Are Working Hours Complements in Production?*

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Abstract

This paper studies the degree of complementarity in working hours among coworkers in production. Using matched employer-employee data, we first present facts on the within-establishment relationship between wages and hours worked that are consistent with the presence of complementarities in working hours. Next, we estimate the elasticity of substitution in working hours and find it to be 0.69 in the aggregate and between 0.52 and 1.03 across industries. We validate our elasticity estimates by showing that industries with higher elasticities exhibit greater flexibility in hours. Our results suggest that working hours are gross complements in production rather than perfect substitutes, as is typically assumed. An accounting exercise using our model estimations suggests that hours-wage penalties, due to complementarities in hours, can explain 5 to 30 percent of the gender wage gap over the life-cycle.

JEL Codes: E23, J22, J23, J31

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1 Introduction

An implicit assumption in most macroeconomic models of production is that the working hours of different workers are perfect substitutes. However, the production process requires coordination between workers who work on different tasks. With this in mind, the assumption of perfect substitutability between working hours becomes less natural. Indeed, a consequence of the need to coordinate tasks is the need to coordinate hours worked. For instance, is a worker who works 40 hours a week equally productive regardless of whether her coworkers work 25, 40 or 60 hours? Recent work suggests that the answer is no. Specifically, Bick et al. (2022) and Yurdagul (2017) document an aggregate, non-linear relationship between hours and wages, whereby workers earn higher wages when they work near the modal hours in the economy. Working hours being complements in production would imply precisely this relationship, as workers would be more productive and therefore earn higher wages when they work a similar number of hours to their coworkers.

Knowing whether and to what extent working hours are complements is essential for understanding various economic phenomena such as individual labor supply decisions, firm productivity, and earnings inequality. For instance, the degree of complementarity between working hours will influence how an individual's labor supply responds to changes in income taxes, child-care provisions, or idiosyncratic shocks. Moreover, in the presence of working hours complementarities, the distribution of working hours within a firm becomes an important determinant of firm productivity, and the degree of earnings dispersion amongst its workers. Yet, despite its relevance, there has been little work exploring whether the working hours of workers are complements in production. In this paper, we use matched employer-employee data from the Canadian Workplace and Employee Survey (WES) to document such evidence.

The WES, unlike many other employer-employee linked data, is ideally suited to study complementarity in working hours within the same workplace as it includes information on both working hours – measured by usual weekly hours rather than contracted hours – and

average hourly wage. Moreover, the unit of a workplace in the data is an establishment which allows us to focus on the hours worked that are most relevant to coworkers while also providing a well-defined proxy of a production unit compared to firm-level data.

Our analysis is divided into three parts. First, we use the WES to document a series of new facts that support the presence of complementarity in working hours. In particular, we find that individual working hours are significantly positively correlated with their median coworkers' hours. We also document that wages *within* establishments exhibit the same "hump-shaped" pattern across hours worked as observed in the aggregate data. Moreover, deviations relative to the establishment median or wage-maximizing hours also result in wage penalties. Finally, by tracking employees in the same establishment over time, we show that movements away from either the median or the wage-maximizing hours are associated with significant wage reductions. These results are robust to controlling for observable characteristics and consistent with a production process where the working hours of workers are complements.

In the second part of our analysis, which is our main contribution, we estimate the degree of working hours complementarities in production. To do this, we propose a simple CES production function that features imperfect substitutability between working hours and use the WES to estimate the elasticity of substitution between the working hours of different workers. The CES production function delivers an endogenous non-linear wage schedule. In particular, as observed in the data, wages are highest at an intermediate level of hours and decline if workers either increase or decrease their hours worked. The endogenous relationship between hours and wages underpins our estimation strategy, which follows an extensive literature that applies the optimality conditions of firms to the data in order to estimate the parameters of production functions (e.g., Katz and Murphy, 1992 and Acemoglu, 2002).[1]

In the aggregate, we estimate the elasticity of substitution between working hours to be 0.69, implying that workers' hours are gross complements in production. We also document

[1] Although our data is at the establishment level, we assume that all establishments in a firm share a production function. As such, we use the terms firm and establishment interchangeably.

significant heterogeneity in this elasticity across industries. We find that manufacturing and construction sectors feature a higher degree of hours complementarity than service sectors, especially low-skill service sectors such as retail. Our estimates range from 0.52 to 1.03, with working hours being gross complements in all but one industry. We exploit this heterogeneity across industries to validate our estimation results. Specifically, we document an intuitive positive relationship between proxy measures of hours flexibility and our estimated elasticities.

The third part of our analysis uses our model to explore how hours heterogeneity across workers can contribute to observed wage inequality. A potential dimension through which this channel might be at play is gender, given the significant differences in the hours distribution between men and women. By comparing the observed gender wage gap to a counterfactual gap which removes wage penalties that arise due to complementarities, we find that around 14% of the gender wage gap can be explained by variation in hours under complementarities.

Overall, our findings challenge a canonical assumption about the nature of production, namely, that the working hours of workers are perfect substitutes. We provide strong evidence supporting coworker hours being gross complements and provide estimates for the degree of complementarities across industries and in the aggregate. Such complementarity has important implications not only for wage inequality, as we show, but also for research on labor supply and the efficacy of policies that aim to influence it.

Related Literature This paper connects to several strands of literature. First, working hours being gross complements in production may act as effective constraints on labor supply. Thus, we relate to a growing literature that studies the implications of constraints on working hours while remaining largely indifferent as to the source of these constraints (e.g., Altonji and Paxson, 1988 and Chetty et al., 2011). Our analysis suggests that complementarities in working hours are a feature of the production process and may generate apparent constraints

on hours studied in the literature. This is in line with Labanca and Pozzoli (2022) who argue that hours constraints within firms result from firms' technology rather than workers' preferences.

Naturally, we contribute to the literature studying the degree of complementarity and coordination between workers. The production function underpinning our estimation is a general version of a Leontief production function studied in Becker and Murphy (1992) and is most closely related to Yurdagul (2017), which studies the flexibility motive behind entrepreneurship.[2] Cubas et al. (2023) use worker-level data to estimate an occupation-specific measure of work schedule coordination – a strict form of hours complementarity which considers workers working *at the same time*. In contrast, we focus on workers working the same number of hours. Our matched employer-employee data allows us to estimate this more general form of complementarity in the same workplace, which is not feasible using worker-level data.

In a related paper, Battisti et al. (2022) use matched employer-employee data from Italy to estimate the elasticity of substitution between the working days of workers. Consistent with our findings, their estimates indicate that working days of coworkers are gross complements, and they argue that this complementarity has important implications for estimating the Frisch elasticity. In contrast, we focus on complementarity in working hours and utilize information on hourly wages. Further, Battisti et al. (2022) employ a structural model with a frictional labor market for their estimation while we employ a relatively parsimonious framework that only specifies a production function and labor market structure.[3]

Our evidence of variation in complementarity across industries relates to the existing literature on structural change and the evolution of gender inequality. This literature argues that women have a comparative advantage in the service sector, and structural shifts

[2]Also related is Rogerson (2011) which introduces the notion of coordinated working hours by imposing (exogenous) constraints on labor supply on the worker side rather than on the firm side as in this paper.

[3]As will be clear below, our estimation only requires workers' wages to be proportional to their marginal product (as in Katz and Murphy, 1992, for example) and thus can accommodate alternative market structures, such as those with constant wage markdowns, which might result from firms having labor market power.

from manufacturing to services benefit women more than men (Ngai and Petrongolo, 2017). Our estimation suggests that this comparative advantage could stem from a combination of women valuing flexibility more than men (Goldin, 2014) and the relative flexibility in hours afforded in service sectors, as implied by our estimation.

Our analysis of the role of hours heterogeneity on the gender wage gap relates to Goldin (2014) and Goldin (2015).[4] In contrast to the reduced-form analysis in these studies, we do not rely on aggregated measures of penalties but can identify both short- and long-hour wage penalties at the individual level that are driven by hours heterogeneity in an establishment. Our analysis suggests that part of the gender wage gap is technological and influenced by the presence of complementarities in hours worked. This also complements Cubas et al. (2023), which argues that the requirement to work at the same time contributes significantly to the gender wage gap.

The rest of this paper is organized as follows. In Section 2, we describe our data and present evidence for the presence of complementarities between the hours of coworkers. In Section 3 we propose a production function and use it to estimate the degree of complementarity between hours within firms, and validate our estimation by relating proxy measures of work schedule coordination to our estimates across industries. In Section 4, we explore the implications of complementarities in working hours for inequality, focusing on the gender wage gap. We conclude in Section 5.

2 Evidence of Complementarities in Working Hours

Our empirical analysis uses matched employer-employee data from the Canadian Workplace and Employee Survey (WES). In this section, we use the WES to present novel evidence supporting the presence of complementarities in working hours.

The WES is an annual survey of Canadian establishments and their workers with a

[4] Also related is Erosa et al. (2016) who explore the role of labor supply for the gender wage gap through the lens of a quantitative life-cycle framework which emphasizes the role of fertility and human capital accumulation.

longitudinal design. The survey tracks surviving employers for seven years from 1999 to 2006. In even-numbered years, a sample of employees from each employer is interviewed for up to two years, conditional on staying with the same employer. A maximum of twenty-four employees are sampled in each year, and in workplaces with fewer than four employees, all employees are interviewed. Importantly, and in contrast to many other matched employer-employee datasets, we observe both the usual weekly hours worked and average hourly wage of employees, which makes the WES particularly well-suited to addressing our primary research question.

Our measure of hourly wages is directly reported in the WES and includes overtime pay, commissions, and tips. We use usual weekly hours worked as our measure of hours.[5] We also observe employee occupation, education and a number of other demographic characteristics such as age, marital status, immigration status and parenthood. We restrict attention to individuals aged between 25 and 64 and, exclude those who usually work less than 10 hours a week or earn less than half the federal minimum wage.[6] Our final sample includes just over 120,000 employer-employee-year observations.[7]

2.1 Correlations Between Own and Coworker Hours

Complementarities between working hours would imply a positive correlation between the hours of individual workers and those of their coworkers. This is due to the sorting of workers with similar desired hours into the same establishments and the wage schedules of individual workers pushing workers towards their peers' hours. Indeed, the crude correlation between a worker's hours and the median hours of her coworkers in our data is 0.35.

While suggestive, the unconditional positive correlation need not be due to complemen-

[5] Appendix D explores the implications of possible measurement error in hours for our findings. It shows that our empirical findings and estimates of the elasticity of substitution are robust to assuming that working hours are reported with varying degrees of (classical) measurement error.

[6] Our sample restrictions follow Bick et al. (2022). The prevalence of low wage and/or low hours workers is relatively low. For example, only 1.2% of private employees work either below 10 hours or earn below half the minimum wage in the 2015 Canadian Labor Force Survey (LFS) – a nationally representative survey of the Canadian labor force.

[7] Summary statistics are reported in Table A.1 in Appendix A.

tarities but instead may be driven by other factors such as sorting of similar workers into production units or may be explained by characteristics of establishments. To control for such (observable) factors, we conduct a more formal evaluation of the correlation between the hours of a worker and those of her coworkers by estimating the following regression,

$$\log(h_{ist}) = \alpha + \gamma \log\left(\overline{h}_{s_{-i}}\right) + \delta X_i + \eta Y_s + \mathbf{B}_t + \epsilon_{ist}, \tag{1}$$

where h_{ist} are hours worked by worker i employed by establishment s in year t and $\overline{h}_{s_{-i}}$ is the median hours worked among i's coworkers in establishment s. X_i is a vector of individual-level control variables which include a quadratic in age, dummy variables for educational status (college degree or not) as well as indicators for marital and immigration status. Y_s is a vector of establishment-level controls that includes establishment age, size and industry and the average establishment wage. $\mathbf{B}_t$ captures year fixed effects.

Table 1: Correlation between own and coworker hours

	(1)	(2)	(3)	(4)
Median Coworker Hours	0.340	0.284	0.278	0.269
	(0.026)	(0.027)	(0.028)	(0.027)
Synthetic Occupational Median	-	-	-	-0.078
	-	-	-	(0.076)
Individual Controls	Y	Y	Y	Y
Establishment Controls	N	Y	Y	Y
Average Wage	N	N	Y	Y
N	120420	118336	118336	118336
R^2	0.169	0.190	0.193	0.217

Notes: The table reports the coefficient γ from estimating Equation (1). The regressions include a set of controls for worker and establishment characteristics, as indicated in the table. Synthetic occupational median hours are a measure of median coworker hours predicted only by the occupational composition of one's coworkers. Robust standard errors are reported in the parentheses.

The first three columns of Table 1 reports the coefficient γ in estimating Equation (1)– the elasticity of worker i's hours with respect to those of her coworkers. Under all these specifications, we document a significant and positive correlation between own and coworker hours with an estimated elasticity between 0.28 and 0.34.

The analysis in the first three columns of Table 1 does not account for the occupational composition in establishments. This can be important since, if occupations vary in their hours worked, then the difference in occupational composition across establishments may drive the positive correlations between coworkers' hours that we document. We address this concern by adding an additional explanatory variable to Equation (1) to control for the occupational composition in an establishment. To do this, we construct a synthetic measure of median coworker hours predicted only by the occupations of one's coworkers and include this as an additional control variable. To compute this synthetic measure of coworker hours, we first measure the median hours in each occupation and then take the median of these occupation-specific hours across one's coworkers. The last column of Table 1 shows that the estimated elasticity of individual hours with respect to coworker hours is robust to controlling for this synethic median hours based on occupational composition.[8]

To summarize, we find that having coworkers that work longer (shorter) hours is associated with one's own hours being longer (shorter) – a key implication of a production process where working hours are complementary. Having said this, we do not interpret this finding to be conclusive in establishing the presence of working hours complementarities. For example, we cannot rule out workers sorting on unobserved individual or establishment characteristics. Instead, we take this evidence to be suggestive, which, combined with the evidence on earnings that we present below, strengthens the case for the hours of workers being complements in production.

2.2 Wage-Hour Profiles within Establishments

If working hours are complements in production, we expect workers to be less productive if they work longer or shorter hours than their coworkers. This lower productivity should be reflected in workers' earnings with relatively lower wages for workers working shorter or

[8]In Appendix B we show the robustness of our results to two further approaches for controlling for occupations. First, include individual occupation fixed effects in Equation (1). Second, we replace the individual and coworker hours in Equation (1) with deviations from the occupation-specific medians (instead of levels) and show that the correlations also hold in the deviations from these occupation-wide hours.

longer hours. Such a relationship between wages and hours has been previously documented in the aggregate by Yurdagul (2017) and Bick et al. (2022) using US labor force surveys.[9] These papers' findings point to wage penalties for working either short or long hours among all workers in the economy. To test whether such penalties are present *within* establishments, we use the WES to estimate the following specification,

$$\log(w_{ist}) = \alpha + \left(\sum_{h \in H} \gamma_h \mathbb{I}_{i,h}\right) + \delta X_i + \mathbf{A}_s + \mathbf{B}_t + \epsilon_{ist}, \tag{2}$$

where w_{ist} is the hourly wage of worker i in establishment s at time t. The indicator variable $\mathbb{I}_{i,h}$ is equal to one if an individual works h hours. We partition weekly hours into a set H by grouping hours in 5-hour bins. We choose the category $40 - 44$ as the reference category of hours worked as most workers work these hours. Then, the coefficients γ_h capture the relative wage penalty/premium from working either more or less than the reference hours bin. X_i is a vector of individual-level control variables which include a quadratic function of age, dummy variables for educational status (college degree or not) as well as indicators for marital and immigration status. $\mathbf{A}_s$ and $\mathbf{B}_t$ are establishment and year fixed effects, respectively.

