Labor Market Competition and Inequality*

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Abstract

Does competition in the labor market affect wage inequality? Standard textbook monopsony models predict that lower employer labor market power reduces wage dispersion. We test this hypothesis using Social Security data from Lithuania. We first fit a two-way fixed effects model to quantify the contribution of worker and firm heterogeneity to wage dispersion and document that the compression of dispersion in firm fixed effects has been the main source of the decline in inequality over the past 20 years. Using a theory-based relationship, we then leverage variation across sectors and over time to show that a 10 percentage point increase in labor market competition leads to a 0.7 percentage point reduction in the variance of firm-specific wage components. A counterfactual exercise using our preferred estimates suggests that the increase in labor market competition can explain at least 15 percent of the observed decline in overall wage inequality.

Keywords: Wage inequality, Firm heterogeneity, Monopsony, Labor supply elasticity

JEL codes: J31, J42, O15

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1 Introduction

Income inequality shapes the economic and political debate around the world. Although returns to capital, tangible or intangible, affect the distribution of income at the top, for millions of individuals around the globe, what matters is how their labor is rewarded in the market (Hoffmann et al., 2020). And even more so in recent decades, when earnings inequality has widened dramatically across the board (Hammar and Waldenström, 2020; Heathcote et al., 2023).

While it is well documented that labor earnings differ across workers with different skills, occupations, or genders, more recent literature has emphasized that firms —i.e., where individuals work, are critical determinants of growing income gaps (Card et al., 2013; Berlingieri et al., 2017; Song et al., 2019; Criscuolo et al., 2020). Not every firm pays the same wage to workers with similar observed and unobserved characteristics (Abowd et al., 1999): some employers pay more than others, and these pay differentials have widened in recent decades (Berlingieri et al., 2017; Haltiwanger et al., 2022).

In this paper, we study whether labor market competition among firms plays any role in the dispersion of earnings among employees. The degree of employers' market power is substantial and widespread across countries (Manning, 2021; Azar et al., 2022; Bassier et al., 2022; Lamadon et al., 2022; Díez et al., 2022; Armangué-Jubert et al., 2023). Standard textbook models of monopsony predict that imperfect labor market competition affects workers' pay (Manning, 2003): when labor supply curves are far from perfectly elastic, firms are enabled with market power and set wages below their competitive level. This would result in a degree of wage dispersion above the level predicted by a model of perfect competition. We empirically test this hypothesis with Lithuanian Social Security data spanning over two decades.

The Lithuanian economy provides a useful laboratory to study how labor market competition has affected inequality for several reasons. First, in contrast to many countries, the economy has experienced a sharp decline in wage inequality over the last two decades, corresponding to a 20 log points decrease in the variance of wages. Second, Lithuania transitioned from being a low-income to an upper-middle-income country in about 20 years, suggesting a negative gradient between wage inequality and development. Third, the number of firms increased dramatically over the same period, while the working-age population shrank. This led to a decline in the number of workers per firm, and possibly to higher competition among employers. Fourth, in 2004 the country joined the European Union, and the free movement of labor created new job opportunities for Lithuanian workers abroad. Finally, a number of labor market reforms were implemented, namely several minimum wage increases, changes in employment protection regulations, and the generosity of unemployment benefits, which plausibly affected the relative bargaining power of workers and firms.

We proceed with our analysis as follows. We begin by documenting the role of firm-specific components in wage inequality. Using Social Security data, we fit two-way fixed effects models to separate worker and firm fixed effects and quantify their contribution to inequality. We show that worker and firm heterogeneity explains about two-thirds of the cross-sectional wage dispersion in Lithuania. Most importantly, when looking at changes over time, we document that the sharp decline in wage dispersion observed between 2000 and 2020 was mainly driven by compression in firm fixed effects, explaining 60 to 90% of the total fall.

Therefore, using a theory-based relationship, we assess what role labor market competition had in the decline in wage inequality. As a first step, we measure the degree of employers' labor market power. To do so, we estimate the firm labor supply elasticity — a key variable in any monopsonistic wage setting.[1] We document that the elasticity of labor supply, akin to labor market competition, has increased over the past two decades. This evidence is robust to alternative measures of labor supply elasticity, i.e., those based on individual wages or firm-specific wage components. As a second step, we exploit cross-sectoral and time variation to estimate a theory-based reduced-form relationship between labor market competition and the dispersion of firm fixed effects. Based on our preferred estimates, which are corrected for both attenuation bias and omitted variable bias, we find that a 10 percentage point increase in labor market competition leads to a 0.7 percentage point reduction in the variance of firm fixed effects. Equipped with these estimates, we quantify that, through the lens of our theory, labor market competition can explain about 15 percent of the observed decline in overall wage inequality.

Our paper contributes to several strands of the literature. A large body of research highlights the role of firms in shaping the earnings distribution in several developed countries (see Card et al., 2018, for a recent review of the literature). Some of these studies exploit overlapping sub-periods to examine changes in wage components, i.e.,

[1]This would be the case in models of imperfect labor market competition if labor market power is a consequence of job differentiation or search frictions (Langella and Manning, 2021).

firms and workers heterogeneity, over time and their contribution to inequality dynamics (e.g., Card et al., 2013; Song et al., 2019; Babet et al., 2022; Silva et al., 2022). With the increasing availability of linked employer-employee data around the world, new evidence indicates that firms tend to explain a larger share of wage dispersion in developing countries (Alvarez et al., 2018; Pérez Pérez and Nuno-Ledesma, 2022; Bassier, 2023). We contribute to this literature by looking at changes in firm-driven wage dispersion over different stages of a country's development, hence documenting a declining contribution of firms to inequality and linking it to changes in labor market competition.

Growing evidence on the contribution of firm-specific components to wage dispersion sparked a large interest in the role of imperfect competition in the labor market (Manning, 2021; Ashenfelter et al., 2022; Card, 2022). Numerous papers have focused on estimating separations-based labor supply elasticities to quantify the degree of employer labor market power (see the meta-analysis by Sokolova and Sorensen, 2021). Within this line of work, Hirsch et al. (2018) finds a procyclical labor supply elasticity in Germany, suggesting that employers' market power increases during recessions. Webber (2022) shows that labor supply elasticities in the U.S. have declined since the 1990s and that this decline accelerated during the Great Recession. Our paper contributes to this literature by documenting how the firm labor supply elasticity has changed over time in a country experiencing high economic growth and how it has affected wage inequality.

Several studies have focused on understanding the link between imperfect labor market competition and workers' earnings. For example, Webber (2015) documents a positive relationship between the firm labor supply elasticity and workers' earnings. Similarly, Autor et al. (2023) shows that labor market competition induced by the Covid-19 pandemic has boosted wage growth among low-wage workers in the US, directly contributing to a reduction in inequality. Bassier (2023) provides evidence that in South African local markets where the labor supply elasticity tends to be lower, the variance of firm-specific wage components explains a larger share of wage dispersion. Using a structural model that allows for firm market power in both product and labor markets, Deb et al. (2022) shows that less competitive market structures are characterized by higher between-firm wage inequality. We complement this literature by showing that labor market competition drives the dynamics of inequality through changes in the dispersion of firm-specific wage components, something that was — using the words of Manning (2021) — still ”unproven”.

Unlike other developed countries, Central and Eastern European economies have experienced high wage growth and a substantial decrease in wage inequality in the last decades, mostly driven by a fall in between-firm wage inequality (Magda et al., 2021). Our paper contributes to understanding the dynamics of inequality in one of these countries. Using comprehensive, high-frequency Social Security data, we are the first to quantify the contribution of worker and firm heterogeneity to the dynamics of wage dispersion in a country transitioning along the development path. Most importantly, we directly characterize that increased labor market competition was one of the drivers of the decline in overall wage inequality, offering an additional explanation beyond minimum wage policy (Magda et al., 2021; Engbom and Moser, 2022).

The rest of the paper is organized as follows. Section 2 provides an overview of the developments in the Lithuanian economy in the last two decades. Section 3 outlines the conceptual framework to decompose the role of workers and firms in the variance of wages, while Section 4 describes the data used to implement the model. Section 5 discusses the contribution of worker and firm heterogeneity to changes in inequality, and Section 6 examines the role of labor market competition in the observed change in inequality. Section 7 concludes.

2 Institutional background

In the last 20 years, Lithuania went through a series of major institutional changes and labor market reforms. As a background to the empirical analysis, this section highlights the most relevant ones and it provides an overview of the dynamics of wage dispersion between 2000 and 2020.[2]

2.1 Economic performance and labor market policies

Macroeconomic developments. First and foremost, in 2004 Lithuania had access to the European Union, whose membership brought significant political, economic, and social developments to the country. Beyond its impact on democracy and the adop-

[2]In Appendix A, we provide graphical evidence on the dynamics of the key macroeconomic variables we discuss in this section.

tion of governance to converge to EU standards, the accession to the European Union granted generous funding to develop infrastructure and implement economic and social policies (Randveer and Staehr, 2021). In addition, joining the EU provided access to new trading partners and helped attract significant foreign investment, sustaining extraordinary economic growth: between 2000 and 2020, the GDP more than doubled (in real terms) and total exports (imports) reached about 80% (70%) of GDP by 2020.

The EU accession introduced also free movements of capital and workers. While access to capital was critical to support economic growth, the right to live and work in other EU members led to a wave of mass emigration (Klüsener et al., 2015): by 2009 more than 5% of the Lithuanian working-age population was residing in a European Country (Fic et al., 2011). The size of emigration flows had significant consequences for the labor market (Zaiceva, 2014), and led to substantial labor shortages affecting wages (Elsner, 2013) and firm productivity (Giesing and Laurentsyeva, 2018). Last but not least, high emigration combined with substantial firm entry, translated into a rise in the number of firms per worker, with potential implications for labor market competition (Bagga, 2023).

