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Abstract

We investigate why firms differ in their policies toward part-time employment. We propose a new measure of minimum hours constraints (MHC) at the firm level that accounts for employees' observable characteristics and their expected probabilities of working part-time. We apply our method to the Structure of Earnings Survey data from 19 European countries. We find substantial variation in MHC within 12 economic sectors, which suggests a significant role of firm-specific factors. To assess the role of firms' organizational practices, we analyze the correlation between the MHC faced by core personnel and by administrative workers. We find that across all economic sectors and countries, non-administrative workers are significantly more likely to face MHC in firms where administrative workers face more rigid MHC. Our results suggest that the quantitative importance of firm-specific practices is similar to the importance of sector-specific factors.

Keywords: Minimum hours constraints, Part-time employment, Working hours, Organizational practices

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1. Introduction

Minimum hours constraints (MHC) are the restrictions imposed by employers that prevent employees from choosing a number of working hours lower than a job-specific minimum (Gustman and Steinmeier 1983). When MHC are applied, employees may find themselves overemployed, that is, working more hours than they would desire. This is particularly likely to occur among older workers and workers with young children or other caring responsibilities.

MHC have substantial effects on labor market outcomes. In particular, MHC tend to decrease employment at an extensive margin. A shortage of part-time jobs can result in some overemployed workers exiting the labor market (Charles and Decicca 2007; Gielen 2009; Blau and Shvydko 2011; Albinowski 2024), and may discourage inactive persons from searching for a job (Ameriks et al. 2020). MHC can also mediate the effects of tax policies on labor supply (Chetty et al. 2011), influence occupational choices (Wasserman 2023), self-employment decisions (Yurdagul 2017), and the gender wage gap (Goldin 2014).

Despite these effects, there has been little research on the causes and the character of MHC. Theoretical explanations for MHC can be categorized into two groups. The first group of explanations posits that MHC are efficient outcomes stemming from the nature of a production function. Employers do not allow a reduction of working hours at the given hourly wage, because shorter working hours may be associated with lower average productivity (Lang and Kahn 2001; Devicienti et al. 2018). According to the second group of explanations, MHC arise due to market imperfections, and are sometimes inefficient solutions.

There are several mechanisms through which a firm's production function can explain MHC. If a labor input of an employee is complementary to the inputs of other employees or capital goods, then the firm's role is to coordinate these inputs by setting work hours (Deardorff and Stafford 1976; Battisti et al. 2024; Labanca and Pozzoli 2023). Fixed costs are another justification for the imposition of MHC (Hurd 1996; Johnson 2011). Examples of fixed costs include the costs of training or activities that need to be done at the start of an employee's shift. Hours constraints may also arise if an employee accumulates valuable knowledge that is costly to convey to others (Goldin 2014).

Market imperfections that may give rise to MHC include information asymmetry and limited commitment. A preference for short working hours may serve as a signal of unobserved low productivity, and the resulting work norms may be socially inefficient (Landers et al. 1996; Sousa-Poza and Ziegler 2003). Indeed, there is a large strand of literature in the sociology of work, confirming the existence of the "flexibility stigma" (Williams et al. 2013; Cech and Blair-Loy 2014; Fernandez-Lozano et al. 2020; Chung 2020). Employees utilizing flexible working arrangements, including part-time work, are more likely to be perceived by their managers and co-workers as being less committed to work. This stigma may prevent employees from requesting part-time work, even if such an arrangement is officially supported by the employer. MHC may also arise due to long-term employment contracts, which decouple hourly wages from workers' productivity (Lazear 1981). However, the empirical significance of this explanation is rather low (Kahn and Lang 1992).

The distinction between these two groups of causes is important as they have different policy implications. If hours constraints stem from production function characteristics, policy measures aimed at increasing hours flexibility would entail efficiency losses. By contrast, hours constraints related to work norms and organizational culture could potentially be relaxed without a loss of productivity.

We make methodological contributions to the literature by proposing a new measure of MHC at the firm level and by proposing a new method for assessing the role of organizational practices in the origination of MHC. Our measure of MHC takes into account the observable characteristics of employees and their expected probability of working part-time. We show that when workers cannot sort freely into jobs that match their hour preferences, our measure of MHC is better at identifying firm-level hours constraints than simple indicators based on the shares of part-time workers.

Our test of the role of organizational practices examines a within-firm correlation in MHC between two groups of workers: administrative employees and core personnel, i.e., all other employees. The tasks of administrative employees are relatively similar across firms, and technological factors that give rise to MHC among the core personnel are unlikely to influence MHC for administrative workers. Therefore, under this identifying assumption, the correlation of MHC between these two groups of employees is informative about the role of firm-wide organizational practices. We conduct a range of tests that support the interpretation of our proxy for organizational practices. In particular, we rule out that it may be driven by underemployment, that is, demand shocks reducing working hours throughout the firms. Furthermore, the role of our proxy for organizational practices is not affected by the inclusion of a firm-specific measure of the part-time pay gap, which may reflect technological constraints preventing part-time work.

We apply our measure of MHC to a large linked employee-employer dataset from 19 European countries. Primarily, we aim to answer the question of whether variation in MHC across firms can be explained by factors explicitly linked to the production function – the firm's sector, size, and occupational structure, or whether firm-specific organizational practices play an important role in the origination of MHC.

We document a large variation in average levels of MHC between economic sectors, with the sectors of industry, and information and communication being characterized by the most rigid MHC. However, the differences between sectors are significantly reduced when firms' occupational structures are taken into account. These observations confirm that MHC are strongly linked to the production function. Interestingly, we also uncover substantial heterogeneity of MHC within economic sectors, even after controlling for firms' occupational structure. We find that MHC are more common in medium and large firms than in small ones, and we also confirm previous findings from the literature that hours constraints are positively linked to higher wages (Labanca and Pozzoli 2023).

We find a significant positive relationship between the MHC for administrative employees and the MHC faced by all other workers. This relationship is observed within all economic sectors and countries. The quantitative importance of our proxy for organizational practices in explaining the variance in MHC is comparable to the importance of sector fixed effects. Our results indicate that in most Central and Eastern European countries, organizational practices seem to explain more of the variation in MHC than the sectoral differences, whereas the opposite is the case for all the Western European countries in our sample.

In the next section, we introduce our measure of MHC and formally demonstrate its properties. In section 3, we outline the empirical strategy and dataset used to investigate the determinants of MHC. In section 4, we report the empirical findings. Section 5 concludes.

2. Measurement of minimum hours constraints

In this section, we introduce our firm-level measure of MHC. First, we review the methods previously used in the literature. Second, we develop a simple theoretical model of MHC under different market settings. Third, we define our measure of MHC and provide a theoretical proof of its advantages. Fourth, we provide theoretical intuition why the correlation between the MHC faced by core personnel and by administrative workers may be used to assess the role of organizational practices. Fifth, we operationalize our measure of MHC and present a method that can be applied to actual data.

2.1 Previous methods

MHC are mostly studied at the level of individual employees. Many employee surveys include a question on the preferred number of working hours. An hours constraint is simply identified when the desired working hours differ from the actual working hours. This method cannot be easily extended to the firm level. First, the linked employer-employee datasets seldom contain information on preferred hours. Second, it can be expected that the workforce composition is endogenous to MHC. Overemployed or underemployed workers can leave a firm if they see no chance to adjust their working hours. Thus, a firm with a low share of overemployed workers may simply be one from which workers preferring part-time jobs have already left.

Hutchens and Grace-Martin (2006) use a firm survey with direct questions about whether the employer permits job sharing or flexible starting times. Although these seem to be valuable measures, they may have certain limitations. First, using these measures requires a dedicated survey. Second, a firm may apply different personnel policies to different groups of workers. In such cases, a single variable may not accurately represent MHC. Third, the truthfulness of the responses may be uncertain.

An easily applicable method is to simply look at the share of part-time workers. Hutchens and Grace-Martin (2006) approximate MHC using the percentage of white-collar employees who work part-time. However, it is unlikely that preferences for part-time jobs are identically distributed across firms and economic sectors. For example, preferences for part-time work may be uncommon in firms where the workforce is composed mainly of prime-aged men. In such cases, a low share of part-time workers may wrongly suggest the existence of rigid MHC.

Blau and Shvydko (2011) approximate MHC with the share of female workers under age 30 in the firm's workforce. They argue that young women are much more likely than other demographic groups to have part-time or flexible-hours jobs. Although firm-level MHC may explain a substantial part of the variation in the employment shares of young women, other independent factors might also play a role. The firm's occupational structure may greatly influence the share of women in the workforce, as women tend to be more heavily represented in occupations that require social skills (Albinowski and Lewandowski 2024). In addition, the variation in local demographic structures may be an important confounding factor.

Labanca and Pozzoli (2022) have developed a measure of hours constraints based on the standard deviation of the mean annual hours worked across different skill groups within a firm. A low variation in hours worked indicates rigid hours constraints. This approach assumes that preferences for part-time work vary across skill groups, and that the degree of this variation is similar across firms. However, this measure is not specifically designed to identify MHC. Consider an example in which the average hours of two skill groups amount to 30 and 35 per week in firm A and to 35 and 40 per week in firm B. Although the standard deviation is the same in both firms, firm B is more likely to impose MHC.

2.2 Theoretical framework

In this subsection, we develop a simple theoretical model to illustrate the properties of our measure of MHC. We consider a static, one-occupation model with full employment. We assume that workers can be characterized by either high or low disutility from full-time work. However, firms vary in their willingness to accept part-time employment. As such, a key aspect of each firm's policy is to determine its optimal ratio of part-time workers.

Worker's choice

As our model is static, we only consider agents who strictly prefer any job over unemployment. We allow only two types of job arrangements: full-time with hours $h = 1$ and part-time with $h = \frac{1}{2}$. There are four types of workers, with observable characteristics $t \in \{f, m\}$ and preferences $k \in \left\{\frac{1}{2}, 1\right\}$ to work either full-time ($k = 1$) or part-time ($k = \frac{1}{2}$). For expositional simplicity, we interpret observable characteristics as gender, with females (f) having a higher propensity to work part-time. Formally, $P(k = \frac{1}{2} \mid f) = \lambda^f > \lambda^m =$

$P(k = \frac{1}{2} \,|\, m)$, where $P(t = f) = \eta$. This reflects the fact that preferences for part-time employment systematically differ between socio-demographic groups. The aggregate measure of all workers who prefer part-time employment is $\lambda = \lambda^f \eta + \lambda^m (1 - \eta)$.[1]

The workers have a simple utility function of:

$$u_k(h) = w_h - d_k(h),$$

where w_h is the total wage earned for working *h* hours, and d_k denotes the relative disutility from work. The types differ in their preference for part-time work, with $d_{1/2}(1) - d_{1/2}\left(\frac{1}{2}\right) > d_1(1) - d_1\left(\frac{1}{2}\right)$. Without loss of generality, we will normalize $d_1(1) - d_1\left(\frac{1}{2}\right) = 0$ and denote $d = d_{1/2}(1) - d_{1/2}\left(\frac{1}{2}\right)$. Therefore, type $k = \frac{1}{2}$, who has a higher disutility from full-time work, would have an incentive to work full-time only if the following incentive compatibility condition was satisfied:

$$w_1 \geq w_{1/2} + d. \tag{1}$$

The incentive compatibility constraint has a relatively simple interpretation: a worker who prefers part-time work will only accept a full-time position if the higher wage w_1 compensates for the increase in disutility from working full-time rather than part-time, denoted by d. Otherwise, type $k = \frac{1}{2}$ strictly prefers part-time work.

Firm's choice

The production process in our model follows a Cobb-Douglas form with technology Z, similar to the approach of Battisti et al. (2024). We follow their assumption that the firm employs a fixed number of N_j workers. Formally, the production function of firm *j* is given by:

$$Q_j = Z\left(\sum_{i=1}^{N_j} h(i)^{\rho_j}\right)^{\beta}.$$

Parameter $\rho_j > 1$ captures the firm-specific elasticity of substitution between employees.[2] Notice that for $\rho_j = 1$ employees would be perfect substitutes. In this case, the firm would be indifferent between full-time

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[1] Here, η denotes the economy-wide share of female workers. In section 2.3, we will allow this share to vary at the firm level, and exploit the resulting variation to construct our measure of MHC.