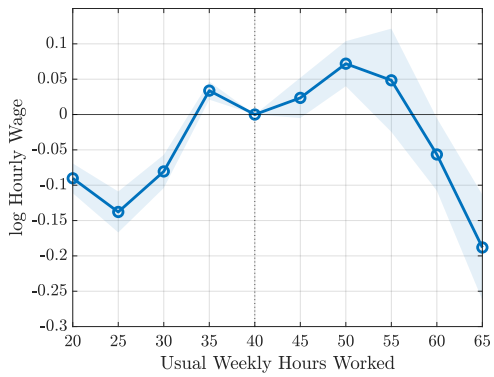
Panels (a) and (b) of Figure 1 report the results from estimating Equation (2). Panel (a) plots the wage-hours profile – that is, the coefficients γ_h – when we exclude establishment fixed-effects but include controls for establishment size, age, and industry. Consistent with existing evidence from worker-level data, the estimated wage-hours profile features a hump-shaped pattern, with relatively long and short hours exhibiting lower wages than those obtained in intermediate hours.

Panel (b) plots the coefficients γ_h when establishment fixed effects are included. This captures the wage-hours profile *within* establishments – a measure that, to our knowledge, is

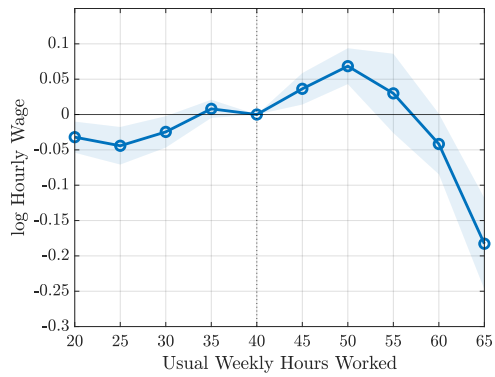
[9] Yurdagul (2017) and Bick et al. (2022) use data from Survey of Income and Program Participation and the Current Population Survey (CPS), respectively.

novel. Importantly, we find that short and long hours penalties exist *within* establishments. Indeed, workers earn around 5% lower wages when working either 25 or 60 hours per week relative to those working around 40 hours. Compared to Panel (a), which excludes establishment fixed effects, the penalties from working short or long hours are relatively smaller but still statistically significant.

(a) γ_h, excluding establishment FE



(b) γ_h, including establishment FE



(c) $\gamma_{\Delta h}$, deviations from median coworker hours

(d) $\gamma_{\Delta h}$, deviations from wage-maximizing hours

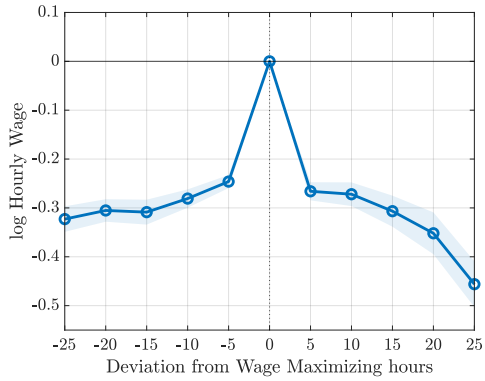


Figure 1: Relationship between wages and hours using within-establishment variation

Notes: Panels (a) and (b) report the coefficient γ_h from estimating variants of Equation (2). In Panel (a), we do not include establishment fixed effects $\mathbf{A}_s$, but instead include a set of establishment characteristics including establishment size and age dummies as well as industry fixed effects. Panel (b) reports the coefficient γ_h when establishment fixed effects are included. Panels (c) and (d) report the coefficient $\gamma_{\Delta h}$ from estimating Equation (3) when the reference hours are the establishment median and establishment wage-maximizing hours, respectively. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

While a hump-shaped wage-hours profile is consistent with complementarities in working hours, there may be other, unrelated drivers of the observed short and long hours penalties

within establishments. For instance, short hours penalties may reflect a (time) startup cost of working, while long hours penalties may be due to diminishing returns. In this case, the wage penalties highlighted in panels (a) and (b) might be driven by workers working an absolute number of hours ("absolute" hours penalties). However, a more specific and important implication of complementarities in working hours is that wage penalties can arise due to workers *deviating* from the hours that most workers work, thereby impacting one's own productivity. In particular, the further a worker's hours deviate from those of her coworkers, the lower her productivity per hour worked will be, resulting in wage penalties ("relative-to-coworker" hours penalties). To identify the presence of relative-to-coworker penalties and thus, provide support for complementarities in working hours, we test whether *deviations* from a measure of the usual hours in an establishment result in wage penalties and whether these penalties increase as the magnitude of deviation increases.

Before describing our empirical specification, it is important to note that without some theoretical structure, there is no natural candidate for the level of hours below or above which workers will experience wage penalties. The presence of complementarities in working hours does not necessitate that wages are maximized at the median, modal, or even average hours worked within an establishment. Indeed, although the median and modal weekly hours worked in Canada is 40 hours, wages within establishments are maximized at around 50 hours, as illustrated in panels (a) and (b) of Figure 1. As will be evident below, our theoretical production function implies that the wage-maximizing hours in an establishment is the appropriate reference level of hours, and due to the complementarities in working hours, these hours are positively related to measures of usual hours worked within an establishment. Defining wage-maximizing hours as the hours worked by the highest wage worker, we test this relationship and find a significant positive correlation between the wage-maximizing hours and median and average hours worked in an establishment.[10]

[10]Figure A.2 in Appendix A shows a strong positive relationship between establishment-level wage-maximizing hours and average or median hours worked. A simple linear regression between median (average) hours and wage-maximizing hours gives a statically significant slope coefficient of 0.94 (0.88). The correlation between median (average) hours and the hours at which wages are highest is 0.84 (0.79) in the WES.

So, in order to identify relative-to-coworker penalties, we consider worker deviations from both the theoretically relevant wage-maximizing hours as well as the median hours worked in an establishment. In particular, we estimate the following,

$$\log(w_{ist}) = \alpha + \left(\sum_{h \in H} \gamma_{\Delta h} \mathbb{I}_{i,\Delta h} \right) + \delta X_i + \mathbf{A}_{st} + \epsilon_{ist}, \tag{3}$$

where $\mathbb{I}_{\Delta h}$ indicates *deviations* of a worker's own hours from a reference level of hours which is either the median or wage-maximizing hours in an establishment. $\mathbf{A}_{st}$ is an interaction of establishment and year fixed effects and all other regressors are as in Equation (2).

Panels (c) and (d) of Figure 1 report the results from estimating this regression. Panel (c) shows the relationship between relative wages and deviations from the median hours worked in an establishment. We find that wages are the highest when workers work around 10 hours longer than the establishment median hours, with larger deviations from this level resulting in larger wage reductions.

Panel (d) shows the relationship between relative wages and deviations from the wage-maximizing hours in an establishment. Deviations from the wage-maximizing hours result in sharp declines in wages, suggesting, intuitively, that wages are, on average, highest around the wage-maximizing hours. Interestingly, and consistent with complementarities in hours, wage penalties monotonically increase as workers' hours deviate from the wage-maximizing hours. Moreover, the wage decrease is roughly symmetric regardless of whether a worker works longer or shorter hours relative to the wage-maximizing hours.

Together, panels (c) and (d) provide support for the presence of relative-to-coworker penalties and, thus complementarities in working hours as workers experience wage penalties for deviating from their coworkers. In Appendix C, we provide further evidence for the presence of relative-to-coworker penalties and our findings suggest that relative-to-coworker penalties account for the bulk of the overall wage penalty from working part-time.

2.3 Changes in Wages when Hours Change

A concern with the above analysis of hours and wages is that the relationships we document may be driven by unobserved individual characteristics. While we cannot fully address this concern, we can control for the fixed unobservable traits of workers by exploiting the short panel nature of the WES. Related to the intuition above, if coworkers' hours are complements in production, the same worker should earn lower wages if they deviate further from the hours of their coworkers between two periods. By tracking workers over time, we control for the time-invariant unobserved characteristics of workers.

We test the relationship between changes in wages and hours worked at the individual level in the WES. More formally, for each worker i working in establishment s in year t, we first compute the absolute log difference between their own hours, $h_{i,t}$, and the median or wage-maximizing hours, $\overline{h}_{s,t}$: $|\log h_{i,t} - \log \overline{h}_{s,t}|$. We then compute the changes in this measure between period t and $t+1$: $\Delta h_{ist} = |\log h_{i,t+1} - \log \overline{h}_{s,t+1}| - |\log h_{i,t} - \log \overline{h}_{s,t}|$. A positive (negative) value for the difference in differences, Δh_{ist}, indicates that worker i moved further (closer) from the reference hours between period t and $t+1$. Similarly, we can compute the changes in wages between t and $t+1$, $\Delta w_{ist} = (\log w_{i,t+1} - \log w_{i,t})$.

The presence of complementarities would imply a negative correlation between Δh_{ist} and changes in wages Δw_{ist}. That is, workers who move further away from their establishments' median or wage-maximizing hours suffer wage losses while those who move closer experience wage gains.

We examine this relationship estimating the following,

$$\Delta w_{ist} = \alpha + \left(\sum_{\Delta h_{ist} \in \mathcal{H}} \gamma_{\Delta h_{ist}} \mathbb{I}_{\Delta h_{ist}} \right) + \delta X_i + \mathbf{A}_{st} + \epsilon_{ist}, \tag{4}$$

where the indicator variable $\mathbb{I}_{\Delta h_{ist}}$ is equal to one if the relative change in difference hours over time is Δh_{ist}. We partition this "difference in difference" measure into a set $\mathcal{H}$ by grouping hours changes into 10% bins. We choose the 0 to +10% bin as the reference group

since most workers fall into this category of hours changes. All other regressors are as in Equation (3).

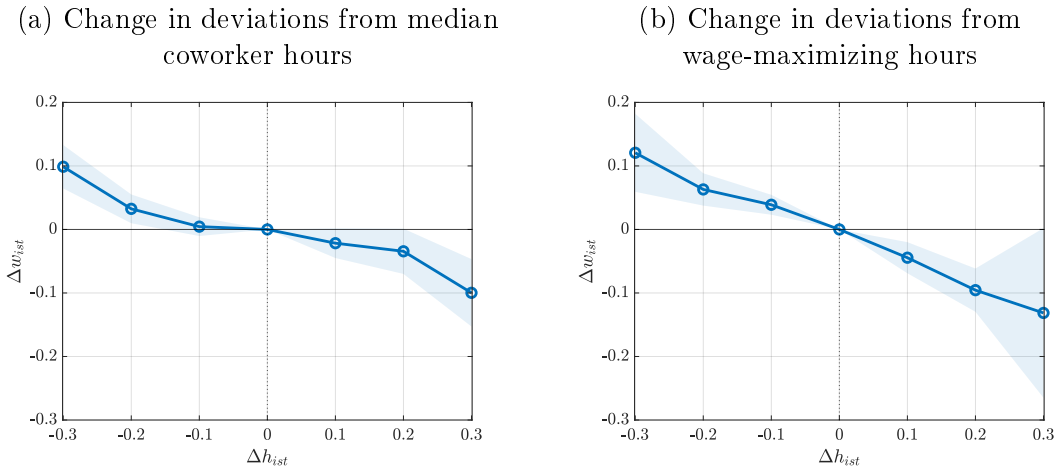


Figure 2: Dynamic changes in hours and wages

Notes: The figure reports the coefficient $\gamma_{\Delta h_{ist}}$ from estimating Equation (4). Panels (a) and (b) report this coefficient when the reference hours are the establishment median and establishment wage-maximizing hours, respectively. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

Figure 2 reports the coefficient $\gamma_{\Delta h_{ist}}$ when using the median (Panel a) or wage-maximizing hours (Panel b) as the reference hours $\overline{h}_{s,t}$. For both reference hours, we find a clear negative correlation between changes in wages and changes in hours worked over time – in line with the presence of complementarities in hours worked. Indeed, moving 10% further from the median and wage-maximizing hours results in a 2% and 5% penalty in wages, respectively.

2.4 Discussion

The evidence documented in this section is consistent with the presence of complementarities in working hours in production. However, it is not necessarily the only mechanism that can explain some of the patterns we present. Here, we briefly discuss alternative mechanisms while reiterating the evidence supporting complementarities.

First, the positive correlation between one's own and their coworkers' hours could also be due to individual preferences. Rogerson (2011) proposes that a motive for working hours coordination may arise from individuals' preferences for coordinating leisure time – in other

words, there may exist complementarities in *leisure*. Although we control for observable characteristics of individuals in our reduced-form analysis, these characteristics do not entirely capture individuals' underlying tastes over market and non-market hours.

Having said this, coordination of hours due to individuals' preferences cannot account for the within-establishment non-linear relationship between hours and wages that we document. Mechanisms behind the non-linear wage-hours profile could include the presence of fixed costs to production, leading to a short hours penalty, and diminishing returns to working hours, leading to a long hours penalty. Eden (2021) emphasizes the link between productivity and working time, highlighting that productivity increases with both working time (due to skill accumulation) and restfulness (through leisure), potentially leading to a non-linear relationship between absolute levels of working hours and wages. However, this work-leisure trade-off may not necessarily generate the static and dynamic, non-linear patterns we document between relative hours – hours in relation to the median or wage-maximizing hours within an establishment – and wages.

Overall, complementarities in working hours in production and alternative mechanisms such as those discussed here are not mutually exclusive. However, in the novel evidence presented here using the WES and related literature, there is significant support for the presence of working hours complementarities. For instance, Bick et al. (2022) suggest that the need to coordinate working hours may generate complementarities in working hours and could explain the economy-wide non-linear relationship between working hours and wages. To support this idea, they show that the modal and mean hours worked in Denmark are lower than in the US and, consistent with complementarities in working hours, the hours at which wages are maximized in Denmark are also lower than in the US.[11]

Labanca and Pozzoli (2022) explore the determinants of constraints on working hours

[11]Figure A.1 in Appendix A compares the aggregate wage-hours profile estimated from the US CPS and the Canadian Labor Force Survey (LFS). The figure shows that (economy-wide) wages peak at higher hours in the US than in Canada. Consistent with complementarities in working hours, the average hours worked in the US are also higher than the average hours worked in Canada. For example, in 2015, US workers worked around 3 hours longer (41.5 vs. 38.2).

and test whether firms' technology or individual preferences drive such constraints. They argue that constraints on hours are driven by the technologies utilized by firms rather than the collective choice of individuals coordinating on leisure. Their findings indicate that firms' technologies, rather than individuals' tastes, are more important for understanding constraints on hours – constraints that would arise naturally under a production process featuring complementarities in worker hours.

Motivated by these findings in the literature and those presented here, in the next section, we move beyond the reduced-form analysis of variation in hours and wages and use this variation to estimate the degree of complementarities in working hours in a more structural framework.

3 Estimating Complementarities in Working Hours

In this section, we first propose a model, which we then use to estimate the elasticity of substitution between the working hours of coworkers.

3.1 Production Function

The model we use to estimate the degree of complementarity in working hours is intentionally simple and limited to the description of the production function and a labor market structure. Firms' production is represented by: $Y = zL^{\eta}$, where L denotes the effective labor input and z is broadly defined as productivity, which can capture non-labor variables at the firm level such as technology, capital, or intermediate inputs.

