Nonlinear Occupations in Equilibrium*

Thimo De Schouwer†

Abstract

Returns to long and late hours differ substantially between occupations. To understand how these occupational wage premiums arise, we construct and estimate an equilibrium model in which both wages and hours are endogeneously determined. We find substantial differences in the valuation of hours across occupations – on *both* sides of the market. Service occupations are characterized by a large productivity premium to long hours that translated into a substantial equilibrium wage premium. Yet in technical occupations an equally large productivity premium is completely offset by workers minding long and late hours less, such that no wage premium arises in equilibrium. We show that these differences in how hours are valued across workers and occupations can be predicted by differences in working conditions, job tasks, and the time and place of work. An aggregate decomposition shows that roughly 75% of the wage premium to long and late hours is due to differences in productivity, 20% is due to differences in employees' valuation of these hours, and 5% due to the relative bargaining power of the worker and the firm.

Preliminary and incomplete – please do not circulate.

JEL Codes: J24, J31, J33

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†Department of Economics, University of Leuven (e-mail: thimo.deschouwer@kuleuven.be).

1. Introduction

Returns to long and late hours differ substantially between occupations. Pharmacists' wages increase roughly linearly when they take on longer and later hours – but lawyers are paid substantial premiums to do so (Goldin, 2014). Several papers have pointed towards differences in production technologies to explain these diverging wage schedules across occupations (see Goldin (2014), Goldin and Katz (2016) Shao et al. (2023), and Bick et al. (2022)). However, both wages and hours are equilibrium outcomes, and thus also depend on the composition of the workforce and how workers value the time and timing of their leisure.

This paper studies how returns to long and late hours arise and why they differ between occupations through the lens of an equilibrium model of the labor market. Both wages and hours are jointly determined at equilibrium in our model, as a function of preferences on both sides of the market and of the relative bargaining power between the worker and the firm. The model builds on the approaches introduced in Choo and Siow (2006) and Dupuy and Galichon (2022) by allowing for complementarities between hours and wages. This extension opens up the channel through which bargaining power affects the premium to long and late hours. Firms that want their employees to work more will have to compensate them for a fraction of the additional utility they would have derived from complementarities – depending on their relative bargaining power.

We document several empirical facts of the German labor market that are in line with our theoretical framework using the Socioeconomic Panel (SOEP). In line with earlier work by Goldin (2014) and Cortés and Pan (2019) we find evidence for significant returns to *long* hours in service occupations. We additionally document large returns to *late* hours in all occupations – and again find the largest premiums service but also technical occupations. We then show that the fraction of employees that works long or late hours has decreased substantially over the past decade, coinciding with a large increase in the excess demand for labor as measured through data on occupational job vacancies. We find that occupations where excess demand has grown the most are also those that show the largest decrease in long and late hours. This suggests that the improved bargaining position of workers may have allowed them to obtain more favorable hours contracts.

We interpret these findings through our model, and find that both the supply and demand side of the market play an important role in determining the equilibrium wage premium in an occupation. In line with the descriptive evidence in Goldin (2014) and Goldin and Katz (2016) we find that the productivity of long and late hours differs significantly between occupations. Technical and service occupations exhibit the largest productivity surplus to long and late hours – primary and manufacturing occupations the smallest. We additionally point to an important – and so far overlooked – role for the supply side. Workers do not value long and late hours the same across occupations. In technical occupations, where the largest fraction of employees has the option to work from home, the disutility of long and late hours is substantially smaller than in manufacturing or service occupations. This completely offsets the large firm-side productivity premium, such that in equilibrium no wage premium arises. On average, we find that roughly 75% of the occupational wage premium stems from differences in the productivity of long hours, 20% is due to differences in how workers value these hours, and 5% is related to bargaining power.

We then study which occupational characteristics best predict a larger productivity premium and a smaller worker-side cost to long and late hours. First, considering the demand side, we find that occupations in which workers have a lot of discretion over their tasks and schedule are characterized by larger productivity premiums. This is in line with workers being less substitutable in these occupations, as argued in Goldin (2014). On the other hand we find that occupations with more physically demanding working conditions exhibit smaller productivity premiums to long and late hours, which is likely due to risks of injury or accidents (see Pencavel (2015)). Considering the supply side we find that workers mind working long hours less if they can work from home or can work on Sundays, and more when working in physically harmful conditions. They also mind long hours less when performing meaningful tasks – which also been shown to increase labor supply in Kesternich et al. (2021).

Roadmap. Section 2 discusses related literature. Section 3 introduces the data and documents the main empirical patterns. Section 4 introduces the model. In section 5 we discuss identification and estimation of the model. The main results are presented and discussed in section 6. Section 7 concludes.

2. Related Literature

This paper first of all relates to the work of Goldin (2014) and Goldin and Katz (2011), who introduce a narrative that relates occupational wage differences to gender differences in earnings. Their argument is occupational differences in how productive long and late hours are give rise to substantial compensating differentials in the spirit of Rosen (1974, 1986). To study these occupational differences in returns to long hours, several papers (e.g. Goldin (2014), Cha and Weeden (2014), Cortés and Pan (2019), and Gicheva (2020)) estimate the earnings elasticity of hours through reduced form regression. They document substantial occupational heterogeneity in wage schedules and find that in several high-skill occupations (e.g. those in the business, financial, and legal sectors) the earnings elasticity of hours exceeds unity. Evidence furthermore suggests that over the last quarter of the 20th century this elasticity has increased (see Cortés and Pan (2019), Jang and Yum (2021), and Mantovani (2023)). We contribute to this literature by allowing for premiums to both long and late hours and by decomposing how these premiums arise.

A growing literature has incorporated the ideas put forth in Goldin (2014) into models of labor supply. For example, Erosa et al. (2022) introduce a household framework that features both sorting in the classic Roy (1951) sense between occupations with larger and smaller premiums to long hours and an endogeneous labor supply choice. They focus on the role of the household and find that family interactions are an important source of occupational sorting and amplify inequality in hours and in wages. Jang and Yum (2021) study an extension to their model and find that dynamic returns to long hours are an important determinant of labor supply choices. Other related work by Adda et al. (2017) and Mincer and Polachek (1974) studies occupational sorting based on expected time employed. In their models, sorting depends on differential skill depreciation between occupations. These papers all focus the labor supply choices of workers that are faced with exogeneously determined differences in either the occupational returns to hours or in skill depreciation.[1] In our model, these premiums arise as a function of workers' and firms' preferences over long and late hours and how these vary between occupations.

Another recent literature focuses on the demand side, and estimates how returns to hours relate to complementarities between workers and the required degree of coordination. For example, Shao et al. (2023) exploit firm-level micro data and find that hours of work are gross complements in production. This explains non-linearities in the hour-wage relation of the form stressed in Bick et al. (2022) – where deviating from the modal hours (particularly by working less) results in a significant wage penalty. A related paper by Cubas et al. (2023) uses time-diaries to construct occupation-level measures of schedule coordination. They find that occupations with higher degrees of coordination pay higher wages. Relative to these studies we leverage data on excess labor demand – in the form of vacant jobs – to estimate the parameters that capture the productivity of hours at the occupational level. We contribute to this literature by allowing for heterogeneity in how workers

[1] Another paper that studies occupational sorting in the presence of large returns to hours is Wasserman (2023), who relies on a natural experiment that limited the hours worked by medical residents. Their estimates show that women are substantially more likely to enter specialties where hours are reduced.

value working longer and later hours across occupations, and we study which occupational traits determine the extent of productivity premiums to hours.