Labor market reforms. Changes in the minimum wage were unarguably the flagship policies implemented in Lithuania to tackle inequality: between 2000 and 2020, the minimum wage increased from 160 to 607 euros, approximately equal to a 380% increase (235% in real terms). Available evidence suggests that this policy was pivotal for raising wages at the bottom of the wage distribution, and it succeeded in spreading the benefits of economic growth to lower-paid workers without having a significant negative impact on their employment prospects, thus plausibly contributing to reducing inequality (Garcia-Louzao and Tarasonis, 2023).

In July 2017, two further reforms were enacted with the aim of providing more flexibility for firms and more protection for workers. First, the New Labor Code was introduced, which reduced statutory severance pay and simplified hiring and firing procedures.[3] The new labor code also had an indirect effect on the level of the minimum wage by prohibiting employers from paying the minimum wage to skilled workers. Second, the new Unemployment Insurance Law was enacted to replace the previous

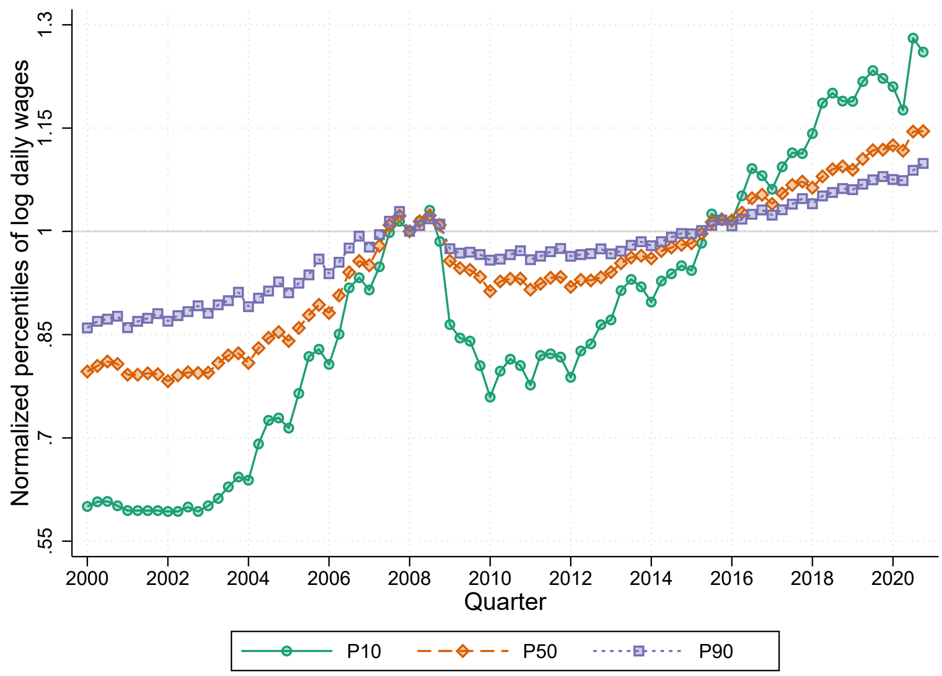
[3] Despite the ambitions of the reform, the changes in separation patterns induced by the reform were not substantial, as before the change in the law, employers usually reached an agreement with the employees, thus avoiding the large statutory severance payments.

(and first) law introduced in 2005. The new law made the system more generous by relaxing eligibility criteria and increasing the duration and level of benefits.

2.2 Stylized facts about wage dispersion in Lithuania

Figure 1 presents the evolution of the 10th, 50th, and 90th percentiles of the quarterly daily log wage between 2000 and 2020, each one expressed relative to their value in the first quarter of 2008. From 2005 to 2020, wages grew at all percentiles supported by the extraordinary economic growth experienced by the country (see Section 2.1). The 10th percentile had the largest relative increase throughout the period, and its evolution somehow mirrored that of the minimum wage.

Figure 1: Dynamics of selected wage percentiles



Source: Social Security records and own calculations.
Notes: The graph shows the evolution of selected percentiles of the private sector wage distribution for workers aged 20 to 60 between 2000 and 2020. Daily wages refer to quarterly income divided by days worked in a given quarter and are expressed in real terms using the 2015 consumer price index. P10, P50, and P90 refer to the 10, 50, and 90th percentile of the log daily wage distribution in a given quarter, respectively. Percentiles are expressed relative to their value in 2008Q1.

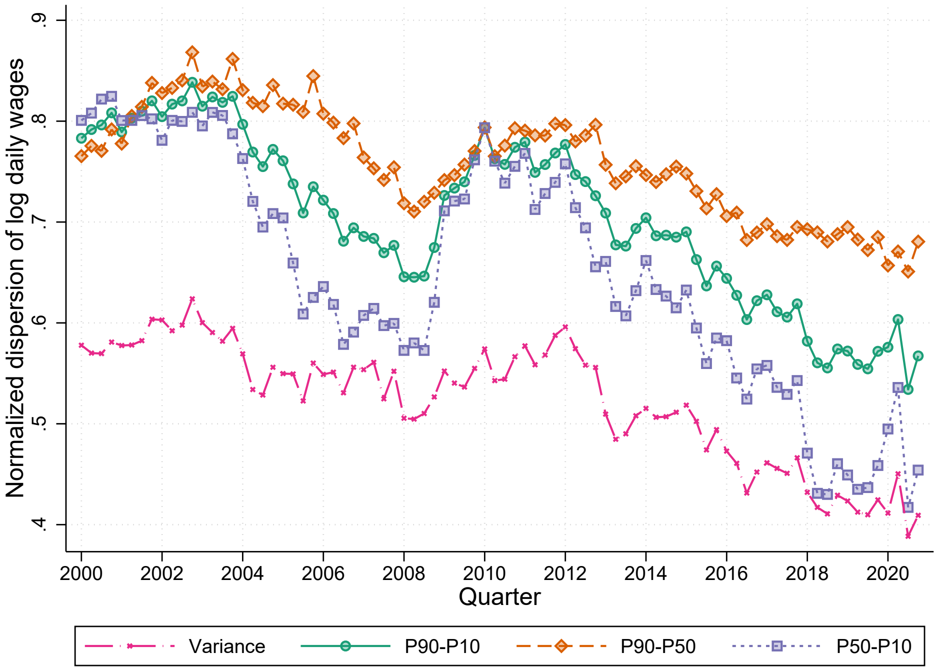
Figure 2 reports different measures of wage dispersion, meaning the P90-P10, the P90-P50, and the P50-P10 ratios in log daily wages, together with the overall variance. To simplify the comparison among ratios, we normalized the differences across percentiles by the corresponding percentile gaps from a standard normal distribution.[4]

[4]For instance, the normalized 50-10 percentile differences is the difference between percentiles 50th

The evidence points to a substantial decline in wage inequality, regardless of the measure we look at: both the P90-P10 ratio and the variance of the log wages declined by about 20 log points. Moreover, the drop in inequality was particularly pronounced at the bottom of the distribution of log wages: while the P50-P10 ratio dropped by nearly 40 log points, the P90-P50 ratio declined by only 10 log points.

To place these numbers into context, consider the case of Brazil. Wage inequality —measured by the overall variance of log wages, declined by 28 log points between 1996 and 2012, and the compression of the lower tail (P50-P10 ratio) was even higher, about 38 log points (Alvarez et al., 2018). Alternatively, from 1985 to 2009 Germany experienced an increase in the P80–P20 and the P50–P20 ratios of about 16 and 18 log points respectively (Card et al., 2013). Similar numbers can be found for the US, where the variance of log earnings increased by 19 log points between 1981 and 2013 (Song et al., 2019).

Figure 2: Evolution of wage dispersion



Source: Social Security records and own calculations.
Notes: The figure shows the evolution of wage inequality among private sector workers aged 20 to 60 between 2000 and 2020. Daily wages refer to quarterly income divided by days worked in a given quarter and are expressed in real terms using the 2015 consumer price index. P($\times$)-P($\cdot$) is the difference between the specific percentiles, i.e., 90, 50, and 10, of the log daily wage distribution in a given quarter. Percentiles differences are normalized using their corresponding differences in percentiles of standard normal distribution, i.e., $\Phi^{-1}(\times) - \Phi^{-1}(\cdot)$.

and 10th divided by 1.2815 ($\Phi^{-1}(0.5) - \Phi^{-1}(0.1)$, with $\Phi(\cdot)$ being the standard normal distribution).

3 Econometric framework

What drove the decline in wage inequality documented in Section 2? Did firms play any role? In this section, we lay out the empirical framework used to estimate and quantify the contribution of worker and firm heterogeneity to the observed wage dispersion in Lithuania.

AKM model. To estimate worker- and firm-specific wage components, we adopt the AKM specification (Abowd et al., 1999), which is widely used in the literature that investigates the role of firms in wage setting (e.g., Card et al., 2013; Song et al., 2019). The model specifies the following additively separable function for (log) wages

$$y_{it} = \eta_i + \psi_{j(i,t)} + X_{it}\Omega + \epsilon_{it} \tag{1}$$

where y_{it} is the (log) wage of worker i in period t. η_i represents worker i fixed effect and it loads any time-invariant wage-specific components of the worker, such as returns to formal schooling or innate ability. $\psi_{j(i,t)}$ is the fixed effect of firm j where worker i is employed in period t, meant to capture persistent wage disparities between firms, such as pay policies or rent sharing. X_{it} includes time-varying covariates, like age and time effects, accounting for common life cycle and macroeconomic fluctuations that might affect wages beyond worker or firm types.[5] ϵ_{it} stands for the error term, reflecting purely transitory wage fluctuations.