In contrast to standard neoclassical models of production, where the effective labor input of a firm is the sum of total hours worked, we follow Yurdagul (2017) and allow for complementarities between the hours of workers. In particular, we assume that the labor input of workers is aggregated in a non-linear manner so that the aggregate labor input depends on

the distribution of hours worked in a firm. The labor input L is given by

$$L = \left(\frac{\int_{i \in N} x_i l_i^{\rho} di}{\int_{i \in N} x_i di} \right)^{\frac{1}{\rho}} \left(\int_{i \in N} x_i di \right), \tag{5}$$

where N is the set of workers, and $\{l_i\}_{i \in N}$ is their hours worked. The first parenthesis in Equation (5) is a CES aggregate of the efficiency-weighted working hours of all workers in a firm, normalized by the total efficiency levels of workers. Note that if a firm scales up the labor demand while maintaining the distribution over workers of different efficiencies, the term in the first parenthesis remains unchanged. Accordingly, the term in the second parenthesis serves to scale up this weighted average. This delivers the property that an increase in the number of workers by a factor, holding constant the hours-efficiency distribution, results in an increase in the aggregate labor input by the same factor. Moreover, it guarantees that our labor aggregation boils down to the standard linear labor aggregation in the case of $\rho = 1$.

Without loss of generality, we assume the working hours range from 0 and 1. To abstract from indices of workers, one can rewrite the aggregation in Equation (5) in terms of the measure of workers employed at each level of hours worked as

$$L = \left(\int_{x \in B_x} \int_0^1 x \mu(l, x) l^{\rho} dl dx \right)^{\frac{1}{\rho}} \left(\int_{x \in B_x} \int_0^1 x \mu(l, x) dl dx \right)^{1 - \frac{1}{\rho}}, \tag{6}$$

where $\mu(l, x)$ is the measure of workers with efficiency x working l hours. The parameter ρ determines the elasticity of substitution ($\frac{1}{1-\rho}$) between hours of different workers and is our key parameter of interest to be estimated.

In order to estimate ρ, we must first provide additional structure on the economic environment. To this end, we assume that labor markets are segmented by firm type, z, and all

firms within a sub-market hire workers in perfectly competitive labor markets.[12] Under this market structure, firms take the wage schedule $w_z(l,x)$ in their market as given and choose the measure, $\mu(l,x)$, of workers with a given hour-efficiency combination to hire in order to maximize their static profits:

$$\pi = \max_{\mu(l,x)} \; zL^{\eta} - \int_{x\in B_x} \int_0^1 w_z(l,x)\mu(l,x)l dl dx, \tag{7}$$

where L is given by (6).

The first-order condition of the firm's maximization problem returns an expression for the equilibrium wage schedule,

$$w_z\left(l,x\right) = \eta z x L^{\eta-1} E\left(l^{\rho}\right)^{\frac{1}{\rho}} \left[\frac{1}{\rho}\frac{l^{\rho-1}}{E\left(l^{\rho}\right)} + \left(1-\frac{1}{\rho}\right) l^{-1}\right], \tag{8}$$

where the right-hand side is the marginal productivity of a worker with efficiency units of x working l hours. $E\left(l^{\rho}\right) \equiv \left(\int_{x\in B_x}\int_0^1 x\mu\left(l,x\right) l^{\rho} dl dx\right) \div \left(\int_{x\in B_x}\int_0^1 x\mu\left(l,x\right) dl dx\right)$ is a weighted average of l^{ρ}, and L is the aggregate labor input.[13]

Equation (8) shows that a worker's wage depends not only on her own hours but those of her coworkers. Indeed, for $\rho \in (-\infty, 1)$ the maximum hourly wage, for each efficiency group, is achieved at the same level of hours $l^* = E\left(l^{\rho}\right)^{\frac{1}{\rho}}$ and wages decrease as working hours move away from l^*.[14] This wage schedule would also generate a channel through which coworkers' hours are positively correlated – as observed in the data. If $\rho = 1$, so that workers' hours

[12]The purpose of the partitioning is simply to accommodate heterogeneous equilibrium wage schedules between firms since perfect competition implies uniform wages within each sub-market. We could also allow for a more general segmentation whereby firms and workers are randomly allocated into an arbitrary number of sub-markets, with perfect competition within each sub-market. Even though we abstract from the possibility of imperfect competition in labor markets (e.g. Berger et al., 2022), our estimation only requires wages to be proportional to workers' marginal product and can accommodate constant wage markdowns which might result from firms having labor market power.

[13]Our estimation relies on variation within firms rather than between firms. Hence, for notational convenience, we omit indexing the variables L, $E(l^{\rho})$, $\mu(l,x)$, Y, π by firms' type although they are all specific to a firm.

[14]Notice, l^* depends on ρ and would in general be different from the median or average hours worked in a firm – as in the data.

are perfect substitutes in production, the hourly wage for the same x-type workers will be the same regardless of their hours. On the other hand, as $\rho \to -\infty$, so that the production function approaches Leontief, the marginal product for all workers will be zero if they do not work l^* hours. As illustrated by these two extremes, different values of ρ represent different relationships between wages and hours worked, which we use to estimate this parameter.

Before applying the implications of our model to estimate the substitution parameter ρ, it is important to note that we do not need to take a position on the labor supply choices of workers to arrive at our wage equation. This includes decisions on the extensive margin, such as the selection of workers into firms, or on the intensive margin, such as decisions on the hours worked given an employer. If we introduced an optimal labor supply decision for workers with varying levels of leisure and arbitrary exogenous or endogenous wealth distributions, our wage equation would remain the same as long as the model is consistent with the observed distribution of working hours. Taking the observed distribution of hours as given, Equation (8) indicates a distinct connection between wages and hours worked (relative to coworkers) within each firm. As a result, our estimation strategy detailed in Section 3.2 would follow in the same manner even if we included additional structure to model the labor supply decisions of workers.

3.2 Estimation Strategy

Estimating ρ directly from Equation (8) requires information on firm level productivity z, the returns to scale parameter η as well as a measure of worker efficiency x. This poses a challenge since there are no natural counterparts to these measures in the WES. However, we can eliminate z and η by normalizing worker earnings $(w_z(l, x)\, l)$ relative to average earnings of her establishment $\overline{W} \equiv \eta z L^{\eta-1} E(l^\rho)^{\frac{1}{\rho}} \mathbb{E}(x)$ where $\mathbb{E}(x)$ is the mean worker efficiency across all workers in the firm. Then, relative worker earnings for a worker i is independent of

measures that are fixed within an establishment and given by,

$$\widetilde{W}_i \equiv \frac{w_z(l_i, x_i) l_i}{\overline{W}} \quad = \quad \frac{x_i}{\mathbb{E}(x)} \left[\frac{1}{\rho} \frac{l_i^\rho}{E(l^\rho)} + 1 - \frac{1}{\rho} \right]. \tag{9}$$

While simpler, estimating ρ from (9) requires information on worker type x which is unobserved. Instead, we construct a proxy for worker efficiency, X, using a function of education, gender and age:

$$X_i = \theta_0 + \theta_1 \text{Education}_i + \theta_2 \text{Gender}_i + \theta_3 \text{Age}_i + \theta_4 \text{Age}_i^2, \tag{10}$$

where Age_i is the age of worker i and Education_i and Gender_i are dummy variables which indicate whether worker i has a college degree or is male, respectively.[15] Given this, we compute the efficiency of worker i relative to the firm average using $\widetilde{X}_i \equiv \frac{X_i}{\mathbb{E}(X)}$ so that the expression for relative earnings becomes,

$$\widetilde{W}_i \quad = \quad \widetilde{X}_i \times \left[\frac{1}{\rho} \frac{l_i^\rho}{E(l^\rho)} + 1 - \frac{1}{\rho} \right]. \tag{11}$$

Finally, we can substitute $E(l^\rho)$ with an observable measure that does not depend on ρ by recognizing that wages for each efficiency group in a firm are maximized when hours worked are $l^* = E(l^\rho)^{\frac{1}{\rho}}$. This allows us to replace $E(l^\rho)^{\frac{1}{\rho}}$ with the observed hours $\widetilde{l}^*$ that return the highest hourly wage in each establishment. Then, for each worker, we compute the hours relative to this establishment-specific reference hour as $\widetilde{h}_i = \frac{l_i}{\widetilde{l}^*}$, which delivers our estimating equation,

$$\widetilde{W}_i \quad = \quad \widetilde{X}_i \times \left[\frac{1}{\rho} \widetilde{h}_i^\rho + 1 - \frac{1}{\rho} \right], \tag{12}$$

[15] An alternative proxy of worker efficiency is a worker fixed effect. There are two issues with identifying worker fixed effects in our data. First, the WES does not track workers that switch employers. Second, it only tracks the stayers for up to two years. Nevertheless, using individual fixed effects in our estimating Equation (3) and using these as additional proxies for worker skill in Equation (10) lead to very similar estimates to what we report below.

where $\widetilde{W}_i$ are the earnings of worker i relative to the average firm earnings, $\widetilde{X}_i$ is a proxy for relative worker efficiency and $\widetilde{h}_i$ are the hours worked of worker i relative to the wage maximizing hours. Assuming that the error term enters Equation (12) linearly, we use nonlinear least squares regression to estimate the substitution parameter ρ through this equation.[16]

3.3 Results

We report our estimation results in Table 2.[17] Panel A reports the estimates of ρ for the aggregate sample for three alternative proxy measures of worker skill x_i. When considering only education as a proxy for skill, we estimate ρ to be around -0.44, implying an elasticity of substitution of around 0.69. Including gender and age leads to a very similar elasticity.[18] Importantly, regardless of the proxy for x_i, we find that the elasticity of substitution between working hours is below 1 – that is, working hours are gross complements in production.

We also separately estimate the working hours' elasticity of substitution by industry by restricting our sample to a particular industry and then estimating the substitution parameter, ρ, using education, age, and gender to proxy for worker skill, x_i. Panel B of Table 2 shows the results for each of the 14 industry groups in the WES. Except for one industry, our estimates imply working hours to be gross complements in production. Indeed, even in "communications and other utilities", where the elasticity of substitution is around

[16] An alternative approach would be assuming that the error terms enter Equation (12) multiplicatively. In this case, the nonlinear least squares regression necessitates taking the log-transformation of the original equation. However, this could create issues, as negative values of $[\frac{1}{\rho}\widetilde{h}_i^{\rho} + 1 - \frac{1}{\rho}]$ would not be used, resulting in information loss, particularly in the lower end of the relative hours distribution. Moreover, as the algorithm iterates over ρ, the sample of observations utilized to evaluate the objective function changes as well. Consequently, these properties of the log-transformed specification could yield inaccurate estimations, diminishing the overall fit of the regression under multiplicative errors.

[17] We jointly estimate the coefficients θ_i for the proxy measure of worker skills along with the substitution parameter ρ. Estimates of θ_i are reported in Table A.2 in Appendix A.

[18] To verify that we have found the global minimum for ρ, we conducted estimations using different starting points within a large range that we believe contains its true value. Specifically, we selected 60 starting points from $[-20, 20] \setminus \{0\}$, with a greater concentration of points around 0. Regardless of the initial guess, the NLS estimation consistently converged to a similar ρ value. For instance, with a full set of controls (age, education, and gender) in our baseline estimation, all initial guesses of ρ led to convergence within the narrow range of $[-0.4601, -0.4593]$.

1.03, the 95% confidence interval does not preclude working hours being gross complements.[19]

Table 2: Estimation results

Panel A: Aggregate

	Substitution Parameter, ρ		Elasticity of Substitution $\frac{1}{1-\rho}$	
	Estimate	95% CI	Estimate	95% CI
Proxy for x_i using only Education	-0.443	[-0.476,-0.410]	0.693	[0.677,0.709]
Proxy for x_i using only Education and Gender	-0.459	[-0.491,-0.426]	0.686	[0.671,0.701]
Proxy for x_i using only Education, Gender and Age	-0.459	[-0.491,-0.427]	0.685	[0.685,0.701]

Panel B: Industry

	Substitution Parameter, ρ		Elasticity of Substitution $\frac{1}{1-\rho}$	
	Estimate	95% CI	Estimate	95% CI
Secondary product manufacturing	-0.940	[-1.265,-0.614]	0.516	[0.441,0.619]
Primary product manufacturing	-0.724	[-0.945,-0.503]	0.580	[0.514,0.666]
Construction	-0.680	[-0.796,-0.565]	0.595	[0.557,0.639]
Transportation, warehousing, wholesale	-0.636	[-0.738,-0.534]	0.611	[0.575,0.652]
Labor intensive tertiary manufacturing	-0.620	[-0.822,-0.418]	0.617	[0.549,0.705]
Education and health services	-0.603	[-0.674,-0.532]	0.624	[0.597,0.653]
Real estate, rental and leasing operations	-0.491	[-0.666,-0.315]	0.671	[0.600,0.760]
Forestry, mining, oil, and gas extraction	-0.487	[-0.658,-0.297]	0.673	[0.602,0.763]
Capital intensive tertiary manufacturing	-0.385	[-0.664,-0.106]	0.722	[0.601,0.904]
Business services	-0.360	[-0.516,-0.204]	0.736	[0.666,0.831]
Finance and insurance	-0.239	[-0.369,-0.110]	0.807	[0.731,0.901]
Retail trade and consumer services	-0.187	[-0.295,-0.080]	0.842	[0.772,0.926]
Information and cultural industries	-0.172	[-0.333,-0.010]	0.854	[0.750,0.990]
Communication and other utilities	+0.033	[-0.145,+0.210]	1.034	[0.874,1.265]

Panel C: Establishment size

	Substitution Parameter, ρ		Elasticity of Substitution $\frac{1}{1-\rho}$	
	Estimate	95% CI	Estimate	95% CI
$<$ 10 Employees	-0.403	[-0.475,-0.329]	0.713	[0.678,0.752]
10 to 99 Employees	-0.453	[-0.502,-0.405]	0.688	[0.666,0.712]
100+ Employees	-0.492	[-0.544,-0.439]	0.670	[0.648,0.653]

Notes: The table reports estimates of the substitution parameter, ρ and the corresponding elasticity of substitution $\frac{1}{1-\rho}$ along with 95% confidence intervals, as estimated from Equation (12) using non-linear least squares. Panel A reports these estimates for the aggregate sample. Panel B and C report the same measures by establishment industry and establishment size, respectively. To limit the influence of outliers, we trim the top and bottom 1 percent of the ratios $\tilde{W}_i$ and $\tilde{h}_i$ from Equation (12).

Our results show significant heterogeneity in the extent of complementarity in working hours. Secondary and primary product manufacturing features the highest degree of complementarities with an estimated elasticity of substitution between working hours of 0.52 and 0.58, respectively.

[19] Table A.3 in Appendix A lists the NAICS industry codes that comprise each WES industry category.

Low-skill service sectors such as retail trade and consumer services, and information and cultural industries exhibit the lowest (statistically significant) degree of complementarities with an elasticity of substitution of around 0.85. In contrast, education and health services, which require higher skills, feature higher complementarities with an elasticity of 0.62.

The manufacturing sector generally features stronger complementarities in working hours than service sectors.[20] This suggests that the manufacturing sector allows less flexibility in terms of allowing workers to choose a "non-standard" number of working hours than the service sector. Such flexibility may give women, who tend to value flexibility more than men (Goldin, 2014), a comparative advantage in service industries. Indeed, our findings complement existing works such as Ngai and Petrongolo (2017) and Rendall (2018) that highlight women's comparative advantage in the service sector. These estimates suggest that this comparative advantage could stem from a relative flexibility in service sector production. We further study how our estimates of complementarities vary with flexibility and female employment in Section 3.4, which aims to validate our estimates.