We also contribute to the large literature that estimates worker-side preferences for different forms of workplace flexibility through discrete choice experiments. This literature finds that workers are willing to significantly reduce their wages for various dimensions of workplace flexibility, such as the option to work part-time or the ability to have control over one's schedule (see among others Mas and Pallais (2017), Maestas et al. (2023), Wiswall and Zafar (2018), He et al. (2021), and De Schouwer and Kesternich (2023)). On the other hand Chen et al. (2019) estimates the value of flexibility using a sample of Uber drivers. While these estimates have been shown to hold external validity – they are for example correlated with actual labor supply decisions (see He et al. (2021) and Mas and Pallais (2017)) – we contribute to this literature by studying a how these differences are reflected in the equilibrium wage structures across occupations.

From a methodological perspective this paper builds on the class of separable transferable utility matching models introduced in the seminal work of Choo and Siow (2006) – whose model has been extended in a multitude of ways. Most related to this paper are first of all the models by Dupuy (2021) and Mourifié and Siow (2021), who introduce an additional endogeneous dimension (respectively in the form of a migration decision and the terms of a match). Other related work is Dupuy and Galichon (2022), who show how information on transfers can be exploited in a labor market setting. Their model has been applied and extended to study issues of taxation (Dupuy et al., 2020), CEO compensation Dupuy et al. (2023) and returns to education Corblet (2023). We contribute to this literature by introducing a model that allows for complementarities, which introduces a role for population supplies to shape the equilibrium levels and premiums to the endogeneous outcome.

3. Empirical Evidence

In this section we document the main empirical trends that motivate our analysis. We start by providing a brief overview of the data sources we use in the remainder of the paper. We then provide evidence that there are substantial premia to long and late hours but that these jobs have become less prevalent. We then show how this relates to the large increase in vacant jobs.

3.1 Data

The German Socio-Economic Panel. The main data source for our analysis is the German Socio-Economic Panel (SOEP). The SOEP is a longitudinal survey that contains up to 30.000 individuals in 2019 (see Goebel et al. (2019)). This survey is well-suited for our analysis because it contains data on the main job-related variables that the analysis relies on: how long and how late each respondent works, their monthly wages, and their occupations. The survey additionally collects information on a rich set of demographics for each respondent, and includes both employed and unemployed individuals. Because of a significant change in how occupations are coded, we restrict our analysis to the years after 2013.

The Job Vacancy Statistics. The German Federal Unemployment Agency (BuA) provides monthly data on the number of reported job vacancies for each occupation. Their data dates back to the 1940s, but the occupational coding has undergone significant changes. The same scheme used in the recent waves of the SOEP (KldB2010) is used from 2011 onward. This dataset comprises of all job vacancies registered with the BuA. As in many other countries, German firms are not obligated to report a vacant position. However, Bossler et al. (2020) use data from the IAB Job Vacancy Survey[2] to estimate that between 40 and 50% of all vacant positions are reported to the BuA. We adjust our data for the missing vacancies and scale all numbers such that that the tightness of the labor market (in terms of vacancies per unemployed person) in the SOEP mimics that of the German population.[3]

3.2 Hours and Wages

We first look at the returns to working long and late hours by running least squares regressions similar to those presented in Goldin (2014) and Cortés and Pan (2019). We differ by allowing for more non-linearity in the wage-hours gradient by introducing dummies for part-time (p, less than 35 hours), full-time (f, between 35 and 45 hours), and long hours (l, more than 45 hours) options. This allows for a more flexible hump-shaped wage-hour profile as stressed in Bick et al. (2022). Next, we introduce an additional measure on how late respondents work in the form of a dummy variable that indicates working on evenings between 19 and 22h (e). We compute hourly wages (w) based on actual weekly working hours and wages and consider a standard full-time job without

[2] A repeated cross section of more than 100.000 German employers

[3] Note that firms select which vacancies to report. Selective posting may cause the *distributions* of reported and actual vacancies to differ. We will look into this later with the IAB Job Vacancy Survey.

evening work as the reference category. We exclude jobs of less than five hours per week. The regressions are of the form:

$$w_{it} = \sum_{h \in p,f,l} \beta_h \mathbb{1}^h_{it} + \beta_e \mathbb{1}^e_{it} + \gamma X_{it} + \tau_t + \sigma_s + \epsilon_i. \tag{1}$$

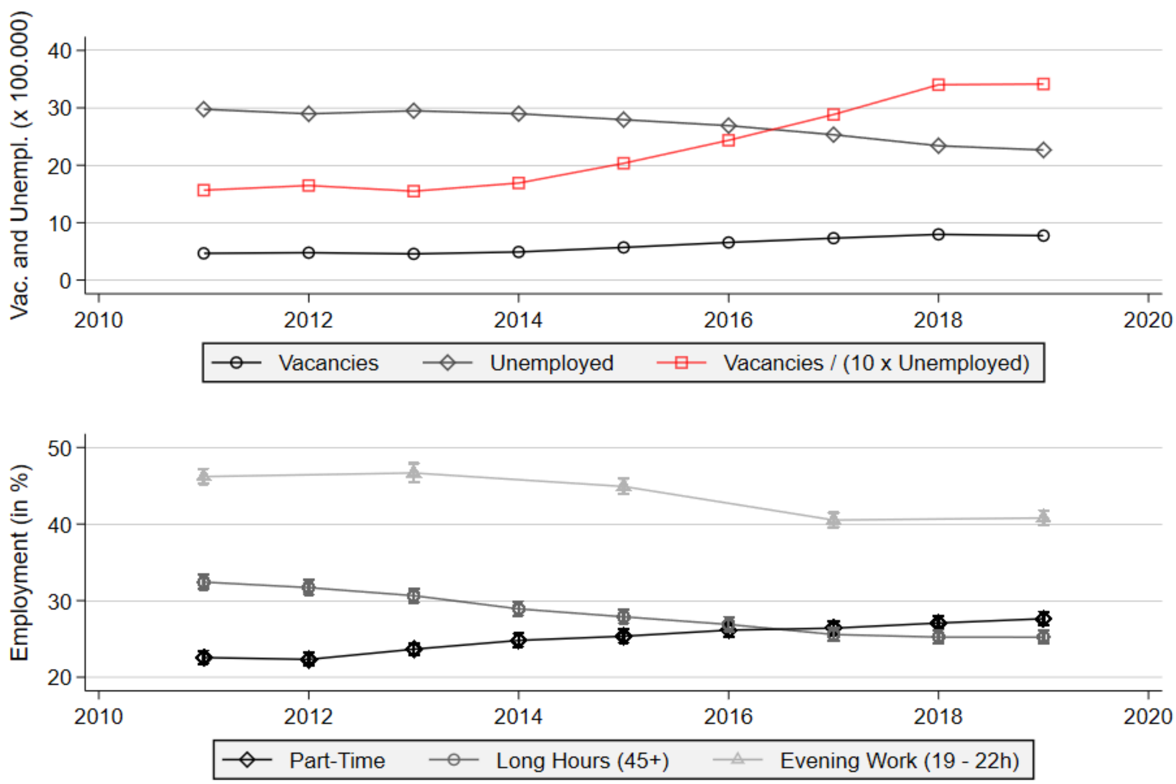
We add a set of demographic controls X_i that consists of quadratic terms in age and education, and a set of state and year fixed effects (τ_t and σ_s). We present the results from an additional specification that adds occupation fixed effects and finally one that interacts longs hours and evening work with each occupations. Since the outcome variable is *hourly* wages, significantly positive or negative coefficients represent nonlinearities in the returns to long hours in terms of monthly wages (which is what the literature typically considers to be non-linear occupations).