In this framework, worker and firm fixed effects can only be separately identified within a set of firms and workers connected through mobility. This "connected set" emerges from workers who have switched jobs at least once. A firm belongs to the connected set if at least one of its workers was employed or will be employed in a different firm within the period analyzed. The identification of the fixed effects hinges on two key interrelated assumptions. The first assumption is *exogenous mobility*: worker mobility is uncorrelated with the time-varying residual components of wages. This means that wages before or after a job switch should be, on average, the same as if there had been no switch. The second assumption is *additive separability*: there must

[5] A classic identification problem arises when estimating AKM models that include age, year, and cohort effects. Since cohort effects load within the person effects, it is not possible to uniquely identify the three objects separately. To address this problem, we adopt a standard strategy in the literature: we impose the age profile to be flat at age 40, use a polynomial of third-degree expressed in deviations from that value, and omit the linear term from the estimating equation (Card et al., 2018).

be no interaction effect between firm type and worker fixed effects. This assumption imposes a proportional firm's markup/down for all workers.

Variance decomposition. To quantify the role of firms and workers in the dispersion of wages, we use the parameters from equation (1) and decompose the variance of (log) wages as follows

$$\begin{aligned} var(y_{it}) &= var(\eta_i) + var(\psi_{j(i,t)}) + var(X_{it}\Omega) + var(\epsilon_{it}) \\ &+ 2 \cdot \left[cov(\eta_i, \psi_{j(i,t)}) + cov(\eta_i, X_{it}\Omega) + cov(\psi_{j(i,t)}, X_{it}\Omega) \right] \end{aligned} \tag{2}$$

where a positive (negative) value of $cov(\eta_i, \psi_{j(i,t)})$ captures positive (negative) sorting effects between worker η_i and firm $\psi_{j(i,t)}$-types.[6] In other words, the covariance term will be positive if high-wage firms hire the most productive workers, and their earnings are above those of the less productive individuals working in the same organization (Abowd et al., 1999).

Limited mobility bias. A well-known problem that arises in AKM models is that a large number of firm-specific intercepts are uniquely identified from workers who change firms, leading to biased estimates for the fixed effect variances and their covariance, or to the so-called *limited mobility bias* (Andrews et al., 2008, 2012; Kline et al., 2020; Bonhomme et al., 2023). To address this issue, we complement the AKM approach with two alternative empirical strategies, both developed by the literature to deal with limited mobility bias.

As a first approach, we follow Bonhomme et al. (2019) (BLM, hereafter) and implement a firm clustering approach. The BLM strategy consists of discretizing firm heterogeneity so that the support of firm wage effects is restricted to a finite number of values or clusters of firms. This approach allows to reduce the dimensionality of firm fixed effects and thus to correct for mobility bias. We implement the strategy as follows. As a first step, we create the firm clusters using a *k-means* clustering algorithm (Bonhomme et al., 2022) based on the quantiles of the wage distribution within firms.[7]

[6] Under the assumption of exogeneity, the error term is by construction uncorrelated with any of the fixed effects as well as the time-varying covariates, thus the covariance terms are zero.

[7] This algorithm clusters firms to maximize the within-class similarity of the wage distribution, so it clusters firms whose latent types based on the wage distribution are most similar. Since the number of firm types must be chosen prior to implementing the clustering algorithm, we set the number of clusters to be 1,500 (around 1% of the original number of firms in our sample).

In the second step, we estimate a two-way fixed effects model as in equation (1) where the firm fixed effects are now reduced to the number of firm clusters.

As a second approach, we apply the leave-one-out estimator proposed by Kline et al. (2020) (KSS). The KSS estimator consists of removing one unit (e.g., observations, worker-firm matches, workers' histories) at a time and re-estimating the variance components using the remaining observations. Specifically, an AKM model is estimated for each excluded unit and the estimates are used to compute an unbiased estimator of the variance of the residuals, which characterizes the limited mobility bias itself. We implement the KSS estimator by excluding a given worker-firm match at each iteration and rely on the resulting estimate of the variance of the error terms to compute bias-corrected estimates of the variance of worker and firm fixed effects.[8]

4 Data

Social Security records. The main data source for our analysis is a 25 percent "de facto random" sample of workers in the Social Security system at any time between 2000 and 2020.[9] The dataset has a longitudinal design with unique identifiers for each individual as well as the firm where they are employed at a given time.[10] These individuals are tracked on a monthly basis as of 2010, whereas before that year the frequency was quarterly, as employers were required to report information on their employees only on a quarterly basis. Thus, one can follow workers over time and across companies, which is key to estimating worker and firm permanent wage components. For each member of the sample, we have information on income and benefits received per period, gender, age, employment status, start and end of employment, location of the firm's headquarters, and industry, as well as firm size and total payroll measured at the end of the year. Unfortunately, the database does not provide information on education, and information on occupation has only been available since 2012.

The labor income variable refers to *all* work-related income subject to Social Security contributions, including base salary, but also non-regular payments such as

[8]The KSS estimator is implemented following the random projection strategy proposed by Kline et al. (2020) using the JLA algorithm.

[9]We observe all Social Security individuals born in an odd-numbered month of each even-numbered year. We follow the labeling of DellaVigna et al. (2017), who coined this type of sampling scheme as "de facto random".

[10]Due to legal reasons, individuals do not appear in our sample until they are 18, even if they were present in the Social Security system at younger ages.

bonuses, allowances, overtime pay, commissions or severance payments.[11] This is a broad measure of earnings, as it directly captures any payment made by the employer in a given quarter. There is an important limitation that is worth discussing. The data set does not report information on hours worked. This implies that we cannot calculate hourly wages or restrict the analysis to full-time workers.[12] Therefore, to mitigate the influence of labor supply, our wage metric is the daily wage computed as quarterly income divided by days worked in the quarter, expressed in real terms using the 2015 consumer price index.

Estimation sample. To obtain the analysis sample, we process the original data as follows. First, we construct a quarterly panel of employment records for workers aged 20 to 60 any time between 2000 and 2020 employed in the private sector. This gives us a homogeneous time frequency throughout all the years.[13] Second, we consider only quarterly employment observations such that an individual works for at least 15 days and earns no less than half of the monthly minimum wage in that quarter. Third, we exclude the last observation of each job spell lasting more than 3 months (the probationary period) to avoid the influence of severance packages or other payments made at the time of contract termination (such as unused vacation time, which are not directly related to firms' wage policies) on our estimates. Finally, if in a given quarter a person has more than one job, we select the one reporting the highest earnings. These restrictions yield a final sample of 532,495 workers observed in 143,461 firms over 16,735,572 observations between the first quarter of 2000 and the last quarter of 2020. As discussed in Section 3, identification of worker and firm fixed effects are based on job switchers and, hence, is only achieved through the so-called *largest connected set*, i.e., the largest set of firms over which workers move. The estimation sample is thus restricted to this set. The largest connected set consists of 526,536 workers observed in 137,783 firms over 16,638,459 observations between 2000 and 2020.

Table 1 reports basic summary statistics for the cleaned data as well as the largest connected set. The figures show that the largest connected set captures virtually all

[11]Given the change in Social Security contributions in 2019, we recalculate income before the 2019 reform by multiplying it by the official re-scaling factor of 1.289.

[12]Nevertheless, part-time employment is not particularly widespread in Lithuania, representing from 5 to 7% of overall wage-employment between 2000 and 2020.

[13]Our focus on the private sector is both due to the peculiarities of the wage-setting process in the public sector as well as the ability to make comparisons with the existing literature.

Table 1: Summary statistics

	Cleaned data	Connected set
Wages		
Mean	2.905	2.909
Std.Dev.	0.779	0.777
Firms	143,461	137,783
Direct movers	297,517	297,295
Movers	392,701	392,255
Workers	532,495	526,536
Direct moves	820,803	820,421
Job changes	1,405,027	1,404,377
Worker-quarters	16,735,572	16,638,459

Notes: Daily wages refer to the (log) quarterly income divided by days worked in a given quarter and are expressed in real terms using the 2015 consumer price index. Firms stand for the unique number of employers. (Direct) movers refer to the *unique* number of workers who switched jobs at least once (between two consecutive quarters). Direct moves are job-to-job transitions, i.e., the number of worker-quarter observations when an employer change is recorded between two consecutive quarters. Job changes stand for all job changes recorded among all worker-quarter observations, regardless of whether there was a period of non-employment between the move.

workers in the cleaned data (98%) and the majority of firms (95%) due to the high mobility rate. In particular, 74% of the workers changed at least one employer between 2000 and 2020, and 56% of the workers did at least one job-to-job transition (employer switch within a quarter) over the same time interval. Moreover, over the whole sample period, the average number of movers per firm is 9.8 (5.7 if only job-to-job transitions are counted). To put patterns of mobility in perspective, the quarterly mobility rate, i.e., the number of job changes divided by the total number of observations, is 7.9% (4.7% if using only job-to-job transitions), while the annual mobility rate using German data form yields a rate of 3% (Card et al., 2013) or a 9% rate for the US in Washington administrative data (Lachowska et al., 2020). Obviously, this substantial degree of mobility in our sample is an advantage of the long time span, as well as of the quarterly frequency of the data, which ameliorates identification problems that might arise when population data is not available (Andrews et al., 2012; Babet et al., 2022; Bonhomme et al., 2023).