Finally, Panel C of Table 2 reports the estimated substitution parameter ρ and corresponding elasticity of substitution by establishment size. We consider three size categories; small establishments with under 10 employees, medium-sized establishments with between 10 and 99 employees, and large establishments with over 100 employees. Our estimated elasticities indicate that complementarities are increasing with establishment size with an estimated elasticity of 0.71 in small establishments compared to 0.69 and 0.67 for larger establishments.

Although these point estimates are not statistically different across size groups, we consider higher levels of substitutability of hours in smaller establishments to be intuitive and consistent with existing evidence. For example, Elfenbein et al. (2010) show that employees in smaller workplaces undertake a larger number of activities related to the business which may decrease the need to coordinate with coworkers. Related to this, Molina-Domene (2018)

[20] The estimated elasticities for all manufacturing and service industries are 0.61 and 0.69, respectively.

shows that workers in larger firms undertake fewer tasks and are more likely to be specialists raising the need to coordinate with coworkers resulting in stronger complementarities in working time between different workers.

3.4 Validation

Here, we explore whether our estimates of complementarities are systematically related to measures of hours coordination across industries. In particular, we use three measures to proxy for worker coordination at the industry level and test whether industries with a lower degree of complementarities in working hours also feature lower levels of coordination in work schedules. The three measures are i) the share of workers that work flexible hours, ii) the standard deviation of hours worked, and iii) the share of female workers in an industry. Figure 3 plots the industry average of these measures and the industry elasticity of substitution.

Panel (a) shows that industries with a larger share of workers with flexible working hours also feature higher elasticities of substitution and, therefore a lower degree of complementarity in working hours.[21] Indeed, the correlation between workers' shares and elasticity is 0.59. Industries with lower shares of flexible hour workers, such as labor-intensive or primary product manufacturing, feature a higher degree of complementarity (a lower elasticity of substitution) than industries with higher shares of flexible hour workers, such as information and cultural industries. This is intuitive since greater flexibility in choosing one's working hours may indicate less need for workers to coordinate their work schedule and hence a lower degree of complementarity in working hours.

Next, we examine how the industry's standard deviation of working hours relates to our estimates of working hour complementarities. Consistent with Labanca and Pozzoli (2022), we view a more significant variation in hours as indicating a production process that requires lower coordination of hours. We expect to see a positive relationship between the degree

[21] The share of flexible workers in an industry is the share of workers giving an affirmative response to the question *Do you work flexible hours?* An affirmative answer implies that workers can vary their daily start and stop times as long as they work a full workweek. That is, on a daily basis, a "flexible" worker may not work the same number of hours as their coworkers nor work at the same time as them.

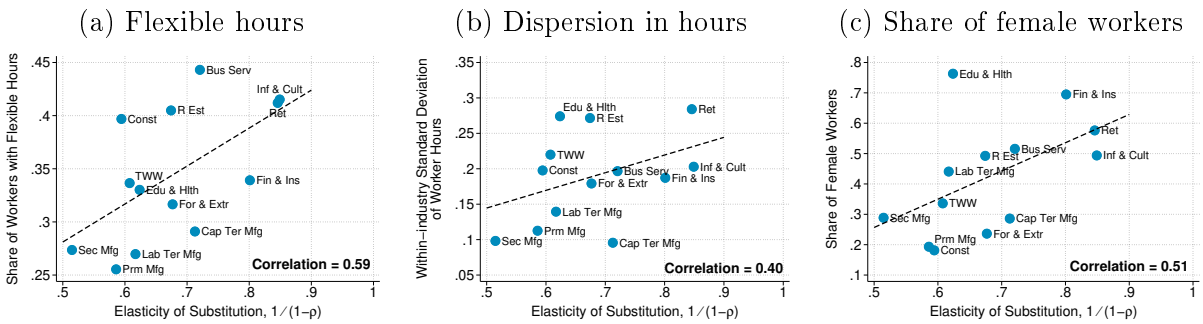


Figure 3: Elasticity of substitution and coordination measures across industries

Notes: Each panel of the figure plots the industry-specific estimate of the elasticity of substitution on the horizontal axis and a different measure of coordination on the vertical axis. Panel (a) plots the share of workers with flexible hours, Panel (b) plots the within-industry standard deviation of hours worked, and Panel (c) plots the share of female workers. The correlation between elasticity of substitution and coordination measure is reported in the panel. The sample excludes "Communication and other utilities" since our estimate does not establish at the 5% significance level whether working hours are either gross complements or substitutes. The correlation between elasticity of substitution and share of flexible hours, the share of female workers, and the standard deviation of working is 0.32, 0.26, and 0.19, respectively, when all 14 sectors are included. Detailed descriptions of industries can be found in Table A.3 in Appendix A.

of substitution in working hours and dispersion across industries. Panel (b) plots these two measures and shows that, as expected, there is a positive correlation (0.40) between our estimated elasticity of substitution and the standard deviation of working hours.

Finally, we consider the share of female workers as a proxy for the degree of flexibility in hours in production. Since female workers tend to work fewer hours and choose more flexible occupations, a higher share of female workers in an industry may proxy for the degree of flexibility in working hours (Goldin, 2014).[22] Panel (c) shows that there exists a strong positive correlation (0.51) between the degree of working hours substitutability and the share of female workers across industries.

Importantly, the measures of hours coordination considered here are not directly related to variation in earnings across workers, which underpinned our estimation strategy. Taken together, the findings in Figure 3 support our estimated measures of complementarities in hours.

[22]The correlation between the share of flexible hour workers and female workers is 0.35.

4 Implications for the Gender Wage Gap

The presence of complementarities in working hours has wide-ranging implications on, among other aspects, wage inequality, the response of labor supply to policies and shocks, and the design of alternative work arrangements. In this section, we explore its implications for the gender wage gap for three reasons. First, the hours distributions between genders are significantly different. Second, we expect differences in hours to play an important role in the wage gaps between these groups since the technologies and skills do not systematically favor one over the other. Finally, gender differences in salaried work, particularly the gender wage gap, have been widely studied and are a prominent area of research.

Although the majority of the gender wage gap remains unexplained by observable characteristics, heterogeneity in hours worked is often cited as an important contributor (see, for example, Blau and Kahn, 2017).[23] For instance, Goldin (2014) discusses how the wage penalty for part-time work lowers women's average wages as they tend to work shorter hours. We reassess the role of hours on the gender wage gap through the lens of our theoretical model. When combined with estimates of ρ, our production function allows us to directly compute both short- and long-hour penalties at the individual level in an establishment. This is in contrast to existing studies, such as Goldin (2015), which use aggregated measures of wage-hour penalties. Instead, our parsimonious structural framework allows us to construct counterfactual wages for each individual that remove wage penalties due to working hours. Comparing the observed gender wage gap to one constructed using these counterfactual wages allows us to quantify the role of hours in driving the gender wage gap.

Notice that wage penalties occur in the presence of complementarities in working hours when workers' hours deviate from those of their coworkers. However, if hours are perfect substitutes (i.e., $\rho = 1$), differences in hours will not generate wage penalties (among identical workers). Accordingly, the degree of complementarities in working hours and the distribution

[23] Pelletier et al. (2019) documents recent trends in the gender wage gap in Canada and finds that, in 2018, around 63% of the wage gap between men and women was not accounted for by observable characteristics.

of hours will be crucial in shaping the role of hours on the gender wage gap.

Revisiting Equation (8) allows us to construct a measure of wages that removes wage penalties while leaving the other components of workers' wages unchanged. Recall, when $\rho < 1$, wages (for each worker type in an establishment) are maximized at $l^* = E\left(l^\rho\right)^{\frac{1}{\rho}}$ and decrease as worker hours deviate from l^*. As such, our model predicts that the ratio of the actual wage of a worker i in establishment j, $w_j\left(l_i, x_i\right)$, and her maximum attainable wage in that establishment, $w_j\left(l_i^*, x_i\right)$, is

$$\frac{w_j\left(l_i, x_i\right)}{w_j\left(l_j^*, x_i\right)} = \frac{l_j^*}{l_i}\left[\frac{1}{\rho}\frac{l_i^\rho}{l_j^{*\rho}} + \left(1 - \frac{1}{\rho}\right)\right]. \tag{13}$$

Using this ratio, we can compute an alternative wage, which removes the effects of the short- and long-hour penalties for each individual i in an establishment. We compute the counterfactual wage as,

$$w_{i,j}^* = w_{i,j}\frac{l_{i,j}}{l_j^*}\left[\frac{1}{\rho}\frac{l_{i,j}^\rho}{l_j^{*\rho}} + \left(1 - \frac{1}{\rho}\right)\right]^{-1}, \tag{14}$$

where we denote the wage in the data for an individual by $w_{i,j}$, her hours by $l_{i,j}$, and the hours of the worker with the highest wage in her establishment is denoted by l_j^*.

This counterfactual wage adjusts each worker's wages by removing the penalties arising from hours deviations while still taking into account any wage components not attributable to the individual's hours (due to unobserved ability, for example). In other words, it eliminates the component of wages that correspond to penalties resulting from working either relatively short or long within a given establishment.[24]

We use Equation (14) to study the contribution of hours (and the corresponding wage penalties) on the gender wage gap. The extent to which counterfactual wages, $w_{i,j}^*$ differ from $w_{i,j}$ depend on i) the degree of deviation in hours, $\frac{l_{i,j}}{l_j^*}$ and ii) the elasticity parameter ρ,

[24]Importantly, when constructing counterfactual wages, we take the observed distribution of hours as given so that the effective labor aggregate L_j and the expectation term $E_j(l^\rho)$ do not change.

which is estimated using the WES and varies based on the industry of the establishment.[25]

Panel (a) of Figure 4 reports the distribution of $\frac{l_{i,j}}{l_j^*}$ across individuals and establishments. As with the absolute level of hours worked, the relative working hours of men and women feature significant differences, with male hours being longer and more concentrated around the wage-maximizing hours than women's. Further, for both genders, a relatively small share of workers work longer than the wage-maximizing hours. As such, we expect the long-hours penalty to play a relatively small role in generating overall wage penalties and the gender wage gap.

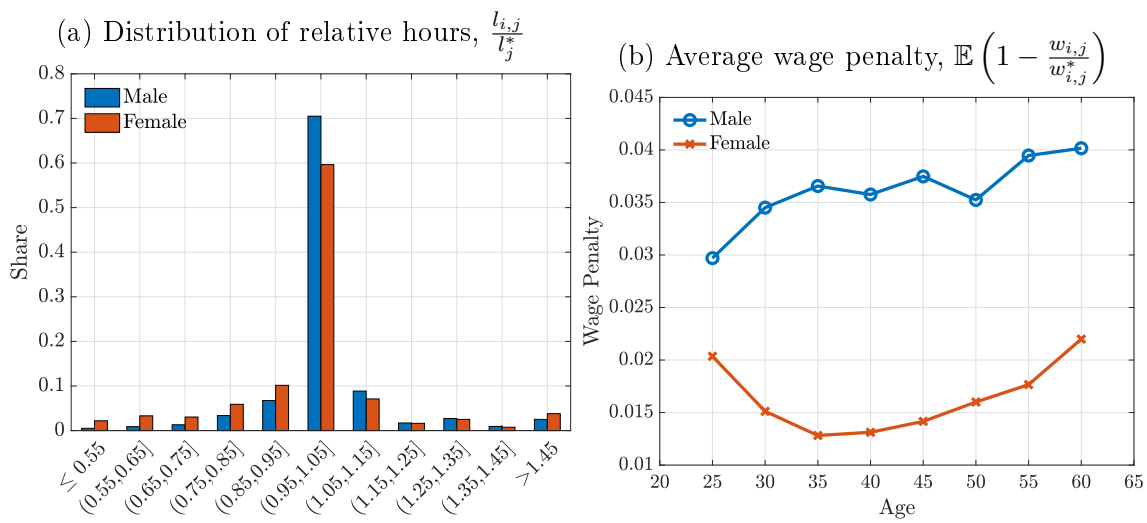


Figure 4: Distribution of relative hours and wage penalties, by gender

Notes: Panel (a) plots the distribution of worker hours relative to the establishment's wage-maximizing hours ($\frac{l_{i,j}}{l_j^*}$) by gender. Panel (b) plots the average wage penalty by gender, where wage penalty for each individual i in establishment j is calculated as $(1 - \frac{w_{i,j}}{w_{i,j}^*})$.

Given the observed variation in relative hours, the presence of complementarities in hours will introduce positive wage penalties for all workers. Panel (b) plots the average wage penalties over the life-cycle, separately by gender. Consistent with the relative hours distribution in Panel (a), the imputed penalties for women are higher than those for men

[25] In this analysis, setting the firm-specific reference hours worked to be l_j^* allows us to compute a uniform measure of hours-wage penalties across all workers. Adjusting the wages of a worker by setting her hours equal to an alternative reference point would generally result in wage penalties for each individual that are not clearly interpreted. For instance, if we set hours equal to an alternative $\tilde{l}$ that is constant across workers, then the wage penalties might increase or decrease for different workers relative to the baseline, depending on their original hours, and the actual wage maximizing hour l_j^* in their firm.

throughout the life-cycle. Women's wage penalties are roughly twice those of men, with the largest difference occurring during the late 30's and early 40's – a point in the life-cycle during which the gender wage gap also peaks as documented by Goldin (2014) in the US. Wage penalties for women rise again in the late 50's and beyond, but so do penalties for men with relatively little changes in differences in penalties.

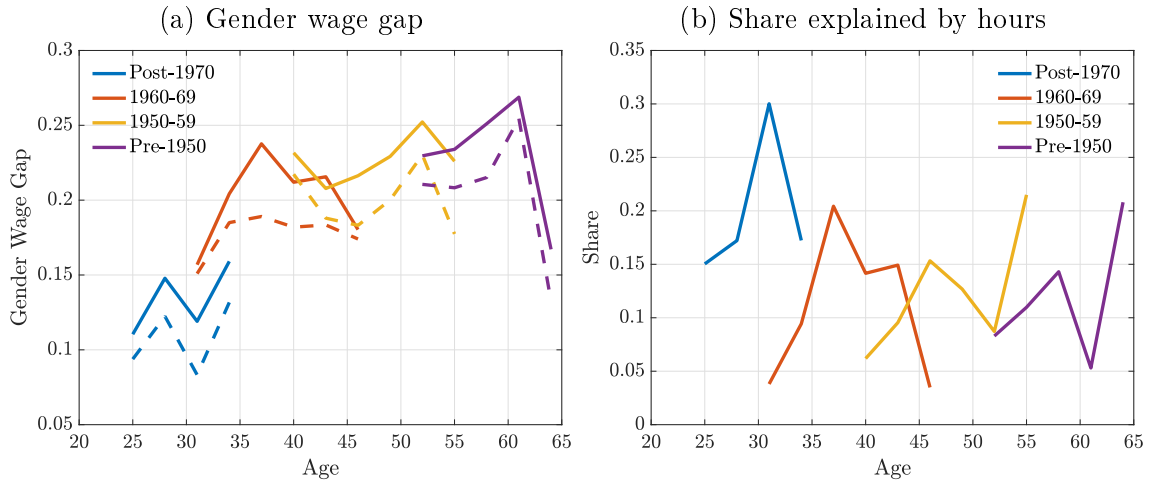


Figure 5: The gender wage gap and the role of hours penalties, all workers

Notes: Panel (a) plots the observed (solid lines) and counterfactual (dashed lines) gender wage gap over the life-cycle by cohort in the WES. The gender wage gap is computed as one minus the ratio of average female to average male earnings. Panel (b) plots the difference between the observed and counterfactual gender wage gaps as a share of the observed gender wage gap.