Results are presented in Table (1). Specification (1) shows that, on average, deviating from a standard full-time position in terms of how long one works is not profitable. This is in line with the results by Bick et al. (2022) for the United States, although we do not find significant *penalties* to working long hours – which could be because we bundle a larger group of hours. We do find evidence of hourly wages increasing significantly in late hours. Specification (2) shows that within occupations the same trends prevail. We now consider our main specification (3) which studies occupation-specific returns to long and late hours. The most important take-away is that both the long- and late hour premium differs substantially between occupations. We find that long hour premia are significantly larger in service occupations than in all other occupations. This is in line with the results presented in Goldin (2014) who finds that occupations in law and business exhibit the largest non-linearities. Returns to working late hours are more widespread. We find that all occupations reward working in evenings, with the effect again being the largest in service occupations. To summarize, these results suggest that both how long and when one works are important determinants of the occupational wage structure.

3.3 Trends in Hours and Excess Demand

This section presents two important time trends that characterize the German labor market over the past decade – and studies how they are related. The first panel in Figure (1) shows that fractions of employees that works long hours and late hours has decreased substantially in favor of individuals working part-time. We find that at the start of the decade roughly 30% of employees

Figure 1: Working Times and Excess Demand and Supply

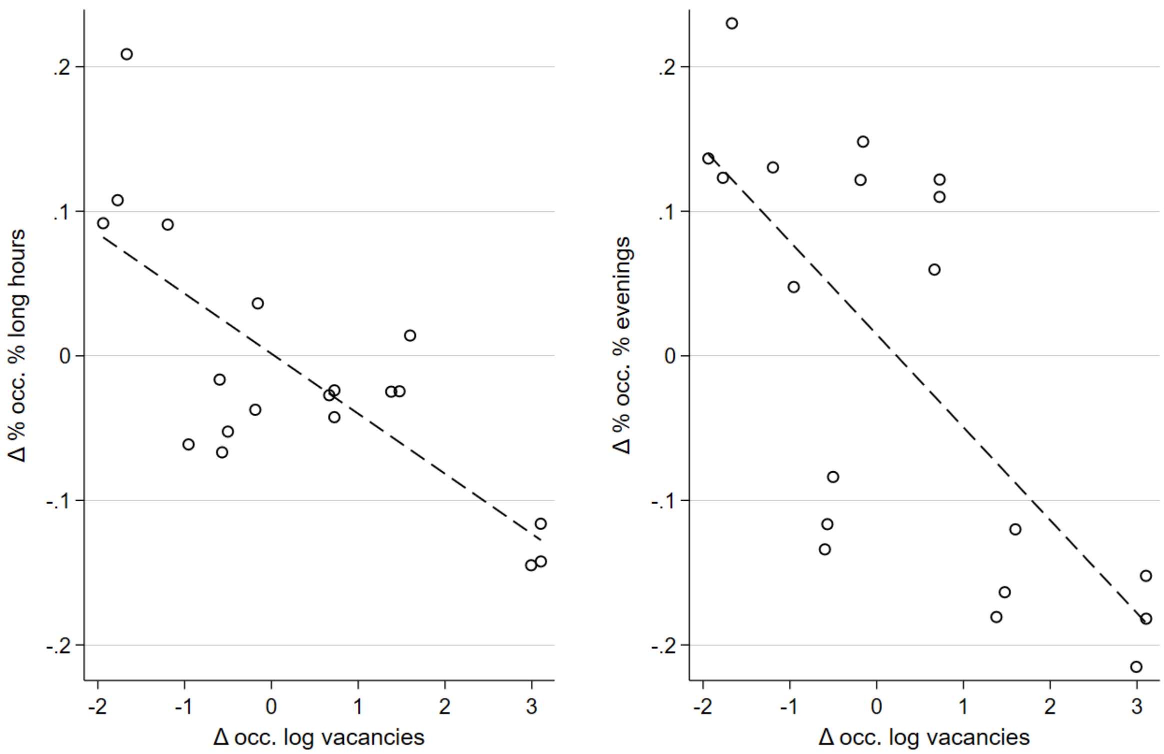


Notes. The first figure is based on job vacancy and unemployment data provided by the German Federal Employment Agency. The second figure uses weighted data from the German Socioeconomic Panel.

worked 45 hours or more per week. This decreased by almost ten percentage points. This decrease has been almost entirely offset by an equally large increase in part-time work, which increased from a little over 20% to almost 30%. Similarly, about 47% of employees reported working in evenings at the start of the decade, and this decreased by almost ten percentage points.

At roughly the same time we notice a substantial increase in aggregate labor market tightness. The number of vacancies per unemployed person has roughly doubled from about 17 per ten unemployed workers to just below 35. This change is driven by both an increase in labor demand and a decrease in supply. This trend is not unique to Germany – many countries have started facing labor supply shortages in recent years (e.g. Autor (2022)). Figure (2) suggests that changes in hours and excess demand may be interrelated. We find that occupations that have seen the largest change in excess demand are also those in which both long and late hours have decreased most.

Figure 2: Differences in Working Times and Excess Supply



Notes. This figure uses data on job vacancies provided by the German Federal Employment Agency and data on the fraction of workers that works long and late hours based on calculations from the German Socioeconomic Panel. The y-axis contains the year over year differences in the fraction of workers that works long or late hours in an occupation, and the x-axis contains the year over year differences in the (log of) the number of vacant positions in an occupation.

Table 1: The Hours - Wage Gradient in Germany

	hourly wages		
	(1)	(2)	(3)
Part-Time	-2.25***	-1.81***	-1.68***
	(0.19)	(0.19)	(0.19)
Long Hours	0.25	0.33	-0.90*
	(0.23)	(0.22)	(0.42)
Evenings	1.08***	1.23***	0.23
	(0.17)	(0.17)	(0.37)
Occupations			
Building, Manufacturing and Transportation		-2.63***	-2.80***
		(0.25)	(0.29)
Technical Occupations		2.91***	2.33***
		(0.45)	(0.54)
Service Occupations		-0.59*	-2.17***
		(0.27)	(0.30)
Health, Education and Culture		-2.37***	-2.95***
		(0.29)	(0.33)
Occupations × Long Hours			
Building, Manufacturing and Transportation × Long Hours			-0.16
			(0.51)
Technical Occupations × Long Hours			1.44
			(0.94)
Service Occupations × Long Hours			3.33***
			(0.59)
Health, Education and Culture × Long Hours			0.59
			(0.64)
Occupations × Evenings			
Building, Manufacturing and Transportation × Evenings			0.77
			(0.48)
Technical Occupations × Evenings			0.59
			(0.82)
Service Occupations × Evenings			1.69***
			(0.49)
Health, Education and Culture × Evenings			0.95
			(0.49)
States	Yes	Yes	Yes
Years	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	31634	31634	31634
R^2	0.264	0.292	0.301

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4. A Multidimensional Matching Model with Endogeneous Hours

Primitives. Consider a labor market populated by workers $i \in \mathcal{I}$ and firms $j \in \mathcal{J}$. We group workers into discrete observable types ($x = 1, 2, ..., X$) and firms into types ($y = 1, 2, ...Y$). Types are discrete and multidimensional. There are n_x workers of type x and f_y firms of type y. Workers and firms may match one-to-one or remain unassigned.[4] When matching, workers and firms additionally decide on an (in)formal hours contract ($h = 1, 2, ..., H$) that determines how much and at what times to work.

