Men	Women	Men	Women	Sorting	Barg.	Sorting	Barg.
All	0.299	0.227	0.077	0.298	0.263	0.081	0.070	0.051	-0.015
By Different Age Groups									
Age <=30	0.224	0.157	0.034	0.266	0.230	0.064	0.059	0.057	-0.021
Age in (30;40]	0.301	0.249	0.097	0.308	0.277	0.080	0.072	0.045	-0.015
Age >40	0.342	0.252	0.088	0.310	0.272	0.090	0.074	0.051	-0.012
By Different Periods									
2002-2006	0.298	0.227	0.085	0.286	0.255	0.074	0.068	0.048	-0.018
2007-2010	0.301	0.229	0.074	0.298	0.262	0.085	0.070	0.051	-0.015
2011-2014	0.298	0.224	0.069	0.314	0.272	0.084	0.071	0.054	-0.012

Note: This table reports results from an Oaxaca decomposition of the gender gap in Earnings. We start by taking the gender gap in firm-premia in earnings between men and women. The latter can be written as the sum of the firm premia in wages and hours. We then decompose each wage and hours component into a sorting channel and a bargaining channel, see text for details. Each row denotes a different group to which we apply the Oaxaca decomposition. All firm effects have been normalized relative to the Accomodation-Food sector as in Card, Cardoso and Kline (2016). The underlying sample corresponds to person-year observations of workers in WA who received at some point a UI check (for whom we have demographic characteristics) and whose corresponding employer belongs to the dual connected set, i.e. we can identify its male-specific and female-specific firm effect in the corresponding leave-out sample. This corresponds to a sample with 7,860,836 person-year observations, 1,316,246 workers and 37,058 (dual-connected) firms.

10 Figures

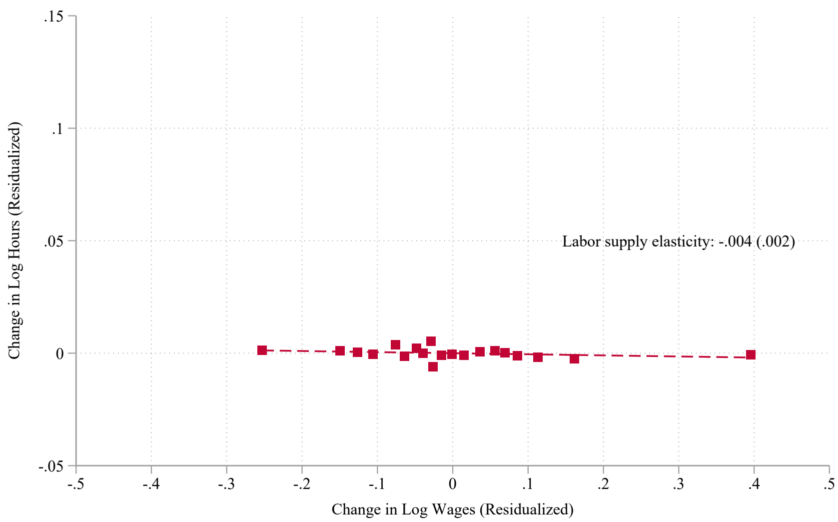
Figure 1: Labor Supply Models with Matched Employer-Employee Data

(a) Changes in coworkers Hours



Each dot corresponds to a vingtile of the coworkers change in hours

(b) Changes in Log Wages (Instrumented)

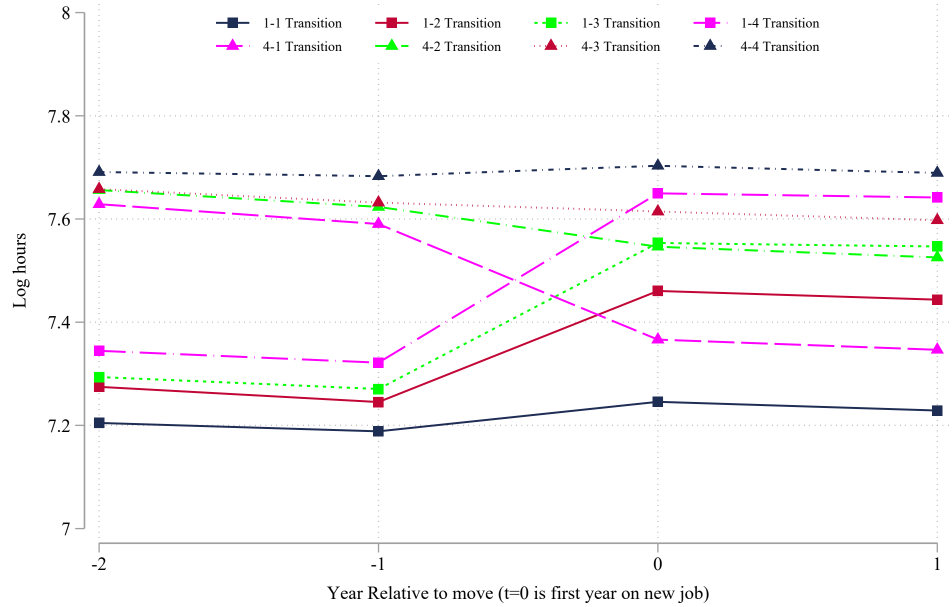


Each dot corresponds to a vingtile of the coworkers change in wage

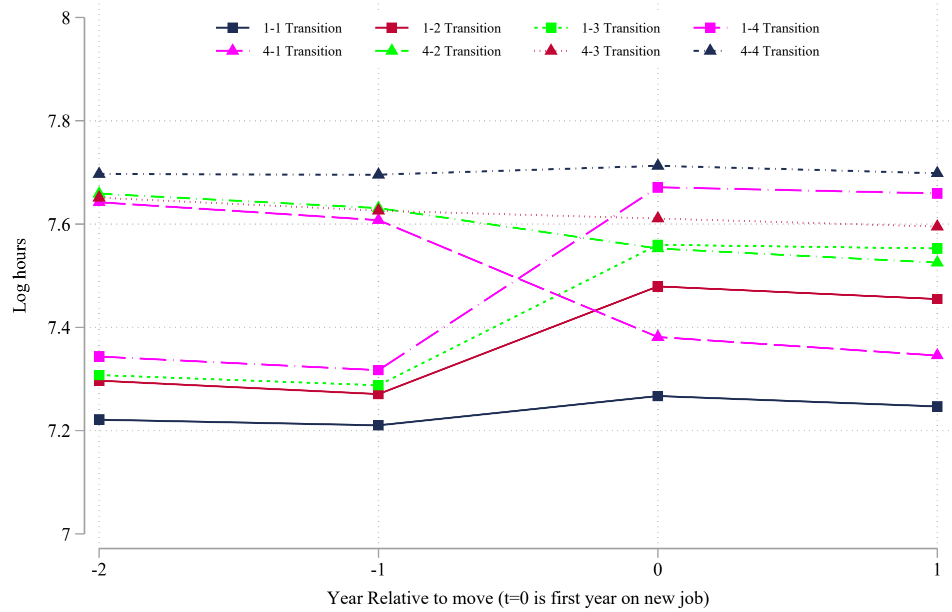
Note: This figure captures the relationship between changes in individual log hours, changes in individual log wages and average changes in coworkers log hours, see equation (2). To account for division bias in equation (2), the change to an individual's wage is instrumented with average changes in coworkers log wages. Panel (a) presents a binscatter plot between changes in individual hours and changes in coworkers hours, where both variables have been residualized against quarter-year effects as well as $\beta \Delta w_{it}$ where β is estimated instrumenting Δw_{it} with leave-out changes in wages, $\Delta \bar{w}_{-it}$. Similarly, Panel(b) presents a binscatter plot between changes in individual hours and changes in individual wages, where both variables have been residualized against quarter-year effects and leave-out changes in hours from coworkers and average within 20 equally size bins of coworkers change in wages. Both panels reports estimates of δ (Panel a) and β (Panel (b)) from equation (2). Equation (2) is estimated on full-employment quarters for stayers only and where employer size is greater or equal to 50.