5 Firms and workers in the variance of wages

We are now ready to discuss the contribution of firm and worker heterogeneity to the variance of wages in Lithuania. We first look at their contribution in the cross-section and examine the validity of our approach. We then quantify the role of each component in the observed decline in inequality in the last two decades.

Pooled estimates. Table 2 reports the variance decomposition obtained with the estimates from the AKM model in equation (1), as well as the estimates from the two alternative approaches to correct for the limited mobility bias, using data from the entire sample period (2000-2020). Worker and firm permanent heterogeneity combined explain two-thirds of the dispersion in (log) daily wages. The estimates from the standard AKM model point to firm-specific pay policies as the most relevant component, with the dispersion of firm fixed effects accounting for about 32% of the dispersion in (log) daily wages. Worker permanent heterogeneity explains 28% of the variance of wages while sorting contributes to roughly 7%. As expected, the estimates from the KSS correction yield a lower contribution of worker and firm fixed effects to the dispersion of wages (26% and 29%, respectively) and a higher contribution of sorting (9%). The differences between AKM and KSS are not substantially large in the cross-section, likely because of the high degree of mobility we observe in our data. The change is more noticeable when using the BLM clustering approach: while the contribution of firms is halved (15%), the contribution of sorting is doubled (13%) relative to the AKM estimates. These differences are potentially related to worker segregation, which might bias the clustering approach: firms could be clustered based on some combination of their own fixed effects and their workers' fixed effects. In such a case, the BLM approach would yield a lower variance of firm effects and a higher sorting (see Bonhomme et al., 2019, for a detailed discussion).

Robustness checks. In Appendix B, we examine in detail the validity of the two-way approach to decompose the variance of wages into worker and firm heterogeneity. This exercise suggests that the identifying assumptions underlying the two-way fixed effects model, meaning exogenous mobility and additive separability, are satisfied. In addition, in Appendix C we evaluate the sensitivity of the results to different model specifications and sample selection criteria. First, in Table C.1 we show that the age

Table 2: Variance decomposition of log daily wages, 2000-2020

	AKM		KSS		BLM	
	Component	Share	Component	Share	Component	Share
$Var(y)$	0.604	-	0.594	-	0.606	-
$Var(\eta)$	0.165	0.274	0.156	0.263	0.204	0.336
$Var(\psi)$	0.189	0.313	0.171	0.287	0.092	0.152
$Var(X\Omega)$	0.089	0.147	0.089	0.149	0.066	0.110
$Var(\epsilon)$	0.121	0.200	0.121	0.204	0.148	0.245
$2 \times Cov(\eta, \psi)$	0.041	0.068	0.052	0.088	0.078	0.129
$2 \times Cov(\eta, X\Omega)$	-0.002	-0.004	-0.003	-0.005	-0.007	-0.012
$2 \times Cov(\psi, X\Omega)$	0.002	0.003	0.003	0.004	0.024	0.040

Notes: Variance decomposition of (log) daily wages based on equation (2). AKM uses estimates from the two-way fixed effects model following Abowd et al. (1999). BLM relies on estimates from the firm-clustering approach of Bonhomme et al. (2019), using 1,500 firm clusters. KSS is based on estimates from the leave-one-out estimator by Kline et al. (2020), excluding worker-firm matches in each iteration. The estimation sample for each method corresponds to the largest connected set based on the firm (or firm clusters) over which workers move using the entire sample period.

normalization we adopt does not affect our results. The AKM estimates are quantitatively the same under alternative specifications of the time-varying effects, such as using sex-specific effects, centering wages at its mean in each calendar time, or netting out age and time effects in a first stage and, then, applying the AKM model to the residuals. Second, we investigate the relative contribution of each term using different sampling restrictions and find that restricting the sample to workers earning at least the minimum wage or including the public sector reduces the contribution of firms to the level of inequality while increasing that of workers by the same proportion (Table C.2). In Table C.3, we either allow firm fixed effects to shift every 5 years, in the spirit of dynamic wage policies of Engbom et al. (2023), or allow both worker and firm effects to vary. The results of the first exercise point to a larger contribution of firms to inequality, while the second one results in a larger contribution of worker-fixed effects and a smaller contribution of firm-fixed effects compared to the baseline specification. This difference suggests the existence of structural changes in the contribution of firms and workers to inequality, something we will investigate further below. Furthermore, performing the KSS estimation by leaving out either workers or observations instead of worker-firm matches in each iteration brings negligible changes to our findings (Table C.4). Finally, in Tables C.5 and C.6, we test the robustness of the BLM exercise using (i) a different number of firm clusters, or (ii) alternative wage definitions to classify firms, and the results are virtually identical.

Changes over time. Our pooled estimates indicate that workers' and firms' permanent heterogeneity along with sorting explains about two-thirds of wage dispersion in Lithuania. However, a key question is how the contribution has evolved over time and what role workers and firms played in the observed decline in wage inequality.

Earlier studies have assumed perfect stability of the bias over time, in which case comparing the results of AKM estimates across periods would be informative about how firms and workers have contributed to the dynamics of inequality (e.g., Card et al., 2013; Alvarez et al., 2018; Song et al., 2019). However, recent work suggests that this may be a strong assumption in environments where mobility patterns may have changed over time (Babet et al., 2022). Given the major economic transformation that Lithuania has experienced in the last 20 years, instead of assuming perfect stability of the bias, we estimate the wage components using the three methods for four selected sub-periods of our data (2000-2005, 2005-2010, 2010-2015, and 2015-2020) and rely on these estimates to provide ranges of the contribution of firms and workers.

Table 3 reports the change in wage inequality from 2000-2005 to 2015-2020 together with the contribution of each component to such change.[14] To assess the role of firms and workers in the decline of inequality, we follow Card et al. (2013) and implement three counterfactual exercises. In the first counterfactual, we compute the change in inequality had the variance of firm fixed effects not changed from its value in 2000-2005. This exercise suggests that the decrease in the dispersion of firm fixed effects might explain between 64% and 93% of the decrease in inequality. In the second counterfactual, we assume that the correlation between firm and worker fixed effects (sorting) did not change over time. The results indicate that sorting can explain no more than 20% of the observed reduction in inequality. In our final exercise, we hold constant both the variance of firm fixed effects and sorting to examine the contribution of worker fixed effects to the decline in inequality. The figures suggest that, had only the variance of worker fixed effects changed over time, the dynamics of wage dispersion might have even been reversed, and there is no scenario where could it explain more than 15% of the actual decline.

We place changes and contributions of firm and worker wage components into perspective by comparing the experience of Lithuania with the outcomes of several countries. Figure 3 reveals that the Lithuanian economy in 2000-2005 exhibited the

[14] The results for each sub-period and estimation method are reported in Appendix C, Tables C.7, C.8, and C.9.

Table 3: Decomposition of the decrease in wage inequality

	2000-05 to 2015-20		
	AKM	KSS	BLM
Change in $Var(y)$	-0.131	-0.136	-0.123
Contribution			
$Var(\eta)$	-0.088	-0.043	-0.233
$Var(\psi)$	0.898	0.930	0.639
$Var(X\Omega)$	-0.067	-0.068	-0.148
$Var(\epsilon)$	0.058	0.059	0.096
$2 \times Cov(\eta, \psi)$	0.184	0.109	0.504
$2 \times Cov(\eta, X\Omega)$	0.036	0.038	0.121
$2 \times Cov(\psi, X\Omega)$	-0.021	-0.024	0.022
Counterfactual change in $Var(y)$			
1. Fixed variance of firm effects	-0.013	-0.017	-0.045
2. Fixed corr. of firm and worker effects	-0.117	-0.150	-0.109
3. Both 1 and 2	0.012	-0.024	0.024

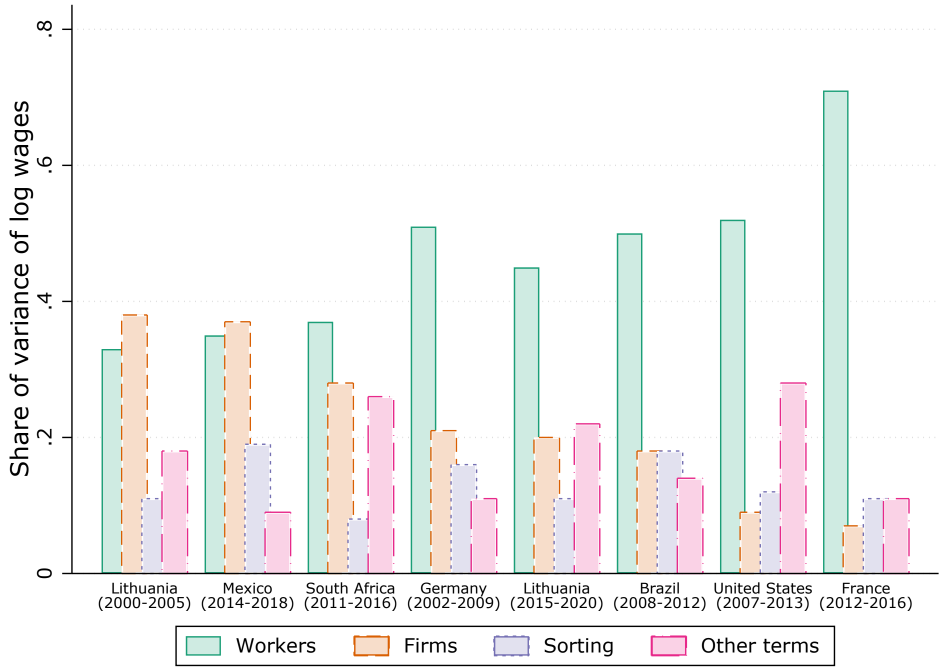
Notes: AKM, BLM, and KSS columns show the change in wage inequality along with the contribution of each component. The contribution of each component is the change in the component divided by the change in the variance of wages. AKM uses estimates from the two-way fixed effects model following Abowd et al. (1999). BLM relies on estimates from the firm-clustering approach of Bonhomme et al. (2019). KSS is based on estimates from the leave-one-out estimator by Kline et al. (2020). All estimates are period-specific. The estimation sample for each method corresponds to the largest connected set based on the firm (or firm clusters) over which workers move within each period. Counterfactual 1 computes the change in inequality fixing the variance of firm effects to that in the 2000-05 period, i.e., $Var_{2000-05}(\psi)$. Counterfactual 2 shows the change in wage inequality between 2000-05 and 2015-20 assuming no change in the correlation of worker and firm effects, i.e., $Cov_{2015-20} = \rho_{2000-05} \times Var_{2015-20}(\eta)^{1/2} \times Var_{2015-20}(\psi)^{1/2}$. Counterfactual 3 measures the change in inequality allowing only the variance of worker effects to vary, i.e., we combine counterfactuals 1 and 2.

