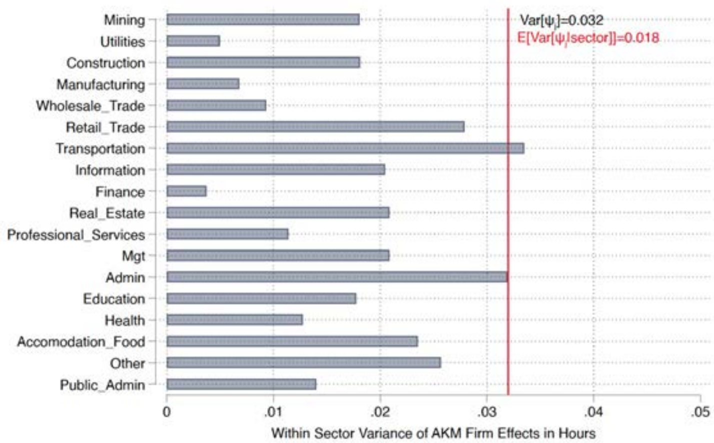
Appendix

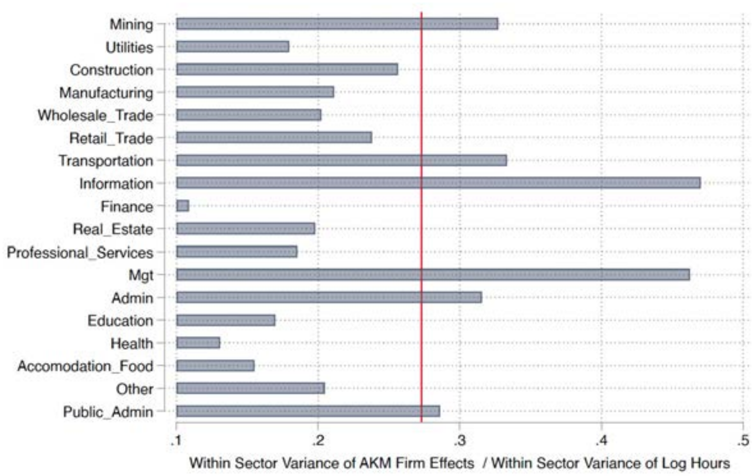
A Additional Tables and Figures

Figure A1: Within-sector variation in employer effects

(a) Levels



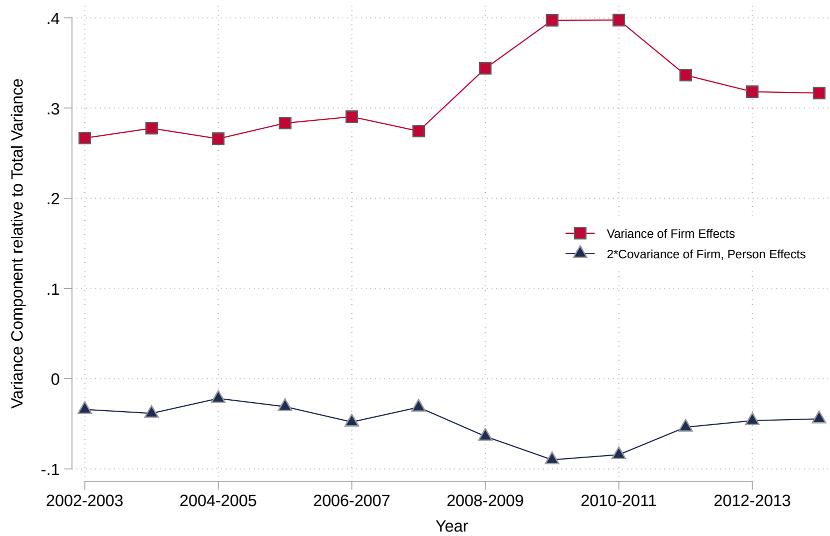
(b) Shares



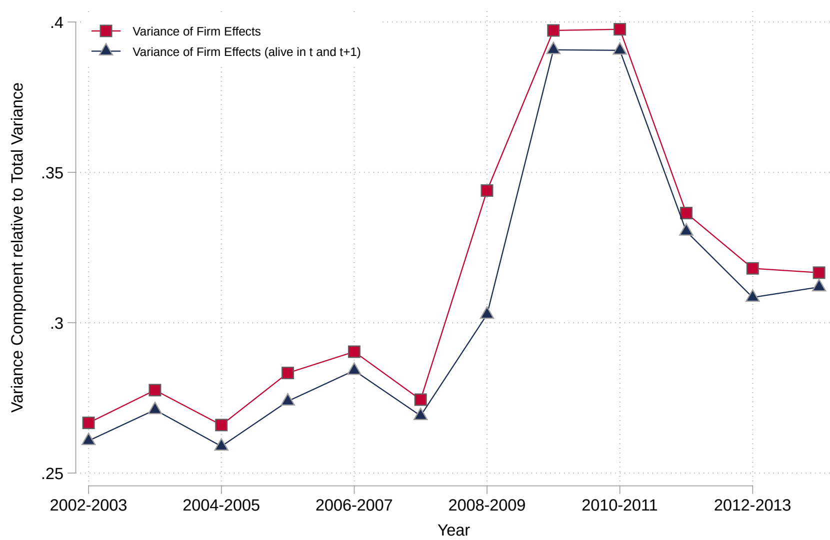
Notes: Panel (a) displays the variation of firm effects within each sector. All variances are KSS corrected. Panel (b) re-scales these within-sector variances of firm effects by the corresponding overall variance of hours observed in a given sector. The vertical red line in panel (a) denotes the overall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