Figure 2: Job Switching and Hours responses

(a) Baseline Event Study

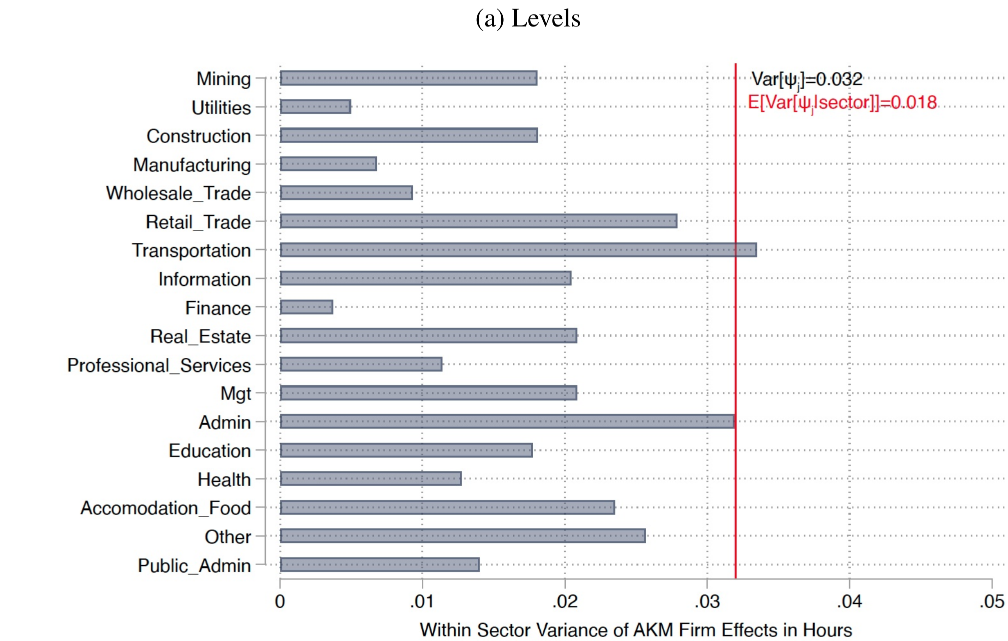


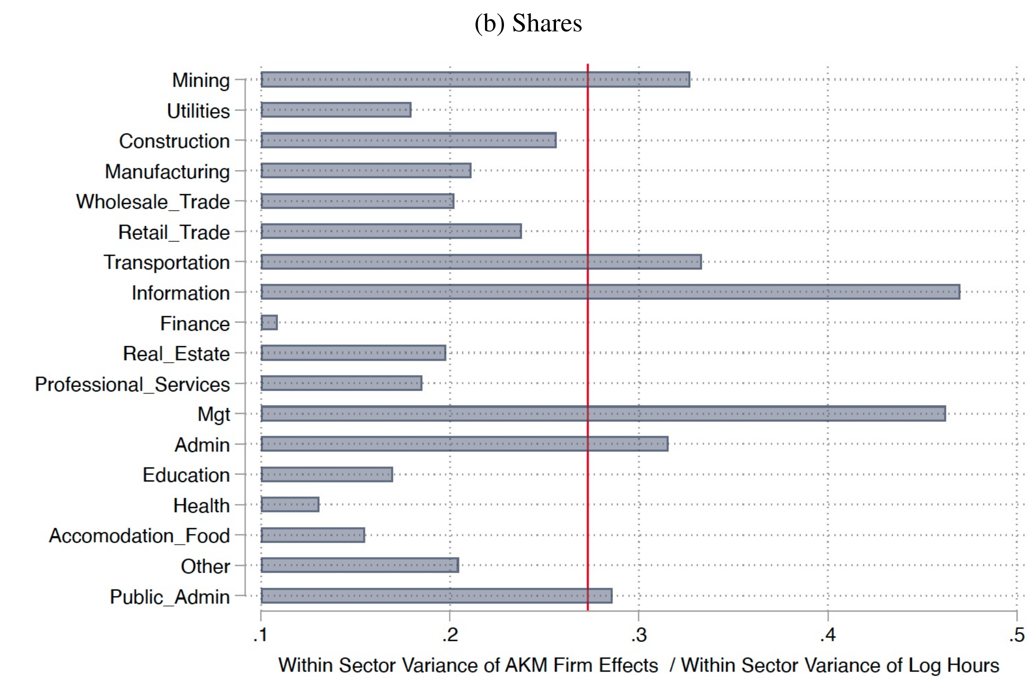
(b) Same quartiles in coworkers wages in origin and destination job



Note: This graph is constructed using all the job transitions 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. For each transition, we calculate quartiles of the leave-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 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 where the origin employer is either in the bottom or in the top quartile of the coworkers hours distribution. Panel (b) is similar but we restrict attention to transitions where origin and destination employers share the same quartile in average coworkers wage distribution.