Worker Problem. Workers' utility functions are defined by:

$$U^h_{xy} = \nu^h_{xy} + (1 + \phi^h) w^h_{xy} + \epsilon^h_{x_i y}. \tag{2}$$

The utility of a type x worker depends on how he values an hours contract h in a type y occupation (ν^h_{xy}) and on the wage associated with this job (w^h_{xy}). We allow for complementarities between consumption and the time and timing of leisure (ϕ^h). The final term ($\epsilon^h_{x_i y}$) is an idiosyncratic preference shock over different job-hours types (y, h) that is assumed iid Type 1 Extreme Value distributed.[5]

Workers maximize utility by either choosing to work a job with a given contract (y, h) or by remaining unemployed. The latter is modeled as a match between a worker x and an outside option denoted $\{0\}$.

$$\max \left\{ \max_{y,h} \{ \nu^h_{xy} + (1 + \phi^h) w^h_{xy} + \epsilon^h_{x_i y} \}, \epsilon_{x_i 0} \right\}. \tag{3}$$

The distributional assumption on the shocks allows us to express the conditional labor supply function of type x workers in type (y, h) jobs (denoted $\mu^s_{y,h|x}$) and the fraction of workers opting for unemployment (denoted $\mu_{0|x}$) in closed form as:

$$\mu^s_{y,h|x} = \exp\left(\nu^h_{xy} + (1 + \phi^h) w^h_{xy} - u_x \right) \tag{4}$$

$$\mu_{0|x} = \exp\left(-u_x \right), \tag{5}$$

[4] In this to one-to-one matching model, job and firm can be used interchangeably. This model is equivalent to a one-to-many matching model where several workers are matched to the same firm, as long as the firm surplus is separable between the different jobs it offers (see Roth and Sotomayor (1989)).

[5] Correlation between the shocks can be introduced as in Galichon and Salanié (2022).

where

$$u_x = \log\left(\sum_{h'}\left[1 + \sum_{y'} \exp\left(\nu_{xy'}^{h'} + (1+\phi^{h'})w_{xy'}^{h'}\right)\right]\right).$$

Firm Problem. Firms' profits functions are defined as:

$$\Pi_{xy}^h = \rho_{xy}^h - w_{xy}^h + \eta_{xy_j}^h \tag{6}$$

The systematic utility of a type y firm depends on the worker type x and the agreed upon hours contract (ρ_{xy}^h) in addition to the wage transfer they pay (w_{xy}^h). We again introduce a separable idiosyncratic preference shock over different worker- and hour contract types (x, h). This shock is also assumed to be iid Type 1 Extreme Value distributed.

Firms maximize profits by either hiring a worker with a given contract (x, h) or by leaving the job vacant, which is also modeled as a match with an outside option $\{0\}$. We have:

$$\max\left\{\max_{x,h}\{\rho_{xy}^h - w_{xy}^h + \eta_{xy_j}^h\}, \eta_{0y_j}\right\}. \tag{7}$$

We obtain symmetric conditional labor demand functions of type y firms for type (x, h) hires (denoted $\mu_{x,h|y}^d$) and for the jobs that remain vacant (denoted $\mu_{0|y}$):

$$\mu_{x,h|y}^d = \exp\left(\rho_{xy}^h - w_{xy}^h - v_y\right) \tag{8}$$

$$\mu_{0|y} = \exp\left(-v_y\right), \tag{9}$$

where

$$v_y = \log\left(\sum_{h'}\left[1 + \sum_{h'} \exp\left(\rho_{x'y}^{h'} - w_{x'y}^{h'}\right)\right]\right).$$

Equilibrium. A competitive equilibrium outcome in our model consists of an equilibrium matching and wage. The equilibrium matching defines the mass of (x, y, h) matches (μ_{xy}^h) in addition to the masses of unemployed workers (μ_{x0}) and vacant jobs (μ_{0y}). The matching should meet a set of scarcity constraints that ensure its feasibility, and be incentive compatible such that no worker or firm wants to leave their current arrangement. The equilibrium wage (w_{xy}^h) prices each type of worker-firm-contract match. Bargaining over these prices equates supply and demand such that the market clears.

Feasibility. Let μ_{xy}^h denote the total mass of (x, y, h) matches, μ_{x0} the mass of unemployed workers, and μ_{0y} the mass of vacant jobs. The following feasibility constraints should hold at equilibrium:

$$\begin{aligned} \sum_y \sum_h \mu_{xy}^h + \mu_{0y} &= n_x \text{ for all } x \\ \sum_x \sum_h \mu_{xy}^h + \mu_{x0} &= f_y \text{ for all } y. \end{aligned} \tag{10}$$

Equilibrium Matching Function. The conditional demand functions ensure incentive compatibility because they are derived from workers (3) and firms (7) solving their respective optimization problems. From the equilibrium market clearing restriction we recover the following matching function M_{xy}^h:

$$\begin{aligned} M_{xy}^h(\mu_{x0}, \mu_{0y}) : = \mu_{xy}^h &= \exp(\Phi_{xy}^h) \mu_{x0}^{\frac{1}{2+\phi^h}} \mu_{0y}^{\frac{\phi^h}{2+\phi^h}} \\ \text{s.t. } \Phi_{xy}^h &= \frac{\nu_{xy}^h + \phi^h \rho_{xy}^h}{2 + \phi^h} \end{aligned} \tag{11}$$

The matching function relates the number of equilibrium matches to the match surplus and to excesses in supply and demand. This function predicts more (x, y, h) matches when these types of matches are more desirable to either workers or to firms, and when excesses increase on either side of the market. We recover the well-known matching function of Choo and Siow (2006) when we assume there are no complementarities ($\phi^h = 0$ for all (h)). Our function looks similar that obtained in Dupuy et al. (2020), where transfers are taxed. Note that the matching function is homogeneous of degree one but not symmetric in its arguments.

Existence and Uniqueness of Equilibrium. The matching function (11) and the feasibility constraints (10) fully characterize the matching equilibrium. This class of models is extensively discussed in Chen et al. (2022). They show that a unique equilibrium exists under minimal assumptions on the structure of the matching function, which has to be continuous, weakly isotone in both arguments, and converge to zero when either argument tends to zero. By Theorem 1 in Chen et al. (2022) a unique equilibrium exists in our model.