Next, we compare the observed gender wage gap to the gender wage gap derived from counterfactual wages. Panel (a) of Figure 5 reports the level of the observed (solid lines) and counterfactual (dashed lines) wage gaps by age and cohort. Consistent with existing literature, the gender wage gap appears to be inverse-U shaped over the life-cycle, peaking in the late 30's. However, given the WES is available for a relatively small number of years, it is difficult to establish a clear distinction between life-cycle and cohort effects. The counterfactual wage gap, which results from removing wage penalties, is lower at each point in the life-cycle, suggesting that the penalties resulting from hours heterogeneity widen the gender wage gap.

How much of the gender wage gap is due to heterogeneity in hours and the resulting

wage penalties due to complementarities? Panel (b) answers this question by reporting the difference between observed and counterfactual gender wage gaps. It shows that hours heterogeneity accounts for between 5 to 30 percent of the gender wage gap over the life-cycle. The largest contribution to the gender wage gap, and the accompanying wage penalties, occurs in the early 30's, accounting for 30% of the observed gender wage gap. This contribution tends to decline with age until reaching a minimum of around 5% during the early 60's. However, as with the gender wage gap itself, the effects of time, age, and cohort are difficult to disentangle without a longer sample period. On average, we find the hours contribute to around 14% of the gender wage gap; put differently, if we remove the wage penalties that arise due to complementarities in working hours, the gender wage gap will shrink by 14% or around 2 percentage points (relative to the 13.3% gender wage gap documented in Pelletier et al., 2019 in Canada in 2018.).

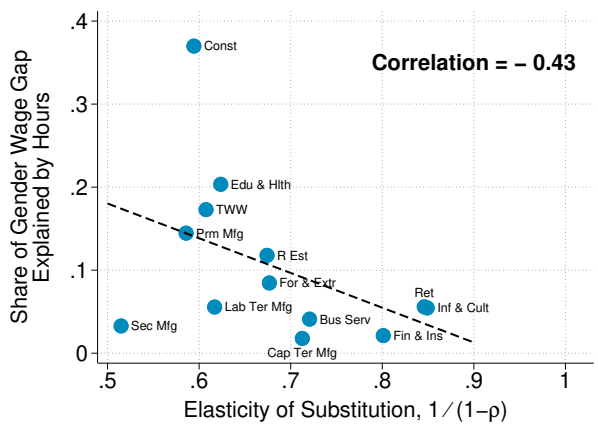


Figure 6: Gender-wage gap and hours penalties, across sectors

Notes: The figure plots industry-specific estimates of the elasticity of substitution. $\frac{1}{1-\rho}$, and the share of the gender wage gap explained by hours penalty across industries. Detailed descriptions of industries can be found in Table A.3 in Appendix A.

Notice, heterogeneity in the degree of complementarities in working hours, as governed by ρ, also influences the magnitude of wage penalties resulting from hours heterogeneity and hence the contribution of hours for the gender wage gap. To illustrate this, we compute the share of the gender wage gap explained by hours separately for each industry in the WES

and plot this share in Figure 6. Industries that feature stronger substitutability in working hours across worker hours also feature a smaller role for hours in the gender wage gap. This is intuitive since strong substitution between working hours implies that deviations in working hours will not lead to large wage penalties. Indeed, given a preference for shorter hours, women may internalize this and sort into industries with highly substitutable hours in order to avoid large penalties from deviations (Panel c of Figure 3).

Much of the variation in hours between genders stems from women working shorter hours than men. Indeed, in the WES, 16% of women work part-time (under 30 hours) compared to only around 4% of men. Thus, a penalty for working part-time will generate wage gaps between genders. However, the implication of complementarities in working hours is more general and will lead to wage gaps whenever there are differences in the hours distributions across workers.[26] To illustrate this, Figure 7 repeats the analysis above when only considering full-time workers (those that work at least 30 hours).

Panel (a) plots the observed (solid lines) and counterfactual (dashed lines) gender wage gap for full-time workers and shows that the observed gender wage gap for full-time workers ranges between 10 and 25 percent, and compared to Figure 5, is only modestly smaller than the gap for all workers. Using the counterfactual wage gap, Panel (b) of Figure 7 plots the share of the gender wage gap that is due to hours penalties arising from deviations from the wage-maximizing hours. Among full-time workers, around 4% of the gender wage gap can be explained by hours penalties arising. This share is lower than the fraction explained in the sample of all workers which varies between 5 and 30 percent across cohort-age pairs. A smaller role for hours penalties among full-time workers is intuitive since wage-hour penalties arise due to hours deviation from coworkers. By restricting the sample of workers to a certain hours category, we remove variation in hours and take away the power of hours variation in

[26] In Appendix E.1 we explore, separately by gender, the role of hours penalties in generating wage gaps between workers with and without children. We find modest wage gaps for male workers with and without children and hours penalties do not significantly impact these gaps. Consistent with Kleven et al. (2019), we find significant wage penalties for women with children. Indeed, for young women in the most recent cohort, hours account for about 22% (or about 4 percentage point) of the wage gap between women with and without children.

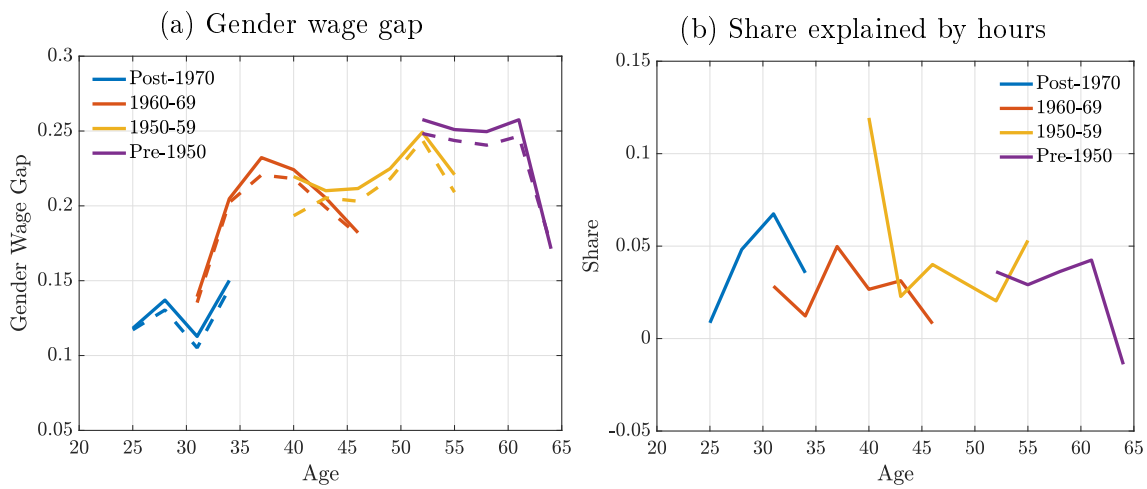


Figure 7: The gender wage gap and the role of hours penalties, full-time workers

Notes: Panel (a) plots the observed (solid lines) and counterfactual (dashed lines) gender wage gap over the life-cycle by cohort in the WES for the same of full-time workers that work at least 30 hours per week. The gender wage gap is computed as one minus the ratio of average female to average male earnings. Panel (b) plots the difference between the observed and counterfactual gender wage gaps as a share of the observed gender wage gap.

explaining the gender wage gap.[27]

The idea that working hours, particularly the shorter hours worked by women, contribute to the gender wage gap is consistent with the analysis in Goldin (2014) and Goldin (2015). While Goldin (2015) relies on reduced form analysis based on aggregated (average) penalties, we propose that the presence of complementarity provides an endogenous mechanism which generates short- and long-hour wage penalties experienced by individuals deviating from their coworkers' hours. This allows us to explicitly quantify the role of these penalties for the gender wage gap. Importantly, our analysis suggests that part of the gender wage gap can be attributed to production technology, namely the presence of complementarities in hours worked. In this regard, our results complement Cubas et al. (2023), which show that the gender wage gap can be explained by, in part, the need to work *at the same time* as one's coworkers.

Taken together, our analysis suggests that hours heterogeneity under complementari-

[27] We further explore the role of short- and long-hour penalties in accounting for the gender wage gap in Appendix E.2. We compare the observed and counterfactual gender wage gaps after i) removing penalties for all workers, and ii) removing penalties only for workers who work short hours ($<$30 hours) or for those who work long hours ($\geq$50 hours).

ties in hours contributes significantly to the gender wage gap and, more generally, to wage inequality.

5 Conclusion and Further Remarks

This paper uses matched employer-employee data from Canada to study complementarities between coworkers' hours in production. We provide novel reduced-form evidence that is consistent with the presence of such complementarities. Specifically, we find (i) coworker hours are strongly positively correlated with individual hours, (ii) wages *within establishments* peak at intermediate hours and feature penalties at extreme levels of hours, (iii) workers that move further away from (closer to) the median or the wage-maximizing hours in an establishment face wage reductions (increases).

We then use a simple model to estimate the degree of complementarities in working hours. The economy-wide elasticity of substitution is estimated to be 0.69, implying that working hours are gross complements in production. Although our industry-specific estimates exhibit significant variation, we find that hours are gross complements for almost all sectors in our data. To validate our estimates, we show that the estimated elasticities of substitution are positively correlated to proxy measures of the degree of coordination in working hours across industries.

Finally, we explore the implications of complementarities in working hours for the gender wage gap. In particular, we investigate the role of heterogeneity in hours in accounting for the gender wage gap. By removing individual-level wage penalties that arise under complementarities in hours, we show that the hours heterogeneity accounts for around 14% of the overall gender wage gap.

Overall, our results challenge a canonical assumption about the nature of production, namely, that the working hours of workers are perfect substitutes. The evidence supporting complementarities between coworker hours has important implications for research on worker

sorting, labor supply responses to shocks and policies, and firm productivity.

First, when wage penalties depend on one's hours relative to coworkers, as is the case under complementarities in working hours, the distance between an individual's desired hours and usual hours in a firm will play a role in workers' sorting into firms. As discussed in Shao et al. (2022), worker sorting into firms where this distance is smaller is important in shaping the distribution of hours and wage inequality across firms.

Second, in the presence of complementarities in working hours, shocks or policies which affect many workers will have different implications than those that affect only one (or fewer) worker. This may be particularly important when considering policies and shocks related to labor supply over the life-cycle or by gender. Further, heterogeneity in the degree of complementarity in working hours implies that changes in income tax or other labor supply policies will have differential impacts depending on the industry.

Lastly, the degree of complementarities in working hours can also help us understand the sources of firm-level differences in productivity. Indeed, under complementarities in working hours, cross-firm variation in how hours are distributed could translate into firm-level heterogeneity in productivity such that firms with greater (within-firm) dispersion in hours would, all else equal, be less productive. Accordingly, policies or alternative work arrangements that address gender inequity or labor force participation through increased flexibility need to internalize this channel.

While the simple model presented here provides a minimal structure to estimate the degree of complementarities in working hours, a thorough analysis of the impact of policies such as work-week restrictions or the provision of flexible work arrangements within a firm requires further theoretical structure, including specifications of the labor supply decisions of workers. These are interesting avenues of research, which we leave for future work.

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Appendix for:
Are Working Hours Complements in Production?

Lin Shao Faisal Sohail Emircan Yurdagul

A Additional Figures and Tables

Table A.1: Summary statistics, WES

	Obs	Mean	Std. Dev.
Age	129,037	42.78	9.89
Usual Weekly Hours Worked	126,613	37.57	8.17
Hourly Wage (CAD)	126,613	20.96	12.94
Hourly Wage (no extra earnings, CAD)	105,005	20.08	11.44
High School Graduate	129,037	0.85	0.36
College Graduate	129,037	0.46	0.50
Establishment Age	126,911	21.77	22.13
Total # Employees in Firm	129,037	402.17	1088.71
Gross operating revenue (mil. CAD)	129,037	37.08	139.05
Average Usual Weekly Hours in Establishment	128,828	37.11	6.50
Average Hourly Wage in Establishment	128,828	20.71	9.75

Notes: The table reports a number of summary statistics from the WES sample.

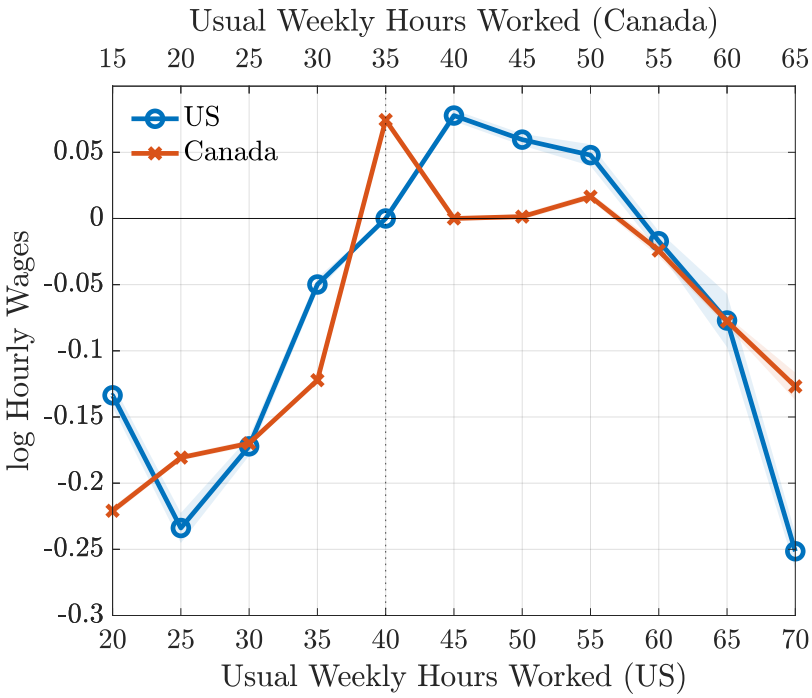


Figure A.1: Aggregate relationship between hours and wages, data from US and Canada worker surveys

Notes: The figure plots the aggregate relationship between weekly hours worked and wages. In particular, it plots the coefficient γ_h as estimated from the following regression,

$$\log(w_i) = \alpha + \left(\sum_{h \in H} \gamma_h \mathbb{I}_{i,h} \right) + \delta X_i + \epsilon_i$$

where $\log(w_i)$ is the log hourly wages of individual i. X_i is a vector of individual-level controls which includes demographic controls including gender, race and education dummies, a quadratic in years of experience as well as state, year, and industry fixed effects. The indicator variable $\mathbb{I}_{i,h}$ is equal to one if an individual works h hours. Weekly hours h are partitioned into a set $H = \{10-14, 15-19, \ldots, 65-69, 70-99\}$. As most workers work 40 hours, the category $40-44$ hours is the omitted (reference) category. Data from the US is from 1991 to 2018 Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). Data from Canada is from the 1997 to 2018 Canadian Labor Force Surveys (LFS). Additional details on the sample construction can be found in Shao et al. (2022). The bottom horizontal axis reports results from the CPS. The top horizontal axis is shifted by 5 hours and reports results from the LFS. The shaded regions indicate the 95% confidence interval.