Figure 3: Within-Sector Variability of Firm Effects

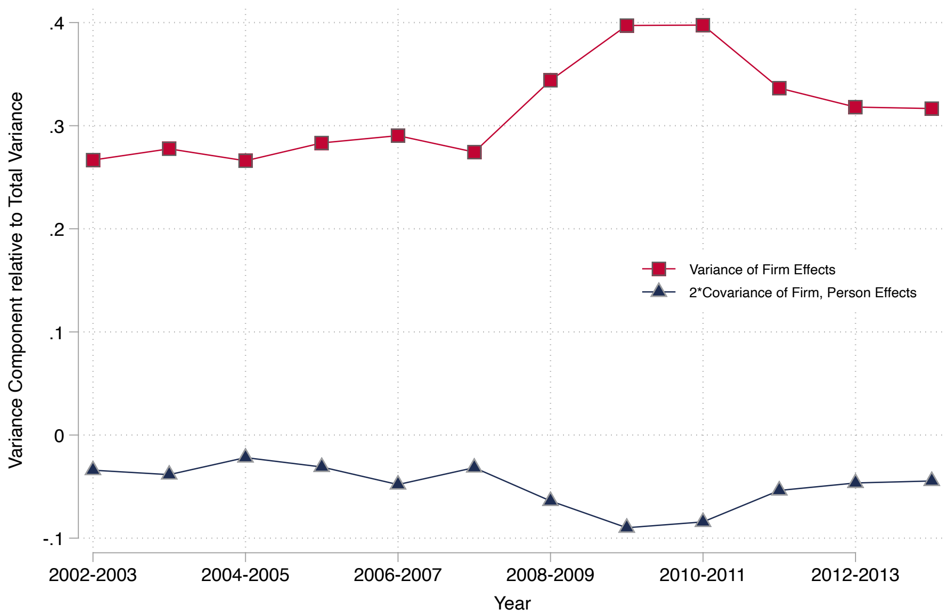




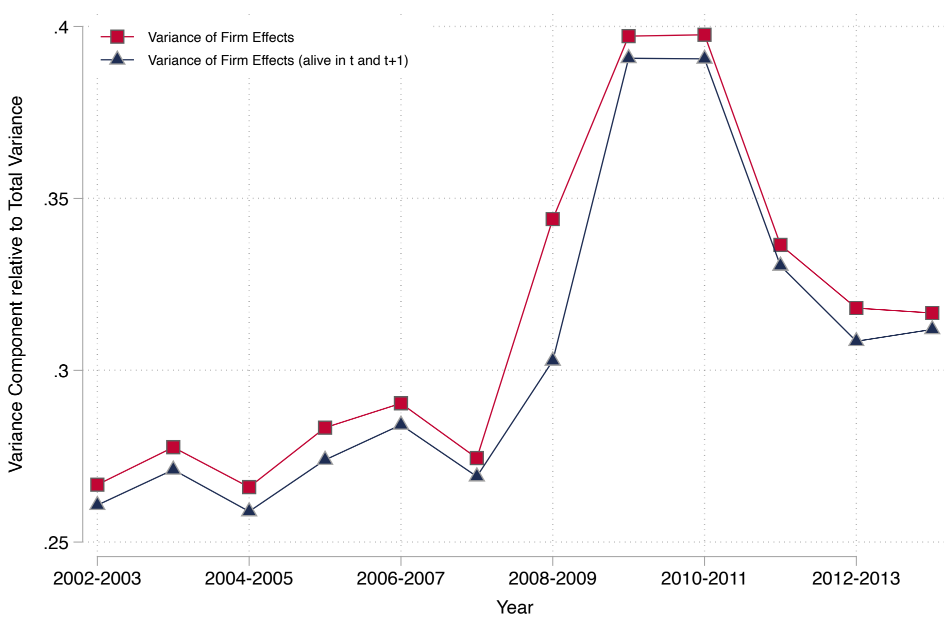
Note: Panel(a) displays the variability of firm effects within each sector. All variances are corrected using KSS-leave out methodology. Panel(b) re-scales these within-sector variances of firm effects by the corresponding overall variance of hours observed in a given sector. The vertical red line in Panel (a) denotes the overall variability of firm effects displayed in Table 1. 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" as described in equation (6. All variances are person-year weighted.