[2] Formally, the elasticity of substitution between workers is equal to $\frac{1}{\rho - 1}$, with a limit case of infinite elasticity, as ρ approaches 1. Notice that for our assumptions on the range of h, the assumption $\rho_j > 1$ is reasonable – in particular, $\rho_j < 1$ would indicate that it's more favorable for the firm to divide its labor input into more and more part-time workers.

and part-time employment, as long as the total supply of labor – measured in person-days – remained unchanged, regardless of how that labor was split between full-time or part-time workers. However, if $\rho_j \to \infty$, the jobs become perfect complements. As ρ_j grows, production depends more on coordination between employees, and the firm, holding labor supply constant, increasingly prefers full-time employment. Thus, it becomes less willing to accept requests for part-time employment from its staff. We shall assume $\rho_j \in \left[\underline{\rho}, \bar{\rho}\right] \subset (1, +\infty)$, in particular, no firm is fully indifferent about whether its employees work part-time or full-time. Moreover, we assume ρ_j are independent draws from some distribution $F(\rho)$ over $\left[\underline{\rho}, \bar{\rho}\right]$.[3]

In our setup, the parameter β, representing returns to scale, is independent of ρ_j. Assuming β is independent, rather than equal to the inverse of ρ_j, implies that two identical-sized firms with only full-time employment would have the same production. Suppose firm A and firm B differ in their ρ_j, with $\rho_A = 2$ and $\rho_B = 3$ (and, for simplicity, $Z = 1$). If both firms employed only 20 full-time workers, their output would be identical, equal to 20^β. However, if both hired 19 full-time workers and 1 part-time worker, the output of firm B (19.125^β) would be lower than the output of firm A (19.25^β).

We now explicitly formulate the firm's problem. Taking wages w_1 and $w_{1/2}$ as given (their determination will be discussed later, when presenting two alternative market settings below), the firm chooses a fraction of workers to work part-time in order to maximize profits. Following the production function as above, the profit function is:

$$\Pi_j = Z\left(\sum_{i=1}^{N_j} h(i)^{\rho_j}\right)^\beta - \sum_{i=1}^{N_j} w_{h(i)}.$$

Let us denote by x the fraction of N_j workers, who supply $h = \frac{1}{2}$. The remaining $(1-x)N_j$ is filled with full-time workers, who supply $h = 1$. This allows us to simplify the profit function:

$$\Pi_j(\mathrm{x}) = ZN_j^\beta \left(1 - x + x\left(\frac{1}{2}\right)^{\rho_j}\right)^\beta - N_j(1-x)w_1 - N_j x \cdot w_{1/2}.$$

The firm's first-order condition gives an interior solution of x_j^*, the firm-preferred fraction of part-time workers, as a function of wages and firm characteristics:

$$x_j^* = x^*(w_1, w_{1/2}, \rho_j):\ \frac{\partial \Pi_j}{\partial x}(x^*) = 0 \qquad (2)$$

[3] To avoid confusion, we will denote by ρ the associated random variable, while ρ_j are individual realisations of this variable. This convention is maintained throughout the paper.

Notice that the functional form of x^* is independent of j. In Appendix A, we derive x^* and show that it is decreasing in $w_{1/2}$ and ρ_j, and increasing in w_1. Whenever the dependence on w_1 and $w_{1/2}$ is irrelevant, we will denote shortly $x_j^* = x^*(\rho_j)$.

Market equilibrium

We now present two benchmark equilibria that differ in the degree of labor market frictions and worker mobility between firms.

Local monopsony in the labor market

We first discuss an equilibrium, which arises under the assumption of no sorting of workers between firms. This is an extreme example of a monopsonistic labor market, where each worker can be employed only by a single firm and is unable to change jobs in the short run.

The timing of the model is as follows:

1. Nature draws firm type ρ_j from $F(\rho)$ over $[\underline{\rho}, \bar{\rho}]$ and allocates workers to firms such that firm j receives a workforce with fraction λ_j of type-$\frac{1}{2}$ workers.
2. Each firm selects its preferred part-time ratio x_j^* and announces a contract that consists of wages $(w_1, w_{1/2})$.
3. Workers at firm j accept the part-time or full-time contract. Workers have no outside option; thus, any contract satisfying the incentive constraint (1) is accepted.
4. Production occurs and payoffs are realized.

In this setting, the supply of type-$\frac{1}{2}$ workers is fixed and given by λ_j, while the demand for part-time workers is equal to $x_j^* = x^*(w_1, w_{1/2}, \rho_j)$. Since any firm is a local monopsonist, the incentive compatibility constraint (1) is binding, which pins down $w_{1/2}$ and makes type-$\frac{1}{2}$ workers indifferent between working full-time and part-time. Note that $w_{1/2}$ is low enough so that type-1 workers strictly prefer to work full-time. Therefore, the supply of workers willing to work $h = \frac{1}{2}$ is equal to λ_j.

If $\lambda_j > x_j^*$, the firm accepts x_j^* requests to work part-time and rejects the rest, and the rejected type-$\frac{1}{2}$ workers work full-time. On the other hand, if a firm faces an undersupply of part-time workers, $\lambda_j < x_j^*$, its realized share of part-time workers will be lower than x_j^*. The firm-specific realized share of part-time workers, y_j, is therefore:

$$y_j = \min\{\lambda_j, x_j^*\}.$$

Perfect competition in the labor market

As a second benchmark, we consider a model, in which employees can freely choose firms. The timing is similar, but notably, it differs in the workers' choice:

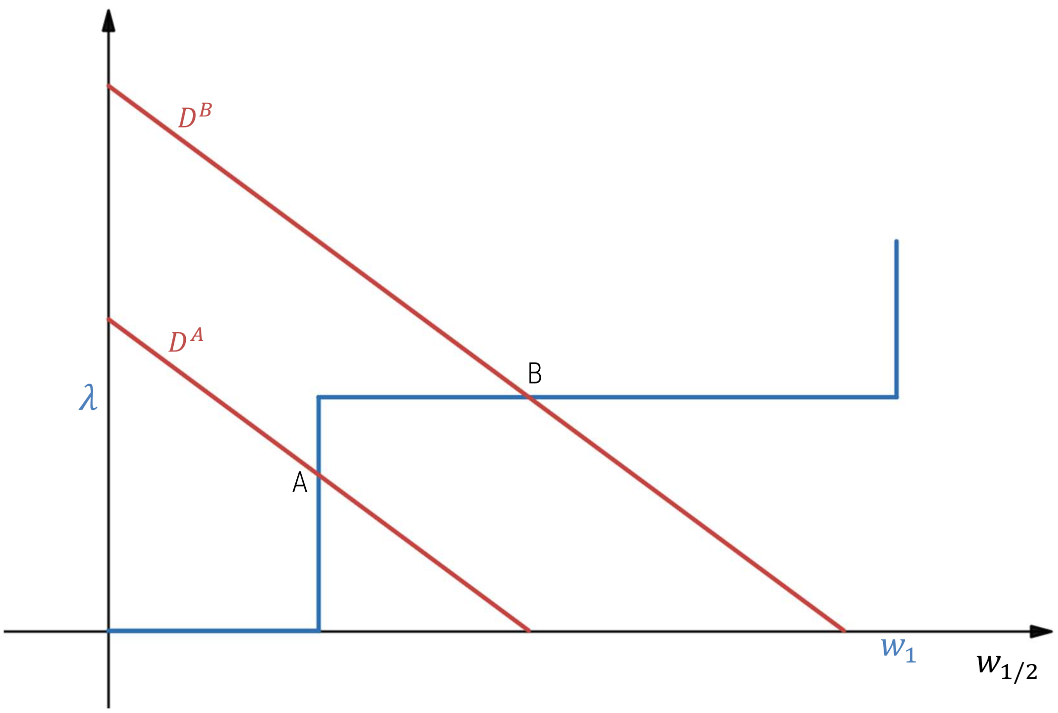
1. Nature draws firm type ρ_j from $F(\rho)$ over $\left[\underline{\rho}, \bar{\rho}\right]$.
2. Firms simultaneously announce their contracts that consist of wages $(w_1, w_{1/2})$.
3. Workers observe all contracts and choose which firm to work for, selecting between full-time and part-time positions.
4. Production occurs and payoffs are realized.

In this setting, there is a market-wide equilibrium, captured by dynamics between aggregated labor demand and the total share of type-$\frac{1}{2}$ workers, λ. The aggregated demand for part-time workers, given the wage $w_{1/2}$, is defined by:

$$D(w_{1/2}) = \int_{\underline{\rho}}^{\bar{\rho}} x^*(w_1, w_{1/2}, \rho)dF(\rho),$$

where x^* satisfies the FOC, defined in (2). Following the previous discussion, $D(w_{1/2})$ is strictly decreasing. We can distinguish two cases, as presented in Figure 1 below.

Figure 1. Two possible equilibria in the case with full sorting



Note: The blue line represents the supply of workers as a function of the part-time wage $w_{1/2}$. The red lines represent two possible demand functions. Source: Own elaboration.

In point A, the demand for part-time workers (D^A) is relatively low compared to their supply, so the aggregate demand $D(w_{1/2})$ is easily satiated. The competition among workers for part-time positions enables firms to fully exploit the incentive compatibility constraint (1) and offer $w_{1/2}$ that makes the inequality binding. Type-$\frac{1}{2}$ workers are therefore indifferent between working full-time and part-time. For any firm j, the realized employment of part-time workers is exactly equal to the firm-optimal level, $y_j = x_j^*$.

In point B, the demand for part-time workers (D^B) is relatively high, and firms compete for part-time workers by offering a higher wage $w_{1/2}$. The market-clearing condition is thus:

$$D(w_{1/2}) = \lambda \Leftrightarrow w_{1/2} = D^{-1}(\lambda).$$

Again, for all firms, $y_j = x_j^*$, that is, the realized employment of part-time workers is exactly equal to the firm optimum. Indeed, if for any firm x_j^* were higher than y_j, it would put upward pressure on $w_{1/2}$ and attract workers to firm j. In equilibrium, firms adjust their wage offers until the demand coincides with the market share of type-$\frac{1}{2}$ workers, λ.

2.3 Measuring minimum hours constraints

Each firm is characterized by unobserved rigidity of hours constraints, $(\bar{x}^* - x_j^*)$, where $\bar{x}^*$ denotes the economy-wide average that is $\bar{x}^* = E[x^*(\rho)]$. This constraint limits working hours flexibility: a higher $(\bar{x}^* - x_j^*)$ lowers the likelihood that workers at firm *j* can choose part-time employment compared with the economy-wide average. Importantly, $(\bar{x}^* - x_j^*)$ is an endogenous object determined by firm characteristics, which we treat as unobserved in the empirical analysis. We develop an empirical measure of MHC to proxy unobserved hours constraints using observable data. Our measure takes into account the firm's observable employment structure and population-wide probabilities of working part-time for given observable types of workers:

$$MHC_j = \eta_j \cdot y^f + (1 - \eta_j) \cdot y^m - y_j, \tag{3}$$

where η_j denotes the share of women in firm j's workforce (recall that η is the corresponding economy-wide share) and y^f (y^m) is the economy-wide part-time rate among female (male) workers, estimated directly from the data.[4]

[4] There is no need to impose any distributional assumption on η_j. Under the monopsony setup, η_j may be safely assumed to be independent of ρ_j, while under partial sorting, η_j may be endogenously correlated with ρ_j, as part-time-preferring workers (a characteristic correlated with being female) tend to sort into firms with less strict MHC. This reinforces, rather than weakens our measure of MHC.

The term $\eta_j \cdot y^f + (1 - \eta_j) \cdot y^m$ is the part-time share that firm j would be expected to exhibit if its MHC were at the economy-wide average, given its gender composition. MHC_j is therefore the gap between that benchmark and the firm's actual part-time share.

We argue that MHC_j is a weakly better predictor of $(\bar{x}^* - x_j^*)$ than the deviation of the share of part-time workers from the economy-wide average, $(\bar{y} - y_j)$. This is because MHC_j is based on more information (namely, η_j) than the latter measure. In fact, depending on the two benchmark cases, we can formulate the following proposition.

Proposition 1. Consider $X \equiv \bar{x}^* - x^*(\rho)$ and two alternative predictors of X:

$$Y = \bar{y} - y = \mathbb{E}[\mathrm{X} \mid y], \quad MHC = \mathbb{E}[X \mid \eta, y].$$

Then:

a) In the monopsonistic labor market, MHC is a strictly better predictor of X, than Y, that is:

$$MSE(MHC) < MSE(Y).$$

b) In the labor market with free sorting of employees, MHC coincides with Y, implying:

$$MSE(MHC) = MSE(Y).$$

The proof of Proposition 1 can be found in Appendix A. The intuition behind the result is relatively simple: in the monopsonistic case, the observed part-time share $y_j = \min\{\lambda_j, x_j^*\}$ depends on both the firm's demand for part-time workers (which we want to infer) and the local supply (which is a confounding factor). The composition variable η_j is informative about λ_j, thus, conditioning on η_j helps separate the effects of demand (x_j^*) and supply (λ_j) on the observed y_j. In the competitive case with full sorting, $y_j = x_j^*$ for all firms, so the workforce composition provides no additional information about X beyond what is already contained in Y. The two measures therefore coincide.