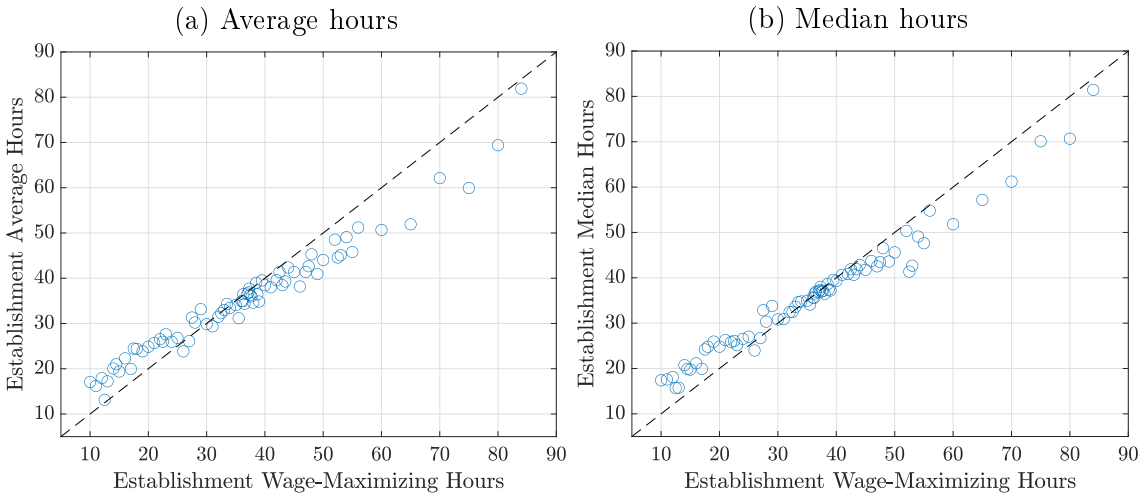


Figure A.2: Wage-maximizing hours and average/median coworker hours

Notes: The figure illustrates the relationship between establishment-level wage-maximizing hours and average/median hours. Each dot represents a group of establishments with the same wage-maximizing hours. Due to data confidentiality restrictions, the panels only display binned groups with more at least ten observations. The horizontal axis reports the wage-maximizing hours while the vertical axis reports the mean value of establishment-level average hours (Panel (a)) and median hours (Panel (b)) in each group.

Table A.2: Estimated coefficient of proxy measure of worker efficiency, $\widetilde{X}_i$

	(1)	(2)	(3)
Coefficient on Education, θ_1	0.142	0.155	1.68
	(0.003)	(0.003)	(0.353)
Coefficient on Gender, θ_2	-	0.203	1.99
	-	(0.003)	(0.417)
Coefficient on Age, θ_3	-	-	0.355
	-	-	(0.084)
Coefficient on Age^2, θ_4	-	-	-0.003
	-	-	(0.001)

Notes: The table reports the coefficient θ_i from estimating Equation (12) using the aggregate WES sample. Robust standard errors are reported in the parentheses.

Table A.3: NAICS industry codes and description

WES Industry Description	Abbreviation	NAICS Industry Description and Code
Forestry, mining, oil, and gas extraction	For & Extr	Forestry and Logging (113), Support Activities for Forestry (1153), Oil and Gas Extraction (211), Mining (except Oil and Gas) (212), Support Activities for Mining and Oil and Gas Extraction (213)
Labor intensive tertiary manufacturing	Lab Ter Mfg	Food Manufacturing (311), Beverage and Tobacco Product Manufacturing (312), Textile Mills (313), Textile Product Mills (314), Clothing Manufacturing (315), Leather and Allied Product Manufacturing (316), Furniture and Related Product Manufacturing (337), Miscellaneous Manufacturing (339)
Primary product manufacturing	Prm Mfg	Wood Product Manufacturing (321), Paper Manufacturing (322), Petroleum and Coal Products Manufacturing (324), Non-Metallic Mineral Product Manufacturing (327), Primary Metal Manufacturing (331)
Secondary product manufacturing	Sec Mfg	Chemical Manufacturing (325), Plastics and Rubber Products Manufacturing (326), Fabricated Metal Product Manufacturing (332)
Capital intensive tertiary manufacturing	Cap Ter Mfg	Printing and Related Support Activities (323), Machinery Manufacturing (333), Computer and Electronic Product Manufacturing (334), Electrical Equipment, Appliance and Component Manufacturing (335), Transportation Equipment Manufacturing (336)
Construction	Const	Prime Contracting (231), Trade Contracting (232), Construction of Buildings (236), Heavy and Civil Engineering Construction (237), Specialty Trade Contractors (238)
Transportation, warehousing, wholesale	TWW	Farm Product Wholesaler-Distributors (411), Petroleum Product Wholesaler-Distributors (412), Food, Beverage and Tobacco Wholesaler-Distributors (413), Personal and Household Goods Wholesaler-Distributors (414), Motor Vehicle and Parts Wholesaler-Distributors (415), Building Material and Supplies Wholesaler-Distributors (416), Machinery, Equipment and Supplies Wholesaler-Distributors (417), Miscellaneous Wholesaler-Distributors (418), Wholesale Agents and Brokers (419), Air Transportation (481), Rail Transportation (482), Water Transportation (483), Truck Transportation (484), Transit and Ground Passenger Transportation (485), Pipeline Transportation (486), Scenic and Sightseeing Transportation (487), Support Activities for Transportation (488), Warehousing and Storage (493)
Communication and other utilities	Comm & Util	Utilities (221), Postal Service (491), Couriers and Messengers (492), Waste Management and Remediation Services (562)
Retail trade and consumer services	Ret	Motor Vehicle and Parts Dealers (441), Furniture and Home Furnishings Stores (442), Electronics and Appliance Stores (443), Building Material and Garden Equipment and Supplies Dealers (444), Food and Beverage Stores (445), Health and Personal Care Stores (446), Gasoline Stations (447), Clothing and Clothing Accessories Stores (448), Sporting Goods, Hobby, Book, and Music Stores (451), General Merchandise Stores (452), Miscellaneous Store Retailers (453), Nonstore Retailers (454), Amusement, Gambling, and Recreation Industries (713), Accommodation (721), Food Services and Drinking Places (722), Repair and Maintenance (811), Personal and Laundry Services (812)
Finance and insurance	Fin & Ins	Monetary Authorities - Central Bank (521), Credit Intermediation and Related Activities (522), Securities, Commodity Contracts, and Other Financial Investments and Related Activities (523), Insurance Carriers and Related Activities (524), Funds and Other Financial Vehicles (526)
Real estate, rental and leasing operations	R Est	Real Estate (531), Rental and Leasing Services (532), Lessors of Nonfinancial Intangible Assets (except Copyrighted Works) (533)
Business services	Bus Serv	Professional, Scientific, and Technical Services (541), Management of Companies and Enterprises (551), Administrative and Support Services (561)
Education and health services	Edu & Hlth	Educational Services (611), Ambulatory Health Care Services (621), Hospitals (622), Nursing and Residential Care Facilities (623), Social Assistance (624), Grantmaking and Giving Services (8132), Social Advocacy Organizations (8133), Civic and Social Organizations (8134), Business, Professional, Labor, Political, and Similar Organizations (8139)
Information and cultural industries	Inf & Cult	Publishing Industries (except Internet) (511), Motion Picture and Sound Recording Industries (512), Broadcasting and Telecommunications (513), Information Services and Data Processing Services (514), Performing Arts, Spectator Sports, and Related Industries (711), Museums, Historical Sites, and Similar Institutions (712)

Notes: The table reports the description of industry groups reported in the WES (first column) and 3-digit NAICS codes that comprise that group (third column). The second column reports the abbreviations of industry groups that are used in Figures 3 and 6.

B Role of Occupational Composition in Coworker Hour Correlations

In this appendix, we further explore the role of occupational composition in shaping the positive correlation between coworker hours documented in Table 1 of the paper. We estimate two additional variants of the estimation underlying Table 1. First, we introduce, to Equation (1), workers' own occupation fixed effects. This aims to further control for variation in hours due to worker occupations. We report the results of this estimation in Table B.1 in this appendix. The similarity in the coefficients of the first rows between Tables 1 and B.1 suggests that coworkers' hours are positively associated with workers' own hours beyond the correlation driven by a worker's occupation.

Table B.1: Correlation between own and coworker hours, including own occupation fixed effects

	(1)	(2)	(3)
Median Coworker Hours	0.328	0.282	0.275
	(0.026)	(0.027)	(0.027)
Synthetic Occupational Median	0.279	0.077	0.074
	(0.071)	(0.077)	(0.076)
Individual Controls	Y	Y	Y
Establishment Controls	N	Y	Y
Average Wage	N	N	Y
Own Occupation FE	Y	Y	Y
N	120420	118336	118336
R^2	0.171	0.191	0.193

Notes: The table reports the coefficient γ from estimating Equation (1) and including (own) occupation fixed effects. Robust standard errors are reported in the parentheses.

Second, we perform the same regression underlying Table 1, but use the difference between the workers' hours and that of their occupation-specific median instead of actual hours worked (own or coworker). In particular, we estimate the following regression,

$$\log\left(h_{ist}/\overline{h}_{io}\right) = \alpha + \gamma\left(\overline{\Delta h}_{s_{-io}}\right) + \delta X_i + \eta Y_s + \mathbf{B}_t + \epsilon_{ist}, \tag{15}$$

where h_{ist} are the hours worked by worker i employed by establishment s in year t and $\overline{h}_{io}$ are the median hours of the occupation o of individual i. Thus, the dependent variable is the log difference between one's own hours and their occupation-specific median. Similarly, $\overline{\Delta h}_{s_{-io}}$ is the median log difference between coworkers' hours and that of their occupation-specific median in establishment s. As in the paper, X_i is a vector of individual-level control variables which include a quadratic in age, dummy variables for educational status (college degree or not) as well as indicators for marital and immigration status. Y_s is a vector of establishment-level controls that includes establishment age, size and industry and the

average establishment wage. $\mathbf{B}_t$ captures year fixed effects.

The results from estimating (15) are reported in Table B.2. In particular, we report the coefficient γ which captures the correlations between deviations from one's own occupational hours and analogous deviations by one's coworkers. We find similar correlations when using differences from occupation-specific medians compared to using actual hours.

Table B.2: Correlation between own and coworker hours deviations relative to occupational median hours

	(1)	(2)	(3)
Median Coworker Hours deviations	0.329	0.282	0.276
	(0.026)	(0.026)	(0.026)
Individual Controls	Y	Y	Y
Establishment Controls	N	Y	Y
Average Wage	N	N	Y
N	120420	118336	118336
R^2	0.145	0.164	0.166

Notes: The table reports the coefficient γ from estimating Equation (15). Robust standard errors are reported in parentheses.

C Absolute Penalties or Relative-to-Coworker Penalties?

A key implication of the presence of complementarities in working hours is that (otherwise identical) workers may experience wage penalties depending on how their hours differ from those of their coworkers. In the introduction of the paper, we highlight the importance of complementarities and the resulting relative-to-coworker wage penalties for worker sorting, labor supply responses to shocks and policies, and firm productivity. However, it is possible that the wage penalties for working shorter or longer hours, summarized in panels (a) and (b) of Figure 1, are not influenced by coworkers' hours, as implied by our theory, but rather by deviations from a fixed absolute level of hours, such as a 40-hour workweek. The regressions underlying panels (c) and (d) of Figure 1 are designed to identify the presence of relative-to-coworker penalties specifically, by using the *deviations* from the reference hours rather than the *level* of hours.

In this section, we conduct additional analysis to quantify the role of deviations from coworkers' hours ("relative-to-coworker" hours penalties) within the penalties across given levels of hours ("absolute" hours penalties) shown in panels (a) and (b) of Figure 1. To do this, we extend the empirical framework which was used to estimate overall wage penalties in Figure 1 in order to tease out absolute and relative-to-coworker penalties. Before describing the details, it is important to emphasize that without some theoretical structure, there are no natural criteria defining when a worker's hours are deviating from their coworkers' hours so as to result in wage penalties. Due to this ambiguity, we considered multiple measures of hours (median and wage-maximizing) as reference levels when considering deviations in Section 2. Under complementarities in working hours, our theoretical production function provides clear guidance on the level of (establishment-specific) reference hours below (or above) which workers will experience wage penalties. Indeed, it is the (establishment-specific) wage-maximizing hours.[1] On the other hand, when considering absolute hours penalties one may pick any level of hours (say 40, the modal weekly hours worked) and ask how deviations from this level impact wages.

Having clarified that the wage-maximizing hours are the relevant measure of reference hours for our theory, we can ask the following question: How much of the wage penalties for working short and long hours are due to workers that deviate from the establishment-specific reference hours (relative-to-coworker penalties) and how much is due to workers that do not deviate from the establishment-specific reference hours (absolute penalties)? To answer this question, we extend the empirical specification in Equation (2), which was used to generate Figure 1(a), by interacting each hour worked bin with an indicator specifying whether a worker's hours deviate sufficiently from the establishment-specific wage-maximizing hours. Formally we estimate the following,

$$\log(w_{ist}) = \alpha + \left(\sum_{h \in H} \gamma_h \mathbb{I}_{i,h}\right) + \left(\sum_{h \in H} \beta_h \mathbb{I}_{i,h} \times \mathbb{I}_{i,\Delta}\right) + \delta X_i + \mathbf{B}_t + \epsilon_{ist}, \tag{16}$$

[1] As shown in Figure A.2 of the Appendix, these hours are correlated but not exactly equal to the average of median hours in an establishment.

where w_{ist} is the hourly wage of worker i in establishment s at time t. As in Equation (2), the indicator variable $\mathbb{I}_{i,h}$ is equal to one if an individual works h hours. The indicator variable $\mathbb{I}_{i,\Delta}$ is equal to 1 if an individual's own hours are different by at least 5 hours compared to the establishment-specific wage-maximizing hours. Then, the coefficient γ_h captures the wage penalty experienced by workers that work h but do not deviate from the wage-maximizing hours, and the coefficient β_h captures the additional penalty experienced by those that work h and deviate from the establishment-specific wage maximizing hours. With this specification, the coefficient β_h captures relative-to-coworker penalties while γ_h captures absolute hours penalties. Roughly speaking, a weighted average of the two coefficients returns Panel (b) of Figure 1 which reports overall wage penalties after controlling for establishment fixed effects. All other regressors are defined as in Equation (2).

Importantly, a mispecification of the reference level of hours used to define relative-to-coworker deviators will result in (incorrectly) attributing relative-to-coworker penalties as absolute hours penalties. For instance, if the wage-maximizing hours in an establishment are 50 but we incorrectly use 40 hours as the reference level of hours, then a worker that works 40 hours will be considered a non-deviator. However, this worker is deviating significantly from the theoretically relevant reference level of hours worked, the wage-maximizing hours, and should incur relative-to-coworker penalties. Thus, using the incorrect reference hours to classify deviations will attribute these wage penalties as absolute hours penalties instead of relative-to-coworker hours penalties. This is especially relevant to exercises that are quantitative in nature such as this one aimed at quantifying relative-to-coworker penalties.