Figure 4: Importance of Firms in Determining Hours over the Business Cycle

(a) R-AKM estimates



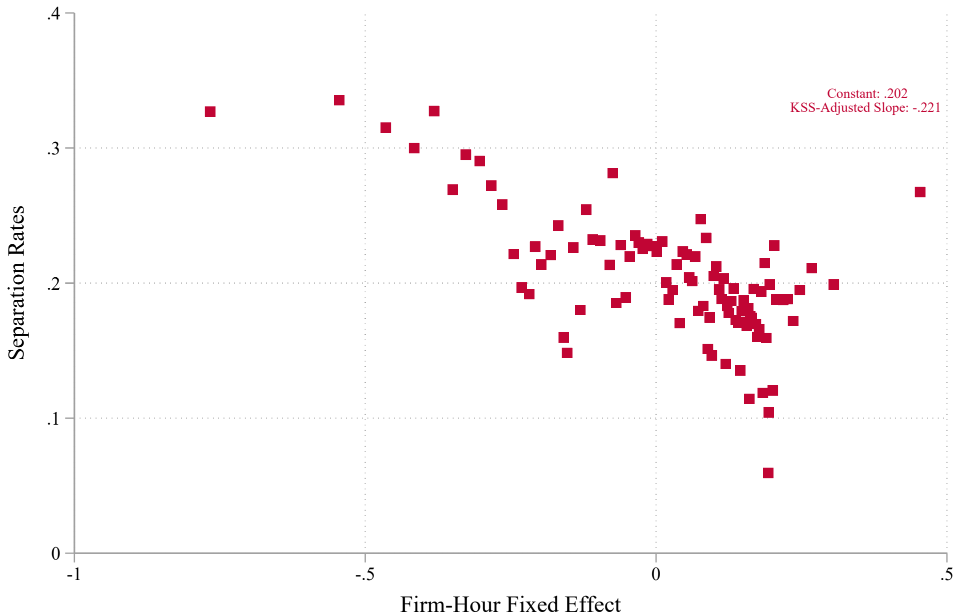
(b) Balanced Version



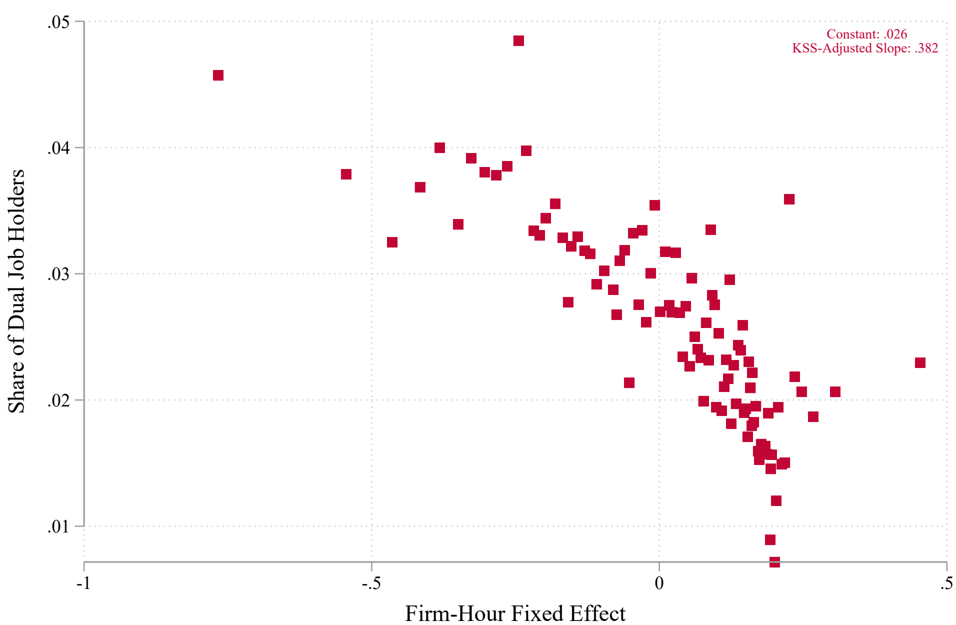
Note: To construct this figure, we start by fitting equation 3 separately to successive overlapping two-year intervals (2002-2003, 2003-2004, etc) and correct the interval-specific variance of firm effects and covariance of worker-firm effects via the KSS methodology (Rolling AKM or R-AKM approach). 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 a time-interval.

Figure 5: Explanatory power of Firm-Hours Fixed Effects for Separation and Dual Job Holding Rates

(a) Separation

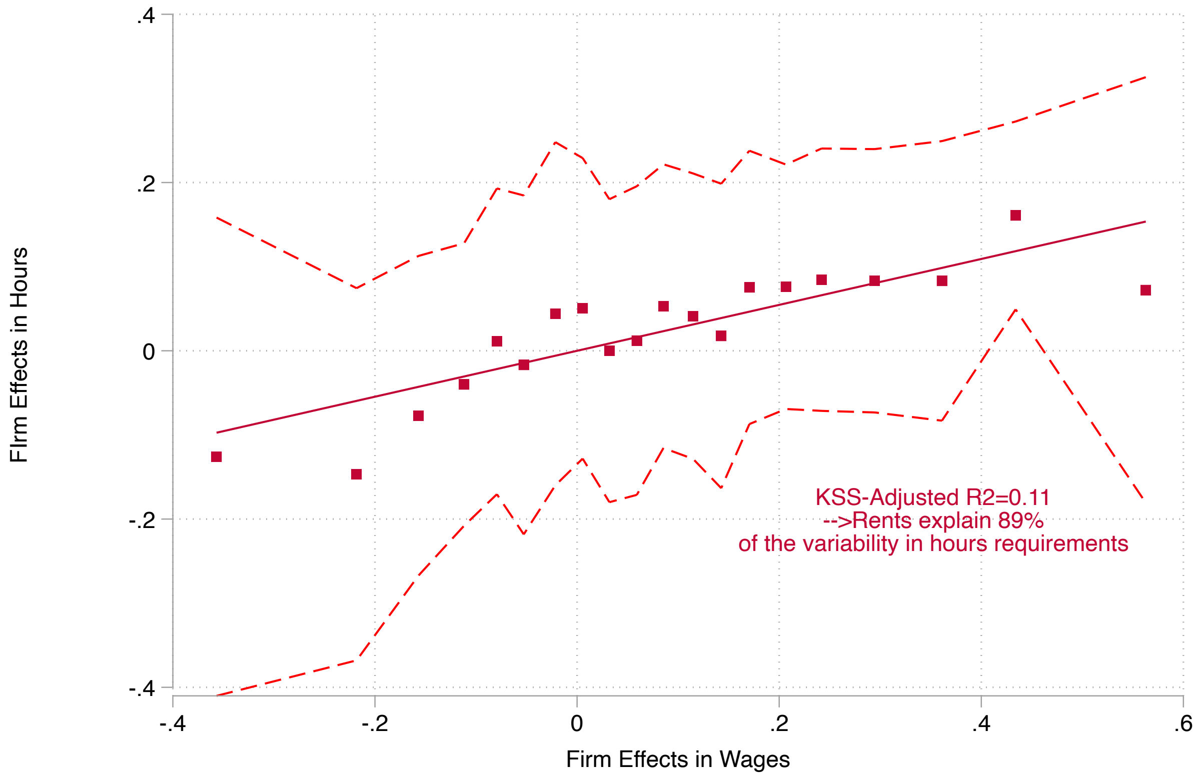


(b) Dual Job Holding



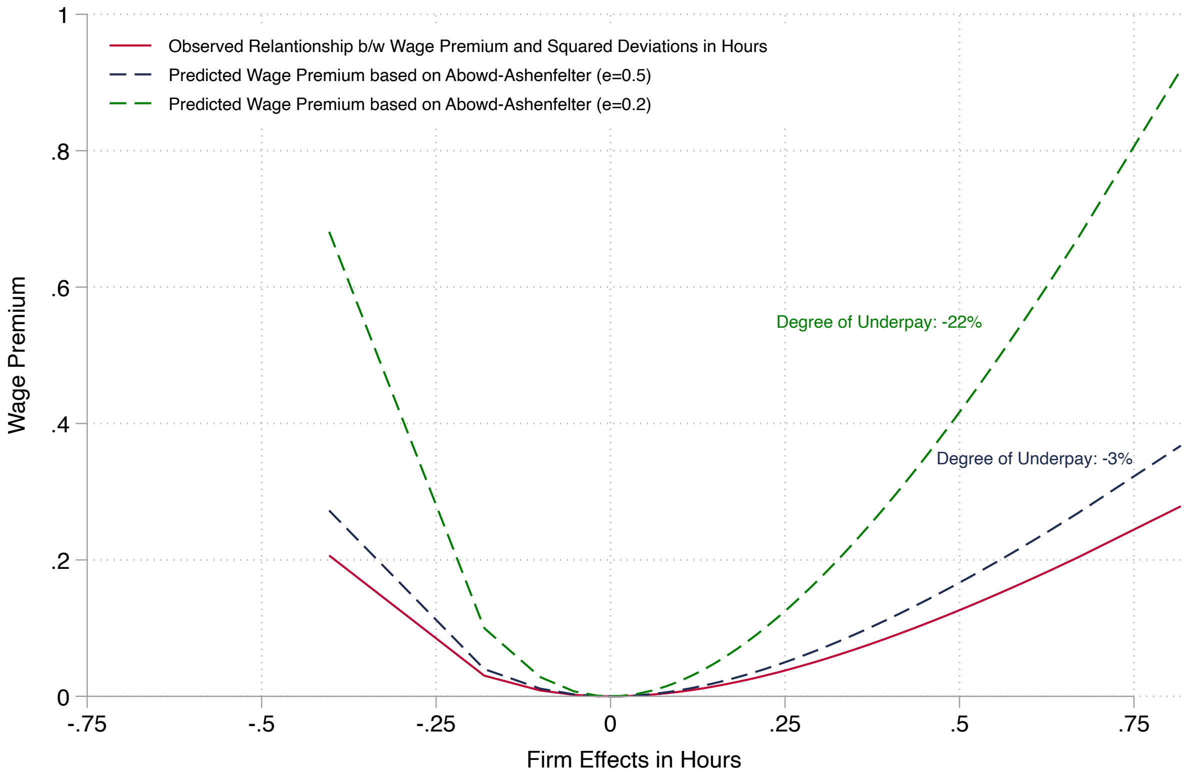
Note: Both panels display a binscatter plots of separation or dual job holding rates across centiles of firm-hour fixed effects estimated from (3). Each figure prints the associated KSS adjusted slope which adjusts for classical measurement error in the firm-hour fixed effects by using the KSS unbiased estimate of the variance of firm effects for hours printed in Table 1.