While actual labor markets differ in the degree of worker mobility, perfect mobility is not a realistic scenario. First, search costs limit the number of firms an employee can consider. Second, the geographical and occupational dimensions of labor demand mean that many workers can choose only from a limited number of employers, representing a small fraction of the labor market in a given country. Third, preferences for part-time employment vary over the life cycle. If an employee accumulates idiosyncratic knowledge that increases her productivity only within a specific firm, leaving that firm due to changing working-time preferences may involve a significant monetary loss. Therefore, in real-life scenarios with labor market frictions, our measure of MHC can be expected to provide a more accurate proxy of unobserved $(\bar{x}^* - x^*)$ than simple part-time employment shares.

It should be noted that although our MHC measure improves, on average, the identification of firm-level hours constraints, there may also be cases in which it is a worse proxy. In particular, this may occur when employees in a given firm have weaker preferences for part-time employment than would be expected based on their observable characteristics.

2.4 Measuring the role of organizational practices

We now extend our model to account for heterogeneity in substitution across occupations. Therefore, we separate workers into those performing core tasks (e.g., industrial production) and support/administrative staff. We impose the modelling assumption that any correlation of the substitution parameter for administrative workers with the analogous parameter for production workers reflects organizational constraints rather than the characteristics of production processes.

This crucial assumption follows two observations. First, tasks performed by administrative workers are similar across firms. For instance, the need for coordination among accountants or HR specialists is not expected to depend on the firm's production processes. Second, while administrative workers do interact with production workers, it is rarely the case that the working hours of these two groups need to overlap perfectly. Therefore, even if the substitution parameter for administrative workers varied across firms due to the characteristics of the tasks they perform, it would not need to be reflected in a similar variation among production workers. In contrast, organizational culture and practices usually apply to all firm employees and are likely to induce a correlation between hours constraints for administrative and production workers.

To make the notation explicit, we assume that the total workforce of firm j is $N_{p,j}$ for core tasks and $N_{a,j}$ for administrative tasks, and the occupation-specific elasticities are $\rho_{a,j}$ and $\rho_{p,j}$, respectively. Following Dupuy (2012), we utilize the additive production function for the two types of occupations:

$$Q_j = Z\left(\sum_{i=1}^{N_{p,j}} h_p(i)^{\rho_{p,j}}\right)^{\beta} + Z\left(\sum_{i=1}^{N_{a,j}} h_a(i)^{\rho_{a,j}}\right)^{\beta}.$$

Following a similar approach to that in the one-occupation model, let us denote by $x_{p,j}$ (respectively, $x_{a,j}$) the fraction of total demand $N_{p,j}$ ($N_{a,j}$) filled with part-time workers, who supply $h = \frac{1}{2}$. The remaining $1 - x_{p,j}$ $(1 - x_{a,j})$ part of the demand is filled with full-time workers, who supply $h = 1$. There are now four wages in the labor market, denoted by $w_{a,1}, w_{a,1/2}, w_{p,1}, w_{p,1/2}$.

Since the two occupations form distinct sectors, the optimal solutions to the firm's problem follow a similar path to that in (2). One can thus derive for each occupation type $\xi \in \{a, p\}$:

$$x^*_{\xi,j} = x^*_\xi\left(w_{\xi,1}, w_{\xi,1/2}, \rho_{\xi,j}\right): \ \frac{\partial \Pi_j}{\partial x_\xi}(x^*_\xi) = 0, \tag{4}$$

where x_ξ^* is decreasing in $w_{\xi,1/2}$ and $\rho_{\xi,j}$, and increasing in $w_{\xi,1}$, in exactly the same way as in the one-occupation model.

Parameter decomposition

To make our empirical approach more specific, we will decompose $\rho_{\xi,j}$ into technological and organizational constraints:

$$\rho_{\xi,j} = \rho_j^{ORG} + \rho_{\xi,j}^{TECH},$$

The key assumption is that for administrative workers the variance of $\rho_{a,j}^{TECH}$ is negligible, so that $\rho_{a,j}^{TECH} \approx c$. This yields:

$$\rho_{a,j} \approx c + \rho_j^{ORG} \; and \; \rho_{p,j} \approx (\rho_{a,j} - c) + \rho_{p,j}^{TECH}.$$

Under this assumption, the variance in hours constraints for administrative workers primarily reflects the variance in organizational practices rather than in technological requirements. In contrast, for production workers the variance in hours constraints can arise due to both technological and organizational factors. The proposition below states that the correlation between hours constraints for administrative workers and hours constraints for production workers is roughly equal to the share of the variation of the organizational component in the total variation of the hours constraints for the production workers.

Proposition 2. Consider a random variable $X_a = \bar{x}_a{}^* - x_a^*$ and $X_p = \bar{x}_p{}^* - x_p^*$, *where* x_a^*, x_p^* *are functions of random variables* ρ_a, ρ_p *satisfying equation (4). Denote* $\sigma_a = \sqrt{\mathrm{Var}(\rho_a)}$ *and* $\sigma_p = \sqrt{\mathrm{Var}(\rho_p)}$. *Then:*

$$\mathrm{corr}(X_a, X_p) \approx \frac{\sigma_a}{\sqrt{\sigma_a^2 + \sigma_{TECH}^2}}.$$

The proof is provided in Appendix A. This framework provides the theoretical foundation for our empirical strategy of using hours constraints for administrative workers as a proxy for organizational practices. In an empirical application, we do not observe directly X_a and X_p. However, we will construct occupation-specific measures of hours constraints, $MHC_{a,j}$ and $MHC_{p,j}$, which are derived according to the same rule as in equation (3), however, for respective occupation-specific subpopulations. The correlation between $MHC_{a,j}$ and $MHC_{p,j}$ is informative about the organizational component of hours constraints, ρ_j^{ORG}.

Sorting on unobserved preferences

In the monopsony case, the variation in the observed measure $MHC_{a,j}$ across firms contains information about the variation in ρ_j^{ORG} (under our assumption that $\rho_{a,j}^{TECH} \approx c$). One may ask whether this relationship is preserved when type-$\frac{1}{2}$ administrative workers sort across firms, so that $\lambda_{a,j}$ is no longer randomly assigned but instead reflects workers' choices. We argue that sorting reinforces, rather than undermines, the informational content of $MHC_{a,j}$.

Recall that x_a^* is decreasing in $\rho_{a,j}$, so firms with higher ρ_j^{ORG} (and thus $\rho_{a,j}$) offer fewer part-time positions to administrative workers. Moreover, if we assume preference-based sorting, so that type-$\frac{1}{2}$ administrative workers are less likely to apply to high-$\rho_{a,j}$ firms, then also $\lambda_{a,j}$ is a decreasing function of $\rho_{a,j}$ in equilibrium. Since $y_{a,j} = \min\{\lambda_{a,j}, x_{a,j}^*\}$ and both $\lambda_{a,j}$ and $x_{a,j}^*$ are decreasing in $\rho_{a,j}$, the realized part-time share among administrative workers, $y_{a,j}$, is also decreasing in $\rho_{a,j}$, regardless of the market regime. It follows from equation (4) that $MHC_{a,j}$ is increasing, hence positively correlated, with $\rho_{a,j}$, thus ρ_j^{ORG}. Therefore, even when type-$\frac{1}{2}$ administrative workers sort into firms based on their working hours preferences, $MHC_{a,j}$ remains a valid proxy for the organizational component of hours constraints. If anything, sorting is likely to reinforce this relationship, as both the firm's demand for part-time work and the share of type-$\frac{1}{2}$ workers are aligned in their dependence on ρ_j^{ORG}.

2.5 Empirical application

To operationalize our MHC measure, we propose a two-step procedure. In the first step, we calculate the expected probability of working part-time for all employees, conditional on their demographic characteristics and educational attainment. Formally, we estimate the following logit model:

$$P(pte_i = 1) = \Theta\left(\beta^{g,a,e} \times D_i^{g,a,e}\right), \tag{5}$$

where pte_i is a dummy variable denoting whether an employee works part-time; $\Theta(\cdot)$ is the logistic distribution function; and $D_i^{g,a,e}$ is a vector of exhaustive and mutually exclusive dummy variables denoting an interaction of gender, 10-year age groups, and three education levels. Depending on the data availability, equation (5) can benefit from the inclusion of other individual supply-side variables, such as information on the household composition or study status. The estimated coefficients should be country- and time-specific. Preferences for working part-time are more likely to arise in high-income countries (Bick et al. 2018). Furthermore, these preferences can be thought of as social norms that spread over time (Wielers et al. 2014), also influenced by changes in labor market regulations (Buddelmeyer et al. 2008).

In the second step, we calculate the expected share of part-time employees at the j-th firm and compare it with the actual share. That is, our firm-level measure of MHC aggregates employee-level differences between the expected probability of part-time employment and actual part-time status.

$$MHC_j = \frac{\sum_{i \in j}\left(P(pt\ \ _i=1) - \mathbf{1}(pte_i=1)\right)}{n(j)}. \tag{6}$$

An average value of MHC_j equals zero (conditioned on the firm's weight being a sum of the employees' weights used in the first step). A positive value, $MHC_j = z > 0$, means that the share of part-time employees is z percentage points lower than expected based on the demographic characteristics of the firm's employees. Negative values, in turn, mean that the MHC in a given firm are less rigid than the MHC in an average firm.

Note that the endogenous sorting of workers is likely to increase the absolute values of our MHC measure, thus helping to identify firms that impose rigid MHC. For example, workers with strong unobserved preferences for part-time employment are likely to end up in firms with less rigid MHC, contributing to higher shares of actual part-time employment in these firms. However, as explained in section 2.3, when workers have higher opportunities to change firms according to their working time preferences, our measure of MHC loses its advantage over the simple share of part-time workers.

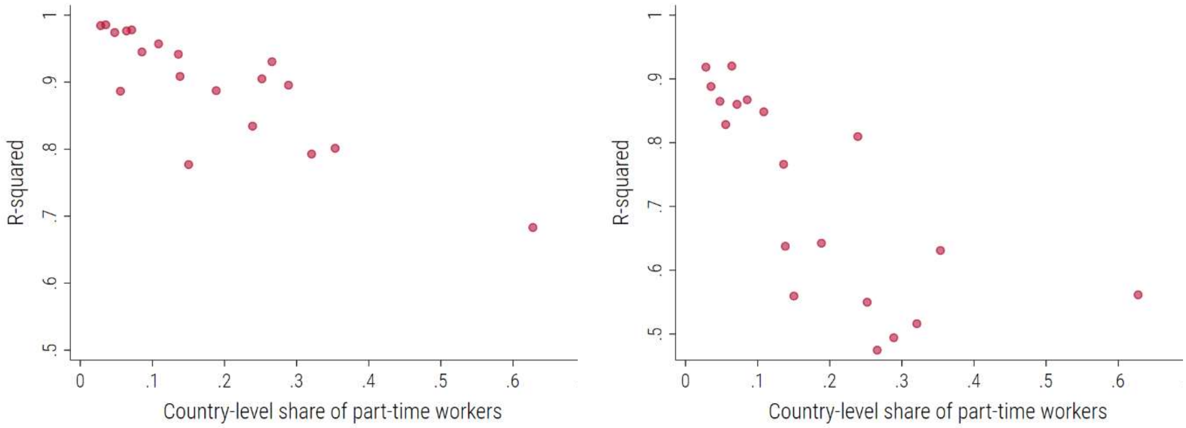
This method of identifying MHC can be modified to answer different research questions. Theory suggests that MHC can be more rigid in certain occupations, e.g., in those where teamwork is essential. The baseline measure of MHC also reflects these occupation-specific rigidities. However, it is easy to calculate a measure of MHC that cannot be attributed to the firm's occupational structure. To do so, one needs to control for occupations when estimating individual probabilities of working part-time. Equation (5) then takes the form:

$$P(pte_i = 1) = \Theta\left(\beta^{g,a,e} \times D_i^{g,a,e} + \gamma^o \times D_i^o\right), \tag{7}$$

where D_i^o is a vector of dummy variables denoting occupation groups. Another way to utilize the regression-based method of identifying MHC is to focus on a subset of employees, e.g., specific occupation groups, and to analyze their probability of working part-time. That is, equation (5) is estimated only for the selected type of workers, and the term $n(j)$ in equation (6) stands for the number of the firm's employees included in the first step of the analysis.