Equilibrium Wage Function. The market clearing condition also yields an expression for the equilibrium wage function:

$$w_{xy}^{h}(\mu_{x0}, \mu_{0y}) = \frac{\rho_{xy}^{h} - \nu_{xy}^{h} + \log\left(\frac{\mu_{0y}}{\mu_{x0}}\right)}{2 + \phi^{h}}. \tag{12}$$

We find that equilibrium wages depend on preferences by workers and firms and on the aggregate tightness of the labor market. Wages increase if hiring a type x worker with hours contract h is particularly productive to a firm ($\uparrow \rho_{xy}^{h}$). Wages decrease if a certain type of job and hours contract is attractive to workers ($\uparrow \nu_{xy}^{h}$). The intuition is that firms or workers competing for certain positions pushes the equilibrium wages up or down. For the same reason hours contracts that allow workers to better enjoy their wages due to complementarities with the amount and timing of leisure offer lower wages ($\uparrow \phi^{h}$). Finally equilibrium wages decreases in excess supply (μ_{x0}) and increase in excess demand (μ_{0y}).

The wage premium to long and late hours can – up to a normalization – be expressed as:

$$\Delta_{h'}^{h} w_{xy} := w_{xy}^{h} - w_{xy}^{h'} =$$
$$\underbrace{\left[\rho_{xy}^{h}\left(2+\phi^{h'}\right) - \rho_{xy}^{h'}\left(2+\phi^{h}\right)\right]}_{\Delta \textit{ productivity}} + \underbrace{\left[\nu_{xy}^{h'}\left(2+\phi^{h}\right) - \nu_{xy}^{h}\left(2+\phi^{h'}\right)\right]}_{\Delta \textit{ amenity}} + \underbrace{\log\left(\frac{\mu_{0y}}{\mu_{x0}}\right)\left[\phi^{h'} - \phi^{h}\right]}_{\textit{relative bargaining power}} \tag{13}$$

To interpret this equation suppose that contract h offers long and late hours whereas h' does not. The first term tells us that the premium to long and late hours in an occupation is larger if these hours are relatively more productive. The second term captures differences in how workers value working long and late hours in this occupation. This difference may be non-negligeable – for example if workers mind certain hours less in an occupation that allow them to work from home. The third term captures the relative bargaining power component. In occupations where there is a large excess in demand, the premium to long and late hours is higher to the extent that this hinders workers from enjoying their wages than short hours would.

Equilibrium Hours Contract. The hours contracts are also determined as a function of both the surplus and bargaining power. The following equation tells us which types of contracts will occur relatively more frequently:

$$\log \frac{\mu_{xy}^{h}}{\mu_{xy}^{h'}} = (\Phi_{xy}^{h} - \Phi_{xy}^{h'}) + \log \frac{\mu_{0y}}{\mu_{x0}} \left(\frac{\phi^{h} - \phi^{h'}}{(2+\phi^{h})(2+\phi^{h'})} \right). \tag{14}$$

We see that the fraction of occupations with long and late hours depends on two terms. The first one captures differences in the complementarity-adjusted surplus, and is such that hours contracts that are relatively more attractive will occur more frequently in equilibrium. The second term tells us that, the higher the employees' bargaining power – as captured by a relatively larger excess demand by firms – the more favorable contracts they can obtain. This effect is mediated by the difference in the marginal utility of wages between these two contracts. The intuition here is that workers are only willing to put effort into bargaining if they are able to enjoy the extra wages they obtain. This is where our model innovates on those in Choo and Siow (2006) and Dupuy and Galichon (2022), where excess demand does not affect the terms of the match. The model by Mourifié and Siow (2021) shares the same feature – excess supply and demand on the marriage market affect the marital contracts – at the cost of a clear structural interpretation in terms of complementarities.

5. Identification and Estimation

Identification. We briefly discuss how the parameters of the model $(\nu_{xy}^{h}, \phi^{h}, \rho_{xy}^{h})$ are identified. Conditional on knowing the transferability parameter (ϕ^{h}) the identification argument follows that in Dupuy and Galichon (2022). The intuition is that the mass of matches with a given hours contract informs us that these types of matches provide a large surplus – meaning they are attractive to either workers or firms. This is reflected in the matching function (11) increasing in both (ν_{xy}^{h}) and (ρ_{xy}^{h}). Because we also observe wages this allows us to separate out the firm's value from that of the worker – as wages increase in the former but decrease in the latter (see equation (12)).

With data on matching patterns and wages in a single market the transferability parameter (ϕ^{h}) is not identified non-parameterically. The $2 \times |X| \times |Y| \times |H|$ parameters of the model (ν_{xy}^{h} and ρ_{xy}^{h}) exhaust all our data moments such that the model is just-identified. As discussed in Galichon et al. (2019) the parameter can be estimated by exploiting variation in matching patterns across markets. We instead estimate it by restricting the number of parameters and relying on the non-linear effect of ϕ^h in the matching function and its interactions with the excesses (μ_{x0} and μ_{0y}) in the wage function to separate it from both ν_{xy}^h and ρ_{xy}^h.

Types and Parameterization. This brings us to the empirical characterization of types and the functional forms imposed on $(\nu_{xy}^h, \phi^h, \rho_{xy}^h)$. We assume that workers are characterized by their gender and whether they have a college degree, such that $|X| = 4$. The hours contracts distinguish between three types of jobs: (i) a part-time, and (ii) a full-time position, neither of which requires late hours, and (iii) a long-hour option that does require late hours, such that $|H| = 3$. Jobs are defined by their occupation as defined in as in section (3) such that $|Y| = 5$. We parameterize the transferability, amenity, and productivity terms by sets of fixed effects:

$$
\begin{aligned}
\nu_{xy}^h &= \sum_y \mathcal{N}_y \mathbb{1}_y + \sum_x \mathcal{N}_x \mathbb{1}_x + \sum_h \mathcal{N}_h \mathbb{1}_h + \sum_{x,h} \mathcal{N}_{x\times h} \mathbb{1}_{x\times h} + \sum_{y,h} \mathcal{N}_{y\times h} \mathbb{1}_{y\times h} \\
\phi^h &= \sum_h \mathcal{P}_h \mathbb{1}_h \\
\rho_{xy}^h &= \sum_x \mathcal{R}_x \mathbb{1}_x + \sum_{y,h} \mathcal{R}_{y\times h} \mathbb{1}_{y\times h}
\end{aligned}
\tag{15}
$$

This specification flexibly captures the main effects of how workers and firms value hours and each other. On the worker-side we allow for heterogeneity by both worker- and job types in how hours are valued. We also allow for heterogeneity in how workers value other aspects of each job that do not relate to hours. On the firm side we allow for firms valuing different types of workers differently and we allow for the productivity of hours to be occupation-specific.