largest contribution of firms in explaining the variance of wages (38%), a value only comparable to Mexico in 2014-2018 (37%), and followed by South Africa in 2011-2016 (35%). The sharp decline in the contribution of firm heterogeneity over time places the Lithuanian economy in 2015-2020 closer to cases of Germany in 2002-2009 and Brazil in 2010-2014, where firms explained about 20% of wage dispersion. These numbers are still above the United States (2007-2013) and France (2012-2016), where the dispersion of firm fixed effects contributes less than 10% to the pay dispersion.

6 Firms, inequality, and labor market competition

We have shown that the sharp decline in wage inequality observed in Lithuania in the last 20 years can be almost entirely attributed to the compression of firm-specific wage components. In this section, we use a textbook model of labor market monop-

Figure 3: Comparison with existing estimates around the world



Source: Social Security records (Lithuania), Song et al. (2019) (United States), Babet et al. (2022) (France), Engbom and Moser (2022) (Brazil), Card et al. (2013) (Germany), Bassier (2023) (South Africa), and Pérez Pérez and Nuno-Ledesma (2022) (Mexico), and own calculations.
Notes: The figure shows the contribution to the variance of log wages of worker and firm effects, their covariance, and other terms (residuals, life-cycle, and time effects together with their correlation with worker and firm effects) across countries. Countries are ranked in decreasing order according to the contribution of firms to the variance of wages. Reported contributions for Brazil, Lithuania, Mexico, and South Africa are based on KSS estimates, while for France they are based on a simplified version of the KSS estimator. Contributions in the US and Germany are obtained from standard AKM estimates.

sony to establish a direct link between changes in firm-driven wage dispersion and changes in the degree of labor market competition. We then estimate firms' labor supply elasticities, akin to labor market competition, across sectors and over time and use a theory-based micro-funded relationship to quantify their contribution to the observed reduction in overall wage inequality.

6.1 Theoretical framework

Consider an economy with a large number of firms indexed $j = 1, ...J$, producing a homogeneous good using the following production function

$$y_j = z_j \log \ell_j$$

where z_j denotes firm-level productivity while ℓ_j is the stock of employees.[15] Firms maximize profit by choosing a wage w_j, subject to an upwards-sloping firm labor supply function $\ell_j(w_j) = w^{\varepsilon}$, i.e.,

$$\begin{aligned} \max_{w_j} \quad & \pi_j = z_j \log \ell_j - w_j \ell_j \\ \text{s.t.} \quad & \ell_j(w_j) = w_j^{\varepsilon} \end{aligned}$$

where ε governs the elasticity of labor supply to wages. Notice that, if $\varepsilon < \infty$, the choice of wage w_j determines the labor supplied to the firm $\ell_j(w_j)$, giving firms market power. Taking first-order condition, we can express w_j in terms of model primitives

$$\log w_j = \left(\frac{1}{1+\varepsilon}\right) \log z_j + \left(\frac{1}{1+\varepsilon}\right) \log \left(\frac{\varepsilon}{1+\varepsilon}\right)$$

It follows that the variance of wages can be expressed as a function of the elasticity of labor supply

$$\text{var}[\log w_j] = \left(\frac{1}{1+\varepsilon}\right)^2 \text{var}[\log z_j]$$

The model predicts that the variation in firm wage premia $\text{var}[\log w_j]$ which maps into the variance of the firms' indicator terms, $\text{var}[\psi_j]$, is driven by firm productivity dispersion, $\text{var}[\log z_j]$, and by the labor supply elasticity ε. Taking changes between two different periods, and using a linear approximation, we can write

$$\begin{aligned} \Delta\text{var}_{t+1}[\log w_j] &\approx -2\text{var}_t[\log z_j]\Delta\varepsilon_{t+1} + (1 - 2\varepsilon_{t+1})\,\Delta\text{var}_{t+1}[\log z_j] \\ &\approx -2\text{var}_t[\log z_j]\Delta\varepsilon_{t+1} + \Delta\text{var}_{t+1}[\log z_j] - 2\varepsilon_{t+1}\Delta\text{var}_{t+1}[\log z_j] \qquad (3) \end{aligned}$$

Since $\text{var}_t[\log z_j] > 0$, a model of monopsony predicts a negative correlation between changes in labor supply elasticity and changes in wage dispersion across firms. This result implies the following proposition.

Proposition 1. *Higher labor supply elasticity, akin to labor market competition, reduces wage dispersion across employers.*

By means of equation (3), proposition 1 provides a testable implication of the model.

[15]Because of the limited role of worker fixed effects documented in Section 5, we abstract from modeling worker-level heterogeneity. Introducing it adds an unnecessary layer of complexity without changing the main predictions of the model.

In what follows we will characterize the observed change in the elasticity of labor supply, $\Delta\varepsilon_{t+1}$ and rely on the relationship that arises from our theory to estimate its effect on $\Delta \text{var}_{t+1}[\log w_j]$.[16]

6.2 Estimation of the firm labor supply elasticity

The first step of our strategy is to estimate the firm labor supply elasticity. To do so, we follow a widely common approach and start by identifying the wage elasticity of job separation (Manning, 2003; Langella and Manning, 2021). Specifically, we relate the separation rate to the (log) wage using the following linear probability model[17]

$$P(s_{ijt} = 1) = \alpha + \varepsilon_{sep} \log w_{ijt} + X_{ijt}\Lambda + \xi_{ijt} \tag{4}$$

where s_{ijt} stands for the separation of worker i from employer j at quarter t and w_{ijt} is the corresponding wage measure. X_{ijt} is a vector of controls including the *estimated* AKM worker fixed effect (capturing permanent heterogeneity across workers that can influence mobility patterns) along with indicators for age groups, gender, 2-digit industries, and time effects.

The theory of labor market monopsony suggests that the relevant elasticity governing the firm wage-setting process is the "quit" elasticity (Burdett and Mortensen, 1998; Manning, 2003). However, the latter might not fully capture the entire span of workers' opportunities to move, especially following Lithuania's accession to the EU and the resulting free mobility of labor across countries, which might have increased their outside options. Therefore, we examine both the elasticity of total separations and that of employer-to-employer transitions. In this setting, ε_{sep} refers to separation elasticity, and it quantifies the separation response of workers to changes in wages. A lower separation elasticity, arising when separation is less sensitive to wage cuts, will reflect a greater employer's labor market power. Following Manning (2003), we compute the firm labor supply elasticity as $\varepsilon_{LS} \approx -2 \times \varepsilon_{sep}$.[18]

[16] Berger et al. (2022) provides evidence for firm size-dependent labor supply elasticities. By introducing this feature into our framework, the dispersion of firm wages will also be a function of the variance of the labor supply elasticity. In our empirical approach, we abstract from this dimension but introduce heterogeneity through sector-period-specific elasticities.

[17] In Table C.10, we also report estimates of the separation elasticity using a complementary log-log hazard model as in Langella and Manning (2021).

[18] Monopsonistic employers set wages based on the labor supply elasticity, which is the sum of the quit and hire elasticities. In steady state, this can be approximated as two times the value of the separa-

It is common in the literature to estimate the separation elasticity using the worker's wage, controlling for relevant individual characteristics that may affect mobility patterns (e.g., Hirsch et al., 2018; Bachmann et al., 2022; Webber, 2022). However, recent work by Bassier et al. (2022) emphasizes that the relevant dimension for workers to decide to leave their current job is the firm-specific or job match component of wages, rather than the worker-specific characteristics or idiosyncratic shocks. Therefore, we also estimate the elasticity using the firm wage premiums from the AKM model as the independent variable. Given that the latter is an estimate itself, the elasticity will suffer from an attenuation bias due to measurement error. We mitigate this issue by instrumenting it with the average firm wage, calculated using information on the wage bill and firm size reported by the employer at the end of the year. Notice that while wage bill and firm size include all workers employed in a given firm on December 31st, the wage measure used in the AKM model refers only to individuals who are in the estimation sample, and these workers are not necessarily employed in the same firm by the end of the year. Because the correlation between individual wages and the average wage in the firm decreases as firm size increases, and the contribution of the individual wage to the wage bill declines with the total number of employees, we ensure that workers' separations do not fully enter both the right and left sides of the equation. In other words, we partially eliminate any mechanical correlation induced by the influence of worker mobility on the estimation of the firm's pay policy.