Compared to relying on a simple indicator of the part-time employment share, our method provides a more informative proxy for MHC, especially in countries with a substantial share of part-time workers. In Figure 2, we report the R-squared values from the firm-level regressions in 19 countries where our MHC measures are the dependent variables and the independent variable is the difference between the country-average share of part-time workers and the firm's share of part-time workers, i.e., $\bar{y} - y_j$. The aim of this exercise is to quantify how much of the variation in the more accurate MHC measure can be explained by the simple part-time employment share. In 13 out of 19 countries, the shares of part-time workers explain less than 95% of the variation in our baseline MHC measure. In the case of MHC adjusted for occupations, the simple indicator based on part-time shares yields much lower values of R-squared: for nine countries, they fall below 70%.

Figure 2. Variation in MHC measures explained by the shares of part-time workers



(a) Baseline measure (b) Adjusted for occupations

Note: In this figure, we report the R-squared derived from the OLS regressions estimated on the data from 2018 where a firm-level measure of MHC is the dependent variable and the independent variable is the difference between the country-average share of part-time workers and the firm's share of part-time workers. Each circle represents one country. Source: Own estimates based on the Structure of Earnings Survey data.

3 Empirical strategy and data

In this section, we outline an application of our method of measuring MHC to explore factors conducive to the origination of MHC. Next, we present data used in the analysis.

3.1 Econometric specification for the firm-level analysis

We aim to assess the relative importance of sector-specific and firm-specific factors in the origination of MHC. The former may reflect production function characteristics that are common to firms in a given sector. Differences between firms within a sector may not only arise due to heterogeneity of production functions, but also result from different managerial practices and organizational cultures.

Given that countries in the sample differ in the prevalence of part-time employment, and thus in the standard deviation of MHC, we standardize all measures of MHC at the country-year level, so that their standard deviation equals one and the mean equals zero. We report the results for two variants of the dependent variable: the baseline measure of MHC (calculated according to equations (5) and (6)) and the measure adjusted for the occupation structure (derived with equation (7) instead of with equation (5)).

As initial descriptive evidence, we analyze variation in MHC values between and within sectors. Large differences between the mean values of MHC would suggest that sectoral characteristics play an important role in the origination of hours constraints. Large variation of MHC values within a sector, in turn, would point to an important role of firm-specific factors. In particular, a standard deviation larger than one implies that the variation of MHC within a sector is larger than the variation across the whole economy.

Importantly, not all variation in our measure of MHC between firms reflects differences in firms' practices regarding hours constraints. Two firms with the same practices and the same socio-demographic employment structures may have different actual part-time shares (and thus different values of the MHC measure) due to differences in employees' unobserved preferences.

To proxy the role of unobserved firms' practices, we examine the within-firm correlation of MHC across two employee groups. Specifically, we test whether the measure of MHC among administrative staff explains a significant share of the variation in MHC observed among all other occupations. As explained formally in section 2.4, such a correlation of MHC among these two groups of workers is likely to reflect the role of organizational practices that apply to all employees within a firm. Administrative employees – such as human resources specialists, accountants, and secretaries – are present in most medium-sized and large firms. Furthermore, the tasks they perform are similar across firms and rarely require perfect overlap in working time with the core personnel. In the next subsection, we discuss potential concerns regarding the choice of this proxy.

Formally, we estimate the following model using the OLS estimator:

$$MHC_j^{excl\ adm} = \lambda \times MHC_j^{adm} + \beta \times F_j + \gamma \times D_s + \eta \times D_{c,t} + \epsilon_j, \tag{8}$$

where $MHC_j^{excl\ adm}$ is the MHC measure (baseline or adjusted for occupations) calculated for all employees excluding administrative workers, MHC_j^{adm} is computed with equations (7) and (6) on the subsample of administrative workers, F_j represents additional firm-level explanatory variables; D_s are the sector fixed effects denoting sections of the NACE Rev. 2 classification, and $D_{c,t}$ are the country-year fixed effects.

An essential variable included in the vector F_j is a standardized wage premium. Both theory and existing evidence suggest that rigid hours constraints may be associated with higher wages (Goldin 2014; Labanca and Pozzoli 2023; Shao et al. 2023). A positive correlation of MHC among administrative workers and core personnel could reflect firm-level sorting, with some firms offering higher wages and attracting more work-oriented individuals. By controlling for the firm-specific wage premium, we take into account this channel.

We derive the firm-level wage premium as an average of the employees' wage premia, $\widetilde{w_i}$, estimated from the model:

$$\begin{aligned} w_i \quad &= \delta^a \times age_i + \delta^e \times edu_i + \delta^o \times occ_i + \psi_i, \\ \widetilde{w_i} &= w_i - \widehat{w_i}, \end{aligned} \tag{9}$$

where w_i is a log of an individual's hourly wage, age is a vector of dummy variables representing age groups, edu is a vector of three dummy variables denoting education levels, and occ is a vector of dummy variables denoting sub-major occupation groups; and $\widehat{w_i}$ is the predicted log of an individual's wage, based on the coefficients estimated in equation (9), which is run separately for each country and year. Our cross-sectional data do not allow us to use the more accurate method of Abowd et al. (1999). In our setup, a positive wage premium may sometimes reflect that a firm employs above-average talented employees, rather than paying wages above the market average.

Other variables in vector F_j include dummies denoting firm size, public ownership, and a collective pay agreement that covers at least 50% of employees. Firm size is likely to influence production function but it may also be correlated with some aspects of organizational cultures and practices. Public ownership and collective bargaining are important institutional characteristics that could influence hours flexibility.

To quantify the importance of organizational practices in the origination of hours constraints, we decompose the variance of a dependent variable into the contributions of individual explanatory variables, following the regression-based decomposition method of Fields (2003). We compare the contribution of the MHC among administrative employees to the joint contribution of the sector fixed effects, D_s.

3.2 Validity of our proxy for hours constraints related to organizational practices

Our proxy for organizational practices is most plausible in settings where tasks performed by administrative employees are similar across firms and where part-time employment is not driven by negative demand shocks. In such settings, the correlation between hours constraints faced by administrative workers and core personnel is unlikely to be driven by technological or demand-related factors and can instead be interpreted as reflecting firm-wide organizational practices. In this subsection, we discuss potential threats to the validity of our proxy and present additional analyses designed to address them.

First, one may argue that the tasks performed by administrative workers differ across detailed occupational groups and sectors, which could generate between-firm variation in hours constraints among administrative employees. Formally, the assumption that the parameter $\rho_{a,j}^{TECH}$ is fixed across firms might not hold. If this parameter varied across firms and was correlated with technologically driven hours constraints faced by core personnel, $\rho_{p,j}^{TECH}$, this could undermine our identification strategy. To reduce this concern, we re-estimate equation (8) separately for each country–sector cell, which reduces potential heterogeneity in the tasks carried out by administrative workers within each estimation sample. In addition, we re-estimate equation (8) using narrower subsamples of administrative workers defined by seven minor occupational groups, which arguably limits heterogeneity in the tasks performed.

Second, the observed correlation between hours constraints among administrative workers and core personnel may be driven by common demand shocks at the firm- or sector-level. For example, firms facing negative demand shocks may be more likely to restrict part-time work across all occupational groups, generating a positive within-firm correlation in hours constraints that is unrelated to organizational practices. To address this concern, we re-estimate equation (8) after excluding country-sector cells with high levels of underemployment, where the prevalence of part-time employment is likely to be related to demand shocks. An individual employee is considered to be underemployed if they work part-time and report that they would like to work more hours.

Third, workers may sort into firms on the basis of unobservable characteristics, which could generate a correlation in MHC between administrative workers and core personnel. If sorting is driven by preferences over working hours, such a correlation would still be informative about firms' organizational practices, as, for example, more work-oriented individuals may choose firms that place little priority on work-life balance. We formally consider this mechanism in section 2.4. However, in principle, some sorting patterns might generate within-firm correlation in the MHC measure that is not driven by organizational practices. For example, if unobserved ethnic background were correlated with preferences over working hours, and workers tended to sort across firms along this dimension, then two firms with identical policies toward part-time employment could exhibit different levels of MHC simply due to differences in the ethnic composition of their workforce. While such a mechanism is theoretically possible, we believe it is unlikely to play a major role in European labor markets.

In general, methods of identifying hours constraints that do not rely on workers' self-reported preferences are never fully robust to sorting on unobservables. For example, the approach proposed by Labanca and Pozzoli (2022, 2023) assumes, based on labor force survey data, that low-skilled workers prefer to work fewer hours than high-skilled workers. They therefore interpret low dispersion in hours worked across skill groups as evidence of rigid hours constraints. However, if workers sort into firms on the basis of unobserved hour preferences, the dispersion of hours worked may lose its credibility as a measure of hours constraints.

Importantly, our strategy accounts for workforce composition to the extent that it is captured by employees' observable characteristics. For example, a firm with a high share of young women may display high part-time employment rates both among core personnel and among administrative workers. However, the MHC measures for these groups net out the average probabilities of part-time employment for each socio-demographic group in a given country-year.

To further assess the credibility of our proxy, we conduct an additional analysis that controls for a firm-level measure of the part-time pay gap. If part-time employment is associated with productivity losses, these may be reflected in part-time wage penalties (Aaronson and French 2004; Fernández-Kranz and Rodríguez-Planas 2011). Controlling for the part-time pay gap may therefore reduce the risk that the remaining correlation in MHC between core personnel and administrative workers reflects constraints related to production processes.

To calculate a firm-level measure of part-time pay gap, we first compute expected hourly wages. We use a specification identical to equation (9), but this time the regression is estimated separately for full-time and part-time employees. Using coefficients from these regressions, we calculate predicted hourly wages for each part-time employee: $\widehat{w}_i^{PT}$, and each full-time employee, $\widehat{w}_i^{FT}$. Next, for each firm j, we compute the average actual hourly wages of part-time and full-time employees, $w_j^{PT}$and w_j^{FT}, as well as the corresponding average predicted hourly wages, $\widehat{w}_j^{PT}$and $\widehat{w}_j^{FT}$. Our firm-level measure of the part-time pay gap is then defined as the ratio of the actual part-time pay gap to the pay gap expected on the basis of employees' observable characteristics:

$$PTgap_j = \frac{(w_j^{PT}/w_j^{FT})}{(\widehat{w}_j^{PT}/\widehat{w}_j^{FT})}. \tag{10}$$

A value of $PTgap_j = 1$ indicates that the part-time pay gap in firm j is in line with the average gap in the economy, conditional on observable characteristics. Values below one indicate a part-time wage penalty that is larger than expected, while values above one indicate a smaller than expected penalty (i.e., higher relative remuneration of part-time employees). We winsorize the values of $PTgap$ at the 1st and 99th percentiles of its distribution. Importantly, the inclusion of part-time pay gap reduces the regression sample as $PTgap$ is missing for firms that have no part-time employees or no full-time employees.

3.3 Data

We use linked employer–employee data from the EU Structure of Earnings Survey (EU-SES), which contains information on employees' age, gender, education level, hours worked, hourly wages, and occupation. To achieve comparability across countries, we aggregate education levels into three categories: basic education (less than primary, primary, and lower secondary education), secondary education (upper secondary and post-secondary non-tertiary education), and tertiary education. In our main analysis, we use sub-major occupation groups, that is, two-digit ISCO-08 codes.

The EU-SES also contains information on firms, including on their economic sector (according to the NACE Rev 2. classification), size category, ownership (public vs. private), and on whether they have a collective pay agreement covering at least 50% of their employees. We use three firm-size categories available in the EU-SES data, based on the number of employees. Small firms have fewer than 50 employees, medium-sized firms have between 50 and 249 employees, and large firms have at least 250 employees. The anonymized ID number does not allow firms to be tracked over time.

The EU-SES data are collected every four years, and we use the waves from 2010, 2014, and 2018. The earlier waves use older classifications of occupations and economic activity, which would hinder the comparability of the results. Our sample consists of 19 European countries, for which all the above variables are available.[5] We drop observations on public administration units, as this sector is not available in all countries. Sectors with small sample sizes are aggregated into broader categories, yielding 12 economic sectors. In particular, mining and utilities (e.g., electricity and water supply) are combined with manufacturing and classified as industry.