Estimation. Assume that we have data on matching patterns $\hat{\mu} = (\hat{\mu}_{xy}^h, \hat{\mu}_{x0}, \hat{\mu}_{0y})$ and a noisy measure of the true transfer $\tilde{w}_{ij}^h$ (as in Dupuy and Galichon (2022)). This means that we have observations defined by:

$$
\tilde{w}_{ij}^h = w_{xy}^h + \delta_{ij}^h, \text{ where } \delta_{ij}^h \sim \mathcal{N}\left(0, s^2\right) \text{ iid },
\tag{16}
$$

where δ_{ij}^h is a centered Gaussian measurement error of variance s^2. The observed average wage for an (x, y, h) match is thus distributed according to:

$$
\tilde{w}_{xy}^h = \mathbb{E}_{\hat{\mu}_{xy}^h}\left[w_{x_i y_i}^h\right] \sim \mathcal{N}\left(0, \frac{s^2}{\hat{\mu}_{xy}^h}\right) \text{ iid }.
\tag{17}
$$

We use these average wages by type instead of individual wages to speed up computation – this does not affect the identification of any of the model's parameters.

We estimate the parameters by maximizing a likelihood function. Let $\theta = \{\nu^h_{xy}, \rho^h_{xy}, \phi^h_{xy}, s\}$ denote the parameters we want to estimate. For each parameter value, we solve the model by substituting the matching function (11) into (10) and computing the values of μ_{x0} and μ_{0y} that solve this equation using the Iterative Projective Fitting Procedure (IPFP) algorithm (see Galichon and Salanié (2022)). We then use the values of μ_{x0} and μ_{0y} to compute the model's prediction for the matching patterns and wages through equations (11) and (12). We update our parameter guess by equating the matching patterns and wages to those observed in the data. This process converges to a unique equilibrium.

The log likelihood of observing an (x, y, h) match at wage $\tilde{w}^h_{xy}$, an unemployed worker of type x, and a vacant job of type y is given by:

$$L_1(\theta) = \hat{\mu}^h_{xy} \log\left(\mu^h_{xy}|\theta\right) + \hat{\mu}_{x0} \log\left(\mu_{x0}|\theta\right) + \hat{\mu}_{0y} \log\left(\mu_{0y}|\theta\right) \tag{18}$$

$$L_2(\theta) = -\hat{\mu}^h_{xy} \frac{\left(\tilde{w}^h_{xy} - w^h_{xy}|\theta\right)^2}{2s^2} - \frac{1}{2}\log\left(\frac{s^2}{\hat{\mu}^h_{xy}}\right). \tag{19}$$

The contribution of the first equation (18) is to equate the model's moment predictions of the number of matches, unemployed workers, and vacant jobs to their sample counterparts. The second equation (19) matches the model's wage predictions with the observations on wages. The log likelihood method solves:

$$\max_{\theta} l(\theta) = \sum_x \sum_y \sum_h L_1(\theta) + \sum_x \sum_y \sum_h L_2(\theta). \tag{20}$$

6. Results

We first discuss the main parameters obtained from estimating the model on the 2017 wave of the Socioeconomic Panel (SOEP) and then consider two applications. The first application look at which occupational characteristics are the main predictors of differences in the productivity and amenity values of long and late hours (section 6.2). We then decompose the equilibrium wage premium to long hours into contributions by the supply and demand sides of the market and by the relative bargaining power of the worker and the firm (section 6.3).

Table 2: Model Estimates – Preferences for Hours

	PT	FT	LT
$\mathcal{N}_h$	-9.1	-2.47	-5.04
	(2.09)	(1.26)	(1.79)
$\mathcal{N}_{h\times f}$	9.44	-3.48	-2.51
	(1.5)	(1.07)	(1.5)

Notes. Model estimates that reflect the amenity value of different hours contracts. The first row reflects the utility associated with different hours contracts. The second row reflects the *additional* (dis)utility for women. Values are measured in hourly wages. Standard errors in parentheses.

6.1 Model Estimates.

We first study the model's main parameters that relate to how the supply and demand of hours is valued on both sides of the market. The model is estimated with hourly wages as the transfer, but note that estimation with monthly wages yields similar patterns. First, we find that our model fits the observed wage distribution relatively well. The R^2 value of the wage equation is 0.238, which is comparable to what we obtained through a hedonic regression. We briefly reflect on the estimates in Table (2). The first row of this table shows us that men prefer working full-time (FT) over the part-time (PT) and long and late hours (LT) alternatives. For women, we find that long and late hours are the least preferred option – and that part-time work is the most preferred alternative. These results are in line with earlier work, suggesting that men on average demand a higher wage when offered a part-time position to cope with the loss in earnings, whereas women prefer part-time options (e.g. Maestas et al. (2023) for the United States).

We now study differences across occupations in how hours are valued – both by the worker and by the firm. Table (3) shows that there is substantial heterogeneity on both sides of the market. We limit ourselves to a discussion of the main results. First, there is substantial heterogeneity across occupations in the productivity of different hours contracts, as predicted by Goldin (2014) and Goldin and Katz (2011). We find that long and late hours are substantially more productive in technical and service occupations than- they are in the other options. This result – that long and late hours are the most productive in technical occupations – is not what we would have predicted based on the equilibrium wage structure. Technical occupations only marginally reward longer hours as seen in the reduced-form estimates of the wage-hours gradient presented in section (3). To understand this result we have to consider the supply-side valuations. We find that, except for

Table 3: Model Estimates – Preferences for Hours Across Occupations

	Farm. & Min.	Manufacturing	Technical	Service	Health & Educ.
Supply ($\mathcal{N}_{y\times h}$)					
PT	2.34	1.08	5.0	3.83	2.27
	(1.05)	(1.01)	(1.32)	(1.02)	(1.01)
FT	6.73	3.77	1.2	0.96	5.53
	(1.17)	(1.06)	(1.03)	(1.21)	(1.35)
LT	4.11	2.68	6.44	4.88	6.59
	(1.03)	(1.12)	(1.33)	(1.09)	(1.02)
Demand ($\mathcal{R}_{y\times h}$)					
PT	0.34	-0.43	2.45	3.31	2.42
	(1.19)	(1.24)	(1.53)	(1.31)	(1.51)
FT	3.16	0.03	5.61	3.84	2.02
	(1.28)	(1.12)	(1.23)	(0.96)	(1.01)
LT	2.97	0.84	7.66	6.54	4.34
	(1.84)	(1.61)	(1.24)	(1.0)	(1.14)

Notes. Model estimates that how the value of hours differs between occupations – for both workers an for firms. Values are measured in hourly wages. Standard errors in parentheses.

in occupations in health and education, employees dislike working long hours the *least* in technical occupations. In the next section we study which occupational characteristics may explain this difference.

6.2 Predicting the Productivity and Utility Premiums to Long and Late Hours.

We now consider which occupational characteristics may explain the productivity and utility premiums to long and late hours. To this end we first calculate for each occupation the difference in the productivity (P_y) and amenity values (V_y) between the least (part-time and no evenings) and most (long hours and late) hours options as:

$$\begin{aligned} P_y &= \left(\mathcal{R}_y^{LT} - \mathcal{R}_y^{PT}\right) \\ V_y &= \left(\mathcal{N}_y^{LT} - \mathcal{N}_y^{PT}\right). \end{aligned} \tag{21}$$

We then regress a set of occupational characteristics on each of these outcomes:

$$Y_y = c + \boldsymbol{\alpha}\mathbf{Tasks}_{i,y} + \boldsymbol{\beta}\mathbf{Demands}_{i,y} + \boldsymbol{\gamma}\mathbf{WorkingConditions}_{i,y} + \boldsymbol{\delta}\mathbf{TimePlace}_{i,y} + \epsilon_{i,y}. \tag{22}$$

Here Y_y is either the productivity or amenity premium defined in (21) and the regressors are vectors of variables that relate to the concepts outlined in bold. We select a model using the LASSO procedure outlined in Belloni et al. (2012) that allows for heteroskedasticity and uses a data driven approach to the selection of the penalization parameter. This is because our analysis uses the German Employment Surveys by the BIBB/BuA – which contains data on a large set of variables (roughly 70) that relate to the working conditions, job tasks, work demands, and variables referring to the time and place of work. This survey of roughly 20.000 workers is the standard dataset on occupational characteristics and tasks in Germany (see e.g. Spitz-Oener (2006) and Böhm et al. (forthcoming)). More information can be found in Appendix B.