Although variation in firm-fixed effects helps isolate the demand component of wages, this exercise is not perfect, as we still lack exogenous variation in wages. This could potentially lead to lower elasticities, as separations may not fully reflect behavioral responses to firms' wage policies (Bassier et al., 2022). However, our interest is not in the actual level of the elasticity, but in how it has changed over time. Thus, to the extent that the worker-specific propensity to move, which is correlated with the firm's wage policy, is constant over time, our results would still be informative.

6.3 The role of competition in the decline of inequality

Table 4 reports the estimates of the quarterly elasticity of separation for the first and the last time span (2000-2005 and 2015-2020, respectively) together with the implied

tion elasticity (Manning, 2003).

firm labor supply elasticity.[19] Three main results emerge from our estimates. First, in terms of levels, the estimated elasticities are at the lower end of existing findings in the literature (see the meta-analysis of Sokolova and Sorensen, 2021). Using the estimates from Columns (1) and (2) in Panel A, a log-point drop in wages increases the overall separation by 6 percent and the employer-to-employer separation by 2.5 percent. These estimates imply an annualized labor supply elasticity of 0.525 and 0.207 respectively, values that are consistent with what Armangué-Jubert et al. (2023) document for low-income countries. Second, the estimates are higher when the wage measure is net of the worker-specific wage components. Compared to the estimates discussed above, the elasticities of separation obtained by combining the IV with firm fixed effects (Columns (5) and (6) of Panel A) are about 2 percentage points higher, leading to a 50% higher estimate of the labor supply elasticity. This is in line with the argument that the relevant constraint of a monopsonistic firm in the wage-setting process is the elasticity of separation with respect to firm-specific wage components (Bassier et al., 2022). Finally, and crucially for our analysis, the results point to a decrease (increase) in the elasticity of separation (firm labor supply) between 2000-2005 and 2015-2020, regardless of the strategy used to estimate the response of separations to wage changes.[20] For example, our estimates in Column (1) of Table 4 imply an increase in the labor supply elasticity of roughly 0.18 percentage points. A change of a similar magnitude is predicted using the IV firm fixed effects estimates in Column (5).

To what extent changes in labor market competition have contributed to the observed compression in the dispersion of firm-specific wage components, and therefore to the decline in wage inequality? As a second step in our strategy, we leverage cross-sectoral variation in the dispersion of firm fixed effects and labor market power and estimate the following reduced-form regression

$$\Delta \text{var}_{st+1}[\psi_j] = \beta_0 + \beta_1 \Delta \varepsilon_{st+1} + \beta_2 X_{st+1} + \upsilon_{st+1} \tag{5}$$

[19]The firm labor supply elasticity is computed using an annualized separation elasticity as follows: Firm LSE $\approx -2 \times [(1+\varepsilon_{sep})^4 - 1]$.

[20]In Appendix C, Table C.11, we check the sensitivity of the estimates to different choices of controls, i.e. i) including tenure to account for potential tenure-specific wage policies (Manning, 2003; Bachmann et al., 2022), ii) excluding worker FE, which may introduce a downward bias in the estimates because of sorting (Bassier et al., 2022), iii) including sector×municipality fixed effects to account for potential differences in amenities across industries and locations, or iv) controlling for family characteristics that may influence mobility. The results show that while the magnitude of the estimates is more or less affected, the change between periods remains quantitatively the same.

Table 4: Firm labor supply elasticity

A. 2000-2005	Worker wage		Firm fixed effect		IV-Firm fixed effect	
	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep
	(1)	(2)	(3)	(4)	(5)	(6)
ε_{sep}	-0.0601	-0.0250	-0.0485	-0.0220	-0.0800	-0.0433
	(0.0004)	(0.0003)	(0.0019)	(0.0010)	(0.0024)	(0.0014)
Firm LSE	0.5263	0.2081	0.4170	0.1819	0.7214	0.3699
	(0.0038)	(0.0023)	(0.0173)	(0.0085)	(0.0245)	(0.0130)
First stage F-statistic					3062.27	
Observations	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923
B. 2015-2020	**Worker wage**		**Firm fixed effect**		**IV-Firm fixed effect**	
	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep
	(1)	(2)	(3)	(4)	(5)	(6)
ε_{sep}	-0.0773	-0.0289	-0.0565	-0.0246	-0.0979	-0.0507
	(0.0005)	(0.0003)	(0.0015)	(0.0009)	(0.0023)	(0.0013)
Firm LSE	0.6936	0.2418	0.4915	0.2043	0.9055	0.4373
	(0.0048)	(0.0028)	(0.0139)	(0.0079)	(0.0248)	(0.0125)
First stage F-statistic					13,757.87	
Observations	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064

Notes: Panel A and B estimate period-specific linear probability models as specified Equation (4) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as the independent variable. Firm fixed effect columns use AKM effects retrieved from estimating equation (1) separately by period. IV-firm fixed effect columns instrument period-specific firm fixed effects with the (log) average firm wage (wage bill divided by firm size). All specifications control for the estimated AKM worker fixed effects along with indicators for age groups, sex, 2-digit industries, and time effects. Standard errors (in parentheses) are clustered at the level of variation of the wage measure, i.e., worker- or firm-level. Firm LSE refers to the firm's labor supply elasticity computed using the annualized quarterly separation elasticity as follows: Firm LSE $\approx -2 \times [(1+\varepsilon_{sep})^4 - 1]$, with standard errors obtained using the Delta method.

where $\Delta\text{var}_{st+1}[\psi_j]$ and $\Delta\varepsilon_{st+1}$ denote changes in the variance of firm fixed effects and changes in the elasticity of labor supply in sector s between 2000-2005 and 2015-2020, respectively; X_{st+1} are controls suggested by the theoretical framework, which include the value of the elasticity in the second period, ε_{st+1}, and the change in the dispersion of employers' log size, $\Delta\text{var}_{st+1}[\log \ell_j]$.[21] Failure to control for X_{st+1} would result in an omitted variable bias, as implied by equation (3).

To estimate equation (5), we first re-estimate the labor supply elasticity separately by sector in the periods 2000-2005 and 2015-2020. We then regress changes in the labor supply elasticity on changes in the dispersion of firm-specific wage premiums

[21] Because the theory predicts that

$$\text{var}[\log \ell_j] = \left(\frac{\epsilon^L}{1+\epsilon^L}\right)^2 \text{var}[\ln(z_j)],$$

changes in the dispersion of employers' log size, $\Delta\text{var}_{st+1}[\log \ell_j]$, are a good proxy for changes in the variance of log productivity, $\Delta\text{var}_{st+1}[\log z_j]$.

between these two periods, exploiting differences across sectors.[22] Table 5 reports the OLS estimates, with and without controls, obtained using the overall firm labor supply elasticity to worker wages as well as to firm-specific wage components.

Consistent with our theory, the estimates suggest a negative correlation between changes in the firm labor supply elasticity and changes in the variance of the firm fixed effects. Using the estimates from Column (2), a 10 percentage point increase in labor market competition leads to a 1.02 percentage point reduction in the variance of firm fixed effects. The corresponding figure obtained using the elasticity of labor supply with respect to firm wage premiums is reported in Column (5) and implies that a 10 percentage point increase in labor market competition reduces the variance of the firm fixed effects by 0.37 points.

We complement the OLS estimates with an IV approach that addresses the attenuation bias induced by measurement error in the estimated regressors. Following (Griliches and Hausman, 1986), we use the obviously related instrumental variables (ORIV) approach and instrument the change in the firm's labor supply elasticity between 2000-2005 and 2015-2020 with the change observed between 2005-2010 and 2010-2015.[23] Columns (3) and (6) of Table 5 report the second-stage IV estimates together with the first-stage F-statistics.

Our preferred estimates in Column (6), i.e., the one where the degree of labor market competition is measured by the firm's labor supply elasticity with respect to the firm-specific wage component, indicate that a 10-percentage point increase in labor market competition leads to a 0.7 percentage point reduction in the variance of the firm fixed effects. Notice that the associated F-value in the first stage regression is sufficiently large to alleviate the concerns over a weak instrumental variable. Importantly, the ORIV also alleviates concerns about the identification of the firm-labor supply elasticity in a given period, which might be affected by the variation of firm fixed effects in the same period. We also evaluate the exclusion restriction assumption by extending equation (5) to contain both the endogenous variable and the instrument as explanatory variables (Du et al., 2022). Intuitively, if a third factor were driving both

[22] In practice, we do not re-estimate the AKM model by sector, as both the limited mobility bias and the computational burden would be substantial. Instead, we compute the variance of the firm fixed effects by sector from our pooled period-specific estimates. This implies that the residual may not be orthogonal to some of the covariates within sectors. However, the fraction of the variance that is due to non-zero correlation is very small.

[23] See Gillen et al. (2019) for a recent application of the ORIV using panel data.