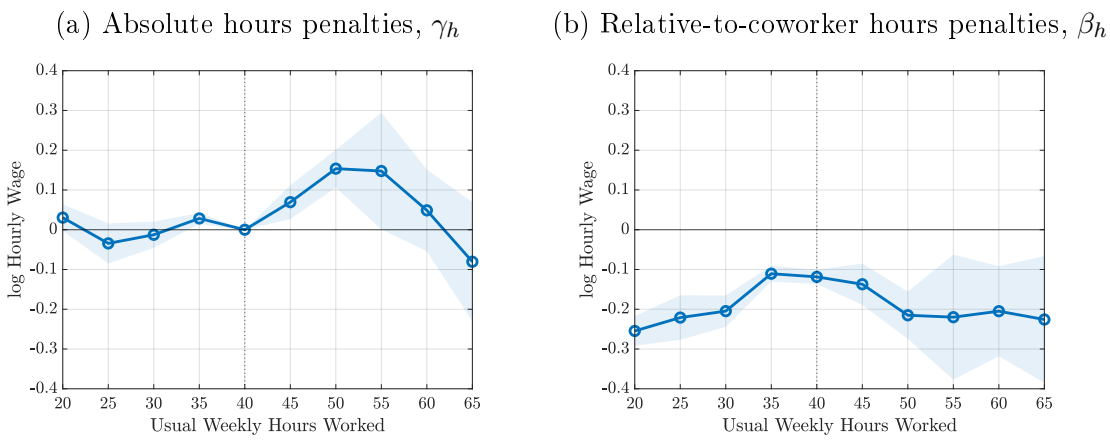


Figure C.1: Estimates of absolute and relative-to-coworker penalties

Notes: Panels (a) and (b) report the coefficient γ_h and β_h, respectively, from estimating Equation (16) where the indicator variable $\mathbb{I}_{i,\Delta}$ is equal to 1 is an individual's own hours are different by at least 5 hours compared to the establishment-specific wage-maximizing hours. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

Panel (a) of Figure C.1 reports the coefficient γ_h for each absolute hours worked bin. It shows that, for non-deviators, compared to working around 40 hours, working 25 hours per week incurs a 3% wage penalty although not statistically significant, while working 55 hours is associated with 10% wage premium. Notice that the estimates of absolute penalties are somewhat monotonic for most of the range of hours worked, from around 0 for those that work 40 hours or less to positive values for longer hour workers. This suggests that a much of wage

penalty from working part-time must be due to relative-to-coworker hours deviations. Panel (b) confirms this and reports the coefficient β_h, which captures the relative to coworker hours penalties. It shows that workers who work 25 hours and deviate from their establishment wage-maximizing hours experience around 20% lower wages compared to workers who work 25 hours and do not deviate. The analogous wage penalty for workers that work 55 hours is similar around 20%. Indeed, Panel (b) indicates that for all levels of hours worked, there is a penalty for deviating from the wage-maximizing hours and it is roughly hump-shaped over the range of hours worked reaching its lowest level for those that work around 40 hours. Comparing panels (a) and (b) shows that relative-to-coworkers penalty are at least as severe as the absolute hours penalty. For part-time workers in particular, the relative-to-coworker penalties are more than three times as large as the absolute hours penalty, suggesting that for this portion of the hours distribution, penalties that arise due to complementarities are crucially important.

(a) Absolute hours penalties, γ_h (b) Relative-to-coworker hours penalties, β_h

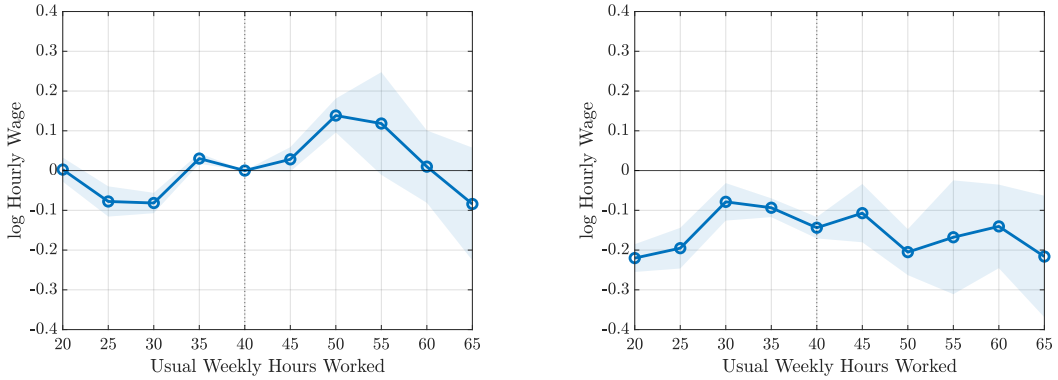


Figure C.2: Estimates of absolute and relative-to-coworker penalties, using ±10 hours as deviating threshold

Notes: Panels (a) and (b) report the coefficient γ_h and β_h, respectively, from estimating Equation (16) where the indicator variable $\mathbb{I}_{i,\Delta}$ is equal to 1 is an individual's own hours are different by at least 10 hours compared to the establishment-specific wage-maximizing hours. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

Figure C.2 in reports the results from estimating Equation (16) using 10 hours as the deviating hours threshold such that $\mathbb{I}_{i,\Delta}$ is 1 if an individual's own hours differ by at least 10 hours compared to the establishment-specific wage-maximizing hours. Our results remain robust, relative-to-coworker penalties persist and are more than twice as large as absolute penalties. However, with a coarser definition of a deviations, the role of absolute penalties become more prominent as workers that are deviating by less than 10 hours are now considered non-deviators and so their penalties are attributed as absolute hours penalties. By a similar token, we find a stronger role for relative-to-coworker penalties when experimenting with using milder thresholds (1, 2 or 3 hours instead of 5 or 10) for identifying deviators.

Taken together, these results suggest an important role of relative-to-coworker penalties, and thus complementarities in working hours, in driving overall wage penalties across the hours distribution. Indeed, Figure C.1 suggests that the part-time penalty as well as the non-monotonic relationship between hours and wages is almost entirely due to relative-to-

coworker penalties.

Our data also allow us to distinguish between absolute and relative penalties using variation in coworker hours. The exercises reported in panels (c) and (d) of Figure 1 uses the hours relative to a reference level of coworker hours (either the median or the wage-maximizing) to capture the effects of deviations from a measure of reference hours (and *not* of absolute hours) on wages. For example, an observation that is considered at the -15 level of the horizontal axis of these figures can correspond to a worker that works 35 hours in an establishment with reference hours equal to 50, or 25 in an establishment with the reference hours equal to 40.

Still, it may be that part of the penalties from deviations we document are driven by some particular combination of individual hours and the reference hours. To address this concern, we estimate Equation (3) by adding the dummy variables $\mathbb{I}_{i,h}$ for individual i indicating workers' hours worked. In particular, we estimate,

$$\log(w_{ist}) = \alpha + \left(\sum_{h \in H} \gamma_{\Delta h} \mathbb{I}_{i,\Delta h}\right) + \left(\sum_{h \in \mathcal{H}} \eta_h \mathbb{I}_{i,h}\right) + \delta X_i + \mathbf{A}_{st} + \epsilon_{ist}, \tag{17}$$

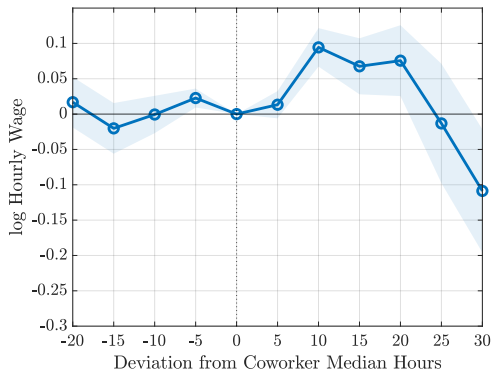
where w_{ist} is the hourly wage of worker i in establishment s at time t and $\mathbb{I}_{\Delta h}$ indicates *deviations* of a worker's own hours from a reference level of hours which is either the median or wage-maximizing hours in an establishment. The indicator variable $\mathbb{I}_{i,h}$ is equal to one if an individual works h hours. We experiment with different partitions of workers hours as denoted by the set $\mathcal{H}$. $\mathbf{A}_{st}$ is an interaction of establishment and year fixed effects. X_i is a vector of individual-level control variables which include a quadratic function of age, dummy variables for educational status (college degree or not) as well as indicators for marital and immigration status.

Excluding the dummy variables $\mathbb{I}_{i,h}$ from (17) would allow us to recreate panels (c) and (d) of Figure 1. The indicator for the level of hours worked controls for absolute penalties resulting from working different levels of hours. Thus, the coefficient $\gamma_{\Delta h}$ can be interpreted as capturing purely relative-to-coworker penalties net of absolute penalties. Figure C.3a reports this coefficient from estimating Equation (17) where the indicator variables control for workers working less than 25 hours and working longer than 60 hours and the reference hours are the coworker median hours. Figure C.3b reports the same coefficient for the case where the reference hours are the establishment-specific wage-maximizing hours – the theoretically relevant reference hours level.

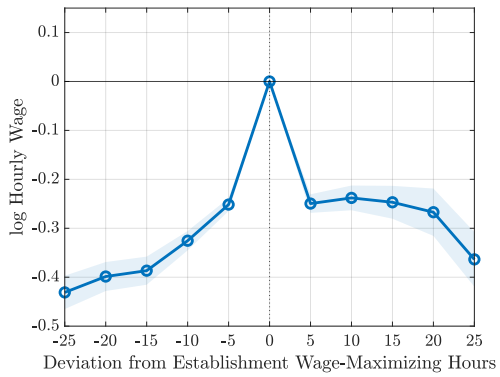
We repeat this exercise by introducing finer hours bins to control for absolute penalties. Figures C.3c and C.3d report the results from estimation Equation (3) while controlling for four different bins of worker hours (≤ 25, $(25, 35]$, $(45, 55]$ and > 55, with the control group being those who work 35 to 45 hours). Figure C.3 shows that controlling for the absolute level of hours worked does not significantly change our estimated penalties from deviations, especially when considering wage-maximizing hours as the reference level of hours. This is consistent with Figure C.1 and reiterates the point that relative-to-coworker penalties, which are present under complementarity in hours, are key drivers of the empirical patterns on wage penalties that we document.

Using three bins of absolute hours

(a) $\gamma_{\Delta h}$, deviations from median coworker Hours

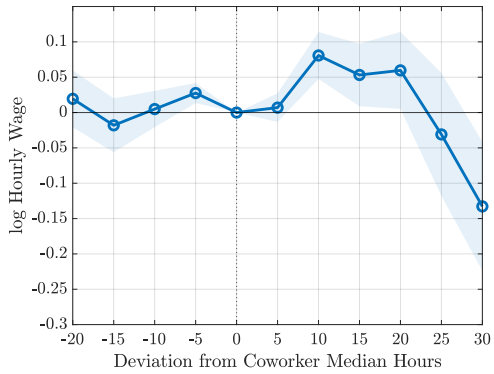


(b) $\gamma_{\Delta h}$, deviations from wage-maximizing hours



Using five bins of absolute hours

(c) $\gamma_{\Delta h}$, deviations from median coworker Hours



(d) $\gamma_{\Delta h}$, deviations from wage-maximizing hours

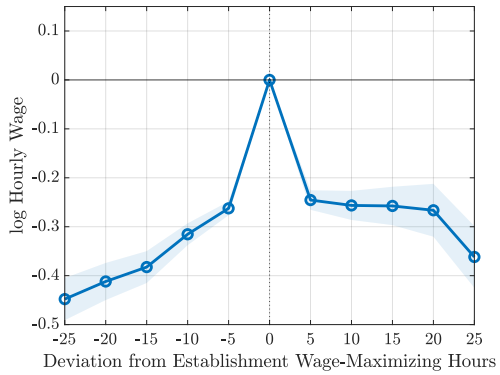


Figure C.3: Relationship between wages and hours using within-establishment variation, controlling for hours worked

Notes: Panels (a) and (b) report the coefficient $\gamma_{\Delta h}$ from estimating Equation (3) when the reference hours are the establishment median and establishment wage-maximizing hours, respectively, and the indicator variable $\mathbb{I}_{i,h}$ controls for working less than 25 hours, between 25 and 60 hours and over 60 hours. Panels (c) and (d) report the analogous coefficient when the indicator variable $\mathbb{I}_{i,h}$ controls for bins of hours worked ≤ 25, $(25, 35]$,$(35, 45]$, $(45, 55]$ and > 55. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

D Measurement Error

In this appendix, we explore whether our primary empirical results and estimates of ρ might be driven by measurement error in the reporting of hours. To do this, we conduct a number of robustness exercises which test how classical measurement error in the reporting of hours impacts our results. We find that our estimates of ρ and our primary empirical findings change little with the introduction of classical measurement error.

To operationalize our robustness checks, we assume that the hours that are reported in the WES, h^r, are reported with noise such that the true level of hours worked, h^t are given by $h^r + \epsilon$ and we denote the standard deviation in reported hours to be σ. Consistent with the assumption of classical measurement error, we assume that ϵ follows a standard normal distribution with mean zero and standard deviation σ_ϵ. The dispersion ϵ governs the degree of measurement error in reported hours and we consider three values of dispersion. In particular, we assume that $\sigma_\epsilon = \lambda\sigma$ where $\lambda \in \{5\%, 10\%, 20\%\}$.

Table D.1 reports the (economy-wide) estimates of ρ under the three alternative values of λ. The baseline estimates of ρ line up closely with estimates derived assuming either 5 or 10% measurement error. Indeed, the confidence intervals for the estimate of the substitution parameter contain the baseline estimate of ρ. Assuming a higher degree of measurement error of 20%, results in a slightly higher estimate of the elasticity of substitution in working hours (0.693 vs. 0.685 in the baseline) but still implies that working hours are complements in production. Given this, it is unlikely that classical measurement error in hours is of first-order concern for our estimates of ρ.

Table D.1: Estimation results, with measurement error in hours

	Substitution Parameter, ρ		Elasticity of Substitution $\frac{1}{1-\rho}$	
	Estimate	95% CI	Estimate	95% CI
Baseline	-0.459	[-0.490,-0.428]	0.685	[0.671,0.700]
Measurement Error, $\lambda = 5\%$	-0.449	[-0.481,-0.417]	0.690	[0.675,0.706]
Measurement Error, $\lambda = 10\%$	-0.452	[-0.516,-0.452]	0.674	[0.674,0.689]
Measurement Error, $\lambda = 20\%$	-0.411	[-0.474,-0.411]	0.693	[0.693,0.709]

Notes: The table reports estimates of the substitution parameter, ρ and the corresponding elasticity of substitution $\frac{1}{1-\rho}$ along with 95% confidence intervals, as estimated from Equation (12) using non-linear least squares. The first row reports the results in our baseline estimation and the next three rows report the estimates assuming classical measurement error, ϵ, for three values of σ_ϵ.

We also re-do the empirical analysis in Section 2 assuming measurement error in hours. In particular, we replicate Table 1 and Figures 1 and 2 assuming that hours are reported with (classical) measurement error with dispersion equal to 20% of the standard deviation in reported hours.

Table D.2 replicates Table 1 and shows that the positive correlation between one's own hours and their coworker's hours changes little if we assume measurement error.

Similarly, Figure D.1 replicates the analysis in Figure 1 assuming a 20% error in reported hours. Panels (a) and (b) report the overall relationship between hours and wages and this

Table D.2: Correlation between own and coworker hours, assuming measurement error of 20%

	(1)	(2)	(3)	(4)
Median Coworker Hours	0.334	0.279	0.272	0.269
	(0.026)	(0.027)	(0.027)	(0.027)
Synthetic Occupational Median	-	-	-	-0.075
	-	-	-	(0.083)
Individual Controls	Y	Y	Y	Y
Establishment Controls	N	Y	Y	Y
Average Wage	N	N	Y	Y
N	120420	118336	118336	118336
R^2	0.169	0.190	0.192	0.218

Notes: The table reports the coefficient γ from estimating Equation (1) under the assumption that hours are reported with error. The regressions include a set of controls for worker and establishment characteristics, as indicated in the table. Robust standard errors are reported in the parentheses.