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

(a) R-AKM estimates

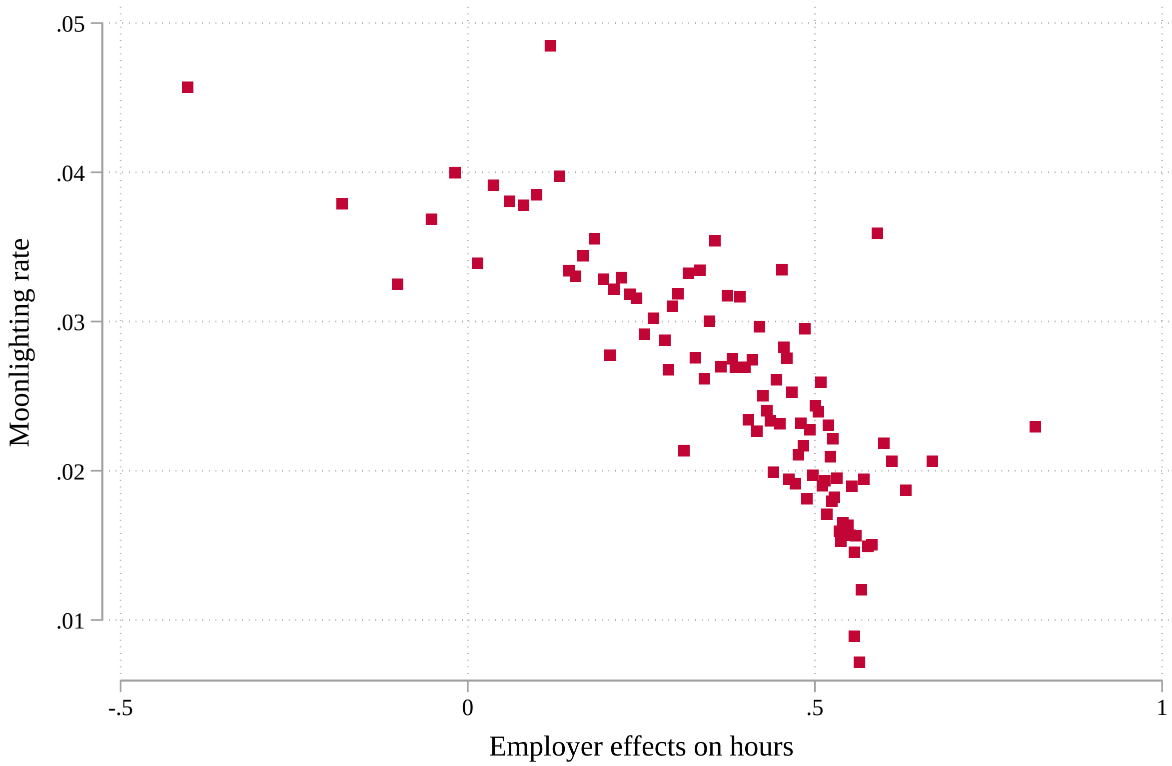


(b) Balanced version



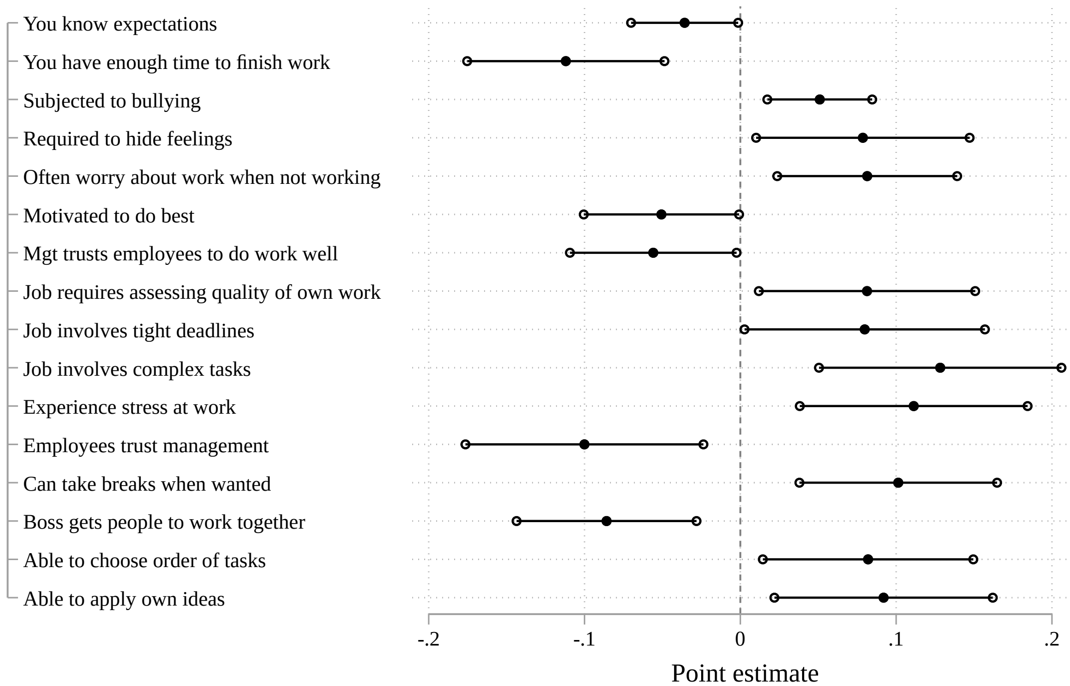
Notes: To construct this figure, we estimate equation (3) separately to successive overlapping two-year intervals (2002–2003, 2003–2004, etc.) and corrects the interval-specific variance of employer effects using the Rolling-AKM (R-AKM) methodology from Lachowska et al. (2023). Both variance components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

Figure A3: Moonlighting and employer hour effects



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

Figure A4: Statistically significant associations between workplace characteristics and hours



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

Table A1: Change of Employer and Change of Hours Worked

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

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

Table A2: Unadjusted Variance Decomposition of Log Hours

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

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

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

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

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

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

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

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

Table A5: Variance Decomposition of Annual Hours in Levels

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

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

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

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

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

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

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

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

Table A8: Within/Between Sector Decomposition of Variance Components

Panel (a): Variance Components	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.2185	0.0378	-0.0064	0.0248
Firm Effect		0.0448	-0.0011	0.0122
Log Hours				
Person Effect			0.0086	0.0008
Firm Effect				0.0320

Panel (b): Between-Sector Components	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.0317	0.0156	-0.0041	0.0129
Firm Effect		0.0161	-0.0009	0.0111
Log Hours				
Person Effect			0.0016	-0.0009
Firm Effect				0.0146