Table 5: Variance of firm fixed effects and firm's labor supply elasticity

	Worker wage			Firm fixed effect		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Firm LSE	-0.1288	-0.1021	-0.2859	-0.0188	-0.0367	-0.0694
	(0.0286)	(0.0372)	(0.1261)	(0.0100)	(0.0130)	(0.0279)
Δ Wage Inequality Explained, %	23.75	18.83	52.72	4.16	8.13	15.38
First stage F-statistic			8.73			20.40
Controls		✓	✓		✓	✓
No. sectors	74	74	74	74	74	74

Notes: The dependent variable in all specifications is the sector-specific change in the variance of the AKM firm fixed effects between the periods 2000-2005 and 2015-2020. Each column corresponds to a different specification for estimating the firm's labor supply elasticity. Worker wage elasticities are based on individual wages, while the IV-firm fixed effect uses AKM firm fixed effects instrumented by the average wage of the firm to compute the elasticity. Firm labor supply elasticities are based on all separations. IV column instruments the change in the firm labor supply elasticity between 2000-2005 and 2015-2020 with the change between 2005-2010 and 2010-2015. Controls include sector-specific time changes in the variance of the log firm size and the elasticity of the labor supply in the final period. Only sectors with at least 20 firms are included. The change of wage inequality explained by the increase in competition is computed as $0.9 \times \sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta}_1 \Delta\varepsilon_{st+1} \times (\sum_{s=1}^{S} \frac{L_{st}}{L_t} \Delta\text{var}_{st+1}[\psi_{jt+1}])^{-1} \times 100$.

inequality and firm labor supply elasticities, then changes in the elasticity observed between 2005-2010 and 2010-2015 should be predictive of changes in inequality between 2000-2005 and 2015-2020, even conditionally on changes in the elasticity between 2000-2005 and 2015-2020. Table C.12 in Appendix C shows that this is not the case: changes in the firm labor supply elasticity between 2005-2010 and 2010-2015 are uncorrelated with changes in the dispersion of firm-specific wage premiums between 2000-2005 and 2015-2020. This suggests that the ORIV is not only accounting for measurement error but it is also potentially addressing other forms of endogeneity.

Finally, using the point estimates, we quantify the contribution of competition to the decline in wage inequality. Everything else equal, the overall change in inequality that can be attributed to an increase in labor market competition through changes in the dispersion of firm fixed effects is equal to

$$\sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta}_1 \Delta\varepsilon_{st+1}$$

where L_{st} is the number of workers employed in sector s at time t, L_t is the overall employment stock at time t, and $\hat{\beta}_1$ represents the estimate from equation (5). Therefore, changes in labor market competition can explain a reduction in wage inequality of

$$0.9 \times \left(\frac{\sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta}_1 \Delta \varepsilon_{st+1}}{\sum_{s=1}^{S} \frac{L_{st}}{L_t} \Delta \mathrm{var}_{st+1}[\psi_{jt+1}]} \right) \times 100\%$$

where 0.90 refers to the share of change in overall wage inequality explained by the change in the dispersion of firms' fixed effects (see Table 3).

Based on our preferred estimates, the counterfactual exercise shows that the contribution of employer market power to the reduction in overall wage inequality is 15.38%. The contribution increases to 52.72% when we consider the separation elasticities to individual wages, rather than firm-specific wages. Our results point to increased competition in the labor market as a key channel behind the observed reduction in the dispersion of firms' wage premiums, and wage inequality overall.

7 Conclusions

Standard models of employer labor market power predict that increases in labor market competition would reduce firm-driven wage dispersion. In this paper, we investigate this hypothesis using Social Security data for Lithuania spanning the last two decades.

We begin by documenting that the sharp decline in wage inequality observed over the last twenty years can be attributed almost entirely to a reduction in the dispersion of firm-specific wage components. In addition, we show that, over the same period, labor market competition, as measured by changes in firms' labor supply elasticities, has increased. We then rely on a reduced-form micro-funded equation derived from our theory to provide direct evidence of a strong negative relationship between labor market competition and wage inequality. Based on alternative estimates of the firm labor supply elasticity, we find that the observed change in labor market competition can explain between 15 and 53 percent of the decline in wage inequality.

Using the words of Langella and Manning (2021), the "agenda of concern about inequality and competition remains as important as ever. We know from basic economics that markets cannot be relied on to produce levels of inequality that are fair and command political legitimacy. Economists do not often regard inequality as a market failure [...], but ordinary people do, and they are right and we are wrong."

Our paper directly speaks to this agenda. It emphasizes the potential role of labor market competition in addressing the growing wage inequality observed in several countries. Pro-competitive policies aimed at tackling labor market power by reducing labor market concentration, increasing worker mobility, or strengthening worker bargaining power can help address firm-driven wage inequality.

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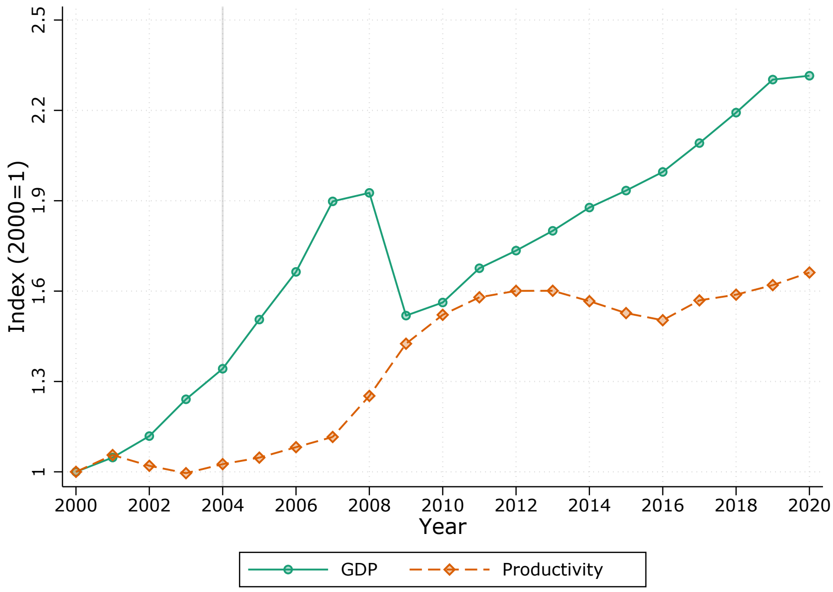
Appendix

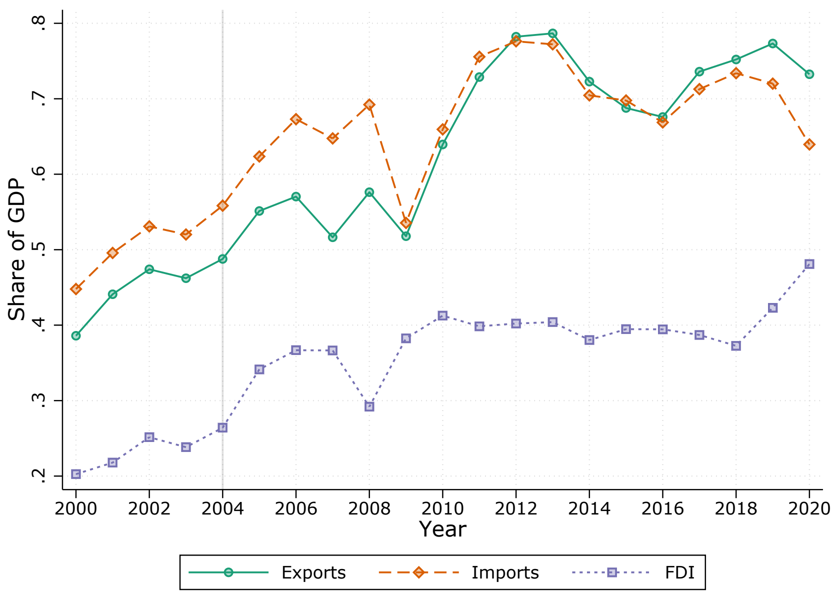
A Institutional background: Graphical evidence

Figure A.1: Economic growth



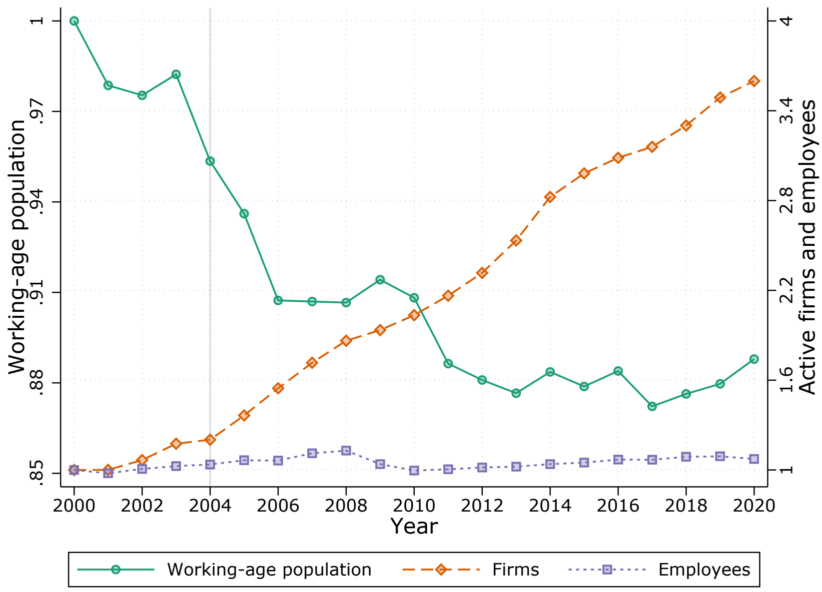
Source: Statistics Lithuania and own calculations.
Notes: The figure shows Lithuania's economic growth between 2000 and 2020, measured by gross domestic product (GDP) and gross value added per worker (productivity). The series are normalized to their value in 2000.

Figure A.2: Openness



Source: Statistics Lithuania and own calculations.
Notes: The figure shows the openness of the Lithuanian economy between 2000 and 2020, considering imports, exports, and foreign direct investment (FDI) as a percentage of GDP.