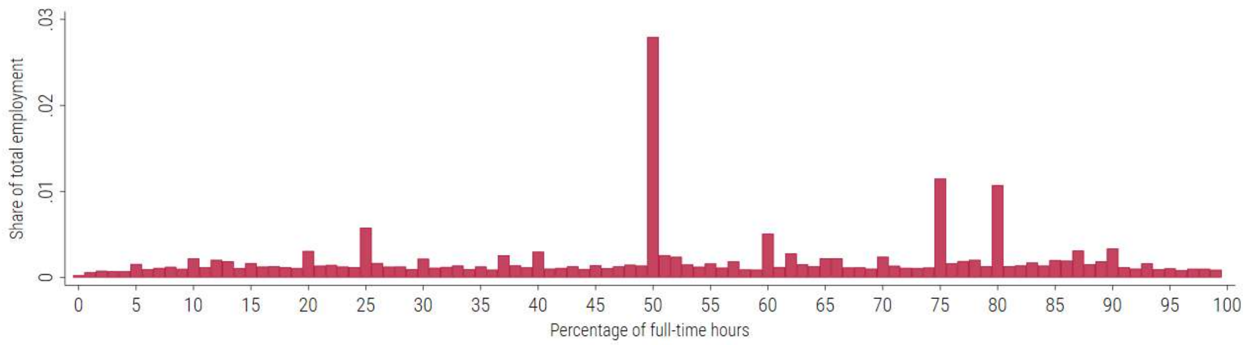
In the first step of the analysis, in which we estimate individuals' probabilities of working part-time, our sample contains over 30 million observations. The sample size ranges from 189,000 in Croatia to over 5 million in Czechia and Norway.

For each employee, firms report working time as the percentage of a full-time worker's normal hours. Using equal weight for all countries, 80.1% of employees in the sample are reported to have working time equal to a full-time worker's normal hours. In Figure 3, we report the distribution of working time among employees working less than full-time hours. In the subsequent analysis, we define part-time employees as those whose working time is less than 95% of the normal hours of a full-time employee. As shown in Figure 3, changing this threshold, for example to 90%, would not significantly affect number of employees classified as part-time.

In the second step of the analysis, we drop firms with fewer than 20 observed employees. We do it because when the number of observations is smaller, a larger part of the variation in estimated MHC might be driven by the unobserved preferences of individual employees. However, our findings are robust to including all firms. The final sample of firms with observations on both administrative and non-administrative employees amounts to 177,389 firms, with Portugal having the smallest sample (1,499) and Norway, Germany and Poland having the largest samples. Detailed information on the sample size for individual countries is reported in Appendix B.

[5] Belgium, Bulgaria, Czechia, Germany, Denmark, Estonia, Spain, France, Croatia, Hungary, Italy, Latvia, the Netherlands, Norway, Poland, Portugal, Romania, Sweden, and Slovakia. Due to low numbers of firm-level observations, we drop Greece, Lithuania, and the United Kingdom.

Figure 3. Distribution of working time as a percentage of a full-time worker's normal hours



Note: In this figure, we report the shares of employees with a given working-time, expressed as a percentage of the full-time working time. Employees working 100% of full-time hours, who make up 80.1% of the sample, are excluded from the figure. Each of 19 countries is given an equal weight. Source: Own calculations based on the Structure of Earnings Survey data.

To analyze MHC in administrative occupations, we focus on two sub-major occupation groups:

- Business and Administration Professionals (ISCO-08: 24), which include, for example, accountants, financial analysts, HR specialists, and advertising and marketing professionals;
- General and Keyboard Clerks (ISCO-08: 41), which include secretaries, general office clerks, and data entry clerks.

Almost 2.1 million individuals are employed in these occupations, which constitutes 7.0% of the overall sample. The share of administrative employees ranges from 2.2% in Hungary to 16.6% in Belgium. The share of administrative employees exceeds 10% in three out of 12 economic sectors: the financial sector (26.0%), professional activities (16.8%), and information and communication (13.2%). In these sectors, business and administration professionals may perform core rather than supportive functions. In other sectors, the share of administrative employees amounts to 5.3%.

Firms' weights are derived from the cumulative weights of their employees. We normalize firms' weights to ensure that each country carries an equal weight. Additionally, each wave of the EU-SES survey holds the same weight within a country.

In Table 1, we report standard deviations of four MHC measures: (i) the baseline measure of MHC estimated according to equations (5) and (6); (ii) the measure of MHC adjusted for occupations estimated with the use of equations (7) and (6); (iii) the measure of MHC in administrative occupations, which estimates equations (7) and (6) on a subsample of the administrative employees; and (iv) the analogous measure of MHC in non-administrative occupations. The average variation in MHC between firms is sizeable: the firm's share of part-time employees is typically 14.4 percentage points lower or higher than the share expected based on the observable characteristics of the employees. The lowest variation is observed in countries where part-time employment is rare. Taking into account the occupations of the employees decreases the variation in MHC between firms, but the degree of this reduction is heterogeneous across countries.

However, we confirm that employees' probabilities of working part-time differ significantly across occupations (Table C1 in Appendix). Controlling for socio-demographic characteristics, ICT professionals, and assemblers seem to face the most rigid hours constraints. The probability of working part-time is, on average, 21 percentage points lower for workers in these occupations than it is for sales workers, who are among the occupation groups with the least rigid hours constraints.

Table 1. Variation of the main MHC measures within countries

	(1)	(2)	(3)	(4)
	Standard deviation of MHC			
	Baseline	Adjusted for occupations	In administrative occupations	In other occupations
Average	14.4	12.3	20.9	12.6
Denmark	23.0	20.1	26.6	20.5
Germany	21.4	17.4	31.2	17.8
Belgium	19.2	14.8	27.9	15.5
Latvia	18.1	17.6	29.4	17.8
Norway	18.0	13.1	28.7	13.5
Italy	15.9	13.2	20.4	13.5
Spain	15.6	13.9	21.4	14.5
The Netherlands	15.4	12.8	25.9	13.1
Portugal	14.7	11.5	8.0	12.1
Sweden	14.5	9.4	17.0	9.6
Estonia	13.6	11.4	23.6	11.6
France	12.7	11.8	26.4	12.3
Hungary	12.2	11.5	21.6	11.7
Poland	12.1	11.4	18.4	11.6
Slovakia	11.4	10.8	14.7	10.9
Bulgaria	10.1	9.9	18.7	10.2
Czechia	9.1	8.5	12.7	8.6
Croatia	8.6	7.7	10.8	8.0
Romania	7.5	7.2	13.8	7.4

Note: In this table, we report the standard deviations of four measures of minimum hours constraints (MHC). In column 1, MHC are calculated according to equations (5) and (6). In columns 2 - 4, the MHC measure accounts for employees' occupations. In column 3, MHC are calculated only for administrative employees (ISCO-08 sub-major occupation groups 24 and 41), and in column 4 for non-administrative employees. The values reported for each country are the averages of the standard deviations from the available waves of the EU-SES data. Source: Own calculations based on the EU-SES data.

4 Results

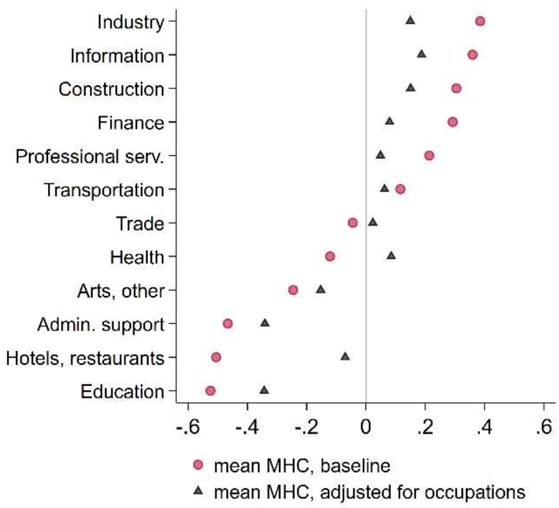
In this section, we report our empirical results. First, we document the differences in average MHC between economic sectors, as well as variation in MHC within sectors. Second, we assess the role of organizational practices and other firm-level variables in the origination of hours constraints. Third, we provide a range of robustness checks showing the validity of our proxy for organizational practices. All analyses in this section are based on the standardized measures of MHC, that enable a consistent cross-country investigation.

4.1 Sectoral variation in hours constraints

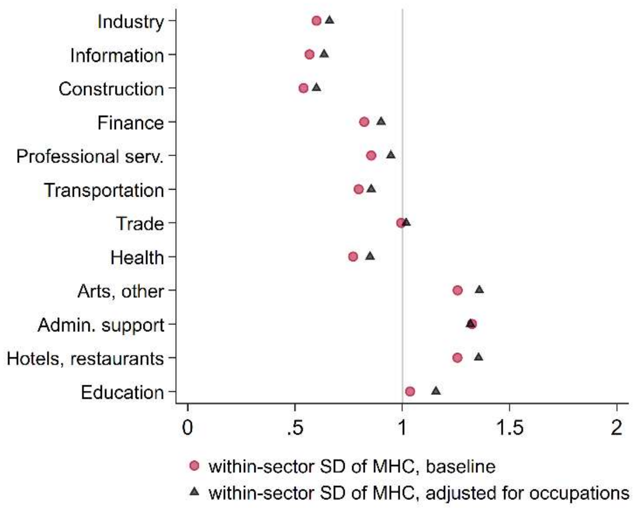
There are significant differences in MHC between economic sectors (Figure 4). MHC are, on average, the most rigid in the sectors of industry, and information and communication. The least rigid MHC are in the sectors of education, hotels and restaurants, and administrative support activities. However, the differences between sectors become much smaller when the measure of MHC accounts for the occupation structure. All these observations confirm that MHC are related to sector-specific production functions.

The variation of MHC within country-sector cells is also large, suggesting the important role of firm-specific factors in the origination of MHC. On the right panel of Figure 4, we report the averages of within-country-sector standard deviations of MHC. The sectors with particularly high variation of MHC include administrative support activities; hotels and restaurants; and arts, entertainment, and other services. In these sectors, the variation in MHC between firms is considerably higher than the variation across the whole economy. These are also the sectors characterized by less rigid hours constraints, as indicated by mean values of MHC. Conversely, the sectors with relatively low variation of MHC are those where hours constraints are the most rigid: construction, information and communication, and industry.

Figure 4. Variation of the standardized MHC measures between and within sectors



(a) Mean values of MHC



(b) Variation of MHC within sectors

Note: In this figure, we report the sectoral means and the average standard deviations of standardized (at the country-year level) measures of MHC. SD is an average of the standard deviations of standardized MHC within a given sector, calculated for each country separately. Each country is given equal weight.
Source: Own estimations based on the EU-SES data.

4.2 The role of organizational practices

Now, we regress the MHC calculated for non-administrative employees on the MHC among administrative employees and other firm-specific variables (see equation 8). We find a significant positive relationship between the MHC experienced by these two groups of workers. While we report the results for both the baseline MHC and the MHC adjusted for occupations, we focus more on the latter measure. The MHC among administrative employees being larger by one standard deviation is associated with the MHC among other employees being larger by 0.26 of a standard deviation (column 4 in Table 2). In other words, if a firm's share of part-time administrative employees is 20.9 percentage points lower than expected based on the observable characteristics of the workers, then the share of non-administrative employees who work part-time is, on average, 3.3 percentage points lower.[6] This finding is robust to using the measure of MHC not adjusted for occupations as the dependent variable (column 2). Moreover, the coefficient of interest is only slightly affected by the inclusion of other observable firm-level characteristics.

Similarly to Labanca and Pozzoli (2023), we find that hours constraints are positively linked to the firm-specific wage premium. However, the quantitative significance of this relationship is rather low: a wage premium one standard deviation higher is associated with a 0.06 increase in standardized MHC adjusted for occupations, which implies that the share of part-time workers among non-administrative employees is lower by around 0.8 percentage points (given that one standard deviation of MHC corresponds, on average, to 12.6 percentage points; see Table 1).

We also observe that small firms are less likely to impose MHC than medium-sized or large firms. On average, the small size is associated with a higher share of part-time workers than in medium firms, by 1.6 percentage points, and by 1.1 percentage points compared with large firms (the standardized MHC measure being lower by 0.13 and 0.09, respectively). Furthermore, public ownership is associated with the MHC measure being higher by 0.21 standard deviations, which translates into the share of part-time workers being 2.6 percentage points lower. In contrast, collective agreements are not a highly statistically significant explanatory variable.

[6] See Table 1 summarizing the standard deviations of the main MHC measures.