Panel (c): Within-Sector Components	Log Wages		Log Hours	
	Person Effect	Firm Effect	Person Effect	Firm Effect
Log Wages				
Person Effect	0.1868	0.0222	-0.0023	0.0119
Firm Effect		0.0287	-0.0002	0.0012
Log Hours				
Person Effect			0.0070	0.0017
Firm Effect				0.0173

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

B Identification, Estimation, and Computation

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

B.1 Exogenous Mobility

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

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

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

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

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

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

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

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

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

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

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

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

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

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

B.2 Estimation and Computation of Variance Components

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

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

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

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

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

All our estimands are variance components of the form

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

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

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

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

where

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

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

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

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

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

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

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

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

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

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

B.3 Computation of PageRank Utility

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

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

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

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

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

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

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

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

B.4 Split-Sample IV

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

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

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

C Salaried Workers in Washington State Administrative Data

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

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

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

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

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

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

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

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

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

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

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

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

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

Management).

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

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

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

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

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

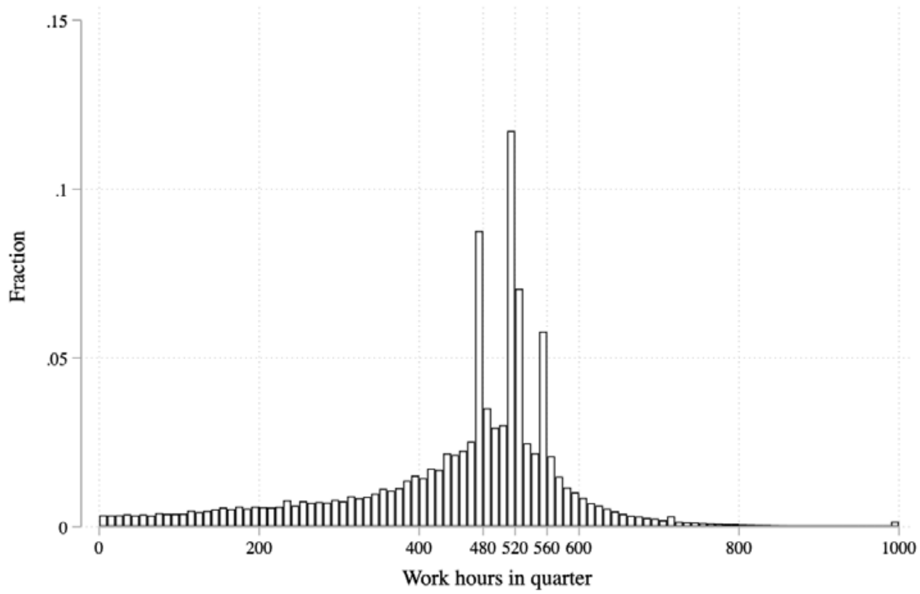
[50] We further retain in the sample jobs observed for fewer than 5 quarters ($\approx$ 10% of the original person-year observations) for which the bunching indicator was not constructed. We retain these jobs to minimize the trimming imposed by the leave-one-out procedure.

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

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

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

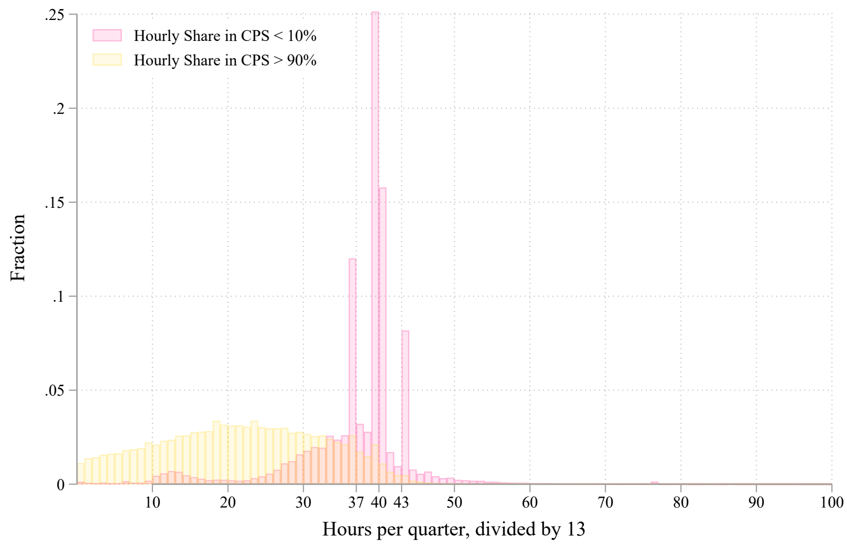
Figure C5: Distribution of quarterly work hours in full quarters and primary employment, Washington administrative records