Figure 6: The Importance of Rents in Setting Hours of Work



Note: This figure plots mean firm effects in hours, $\hat{\psi}_j^h$, and wages, $\hat{\psi}_j^w$ within each vingtile of the firm-effects in wages. The solid line represents the linear fit obtained from a regression of $\hat{\psi}_j^h$ onto $\hat{\psi}_j^w$ and a constant. Adjusting for non-classical measurement error using the leave-out KSS methodology returns a slope of 0.27 and thus a KSS adjusted R^2 of around 0.11. As shown in Section 6.1, this implies that 89% of the variability in hours firm effects is due to variability in rents while holding technology fixed.

Figure 7: Quantifying Deviations from Compensating Differential Framework of Abowd-Ashenfelter (1981)



Note: The red and blue locus display the Abowd-Ashefelter relationship between firm wage premiums and squared deviations in firm hours effects—see equation (18)—for different hypothetical values of the compensated labor supply elasticities, $\varepsilon^c = 0.2$ and $\varepsilon^c = 0.5$. The red line captures the fitted relationship as observed in the Washington State data. The latter is computed as follows: we divide the data in 100 equally size bins based on the estimated normalized firm effects in hours. Within each bin, we then compute average firm-wage premium and regress it on $\frac{(\psi_j^h)^2}{1+\psi_j^h}$ where the latter is constructed using within-bin averages of the estimated firm-hours effects. The red line then captures the fitted values from that regression. Firm effects normalized relative to the average firm effects observed among firms that belong to the 100th centile of the within-firm dispersion of hours. The degree of underpay captures the average difference between the realized fitted values (the red line) and the two hypothetical locuses evaluated over the 100 bins of firm effects in hours described above.

Appendix

A Additional Tables

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 A.2: Summary Statistics

	Universe of WA Data			Sample with Demographic Characteristics		
	Initial Sample	*Largest Connected Set*	*Leave-Out Connected Set*	*Initial Sample*	*Largest Connected Set*	*Leave-Out Connected Set*
Number of Person-Year Obs	27,895,747	27,662,224	26,233,816	9,565,645	9,490,805	8,780,456
Number of Workers	4,590,341	4,526,772	3,713,075	1,472,764	1,454,060	1,244,170
Number of Firms	301,289	252,571	168,186	213,299	194,999	118,355
Summary Statistics on Outcomes						
Mean Log Hourly Wage	3.02	3.02	3.03	2.88	2.88	2.88
Variance of Log Hourly Wages	0.41	0.41	0.41	0.30	0.30	0.29
Mean Log Hours	7.46	7.46	7.47	7.48	7.49	7.49
Variance of Log Hours	0.13	0.13	0.12	0.11	0.11	0.11
Mean Log Earnings	10.48	10.48	10.50	10.36	10.36	10.37
Variance of Log Earnings	0.60	0.60	0.59	0.44	0.44	0.43

Note: This table provides summary statistics on the Washington state administrative data (WA data). 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. Columns 4 to 6 are similar but focuses on the subsample of UI recipients in the WA state for whom we can also measure demographic characteristics.

Table A3: 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 A4: Covariance Matrix in Firm/Person Effects, Between/Within Outcomes

	Log Wages		Log Hours		Log Earnings	
	Person Effect	Firm Effect	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages						
Person Effect	0.2185	0.0378	-0.0064	0.0248	0.2145	0.0616
Firm Effect		0.0448	-0.0011	0.0122	0.0374	0.0564
Log Hours						
Person Effect			0.0086	0.0008	-0.0147	0.0009
Firm Effect				0.0320	0.0271	0.0421
Log Earnings						
Person Effect					0.2017	0.0636
Firm Effect						0.0973

Note: This table reports the correlation matrix between the worker and firm component based from an AKM-SURE fit on log hours, log hourly wage and log earnings using the WA data over the perioods 2002-2014. 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 Hours, Wages and Earnings based on AKM model (fitted separately by Gender)

	Men			Women		
	Log Wages	Log Hours	Log Earnings	Log Wages	Log Hours	Log Earnings
Mean of Outcome	2.9712	7.5371	10.5083	2.7628	7.4387	10.2015
Variance of Outcome	0.2968	0.0924	0.4069	0.2665	0.1137	0.4122
Importance of Firm Effects						
Variance of Firm Effects	0.0468	0.0255	0.0741	0.0332	0.0264	0.0459
Covariance of Worker, Firm Effs	0.0309	0.0003	0.0457	0.0270	0.0028	0.0457
# of Person-year Observations	4,857,211	4,857,211	4,857,211	3,558,670	3,558,670	3,558,670
# of Workers	688,228	688,228	688,228	504,926	504,926	504,926
# of Firms	77,239	77,239	77,239	67,133	67,133	67,133

Note: This table reports the variance decomposition based on an AKM model on log hours, log hourly wage and log earnings using the WA data over the perioods 2002-2014 fitted separately by gender. 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.