Table 2. The links between MHC for administrative employees and MHC for all other employees

	(1)	(2)	(3)	(4)
MHC for administrative workers	0.29***	0.25***	0.27***	0.26***
	(0.02)	(0.02)	(0.02)	(0.02)
Wage premium		0.04*		0.06**
		(0.02)		(0.02)
Size: small		-0.12**		-0.13***
		(0.04)		(0.03)
Size: large		0.00		-0.04
		(0.04)		(0.03)
Public ownership		0.19***		0.21***
		(0.05)		(0.04)
Collective agreement		-0.04		-0.04
		(0.05)		(0.03)
Sector effects?	NO	YES	NO	YES
Country-year effects?	NO	YES	NO	YES
Adjustment for occupation structure?	NO	NO	YES	YES
R-squared	0.086	0.168	0.075	0.102
Number of firms	177,389	177,389	177,389	177,389

Note: The dependent variable in all columns is the standardized measure of minimum hours constraints (MHC) in non-administrative occupations. In columns 1 and 2, it is calculated according to equations (5) and (6). In columns 3 and 4, it is adjusted for occupation structure, that is, equation (7) is used instead of equation (5). In all columns, MHC for administrative workers (ISCO-08 sub-major occupation groups 24 and 41) are adjusted for occupation structure. In columns 1 and 3, the explanatory variables include only the standardized measure of MHC in administrative occupations (ISCO-08 sub-major occupation groups 24 and 41) and a constant. In the regression for columns 2 and 4, we apply a specification given by equation (8). Standard errors clustered at the country-sector level are reported in parentheses. * p < .05 ** p < .01 *** p < .001. Source: Own estimations based on the EU-SES data.

The full specification explains 16.8% of the variance in the baseline measure of MHC among non-administrative employees. Over half of that is explained by the differences in MHC between the 12 economic sectors (Table 3). MHC among administrative employees has comparable explanatory power, accounting for 7.4% of the variance. In contrast, the firm-level wage premium explains only 0.6% of the variance in the MHC among non-administrative employees. For the specification using MHC adjusted for occupations as a dependent variable, the sector fixed effects lose most of their explanatory power. However, the importance of the MHC for administrative workers remains almost unaffected.

Table 3. Regression-based variance decomposition

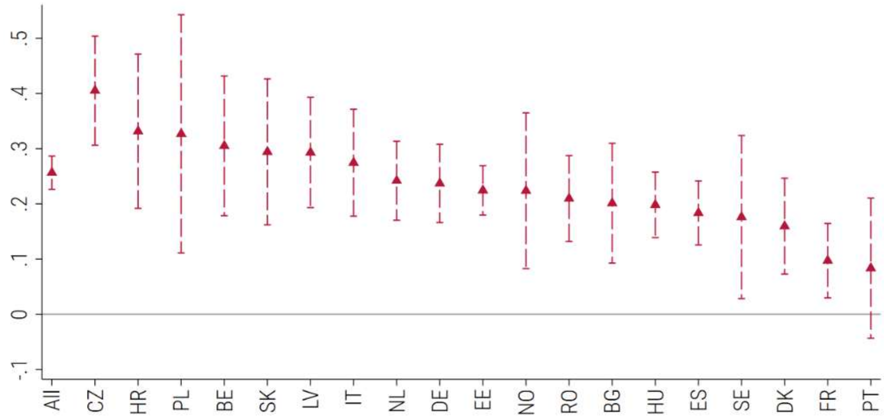
	(1) Baseline	(2) Adjusted for occupations
MHC for administrative workers	7.41%	7.02%
Sector fixed effects	9.17%	2.12%
Size fixed effects	0.21%	0.20%
Wage premium	0.56%	0.54%
Public ownership	-0.56%	0.36%
Collective agreement	-0.02%	-0.01%

Note: In this table, we report the decomposition of the variance in the MHC for non-administrative workers into the contributions of explanatory variables. The decompositions reported in columns 1 and 2 use, respectively, the regressions from column 2 and 4 of Table 2. The decomposition is computed with the ineqrbd Stata module (Fiorio and Jenkins 2021). Source: Own estimations based on the EU-SES data.

The role of firms' practices in explaining the within-country variation in MHC seems to be heterogeneous across countries. The largest coefficient is estimated for Czechia (point estimate: 0.41), and the smallest coefficient is estimated for Portugal (0.08, Figure 5). Among the six countries with the largest estimated coefficients, five are from Central and Eastern Europe, whereas five countries with the smallest coefficients are from Northern and Western Europe.

In Tables C3-C6 in the Appendix, we report the variance decompositions computed for individual countries. In 15 out of 19 countries, the MHC for administrative workers explains at least 4% of the variance in the baseline measure of MHC for non-administrative workers. Furthermore, in five countries, the measure of MHC for administrative workers is more important than the sector fixed effects. Interestingly, all of these five countries are in Central and Eastern Europe, and are characterized by a low incidence of part-time employment. In contrast, in Western European countries, the differences between economic sectors account for a much larger share of the variation in MHC. When the MHC measure adjusted for occupations is considered, MHC for administrative workers explains a larger share of variance than the sector fixed effects in 12 countries, including some Western European countries.

Figure 5. The links between MHC in administrative occupations and MHC in all other occupations, by countries

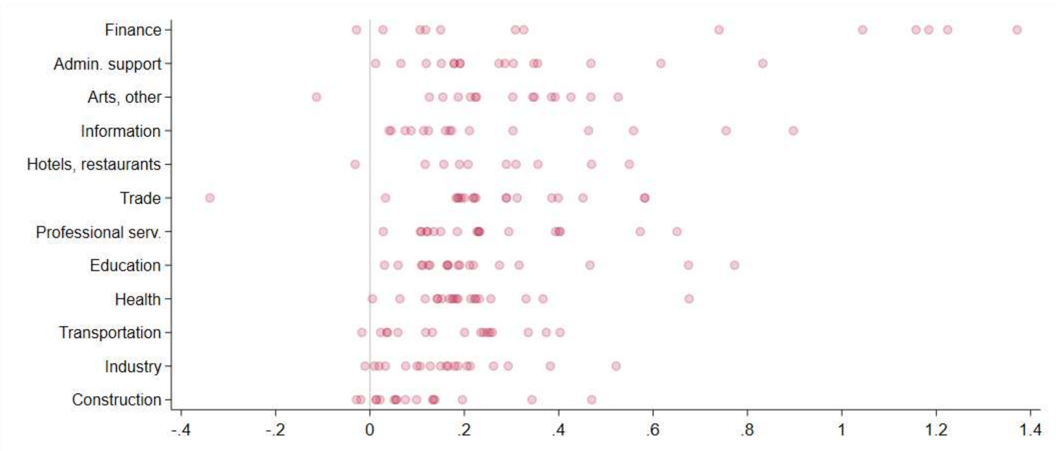


Note: In this figure, we report the results of the model given by equation (8), estimated for the whole sample, and for each country separately. The dependent variable is the standardized MHC for non-administrative employees (adjusted for occupations), and we plot the coefficients for the standardized MHC for administrative employees. Error bars represent a 95% confidence interval with standard errors clustered at the country-sector level. Source: Own estimations based on the EU-SES data.

4.3 Robustness analysis

As a first robustness check, we limit potential heterogeneity of tasks performed by administrative employees. In Figure 6, we report the coefficients estimated separately for each country-sector cell (excluding cells with less than 100 firms). In 185 out of 193 available cells, this relationship is positive. The weighted average coefficient of interest amounts to 0.23, so it is only slightly smaller than the coefficient of 0.26 yielded by the regression estimated on the whole sample.

Figure 6. The links between MHC in administrative occupations and MHC in all other occupations



Note: In this figure, we report the results of the model given by equation (8), estimated separately for each country-sector cell. We drop cells in which the number of firms is lower than 100. The dependent variable is the standardized MHC for non-administrative employees, adjusted for occupations. We plot the coefficients pertaining to the standardized MHC for administrative employees. Source: Own estimations based on the EU-SES data.

Next, we focus on narrow definitions of administrative workers, re-estimating equation (8) for seven minor occupation groups. This approach not only limits the heterogeneity of tasks within the group of administrative workers, but it also verifies whether our main finding depends on the definition of administrative workers. This analysis uses a limited sample of 10 countries, for which ISCO codes are available at the 3-digit level.

We find that the relationship between MHC for administrative employees and MHC for other employees is positive and significant across all minor occupation groups (Table 4). It is most pronounced for Keyboard Operators (ISCO-08 code: 413) and General Office Clerks (ISCO-08 code: 411). The smallest coefficient is estimated for Sales, Marketing and Public Relations Professionals (ISCO-08 code: 243). For this group, the MHC being larger by one standard deviation translates into the MHC for non-administrative employees being larger by 0.17 of a standard deviation. The coefficients are slightly lower than in the main specification, which is consistent with greater measurement error in the regressor. The MHC measures for narrowly defined administrative occupation groups are based on smaller numbers of observed employees than the measure for all administrative employees.

Table 4. The links between MHC for detailed groups of administrative employees and MHC in non-administrative occupations

ISCO-08 code:	241	242	243	411	412	413	431
MHC for administrative workers	0.19***	0.20***	0.17***	0.25***	0.20***	0.26***	0.19***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)
Wage premium	0.08***	0.03	0.07***	0.02	0.10***	0.12***	0.09***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Size: small	-0.16***	-0.16**	-0.09	-0.13**	-0.29***	-0.09	-0.19***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.08)	(0.06)
Size: large	-0.02	0.03	-0.02	0.01	-0.01	-0.06	-0.05
	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)
Public ownership	0.06	0.22***	0.15*	0.26***	0.29***	0.24*	0.08
	(0.08)	(0.06)	(0.06)	(0.07)	(0.07)	(0.09)	(0.07)
Collective agreement	0.01	-0.06	0.02	-0.08	-0.11	-0.14	-0.04
	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)	(0.05)
R-squared	0.101	0.102	0.098	0.111	0.112	0.164	0.096
Number of firms	31,961	34,097	23,524	45,955	21,730	5,013	22,096

Note: The dependent variable is the standardized measure of minimum hours constraints (MHC) in non-administrative occupations, adjusted for occupation structure. The main explanatory variable of interest is the standardized measure of MHC for one of the minor administrative occupation groups. The column header denotes the ISCO-08 code of the occupation group. 241: Finance Professionals; 242: Administration Professionals; 243: Sales, Marketing and Public Relations Professionals; 411: General Office Clerks; 412: Secretaries; 413: Keyboard Operators; 431: Numerical Clerks. Sector and country-year fixed effects are included. Standard errors clustered at the country-sector level are reported in parentheses. * $p < .05$ ** $p < .01$ *** $p < .001$.

Next, we exclude country-sector-year cells, where it might be less plausible that the correlation between the MHC among administrative employees and the MHC between the core personnel reflects only the role of organizational practices. In column 2 of Table 5, we report the results that exclude the cells with the underemployment rate above the sample median, that is, 2.58%. With the sample size reduced by 50%, the coefficient of interest is barely affected with respect to the full-sample results (column 1). When the sample is further reduced to the cells with underemployment lower than 1% of total employment (column 3), the coefficient of interest is even slightly higher than in the case of full-sample results.

Interestingly, the coefficient on public ownership decreases to zero when high-underemployment cells are being excluded. This sheds light on the likely mechanism behind the positive relationship between public ownership and the MHC measure in the full sample. Privately owned firms may be more concerned with their financial results and more likely to reduce working hours of employees during economic downturns than publicly owned firms that may prioritize stability and satisfaction of various stakeholders.

We also exclude sectors where administrative workers are most likely to perform core services of the companies, that is financial sector and professional services. The coefficient of interest amounts to 0.24 (column 4) and is only slightly lower than the results for the full sample.

Table 5. Robustness analysis: excluding certain country-sector-year cells

	(1) Full-sample results	(2) Excluding the top 50 pc of under-employment	(3) Excluding under-employment larger than 1%	(4) Excluding financial sector and prof. services
MHC for administrative workers	0.26***	0.25***	0.27***	0.24***
	(0.02)	(0.02)	(0.03)	(0.01)
Wage premium	0.06**	0.05***	0.05***	0.05*
	(0.02)	(0.01)	(0.01)	(0.02)
Size: small	-0.13***	-0.11***	-0.12***	-0.14***
	(0.03)	(0.02)	(0.03)	(0.04)
Size: large	-0.04	-0.03	0	-0.04
	(0.03)	(0.02)	(0.02)	(0.03)
Public ownership	0.21***	0.11**	0.01	0.27***
	(0.04)	(0.04)	(0.04)	(0.05)
Collective agreement	-0.04	0.04	0.04	-0.05
	(0.03)	(0.03)	(0.02)	(0.04)
R-squared	0.102	0.100	0.113	0.103
Number of firms	177,389	88,782	36,876	157,612

Note: The dependent variable in all columns is the standardized measure of minimum hours constraints (MHC) in non-administrative occupations, adjusted for occupation structure. In column 1, we repeat the results from column 4 of Table 2. In column 2, we exclude country-sector-year cells with the share of underemployed workers above the median. In column 3, we exclude country-sector cells with the share of underemployed workers exceeding 1%. In column 4, we exclude sectors of Finance and Professional Services. Standard errors clustered at the country-sector level are reported in parentheses. * p < .05 ** p < .01 *** p < .001.