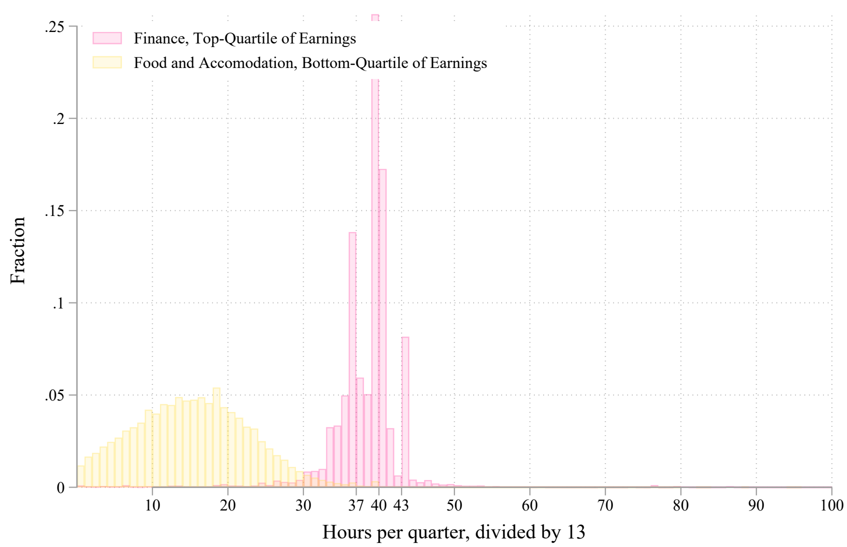
Note: The sample is restricted to worker-quarter observations representing full quarters and primary employment. Values with more than 1,000 hours per quarter are not displayed.