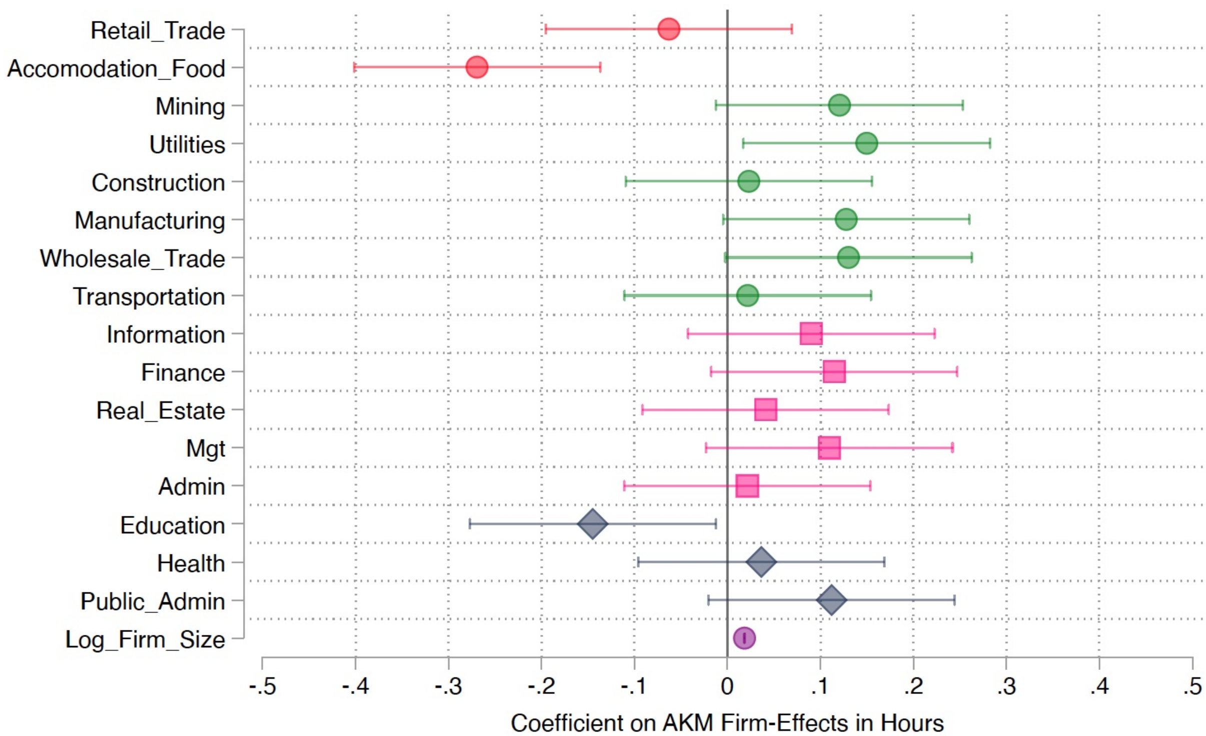
Table A6: Alt. Oaxaca Decomposition of the Gender Gap in Earnings according to Firm Effects in Wages and Hours

		Mean Firm Wage		Mean Firm Hours		Oaxaca Decomposition			
						Wages		Hours	
	Gender Gap in Earnings	Men	Women	Men	Women	Sorting	Barg.	Sorting	Barg.
All	0.30	0.23	0.08	0.30	0.26	0.06	0.09	0.05	-0.01
By Different Age Groups									
Age <=30	0.22	0.16	0.03	0.27	0.23	0.05	0.08	0.05	-0.01
Age in (30;40]	0.30	0.25	0.10	0.31	0.28	0.05	0.10	0.04	-0.01
Age >40	0.34	0.25	0.09	0.31	0.27	0.07	0.09	0.05	-0.01
By Different Periods									
2002-2006	0.30	0.23	0.08	0.29	0.26	0.05	0.09	0.04	-0.01
2007-2010	0.30	0.23	0.07	0.30	0.26	0.06	0.09	0.05	-0.01
2011-2014	0.30	0.22	0.07	0.31	0.27	0.07	0.09	0.05	-0.01

Note: This table reports results from an Oaxaca decomposition of the gender gap in Earnings. We start by taking the gender gap in firm-premia in earnings between men and women. The latter can be written as the sum of the firm premia in wages and hours. We then decompose each wage and hours component into a sorting channel and a bargaining channel, see text for details. Each row denotes a different group to which we apply the Oaxaca decomposition. All firm effects have been normalized relative to the Accomodation-Food sector as in Card, Cardoso and Kline (2016). The underlying sample corresponds to person-year observations of workers in WA who received at some point a UI check (for whom we have demographic characteristics) and whose corresponding employer belongs to the dual connected set, i.e. we can identify its male-specific and female-specific firm effect in the corresponding leave-out sample. This corresponds to a sample with 7,860,836 person-year observations, 1,316,246 workers and 37,058 (dual-connected) firms.

B Additional Figures

Figure B1: Projecting Firm Effects in Hours on Sector Firm Effects and Log Size



Note: This figure displays the regression coefficients obtained after projecting the estimated firm-hour fixed effects onto sector fixed effects and log firm size. Standard errors computed using the low-rank procedure detailed in KSS.

C Data

This section draws much of its content from Lachowska et al. (2020).

C.1 Other Aspects of the Data

Although we use the terms ”employer” and ”firm” interchangeably, they are not always the same. The employer is the entity from which UI payroll taxes are collected and is the unit of observation in the earnings records. For firms with a single establishment, and for firms with multiple establishments all located in Washington, the employer is also the firm. (In some cases, a multi-establishment firm may be divided into more than one employer.) For firms with multiple establishments some of which are located outside Washington, the employer covers only the firms' establishments located in Washington.

An employer identification (ID) number may disappear if the employer becomes inactive or reorganizes in some wayâthrough merger, acquisition, spinoff, breakout, or other reason. The available data do not include an employer âsuccessor file,â so we cannot distinguish among these cases with certainty. Using information on worker flows, Benedetto et al. (2007). develop probabilistic approach to identifying employers that have undergone an employer identification number change due to merger, acquisition, spin off, or breakout. but like Card, Heining and Kline (2013), we take the view that a new employer ID likely implies reorganization and new employment policies, so it makes sense to treat an employer ID change as the creation of a new entity and to estimate a separate (new) employer fixed effect. As Card, Heining and Kline (2013) point out, treating assignment of a new ID to an existing employer leads to a loss of efficiency but no bias.

D Computation

E Identifying the Variance Component due to Rents

Here we prove that, according to the partial equilibrium framework described in Section 6.1, we can identify $\frac{1}{(1-\gamma)^2}\operatorname{Var}(v_j)$ as the variance of the regression residual obtained after projecting the firm hours effects onto the firm wage effects.