Next, we examine whether the importance of our proxy for organizational practices is affected by the inclusion of a firm-specific measure of the part-time pay gap. Part-time wage penalties may reflect costs associated with part-time employment at the firm level. Consistent with this interpretation, higher remuneration of part-time employees is associated with less rigid hours constraints (column 2 of Table 6). However, including this variable does not affect the main coefficient of interest. The coefficient on MHC among administrative workers is lower than in previous analyses, as the sample excludes 22% of firms, primarily those that do not employ part-time workers.

Table 6. Robustness analysis: inclusion of a firm measure of the part-time pay gap

	(1) Main specification	(2) Part-time pay gap included
MHC for administrative workers	0.17*** (0.02)	0.17*** (0.02)
Part-time pay gap		-0.29** (0.13)
Wage premium	0.07** (0.02)	0.07** (0.02)
Size: small	-0.22*** (0.06)	-0.22*** (0.06)
Size: large	0.04 (0.04)	0.04 (0.04)
Public ownership	0.26*** (0.05)	0.26*** (0.05)
Collective agreement	-0.05 (0.04)	-0.05 (0.04)
R-squared	0.104	0.105
Number of firms	138,023	138,023

Note: The dependent variable in all columns is the standardized measure of minimum hours constraints (MHC) in non-administrative occupations, adjusted for occupation structure. In column 1, we report the results of the main specification estimated on the sample for which our measure of part-time pay gap is available. In column 2, we add our measure of part-time pay gap, derived with equation (10). Standard errors clustered at the country-sector level are reported in parentheses. * p < .05 ** p < .01 *** p < .001. Source: Own estimations based on EU-SES data.

4.4 Discussion

The obtained results indicate that there is a substantial variation in firms' policies toward part-time employment that is not explained by sector characteristics, occupational structure, or firm-specific wage premia. What are the reasons behind this variation? It cannot be ruled out that firm-specific production processes may influence both hours constraints for administrative employees and for core personnel.

However, in our view, this is not the main explanation. While administrative employees do interact with core personnel, it is rarely the case that the working hours of these two groups need to overlap perfectly.

Our results are consistent with the view that organizational culture and managerial practices play an important role in shaping hours constraints. In some firms, part-time work may be perceived as a signal of low productivity or low engagement (Landers et al. 1996; Sousa-Poza and Ziegler 2003). Managers may view part-time employees as difficult to oversee, and the resulting working practices may discourage flexible working arrangements. In contrast, other firms may prioritize work-life balance and pay attention to workers' preferences. Our results suggest that such managerial attitudes may be a quantitatively important determinant of hours flexibility, especially in Central and Eastern European countries.

The difference in the importance of organizational practices between Central and Eastern European countries and Western European countries may reflect the long-term effects of the socialist system on work norms. While in Western Europe part-time employment among women, and especially mothers, has long been common, socialist states encouraged full-time work and equal labor market participation of men and women (Buckley 1981; Campa and Serafinelli 2019). After the fall of socialism, part-time employment remained low in most of these countries (Albinowski 2026). As a result, firms offering flexible working hours deviate more strongly from prevailing country-level work norms. By contrast, in Western Europe it is common practice to allow some degree of hours flexibility, and firms differ mainly in its extent. While this appears to be the most plausible explanation, a more in-depth exploration of the differences between Eastern and Western Europe lies beyond the scope of this paper.

5 Conclusions

In this paper, we develop a novel approach for identifying minimum hours constraints (MHC), which measures the difference between the expected share of part-time employees (based on their socio-demographic characteristics) and the actual part-time employment share at a given firm. We apply this approach to a large dataset covering firms in 19 European countries. In countries where part-time employment is common, our method provides significantly different approximations of MHC compared to a simple indicator of the part-time employment share.

We investigate the reasons behind the variation in MHC across firms. It is undoubtedly the case that MHC are related to the characteristics of the production function. We confirm this by showing that an employee's probability of working part-time depends on their occupation and economic sector. However, we also uncover a substantial degree of variation in MHC within economic sectors that cannot be attributed to the occupation structure.

We examine the role of unobserved firm practices by estimating the relationship between MHC faced by two employee groups within a firm. We find that MHC faced by administrative workers is a statistically and economically significant predictor of MHC among all other workers. This relationship holds across all countries and sectors in our sample. Our proxy for the role of organizational practices is robust to excluding settings where demand shocks are likely to be important. Interestingly, organizational practices appear to play a particularly important role in Central and Eastern European countries, where the incidence of part-time employment is relatively low.

Our analytical framework does not allow us to distinguish what part of organizational practices is related to the characteristics of the production function, and what can be linked to firms' organizational culture and managerial practices. However, it seems likely that the latter group of factors accounts for much of the unobserved firm-specific practices identified by the relationship between MHC among administrative employees and core personnel. If so, changes in work norms might, to some extent, increase the availability of part-time employment without hampering production processes.

Governments have a number of policy options to influence work norms and increase flexibility of working hours. First, they can set an example as an employer in the public sector. Second, they can implement regulations that limit employers' ability to refuse part-time work requests (OECD 2010). This is a powerful tool that can, however, be fine-tuned by defining the group of eligible employees, exemptions, and the length of the notice period before a part-time work request becomes effective. Third, they can subsidize reduced working time for certain groups of workers, although this approach may be costly and generate negative effects on total working hours (Graf et al. 2011).

Understanding the origins of MHC is vital for both policymakers and firm management. The relaxation of hours constraints can increase labor market participation, especially among parents and older people, and can improve job satisfaction for some workers. However, labor market regulations and firms' policies should take into account the costs of accommodating part-time employment borne by employers. Further research, both quantitative and qualitative, is needed to identify the detailed reasons for the presence of hours constraints in workplaces.

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Appendix A Mathematical proofs

Properties of x^*

Let us denote by x the fraction of total workers N_j filled with part-time workers, who supply $h = \frac{1}{2}$. The remaining $1 - x$ part of the demand is filled with full-time workers, who supply $h = 1$. This allows us to simplify the profit function:

$$\Pi_j = ZN_j^\beta \left(1 - x + x\left(\frac{1}{2}\right)^{\rho_j}\right)^\beta - N_j(1-x)w_1 - N_j x \cdot w_{1/2}.$$

The first-order condition becomes:

$$\frac{\partial \Pi_j}{\partial x} = ZN_j^\beta \cdot \beta(1 - x + 2^{-\rho_j}x)^{\beta-1} \cdot (2^{-\rho_j} - 1) + N_j \cdot \mathrm{w}_1 - N_j \cdot w_{1/2} = 0,$$

equivalent to:

$$x_j^* = \frac{2^{\rho_j}}{2^{\rho_j} - 1}\left[1 - \frac{1}{N_j}\left(\frac{(1-2^{-\rho_j})\beta Z}{2^{\rho_j}(w_1 - w_{1/2})}\right)^{\frac{1}{1-\beta}}\right].$$

Also, as long as $\beta < 1$, the second-order condition is satisfied:

$$\frac{\partial^2 \Pi_j}{\partial x^2} = ZN_j^\beta \cdot \beta(\beta - 1)(1 - x + 2^{-\rho_j}x)^{\beta-2} \cdot (2^{-\rho_j} - 1)^2 < 0.$$

It is easy to observe that x_j^* increases with w_1 and decreases with $w_{1/2}$. As for ρ_j, observe that by substituting $\theta_j = \frac{2^{\rho_j}}{2^{\rho_j} - 1}$ (recall that $\rho_j > 1$, otherwise ill-defined) and having in mind that $\beta < 1$ we arrive at:

$$x_j^* = \theta_j\left[1 - \frac{1}{N_j}\left(\frac{\beta Z}{\theta_j(w_1 - w_{1/2})}\right)^{\frac{1}{1-\beta}}\right] = \theta_j - \theta_j^{\frac{-\beta}{1-\beta}} \cdot \frac{1}{N_j}\left(\frac{\beta Z}{w_1 - w_{1/2}}\right)^{\frac{1}{1-\beta}}.$$

Therefore any change in ρ_j influences x_j^* only through θ_j. As a result:

$$\frac{\partial x_j}{\partial \rho_j} = \underbrace{\frac{\partial \theta_j}{\partial \rho_j}}_{<0} \underbrace{\left[1 + \frac{\beta}{1-\beta}\frac{1}{N_j}\left(\frac{\beta Z}{\theta(w_1 - w_{1/2})}\right)^{\frac{1}{1-\beta}}\right]}_{>0} < 0.$$

Also, denote $x_j^* = x^*(w_1, w_{1/2}, \rho_j)$ and notice that the function x^* is identical for all j.

Proof of Proposition 1

We will show that MHC is a weakly better predictor, that is, has smaller mean squared error (MSE) than Y. Intuitively, this must be true, as the former is based on more information than the latter.

Notice that the two predictors are unbiased by construction, as $\mathbb{E}[X] = 0 = \mathbb{E}[Y] = \mathbb{E}[MHC]$. Moreover, the MSE of any unbiased predictor T is just equal to the variance of its prediction error.

$$\text{MSE}(T) = \mathbb{E}[\text{Var}(X \mid \sigma)],$$

where σ denotes the information used to form T.

By the law of total variance

$$\text{Var}(X) = \mathbb{E}[\text{Var}(X \mid y)] + \text{Var}(\mathbb{E}[X \mid y]) = \underbrace{\mathbb{E}[\text{Var}(X \mid y)]}_{\text{MSE}(Y)} + \text{Var}(Y),$$

$$\text{Var}(X) = \mathbb{E}[\text{Var}(X \mid \eta, y)] + \text{Var}(\mathbb{E}[X \mid \eta, y]) = \underbrace{\mathbb{E}[\text{Var}(X \mid \eta, y)]}_{MSE(MHC)} + \text{Var}(MHC).$$

Since $\sigma(y) \subseteq \sigma(\eta, y)$:

$$\text{MSE}(Y) = \mathbb{E}[\text{Var}(X \mid y)] \geq \mathbb{E}[\text{Var}(X \mid \eta, y)] = \text{MSE}(MHC).$$

The weak inequality holds regardless of further assumptions. To analyze the two cases of Proposition 1, notice:

a) When there is *no sorting*, firms face heterogeneous pools of workers. As η is neither independent nor perfectly dependent on y, it must be that $\sigma(y) \subsetneq \sigma(\eta, y)$; and since η is informative about X given y, we obtain:

$$\text{MSE}(Y) > \text{MSE}(MHC),$$

so MHC strictly outperforms Y in terms of mean squared error.

b) On the other hand, under *full sorting*, firms hire exactly their optimum, so $y = x$ and thus $X = Y = MHC$. The probability of being approached by a female worker faced by each firm, η, is a function of y, thus it provides no further information, with $\sigma(y) = \sigma(\eta, y)$.

Proof of Proposition 2

For simplicity, denote the correspondence between X_a and ρ_a by $f(\rho_a)$ and notice the same correspondence governs the correspondence between X_p and ρ_p. Notice also that $\rho_p = (\rho_a - c) + \rho^{TECH}$ and the two components are independent random variables. Denote also, in a standard way, $\bar{\rho}_\xi = \mathbb{E}[\rho_\xi]$ and $\bar{\rho}^{TECH} = \mathbb{E}[\rho^{TECH}]$.