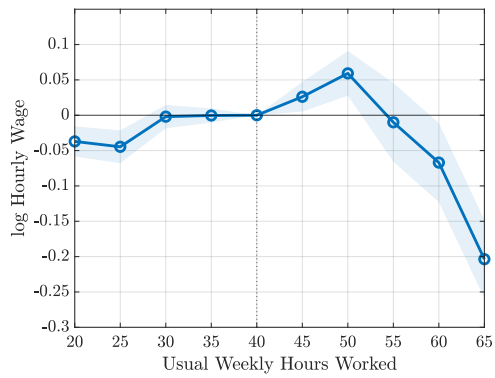
relationship changes little under the assumption of measurement error. Similarly, panels (c) and (d), which report how deviations from either the establishment median or wage-maximizing hours relate to wages, are qualitatively similar to the results using reported hours. The inclusion of measurement error does widen the confidence intervals of these estimated relationships while the point estimate changes little.

Finally, Figure D.2 plots the analog of Figure 2 in the paper under the assumption of a 20% measurement error. Compared to the estimates derived using reported hours, the assumption of measurement error leads to less precise estimates, resulting in wider confidence intervals, but does not differ significantly from the point estimates reported in the baseline results.

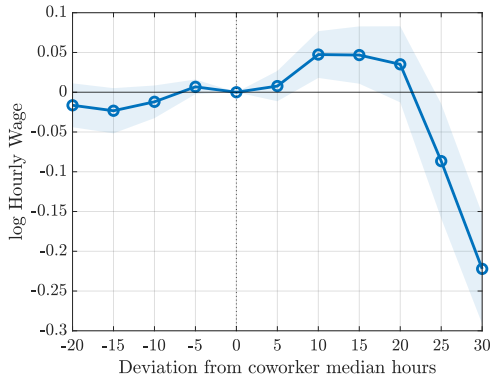
To summarize, accounting for measurement error in the reporting of hours does not significantly impact our empirical analysis or our estimates the elasticity of substitution. However, measurement error in hours could also introduce measurement error in wages via division bias. Division bias in wages is not a concern when estimating ρ since we use total earnings, that is the product of hours and wages, in our estimation. Further, our measure of hourly wages is obtained directly from the WES, instead of being inferred using measures of annual (or weekly) earnings, which mitigates concerns of division bias in our empirical analysis.

(a) γ_h, excluding establishment FE

(b) γ_h, including establishment FE



(c) $\gamma_{\Delta h}$, deviations from median coworker hours



(d) $\gamma_{\Delta h}$, deviations from wage-maximizing hours

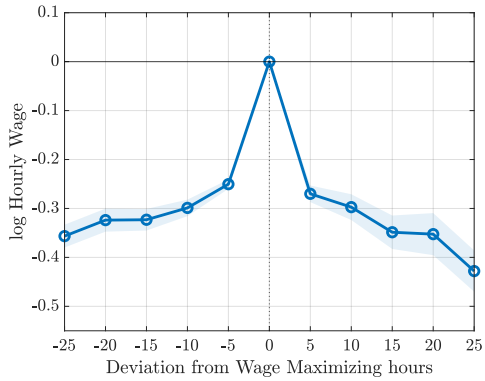


Figure D.1: Relationship between wages and hours using within-establishment variation, assuming measurement error of 20%

Notes: Panels (a) and (b) report the coefficient γ_h from estimating variants of Equation (2). In Panel (a), we do not include establishment fixed effects $\mathbf{A}_s$, but instead include a set of establishment characteristics including establishment size and age dummies as well as industry fixed effects. Panel (b) reports the coefficient γ_h when establishment fixed effects are included. Panels (c) and (d) report the coefficient $\gamma_{\Delta h}$ from estimating Equation (3) when the reference hours are the establishment median and establishment wage-maximizing hours, respectively. All panels are estimated under the assumption that hours are reported with error of 20%. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

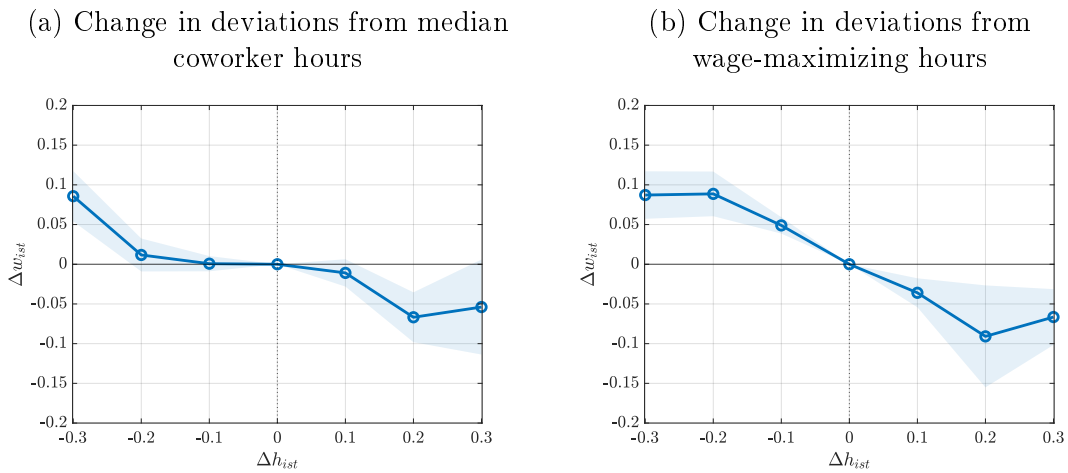


Figure D.2: Dynamic changes in hours and wages, assuming measurement error of 20%

Notes: The figure reports the coefficient $\gamma_{\Delta h_{ist}}$ from estimating Equation (4). Panels (a) and (b) report this coefficient when the reference hours are the establishment median and establishment wage-maximizing hours, respectively. Both panels are estimated under the assumption that hours are reported with an error of 20%. The shaded area represents the 95% confidence interval of the coefficient using robust standard errors.

E Additional Implications for Wage Gaps

In this appendix, we conduct two additional exercises that explore the implications of wage gaps resulting from complementarities in working hours. First, we study wage differences between workers with and without children. Second, we revist our analysis of the gender wage gap and explore the role of short- and long-hour penalties in contributing to the gender wage gap.

E.1 Workers with and without Children

Wage penalties due to complementarities could be applied to study wage gaps between any two groups that feature sufficient differences in their working hours distributions. Here, we compare differences in wages between workers with children vs. without children. We find that men without children tend to work *shorter* hours than men with children. Panel (a) of Figure E.1 illustrates this by plotting the distribution of hours (relative to the establishment wage-maximizing hours) for men with and without children. It shows that men without children are slightly over-represented in working shorter hours while men with children are slightly more heavily concentrated in the usual hours interval ((0.95,1.05]). On the other hand, women with children tend to work systematically shorter hours than women without children. As shown in Panel (b) of Figure E.1, women without children have a higher concentration around the usual hours interval (0.95,1.05]) compared to women with children.

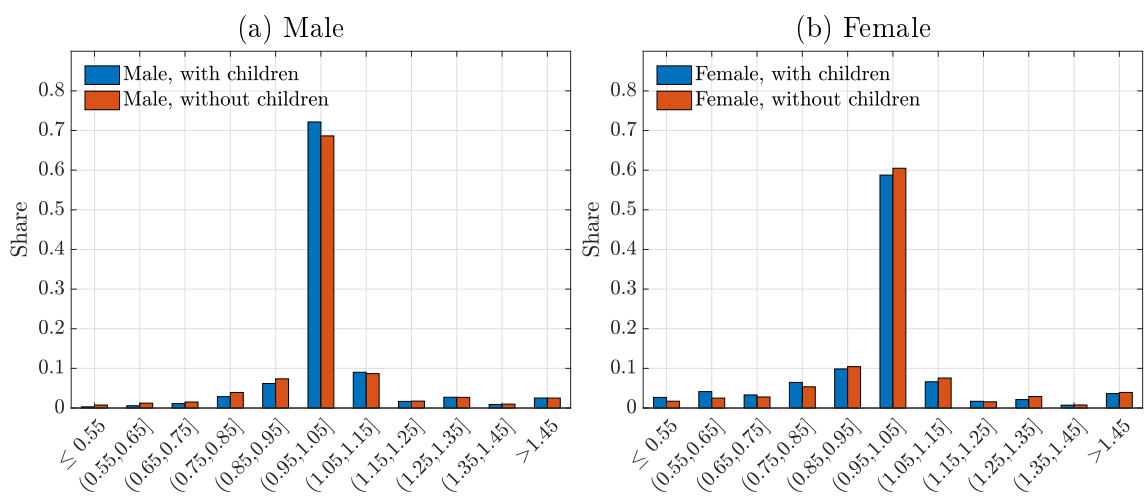


Figure E.1: Distribution of relative hours for workers with and without children, by gender

Notes: Panel (a) plots the distribution of male worker hours relative to the establishment's wage-maximizing hours $\left(\frac{l_{i,j}}{l_j^*}\right)$ separately for workers with and without children. Panel (b) plots the analogous measure for females. The wage establishment's wage-maximizing hours l_j^* are measuring using the entire hours distribution in the establishment.

Motivated by the observed differences in hours distributions between workers with and without children, we repeat our analysis of the gender wage gap above and focus instead on wage gaps between workers with and without children, by gender. Analogous to Panel (a) of Figure 5, in Figure E.2, we plot the observed wage gaps for workers with and without children

and compare it to the counterfactual wage gap which results from removing wage penalties arising from deviating from the establishment-specific wage-maximizing hours. Recall, the counterfactual wage adjusts each worker's wages by removing the penalties arising from hours deviations while still taking into account any wage components not attributable to the individual's hours (due to unobserved ability, for example). Panels (a) and (b) plot these comparisons for male and female workers, respectively, where positive values indicate a wage premium for workers with children and negative values indicate a wage penalty for workers with children.

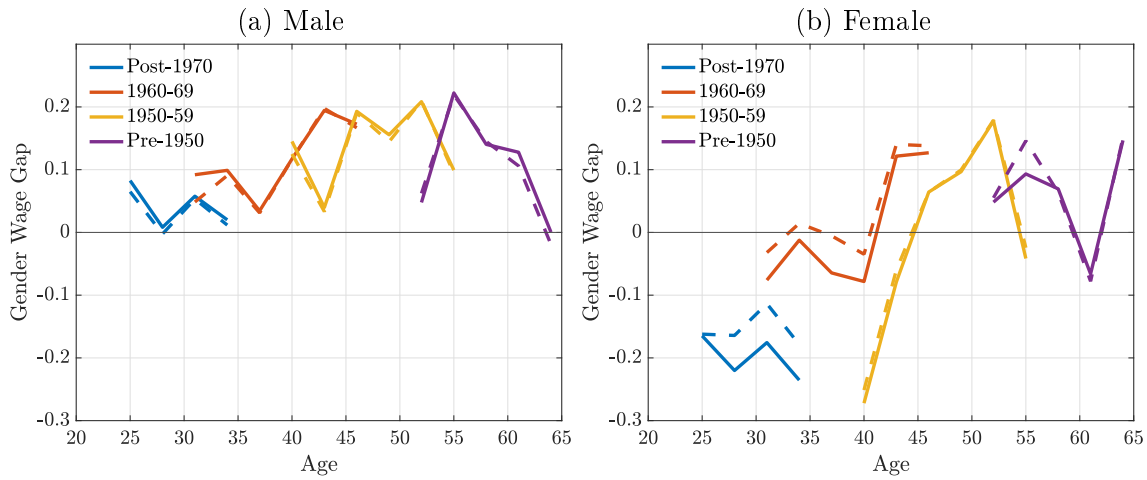


Figure E.2: Wage gaps between workers with and without children, by gender

Notes: Figures plot separately for men and women, the observed (solid lines) and counterfactual (dashed lines) wage gap over the life-cycle, between workers with and without children, by cohort in the WES. The wage gap is computed as one minus the ratio of average without-children to with-children earnings.

Focusing first on Panel (a), we find that observed wages tend to be higher for men with children. That is, there is a premium associated with children for men. This wage premium for men diminishes slightly if we remove wage penalties implied by complementarities in working hours. However, the difference between observed and counterfactual wage gaps is rather small, in line with the modest differences in the hours distributions between these groups. Panel (b) plots observed and counterfactual wage differences among women with and without children. Consistent with recent evidence in Kleven et al. (2019), we find that women with children, particularly younger women, tend to experience wage penalties compared to women without children. Eliminating wage penalties that arise due to complementarities tends to diminish the overall wage penalties associated with children as the counterfactual wage gaps (dashed lines) are generally above the observed wage gaps (solid lines). Indeed, for young women in the most recent cohort, hours account for about 22% (or about 4 percentage points) of the wage gap between women with and without children.

E.2 The Role of Short- and Long-Hour Penalties for the Gender Wage Gap

The results in Figure 7 show that, among full-time workers, wage penalties arising from complementarities in hours contribute only modestly towards the gender wage gap. This

suggests that much of the role of hours in contributing to the gender wage gap among all workers is due to short-hour penalties. This raises a natural question: How does the short-hours (part-time) and long-hour penalty contribute to the gender wage gap? Women work shorter hours while men work longer hours, and both groups suffer from hours penalties as their hours deviate from the wage-maximizing level. However, short- and long-hour penalties act in opposite directions in affecting the gender wage gap. The short-hour penalty widens the gender wage gap by lowering women's hourly wage relative to men, and the long-hour penalty narrows the gender wage gap by penalizing men for working longer hours. To quantify the role of short, long and intermediate hour penalties in driving the gender wage gap, we compute counterfactual (average) gender wage gap by removing hour penalties separately for different sub-samples of workers. These are average over all ages and cohorts and computed in the same manner as the counterfactual wage gaps plotted in Figures 5 and 7.

Table E.1: Gender wage gaps

Data	Counterfactual		
	Remove all	Remove Short	Remove Long
0.206	0.176	0.180	0.207

Notes: The first column of the table reports the observed gender wage gap among all workers. The second column reports the counterfactual gender wage gap by removing penalties arising from hours deviations for all workers. The third and fourth columns report the counterfactual gender wage gap by removing penalties arising from working hours deviations for workers working under 30 hours (short) and over 50 hours (long), respectively.

Table E.1 reports these gender wage gaps, with the first column reporting the observed gender wage gap as a reference. The second column ("Remove All") indicates the wage gap when penalties arising from hours deviations for all workers are removed and is akin to the wage gaps plotted in Panel (b) of Figure 5. This column shows that removing penalties from any hours deviations account for 14 percent of the observed gender wage gap. The third column ("Remove Short") of Table E.1 reports the gender wage gap when wage penalties for only part-time workers (working under 30 hours) are removed. Removing these short-hour penalties reduces the gender wage gap by about 13 percent, close to the reduction obtained by shutting down penalties for all workers. This suggests that much of the role of hours in explaining the gender wage gap is driven workers that work shorter hours. This is intuitive since women tend to work shorter hours and it is exactly this behaviour that widens the gender wage gap. On the other hand, removing wage penalties for only long-hour workers (those working over 50 hours) tends to very slightly *raises* the gender wage gap. This too is intuitive since long-hour penalties primarily impacts men who work longer and brings their wages closer to women's wages. Together with Figure 7, Table E.1 shows that the role of relative hours penalties in explaining the gender wage gap is driven primarily by part-time workers (and the associated penalties), in which women are more heavily represented.