Consider the linear projection coefficient obtained after projecting the observed firm-hour effects onto firm-wage effects: $\eta \equiv \frac{Cov(\psi_j^w, \psi_j^h)}{Var(\psi_j^w)}$. Notice that, given the DGP in (12) and (13), this projection suffers from an omitted-variable bias (OVB) and therefore does not identify γ. Specifically,

$$\eta = -\frac{1}{1-\gamma} + \underbrace{\frac{1}{1-\gamma}\frac{Cov(V_j,\theta_j)}{Var(\theta_j)}}_{\text{OVB}}$$

so the OVB=0 when $Cov(V_j,\theta_j) = 0$. Nevertheless, we can still identify $\frac{1}{(1-\gamma)^2}\operatorname{Var}(v_j)$. First note that $\operatorname{Var}(v_j)$ represents the variance of a residual from a regression of V_j onto θ_j and therefore it is given by

$$\operatorname{Var}(v_j) \equiv \operatorname{Var}(V_j) - \frac{\operatorname{Cov}(V_j,\theta_j)^2}{\operatorname{Var}(\theta_j)} \tag{19}$$

Now consider the variance of the residual obtained after regressing ψ_j^h onto ψ_j^w, this is given by

$$\begin{aligned}
Var(\psi_j^h) - \eta^2 Var(\psi_j^w) &= \frac{\operatorname{Var}(V_j)}{(1-\gamma)^2} + \frac{\operatorname{Var}(\theta_j)}{(1-\gamma)^2} - \frac{2\operatorname{Cov}(V_j,\theta_j)}{(1-\gamma)^2} - \\
&\quad - \left[\frac{1}{(1-\gamma)^2} + \frac{\operatorname{Cov}(\theta_j,V_j)^2}{(1-\gamma)^2\operatorname{Var}(\theta_j)^2} - \frac{2}{(1-\gamma)^2}\frac{\operatorname{Cov}(\theta_j,V_j)}{\operatorname{Var}(\theta_j)}\right]\operatorname{Var}(\theta_j) \\
&= \frac{1}{(1-\gamma)^2}\left[\operatorname{Var}(V_j) - \frac{\operatorname{Cov}(\theta_j,V_j)^2}{\operatorname{Var}(\theta_j)}\right] \\
&= \frac{1}{(1-\gamma)^2}\operatorname{Var}(v_j) \\
&= QED.
\end{aligned} \tag{20}$$

F Workplace Differentiation and Firms's Market Power in Setting Wages

This section presents a model where firms have latitude to set up both wages and hours. This market power stems from heterogeneous preferences of workers over workplaces as in Card, Cardoso, Heining and Kline (2018). Firms post both hours and wages that maximize their profits given knowledge of a firm-specific labor supply curve that depends on their posted wage-hours bundle.

The key insights from the model are the following

1. Posted hours of work by firms directly affect workers' effort and ultimately production. Posted hours also directly affect the utility of workers. Hours therefore represents both an input in the production function of firms as well as an amenity for workers (Pencavel, 2015).

2. The heterogeneity in preferences for different employers endows firms with market power to set the wage below the marginal product of labor (MPL) which is the usual monopsony result. What's new here is that the monopsonistic employer also distorts the hours allocation relative to several benchmarks based on perfect competition.

3. The model can be interpreted as an extension of Lewis (1967). As in Lewis (1967), firms decide hours allocation given their technology and workers' preferences while moving along an hedonic wage curve. The difference is that now each firm has its own firm-specific wage curve as opposed to a common market based one.

4. Under a reasonable parameterization, this model delivers an AKM-style additive form for hours, wages and earnigns.

Labor Supply

There are J firms. Each firm $j \in \{1, \dots J\}$ post wage and hours bundles (w_j, h_j) which are observed by all workers who have total mass equal to 1. Workers in this economy are equally productive but hold idiosyncratic preferences across employers. For a given worker, the indirect utility of being employed at firm j at a wage-hour bundle (w_j, h_j) is given by

$$u_{ij}(w_j, h_j) = v_j(w_j, h_j) + \varepsilon_{ij}$$

where $v_j(w_j, h_j)$ captures the common values of being employed by firm j and ε_{ij} are independent idiosyncratic draws from a EV-1 distribution. Therefore, the probability to work at employer j posting a bundle (w_j, h_j) is given by

$$p_j = \frac{\exp(v_j(w_j, h_j))}{\sum_{k=1}^{J} \exp(v_k(w_k, h_k))}$$

When J is large we can approximate p_j as

$$p_j = q \exp(v_j(w_j, h_j))$$

for some known constant q. It follows that the (log) of the labor supply faced by firm j is given by

$$\ln L_j(w_j, h_j) = \ln(q) + v_j(w_j, h_j) \tag{21}$$

We define $L_j^w(w_j, h_j)$ as the partial derivative of the labor supply supply with respect to the wage. The associated partial elasticity is denoted by $e_w(w_j, h_j)$ which for simplicity we abbreviate as e_w but stress that can depend on the leves of posted hours and wages. Similarly, $L_j^h(w_j, h_j)$ is the partial derivative of the labor supply with respect to hours and e_h the partial elasticity.

Labor Demand

Each firm $j \in \{1, \ldots J\}$ hires L_j workers. Each worker is required to work the amount of posted hours h_j. Posted hours and total employment are combined to produce an output Y_j according to

$$Y_j = T_j f_j(h_j, L_j(w_j, h_j)), \tag{22}$$

where T_j is a TFP shifter. The function $f_j(\cdot,\cdot)$ captures how posted hours affect workers' effort and therefore final output (Pencavel, 2015).[29] The expression in (1) highlights that hours of work is both an input for the firm's production as well as an amenity that firms can offer to workers that can make the firm more/less attractive depending on workers' preferences, i.e. hours also shift the labor supply.

Notation-wise, we denote with $f_{h_j}(\cdot,\cdot)$ and $f_{L_j}(\cdot,\cdot)$ the partial derivative of $f_j(\cdot,\cdot)$ with respect to hours and total employment, respectively. Finally, we define the MRTS between total labor and per-worker hours as $MRTS_j \equiv \dfrac{f_{L_j}(h_j, L_j)}{f_{h_j}(h_j, L_j)}$.

Firm Optimization / Wages

Firm j posts a set of wage and hours that minimizes total cost of labor given its knowledge of the labor supply curve: $L_j(w_j, h_j)$. The optimal pair (w_j, h_j) thus solves

$$\min_{w_j, h_j} w_j h_j L_j(w_j, h_j) \qquad \text{s.t. } T_j f(h_j, L_j(w_j, h_j)) \geq Y$$

Optimization with respect to wages leads to the usual mark-down wage-equation:

$$w_j = \frac{\mu_j T_j f_L(h_j, L_j)}{h_j} \frac{e_w}{1 + e_w} \tag{23}$$

where μ_j represents the marginal cost of production. This is the usual monopsony result: the hourly wage is set equal to the marginal per-hour revenue product of labor $\dfrac{u_j T_j f_L(h_j, L_j)}{h_j}$ times a

[29] Most studies typically either ignore hours or assume that the labor input is given by total employment times hours worked per worker, i.e. $h_j L_j$. The latter, however, assumes that the elasticity of output with respect to hours and total employment to be the same, an assumption questioned by many (e.g. Feldstein, 1967).

mark-down that depends on the labor supply elasticity with respect to the posted wage, e_w.