Predicting Productivity Premiums. We first consider what determines the productivity premium to long and late hours in Table (4). The LASSO selects a list of roughly twenty five variables as the main predictors of the productivity premium to long hours. We find that occupations associated with physically demanding working conditions (e.g. working standing up, cold / hot / moist environments, ...) or tasks (e.g. nursing / caring, protecting / guarding, training / educating) are characterized by lower productivity premiums to long hours. This is consistent with physical exhaustion reducing workers' productivity which may be due to exhaustion and an increased risk of injury or accidents (see for example Pencavel (2015)). A similar reasoning could explain our finding of larger productivity premiums when workers can work from home or sit down and work from a computer.

We also find that jobs in which workers have a lot of autonomy in terms of how they perform and schedule their work, or occupations in which workers are often confronted with new tasks, are characterized by larger productivity premiums. This is consistent with the results of Goldin (2014), who documents larger *wage* premiums in occupations of similar characteristics. The argument is that in these occupations, workers are not easily substitutable for one another – because they have a lot of discretion over how work is performed. Employing a single worker for longer and later is thus more productive in these occupations.

Predicting Amenity Premiums. We now study which traits are the main predictors of employees' valuations of longer and late hours in Table (5). We find that, when working in harmful physical conditions (e.g. cold / hot / moist or outdoor environments, having to work with oil / grease) or when having to sit for long times, employees dislike long and late hours more. The same holds for when they are often disturbed, have to perform repetitive and detailed tasks or have to work

Table 4: Predicting the Productivity Premium to Long and Late Hours

	Productivity Premium
Working Conditions	
Work Standing	-0.12***
	(0.02)
Sitting Continuously	0.07***
	(0.02)
Cold / Hot / Moisture	-0.11***
	(0.03)
Work Bent / Kneeled	-0.05**
	(0.02)
Handle Pathogens / Bacteria	-0.13***
	(0.03)
Outdoors	-0.32***
	(0.03)
Decide on Break	0.14***
	(0.02)
Feeling of Important Job	-0.12***
	(0.02)
Work Demands	
Confronted with New Tasks	0.04**
	(0.02)
Improve Existing Procedures	0.05**
	(0.02)
Disturbed at Work	0.08***
	(0.02)
Prescribed Exact Output / Time	-0.08***
	(0.02)
Job Tasks	
Manufacturing / Producing	0.41***
	(0.03)
Purchasing / Selling	0.16***
	(0.02)
Monitoring / Controlling Machines and Processes	-0.24***
	(0.02)
Developing / Researching	0.14***
	(0.03)
Training / Instructing / Educating	-0.28***
	(0.02)
Providing Advice / Information	0.09***
	(0.02)
Entertaining / Accomodating	0.22***
	(0.02)
Nursing / Caring	-0.25***
	(0.02)
Protecting / Guarding	-0.11***
	(0.02)
Working with Computers	0.22***
	(0.02)
Use Internet / Email	0.14***
	(0.02)
Work Time and Place	
Work Sundays	-0.10***
	(0.02)
Telecommute	0.06***
	(0.02)
Observations	19879
R^2	0.257

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. Results from a LASSO regression following Belloni et al. (2012) of a rich set of occupational tasks and characteristics on the productivity and amenity premiums to long and late hours (as defined in (21)) . Data from the German Employment Surveys.

Table 5: Predicting the Amenity Premium to Long and Late Hours

	Amenity Premium
Working Conditions	
Work Standing	0.24***
	(0.02)
Sitting Continuously	-0.07***
	(0.02)
Cold / Hot / Moisture	-0.15***
	(0.03)
Work with Oil / Grease	-0.08***
	(0.02)
Handle Pathogens / Bacteria	0.50***
	(0.03)
Outdoors	-0.18***
	(0.03)
Decide on Break	-0.18***
	(0.02)
Work Demands	
Work Prescribed in Detail	-0.07***
	(0.02)
Work Repeated in Detail	-0.10***
	(0.02)
Disturbed at Work	-0.10***
	(0.02)
Work Very Fast	-0.07***
	(0.02)
Job Tasks	
Monitoring / Controlling Machines and Processes	-0.09***
	(0.02)
Reparing / Renovating	-0.08***
	(0.02)
Purchasing / Selling	-0.28***
	(0.02)
Monitoring / Controlling Machines and Processes	-0.13***
	(0.02)
Developing / Researching	0.16***
	(0.03)
Training / Instructing / Educating	0.53***
	(0.03)
Gathering Information / Documenting	0.17***
	(0.02)
Nursing / Caring	1.11***
	(0.03)
Use Internet / Email	-0.13***
	(0.02)
Work Time and Place	
Work in Shifts	-0.16***
	(0.03)
Work Sundays	0.24***
	(0.02)
Telecommuting Frequently	0.14***
	(0.01)
Supervise Employees	-0.16***
	(0.02)
Observations	19879
R^2	0.432

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. Results from a LASSO regression following Belloni et al. (2012) of a rich set of occupational tasks and characteristics on the productivity and amenity premiums (as defined in (21)) . Data from the German Employment Surveys.

very fast. These are all tasks that are hard to perform for long stretches on end, because they test a worker's physical or mental capabilities. On the other hand, when working in occupations that involve a lot of training, teaching, researching, or nursing, employees do not mind working long hours as much. These are tasks associated with jobs that are usually considered to be meaningful, which has been shown to increase labor supply (see Kesternich et al. (2021)).

We also find that employees in occupations where one can frequently work from home mind or work on Sundays mind long and late hours less. On the other hand, when work has to be performed in shifts or when employees have to supervise people, long and late hours are a larger burden. These results suggests that, when employees have discretion over where and when they work, they mind longer and later hours less. On the other hand when these hours are performed in rigid schedules or when they are forced upon them (which may be more often when one has to supervise people) they are more costly to employees.

6.3 Decomposing the Premium to Long and Late Hours.

We now look at how forces on either side of the market and the relative bargaining power of workers and firms contribute to shaping the equilibrium occupational wage premiums to long hours (as defined in equation (13)). Results from this analysis can be seen in Table 6. First of all we find substantial heterogeneity between occupations. In two of the five occupations (farming and mining and manufacturing) we find that the contribution of the supply side substantially outweighs that of the demand side (between two and five to one). In these occupations bargaining power contributes little to the overall wage premium. In technical, service, and health occupations, we find that the productivity component is roughly twice as important as the amenity premium in shaping the occupational wage premium. On average we find that roughly three quarters of the wage premium to long and late hours stems from differences in productivity, twenty percent is due to occupational differences in how long and late hours are valued, and five percent is due to the bargaining power component.