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

(a) By Corresponding Share of Hourly



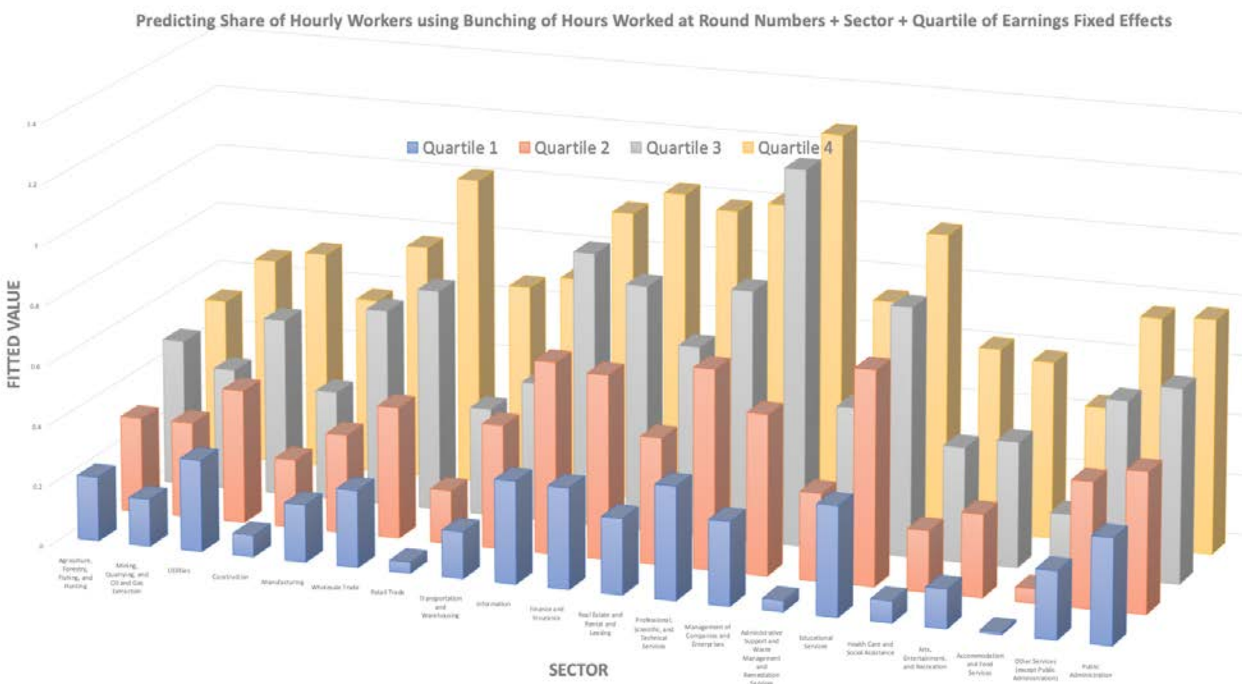
(b) By Sector



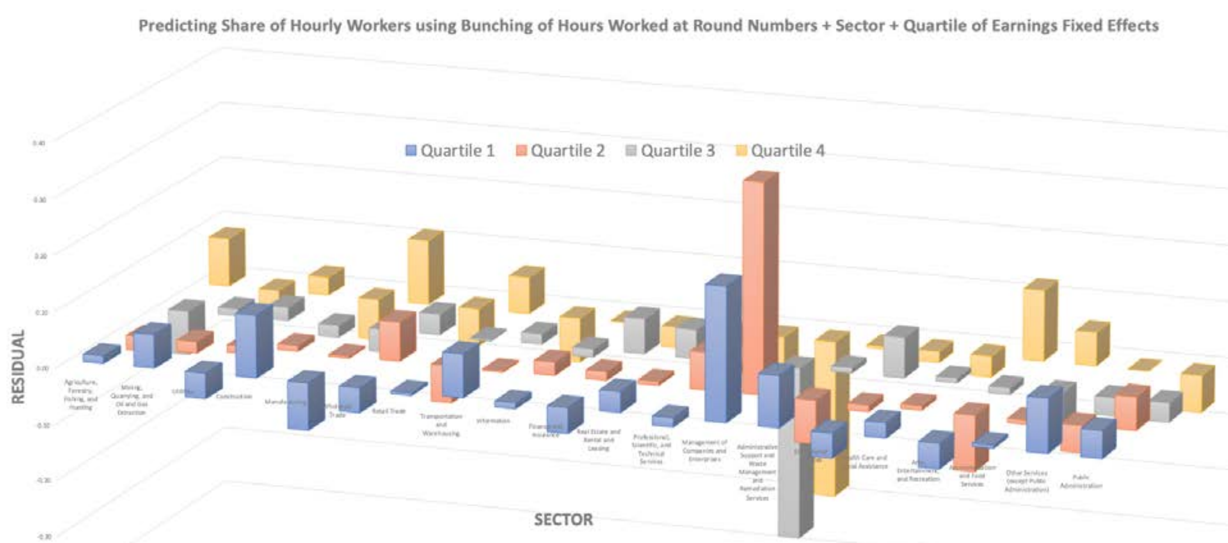
Note: We calculate the sector-by-earnings quartile share of hourly workers in the CPS and merge the shares to the Washington administrative records. We then calculate the histogram of weekly work hours worked (quarterly hours divided by 13) by whether the share of hourly workers is above 90% or below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

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

(a) Fitted Values



(b) Residuals



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

Table C1: Predicting Hourly Shares Calculated from the CPS

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

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

Table C.2: Summary Statistics after Excluding Salaried Jobs

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

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

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

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

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

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

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

D Estimating the Relationship Between Fringe Benefits and Hours

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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