Firm Optimization / Hours

The first order condition with respect to h_j is:

$$w_j L_j(w_j,h_j) + w_j h_j L_j^h(w_j,h_j) = \mu_j T_j f_L(h_j,L_j) L_j^h(w_j,h_j) + \mu_j T_j f_h(L_j,h_j). \tag{24}$$

An additional hour of work increases revenue by $\mu_j T_j f_h(L_j,h_j)$ and costs by $w_j L_j(w_j,h_j)$. These two terms capture the standard marginal revenue / marginal cost tradeoff based on the interpretation of hours as an input in production.

However, hours also have a direct effect on the utility of workers. Suppose $e_h > 0$, then posting higher hours h_j will make firm j more attractive causing labor supply to increase which ultimately impacts the marginal product of labor, as captured by $\mu_j T_j f_L(h_j,L_j) L_j^h(w_j,h_j)$. Similarly, more people showing up at employer j's door cause an increase in total wage bill driven by $w_j h_j L_j^h(w_j,h_j)$.

Note that, in a perfect competitive environment, $w_j h_j L_j^h(w_j,h_j)$ will be equal to $\mu_j T_j f_L(h_j,L_j) L_j^h(w_j,h_j)$ and so firms will choose hours by simply equalizing marginal revenue for hours to its marginal cost. If the wage is not equal to the marginal product of labor, this will then give room to firms to distort the allocation of hours.

One can rearrange (24) to show that monopsony/employment satisfy:

$$\frac{h_j}{L(w_j,h_j)} = \frac{e_w - e_h}{1+e_w} MRTS_j \tag{25}$$

We now contrast this expression to what would occur in perfect competition when firms are price takers and there exists a unique market wage. Firms take the latter as given and decide the optimal quantity (L_j) and intensity (h_j) of labor. This corresponds to a standard situation in which the ratio of marginal cost of the two inputs is equal to the MRTS, that is

$$\frac{h_j}{L_j} = s_j. \tag{26}$$

which coincides with the monopsonistic solution of equation (25) as the labor supply elasticity of total employment with respect to posted wage goes to infinity, i.e. $e_w \to \infty$.

However, assuming a market wage that does not depend on posted hours seems unrealistic as hours clearly affect the utility of workers. An alternate benchmark that one can use to constrant the monopsony result above is one where firms set hours and employment taking as given a *function* that maps required hours demanded by firms into a market wage as in Lewis (1969), see also Kinoshita (1987).

Specifically, firms set hours and employment to maximize profits taking as given the market-equalizing wage curve: $\bar{w}(h)$. As a result, we obtain the following equilibrium condition

$$\frac{h_j}{L_j} = (1 + e_{hedonic})MRTS_j. \tag{27}$$

where $e_{hedonic}$ is the elasticity of the market equalizing wage curve at the optimal required hours of the firm h_j. Thus, here, the degree of distortion will depend upon the relationship between $e_{hedonic}$ and (e_w, e_h). We now characterize the solution for monospony hours under a linear production function.

Linear Technology

We now consider a simple case that imposes some assumptions on both the demand and supply side to develop intuition over the model and see how can one obtain an AKM-style reduced form equations. These parametric assumptions follow the ones used by Card, Cardoso, Heining and Kline (2018) as well as Lamandon, Mogstad and Seltzer (2020).

1. Product Market: Each firm faces a competitive product market with output price given by P_j. The firm will then equal the marginal value of production, μ_j, to P_j.

2. Production Function: We assume a linear production function of the form

$$Y_j = T_j(\theta L_j + \sigma_j h_j) \tag{28}$$

Note that here firms have heterogenous (linear) isoquants shaped by σ_j; θ measures the marginal product of labor (we are going to make this term heterogenous across workers).

3. Utility Function: The utility of being employed by firm j posting hours-wage bundles (h_j, w_j) takes a Stone-Geary form

$$u_{ij}(w_j, h_j) = q + \lambda + \beta \ln(w_j h_j - b) - \gamma \ln(h_j) + \varepsilon_{ij}. \tag{29}$$

where b is some reference level of earnings that the worker might obtain in perfectly competitive sector (e.g. Uber) and λ is an intercept that shifts the utility from work (we are going to make this term heterogenous across workers).

Earnings: Using (23), we see that earnings can be written as

$$w_j h_j = \frac{b}{1+\beta} + P_j T_j \theta \frac{\beta}{1+\beta} \tag{30}$$

If we further assume that the outside competitive earnings b are proportional to the marginal product of labor, i.e. $b = \theta \bar{b}$, then we obtain that earnings obeys a log additive structure of the form

$$\ln w_j h_j = \ln \frac{\theta \bar{b}}{1+\beta} + \ln(1 + \frac{P_j T_j \beta}{\bar{b}}) \tag{31}$$

which can be approximated as

$$\ln w_j h_j \approx \underbrace{\ln \frac{\theta \bar{b}}{1+\beta}}_{\text{Portable Component for Earnings}} + \underbrace{\beta v_j}_{\text{Employer Premia}} \tag{32}$$

The portable component represents a constant value that workers carry across employers that depends upon the marginal product of labor and worker preferences. The firm-premia $v_j = \frac{P_j T_j}{\bar{b}}$ represents the proportional gap in labor productivity between firm j and the outside competitive sector

Hours: According to equation (25), hours are set according to

$$
\begin{aligned}
\ln(h_j) &= \frac{q+\lambda+\ln(\gamma)}{1+\gamma} + \frac{\ln(\theta)}{1+\gamma} - \frac{\ln\sigma_j}{1+\gamma} + \ln(1-\frac{1}{v_j})\frac{1}{1+\gamma} \\
&\approx \underbrace{\frac{q+\lambda+\ln(\gamma)}{1+\gamma}}_{\text{Preferences for Hours (Worker)}} + \underbrace{\frac{\ln(\theta)}{1+\gamma}}_{\text{Productivity of the Worker}} - \underbrace{\frac{\ln(\sigma_j)}{1+\gamma}}_{\text{Preferences for Hours (Employer)}} - \underbrace{\frac{1}{(1+\gamma)v_j}}_{\text{Productivity of the Employer}}
\end{aligned} \tag{33}
$$

which also obey a log additive structure. Specifically, the portable/worker component for hours is now represented by two pieces: the first piece is given by a combination of workers' preferences (and market structure): $\ln\frac{q+\lambda+\ln(\gamma)}{(1+\gamma)}$. The second term is related the worker's MPL: $\frac{\ln(\theta)}{1+\gamma}$.

The employer premia in hours is also composed by two terms. The first term depends upon a firm's marginal revenue w.r.t. to hours (as captured by σ_j). The second term depends upon the (relative) productivity of the firm. Thus, an AKM firm effect for hours will capture two (potentially correlated) attribute of the firm: (i) its preferences towards hours of work (ii) its (relative) productivity.

The firm component is also composed by two terms. The first one captures firms' technology in combining hours into production, given by σ_j. The last term captures worker responses to hours driven by differences in productivity across firms.