Table 6: Decomposition – Occupational Wage Premiums

	Farm. & Min.	Manufacturing	Technical	Service	Health & Educ.	**Average**
$\mathbb{E}_x\left[\Delta_{PT}^{LT} w_{xy}\right]$	-0.37	-1.11	2.31	1.67	0.18	0.54
Decomposition						
Δ Productivity	0.69	0.23	1.59	1.0	0.55	0.81
Δ Amenity	-1.03	-1.3	0.83	0.7	-0.33	-0.23
Relative Bargaining Power	-0.02	-0.03	-0.11	-0.03	-0.04	-0.05

Notes. Decomposition of the model's predicted wage premium to long and late hours – by occupation and on average across occupations – into a contribution by its three components (as introduced in equation (13)). Values measured in terms of hourly wages.

7. Conclusion

Several recent papers have studied the consequences of large returns to long and late hours and how they differ across occupations. These papers usually posit that wage premiums arise due to differences in production technologies. We introduce a multidimensional matching model in which hours and wages are jointly determined at equilibrium – building on the approaches introduced in Choo and Siow (2006) and Dupuy and Galichon (2022). We use the model to study how occupational wage-hour profiles arise and how they relate to preferences on both sides of the market and to the relative bargaining power of workers and firms.

Estimates from our model show that roughly a quarter of the premium is unrelated to differences in productivity – and instead stems from people valuing hours in different occupations differently. There nonetheless a lot of heterogeneity between occupations. For example, we find that in technical occupations the large productivity premium to long and late hours is completely offset by employees minding long and late hours less in these occupations. To explain this finding we study which occupational traits can predict individuals' valuation of longer and later hours. We find that when people can work from home or perform meaningful work they mind long and late hours less – when they work in physically or mentally stressful situations, they mind long hours more.

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Appendices

A. Details on Estimation

A.1 The IPFP Algorithm

Computing equilibria consists of solving the system of equations defined by substituting (11) into (10):

$$\begin{aligned} &\sum_y \sum_z M_{xyz}\left(\mu_{x0}, \mu_{0y}\right) + \mu_{0y} = n_x \text{ for all } x \\ &\sum_x \sum_z M_{xyz}\left(\mu_{x0}, \mu_{0y}\right) + \mu_{x0} = f_y \text{ for all } y. \end{aligned} \tag{23}$$

We use the Iterative Projective Fitting Procedure (IPFP) algorithm to solve for the masses of singles μ_{x0} and μ_{0y}. As shown in Galichon et al. (2019) this converges to a unique equilibrium. We follow their presentation of the algorithm:

Step 0	Fix the initial value of μ_{0y}, at $\mu_{0y}^{0} = f_y$.
Step $2t+1$	Keep the values μ_{0y}^{2t} fixed. For each x, solve for the value μ_{x0}^{2t+1} of μ_{x0}, such that the following equality holds $\sum_y \sum_z M_{xyz}\left(\mu_{x0}, \mu_{0y}^{2t}\right) + \mu_{x0} = n_x$.
Step $2t+2$	Keep the values μ_{x0}^{2t+1} fixed. For each y, solve for the value μ_{0y}^{2t+2} of μ_{x0}, such that the following equality holds $\sum_x \sum_z M_{xyz}\left(\mu_{x0}^{2t+1}, \mu_{0y}\right) + \mu_{0y} = f_y$.

The algorithm terminates when, $\sup_y \left|\mu_{0y}^{2t+2} - \mu_{0y}^{2t}\right| < \epsilon$, where ϵ is a sufficiently small positive value.

A.2 The Likelihood Gradient

To speed up computation, we provide the analytical gradient in the optimization algorithm. Let $\boldsymbol{\theta}$ again denote the parameter vector we want to estimate. We obtain the derivative of the likelihood function with respect to each parameter $\theta \in \boldsymbol{\theta}$ as:

$$
\begin{aligned}
\frac{\partial l\left(\theta, n, f, s\right)}{\partial \theta} = & \sum_x \sum_y \sum_z \hat{\mu}_{xyz} \frac{\partial \log \mu^{\theta}_{xyz}}{\partial \theta} \\
& + \sum_x \frac{\partial \hat{\mu}_{x0} \log \mu^{\theta}_{x0}}{\partial \theta} + \sum_y \frac{\partial \hat{\mu}_{0y} \log \mu^{\theta}_{0y}}{\partial \theta} \\
& - \sum_x \sum_y \sum_z \frac{\hat{w}_{ijz} - \frac{\partial w_{xyz}}{\partial \theta}}{2s^2}
\end{aligned}
$$

where we have:

$$
\begin{aligned}
\frac{\partial \log \mu^{\theta}_{xyz}}{\partial \theta} &= \frac{\partial \Phi_{xyz}}{\partial \theta} - \left(\frac{\partial \Upsilon_{xyz}}{\partial \theta} u_x + \Upsilon_{xyz} \frac{\partial u_x}{\partial \theta} \right) + \left(\frac{\partial \Upsilon_{xyz}}{\partial \theta} v_y + \Upsilon_{xyz} \frac{\partial v_y}{\partial \theta} \right) \\
\frac{\partial \log \mu^{\theta}_{x0}}{\partial \theta} &= -\frac{\partial u_x}{\partial \theta} \\
\frac{\partial \log \mu^{\theta}_{0y}}{\partial \theta} &= -\frac{\partial v_y}{\partial \theta} \\
\frac{\partial w^{\theta}_{xyz}}{\partial \theta} &= \frac{\partial \Upsilon_{xyz}}{\partial \theta} \left(\gamma_{xy} + u_x - v_y \right) + \Upsilon_{xyz} \left(\frac{\partial \gamma_{xy}}{\partial \theta} + \frac{\partial u_x}{\partial \theta} - \frac{\partial v_y}{\partial \theta} \right).
\end{aligned}
$$

The only derivatives that cannot be directly computed are $\frac{\partial u_x}{\partial \theta}$ and $\frac{\partial v_y}{\partial \theta}$. However note that differentiating (10) yields a linear system in the two partial derivatives $\frac{\partial u_x}{\partial \theta}$ and $\frac{\partial v_y}{\partial \theta}$. We can solving this system for $\frac{\partial u_x}{\partial \theta}$ and $\frac{\partial v_y}{\partial \theta}$.

B. Data Appendix

B.1 Tasks

The BIBB/BuA Employment Surveys. We use data on occupational characteristics from the "Employment Surveys" conducted by the the *Federal Institute for Vocational Education and Training (BIBB)*. The Employment Surveys are repeated cross-sections of a representative sample that varies around 25.000 respondents depending on the wave. We use the 2012 wave to determine occupational tasks. They are the standard dataset on occupational tasks for Germany (see for example Spitz-Oener (2006), Gathmann and Schönberg (2010), and Böhm et al. (forthcoming)). We follow the literature in computing task intensities by assigning values of 0, $\frac{1}{3}$, or 1 if respondents answers that they 'never', 'sometimes', or 'frequently' perform a tasks, and values of of 0 or 1 if the admissible answers are 'yes' or 'no'.