By Taylor expansion we have:

$$
\begin{aligned}
X_a &\approx f(\bar{\rho}_a) + f'(\bar{\rho}_a)\,(\rho_a - \bar{\rho}_a),\\
X_p &\approx f(\bar{\rho}_p) + f'(\bar{\rho}_p)\,(\rho_p - \bar{\rho}_p) = f(\bar{\rho}_p) + f'(\bar{\rho}_p)\,(\rho_a - \bar{\rho}_a + \rho^{\,TECH} - \bar{\rho}^{TECH}).
\end{aligned}
$$

Taking expectations, we have:

$$
\begin{aligned}
\mathbb{E}[X_a] &\approx f(\bar{\rho}_a),\\
\mathbb{E}[X_p] &\approx f(\bar{\rho}_p).
\end{aligned}
$$

And the variances are:

$$
\begin{aligned}
\mathrm{Var}(X_a) &\approx [f'(\bar{\rho}_a)]^2\ \sigma_a^2,\\
\mathrm{Var}(X_p) &\approx [f'(\bar{\rho}_p)]^2(\sigma_a^2 + \sigma_{TECH}^2),
\end{aligned}
$$

The covariance is therefore:

$$
\begin{aligned}
\mathrm{Cov}(X_a, X_p) &= \mathbb{E}\left[(X_a - E(X_a)) \cdot (X_p - E(X_p))\right]\\
&\approx \mathbb{E}[(f'(\bar{\rho}_a)(\rho_a - \bar{\rho}_a)) \cdot f'(\bar{\rho}_p)(\rho_a - \bar{\rho}_a + \rho^{TECH} - \bar{\rho}^{TECH})]\\
&= f'(\bar{\rho}_a)f'(\bar{\rho}_p)\mathbb{E}[(\rho_a - \bar{\rho}_a)^2 + (\rho_a - \bar{\rho}_a)(\rho^{TECH} - \bar{\rho}^{TECH})] = f'(\bar{\rho}_a)f'(\bar{\rho}_p)\sigma_a^2.
\end{aligned}
$$

Therefore:

$$
\mathrm{corr}(X_a, X_p) \approx \frac{f'(\bar{\rho}_a)f'(\bar{\rho}_p)\sigma_a^2}{\sqrt{(f'(\bar{\rho}_a))^2\sigma_a^2} \cdot \sqrt{(f'(\bar{\rho}_p))^2\,(\sigma_a^2 + \sigma_{TECH}^2)}}.
$$

Notice that $f'(\bar{\rho}_a)\ and\ f'(\bar{\rho}_p)$ are of the same (negative) sign, we can thus simplify:

$$
\mathrm{corr}(X_a, X_p) \approx \frac{\sigma_a}{\sqrt{(\sigma_a^2 + \sigma_{TECH}^2)}},
$$

which concludes the proof.

Appendix B Information on sample sizes

In this appendix, we report the sample sizes for subsequent steps of the econometric analysis, broken down by countries. We derive firm-level measures of MHC using data on 30.1 million employees (Table B.1). For the firm-level analysis, we utilize data on 177,389 firms representing 17.6 million employees. The decrease in the sample size by 12.5 million workers results primarily from the exclusion of firms with fewer than 20 observations (6.0 million workers) or with no observed administrative employees (an additional 5.4 million workers excluded). Missing institutional variables and firm size are responsible for the remaining 1.1 million workers excluded.

Table B1. Sample size by country

Analysis	(1) equation (5)	(2) equation (8)	
	Employees	Employees	Firms
Belgium	463,147	198,433	5,358
Bulgaria	592,510	276,764	5,017
Czechia	5,771,174	4,912,293	12,471
Germany	3,458,994	1,549,826	28,456
Denmark	3,190,552	1,821,114	17,787
Estonia	373,066	207,926	3,005
Spain	615,574	93,290	3,945
France	648,678	88,784	2,939
Croatia	189,494	110,944	2,630
Hungary	1,644,526	848,133	7,315
Italy	661,831	207,987	5,472
Latvia	521,625	261,957	4,323
The Netherlands	461,744	163,861	2,524
Norway	5,254,340	2,765,814	32,107
Poland	2,094,230	1,601,185	24,046
Portugal	302,232	74,013	1,499
Romania	769,776	284,542	8,462
Sweden	782,090	207,084	1,378
Slovakia	2,347,167	1,927,353	8,655
Total	30,142,750	17,601,303	177,389

Note: In this table, we report the country-level sample sizes used in the econometric analyses.

Appendix C Additional results

Table C1. Occupational probabilities of working part-time

Chief Executives, Senior Officials and Legislators (11)	-0.097***
Administrative and Commercial Managers (12)	-0.173***
Production and Specialized Services Managers (13)	-0.188***
Hospitality, Retail and Other Services Managers (14)	-0.169***
Science and Engineering Professionals (21)	-0.187***
Health Professionals (22)	-0.069***
Teaching Professionals (23)	-0.076***
Business and Administration Professionals (24)	-0.166***
ICT Professionals (25)	-0.206***
Legal, Social and Cultural Professionals (26)	-0.106***
Science and Engineering Associate Professionals (31)	-0.199***
Health Associate Professionals (32)	-0.066***
Business and Administration Associate Professionals (33)	-0.157***
Legal, Social, Cultural and Related Associate Professionals (34)	-0.029***
Information and Communications Technicians (35)	-0.175***
General and Keyboard Clerks (41)	-0.099***
Customer Services Clerks (42)	-0.075***
Numerical and Material Recording Clerks (43)	-0.137***
Other Clerical Support Workers (44)	-0.049***
Personal Services Workers (51)	-0.010***
Sales Workers (52)	0
Personal Care Workers (53)	0.018***
Protective Services Workers (54)	-0.055***
Market-oriented Skilled Agricultural Workers (61)	-0.125***
Market-oriented Skilled Forestry, Fishery and Hunting Workers (62)	-0.090***
Building and Related Trades Workers (71)	-0.172***
Metal, Machinery and Related Trades Workers (72)	-0.201***
Handicraft and Printing Workers (73)	-0.154***
Electrical and Electronics Trades Workers (74)	-0.198***
Food Processing and Other Craft Workers (75)	-0.110***
Stationary Plant and Machine Operators (81)	-0.192***
Assemblers (82)	-0.209***
Drivers and Mobile Plant Operators (83)	-0.136***
Cleaners and Helpers (91)	0.106***
Agricultural, Forestry and Fishery Labourers (92)	-0.034***
Labourers in Mining, Construction, Manufacturing and Transport (93)	-0.088***
Food Preparation Assistants (94)	0.055***
Street and Related Sales and Services Workers (95)	0.024**
Refuse Workers and Other Elementary Workers (96)	-0.037***

Note: In this table, we report the average marginal effects from a logit model with a part-time work dummy as the dependent variable (equation 7). This regression is estimated jointly for all countries and time periods. The explanatory variables include occupation dummies (with Sales Workers as the reference value) and, not reported in the table, country fixed effects and interactions of gender, age group, and education level. *** p < .001.

Table C2. Main results with sector fixed effects reported

	(1)	(2)	(3)	(4)
MHC for administrative workers	0.29***	0.25***	0.27***	0.26***
	(0.02)	(0.02)	(0.02)	(0.02)
Wage premium		0.04*		0.06**
		(0.02)		(0.02)
Size: small		-0.12**		-0.13***
		(0.04)		(0.03)
Size: large		0.00		-0.04
		(0.04)		(0.03)
Public ownership		0.19***		0.21***
		(0.05)		(0.04)
Collective agreement		-0.04		-0.04
		(0.05)		(0.03)
Industry (NACE: B, C, D, E)		0.54***		0.19***
		(0.07)		(0.05)
Construction (NACE: F)		0.49***		0.23***
		(0.09)		(0.07)
Trade (NACE: G)		0.17*		0.13
		(0.08)		(0.07)
Transportation (NACE: H)		0.22**		0.07
		(0.07)		(0.06)
Hotels, restaurants (NACE: I)		-0.12		0.18
		(0.16)		(0.12)
Information (NACE: J)		0.55***		0.24***
		(0.08)		(0.06)
Finance (NACE: K)		0.49***		0.15
		(0.11)		(0.09)
Professional services (NACE: L, M)		0.42***		0.13
		(0.09)		(0.07)
Admin. support services (NACE: N)		-0.28*		-0.24*
		(0.12)		(0.10)
Education (NACE: P)		-0.25*		-0.18*
		(0.11)		(0.07)
Health (NACE: Q)		-0.06		0.09
		(0.10)		(0.06)
Country-year effects?	NO	YES	NO	YES
Adjustment for occupation structure?	NO	NO	YES	YES
R-squared	0.086	0.168	0.075	0.102
Number of firms	177,389	177,389	177,389	177,389

Note: In this table, we repeat the main results from Table 2, but here we report sector fixed effects. The sector of Arts and other services (NACE codes: R, S) is used as a reference category. Standard errors clustered at the country-sector level are reported in parentheses. * p < .05 ** p < .01 *** p < .001. Source: Own estimations based on the EU-SES data.

Table C3. Regression-based variance decomposition of the baseline MHC measure, by countries

	Belgium	Bulgaria	Czechia	Germany	Denmark	Estonia	Spain	France	Croatia	Hungary
MHC for administrative workers	9.9%	5.4%	17.8%	8.3%	4.5%	5.2%	3.1%	1.2%	10.8%	4.0%
Sector fixed effects	15.0%	4.5%	12.7%	23.9%	24.8%	26.0%	12.3%	13.3%	14.6%	4.3%
Size fixed effects	1.3%	2.3%	0.0%	-0.1%	4.0%	0.1%	0.0%	1.2%	1.8%	1.0%
Wage premium	0.0%	0.8%	1.3%	1.9%	4.5%	0.3%	1.4%	-0.3%	0.0%	0.0%
Public ownership	0.4%	-0.1%	0.6%	-0.1%	6.6%	-2.2%	1.8%	-1.7%	0.1%	0.0%
Collective agreement	0.0%	0.3%	0.2%	0.6%	0.4%	0.0%	1.5%	0.1%	0.1%	1.6%

Note: In this table, we report the decomposition of variance in the baseline measure of MHC for non-administrative workers into the contributions of explanatory variables. The decomposition is computed with the ineqrbd Stata module (Fiorio and Jenkins 2021).

Table C4. Regression-based variance decomposition of the baseline MHC measure, by countries, continued

	Italy	Latvia	Netherlands	Norway	Poland	Portugal	Romania	Sweden	Slovakia
MHC for administrative workers	8.7%	9.5%	8.4%	6.3%	11.5%	1.2%	4.7%	3.5%	8.0%
Sector fixed effects	17.5%	7.8%	31.5%	30.9%	7.2%	22.9%	4.9%	36.0%	4.0%
Size fixed effects	-0.1%	0.7%	0.0%	1.2%	1.0%	0.9%	0.1%	0.5%	0.1%
Wage premium	4.1%	1.6%	4.9%	1.1%	0.2%	0.1%	1.1%	2.8%	0.4%
Public ownership	5.2%	1.2%	0.8%	-1.8%	0.3%	1.6%	0.0%	-0.2%	0.5%
Collective agreement	0.0%	1.0%	0.5%	2.6%	0.1%	1.5%	0.0%	-0.1%	0.0%

Note: In this table, we report the decomposition of variance in the baseline measure of MHC for non-administrative workers into the contributions of explanatory variables. The decomposition is computed with the ineqrbd Stata module (Fiorio and Jenkins 2021).

Table C5. Regression-based variance decomposition of the MHC measure adjusted for occupations, by countries

	Belgium	Bulgaria	Czechia	Germany	Denmark	Estonia	Spain	France	Croatia	Hungary
MHC for administrative workers	9.0%	4.7%	18.4%	7.0%	4.6%	5.6%	3.6%	1.0%	11.7%	4.1%
Sector fixed effects	1.4%	2.9%	6.0%	9.5%	12.8%	6.0%	3.2%	3.0%	3.8%	1.6%
Size fixed effects	1.1%	1.8%	0.0%	0.1%	3.7%	0.2%	0.0%	1.1%	1.4%	0.5%
Wage premium	0.8%	0.9%	1.3%	2.1%	5.8%	0.8%	1.2%	0.3%	0.0%	0.0%
Public ownership	0.3%	0.3%	0.1%	-0.3%	10.6%	-0.6%	2.9%	0.3%	0.0%	0.3%
Collective agreement	0.0%	0.2%	0.2%	0.5%	0.0%	0.0%	1.8%	0.1%	0.0%	1.6%

Note: In this table, we report the decomposition of variance in the adjusted for occupations MHC measure for non-administrative workers into the contributions of explanatory variables. The decomposition is computed with the ineqrbd Stata module (Fiorio and Jenkins 2021).

Table C6. Regression-based variance decomposition of the MHC measure adjusted for occupations, by countries, continued

	Italy	Latvia	Netherlands	Norway	Poland	Portugal	Romania	Sweden	Slovakia
MHC for administrative workers	9.3%	9.8%	8.6%	6.0%	11.1%	1.1%	4.8%	4.0%	8.7%
Sector fixed effects	8.5%	5.0%	20.9%	4.8%	2.5%	10.2%	1.4%	4.1%	1.0%
Size fixed effects	-0.1%	0.6%	0.0%	0.6%	1.0%	0.8%	0.1%	0.0%	0.1%
Wage premium	4.5%	1.8%	3.5%	2.5%	0.1%	0.4%	0.9%	1.9%	0.3%
Public ownership	6.8%	1.0%	0.1%	-0.7%	0.0%	2.1%	0.7%	0.3%	0.0%
Collective agreement	0.0%	0.9%	0.1%	0.3%	0.0%	0.9%	0.0%	0.2%	0.1%

Note: In this table, we report the decomposition of variance in the adjusted for occupations MHC measure for non-administrative workers into the contributions of explanatory variables. The decomposition is computed with the ineqrbd Stata module (Fiorio and Jenkins 2021).

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