Figure A.3: Working-age population, firms, and employees

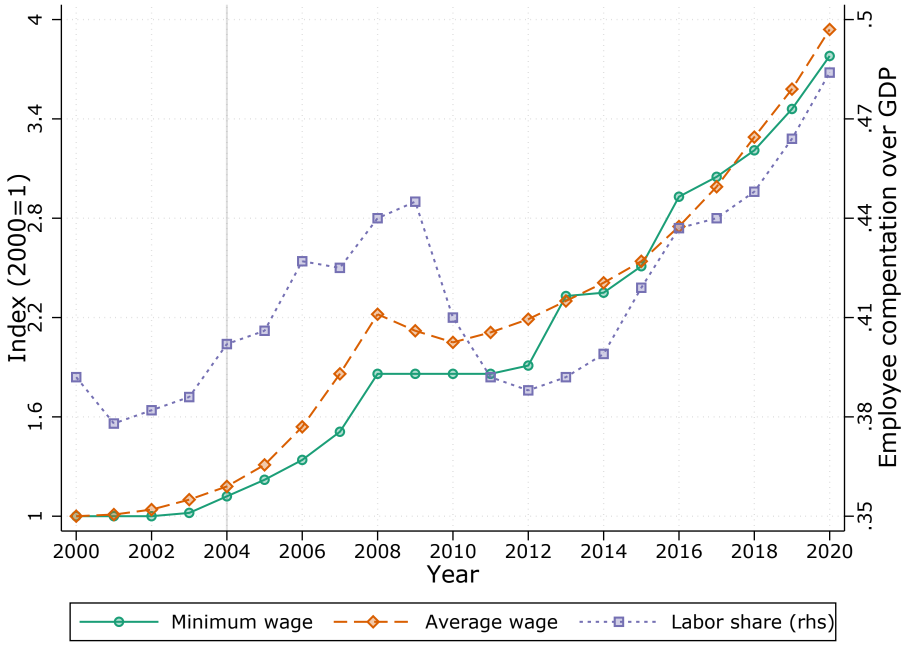


Source: Statistics Lithuania and own calculations. Notes: The figure shows the evolution of the working-age population together the number of active enterprises and employees (rhs) in the Lithuanian economy between 2000 and 2020. The series are normalized relative to their value in 2000.

Figure A.4: Labor supply and demand

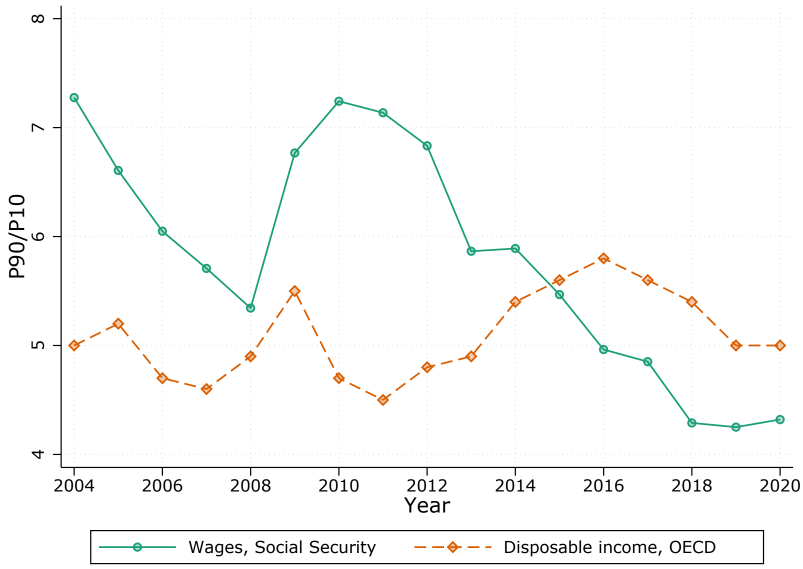
Source: Statistics Lithuania and own calculations.
Notes: The figure shows the labor supply (nonemployment and unemployment) and labor demand (job vacancies) in Lithuania between 2000 and 2020. Nonemployment is the share of the total working-age population without a job. Unemployment refers to the ratio of jobless workers over the labor force. Job vacancy rate data is only available since 2008.

Figure A.5: Workers' remuneration



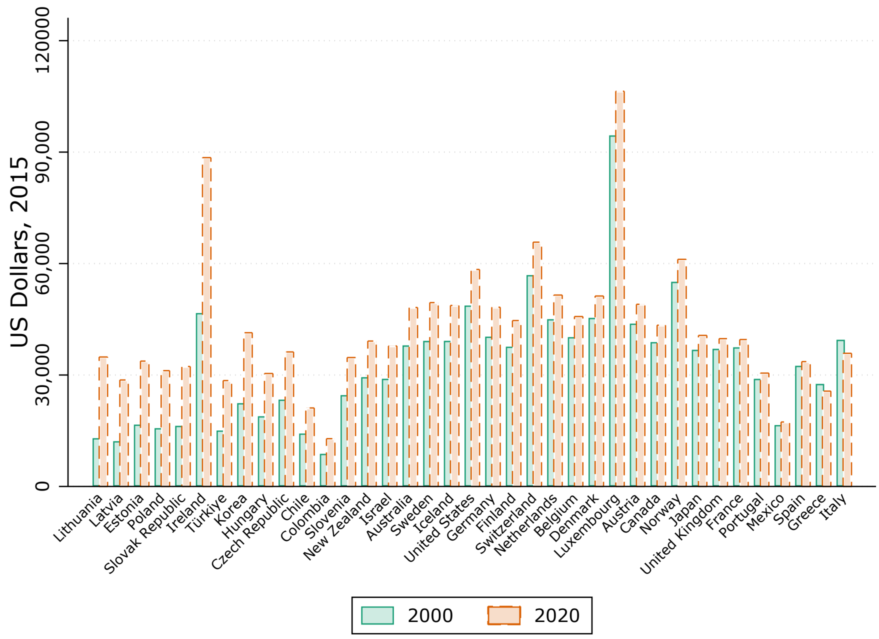
Source: Statistics Lithuania and own calculations.
Notes: The figure shows the evolution of the statutory minimum wage and average wages in Lithuania between 2000 and 2020, as well as the share of GDP allocated to employees' remuneration. Labor share is the ratio of total employee compensation over GDP. The minimum and average wages series are normalized to their value in 2000.

Figure A.6: Wage vs disposable income inequality



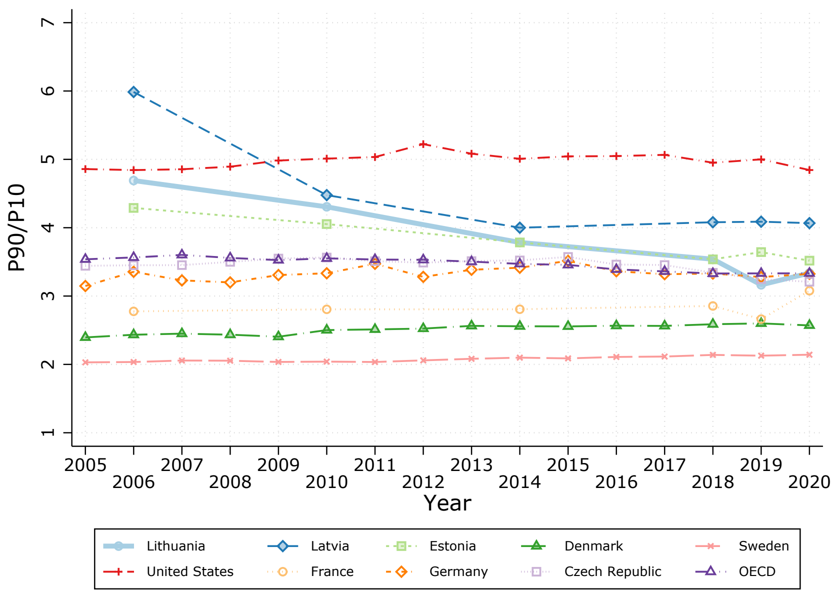
Source: Social Security records, OECD, and own calculations.
Notes: The figure compares the evolution of wage inequality and disposable income inequality. Wages refers to labor income divided by days, where labor income in the Social Security records corresponds to the insured income of workers between the ages of 20 and 60 whose primary job lasted at least 15 days and did not pay less than half the minimum wage in a quarter (see Section 4 for more details on the sample). Disposable income comes from OECD data and consists of earnings, self-employment, and capital income, and public cash transfers; income taxes and social security contributions paid by households are deducted.

Figure A.7: GDP per capita across selected countries, 2000 vs 2020



Source: OECD and own calculations.
Notes: The figure shows the GDP per capita of selected countries in real terms and in purchasing parity power. Selected countries are ranked in descending order by GDP per capita growth between 2000 and 2020.

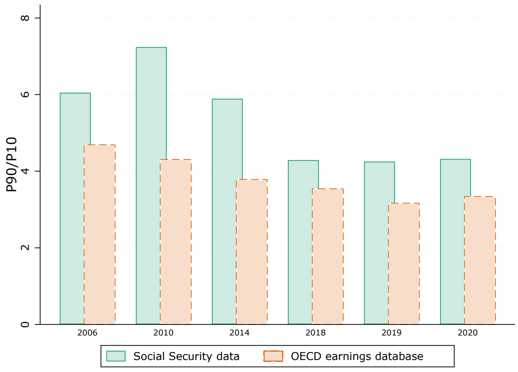
Figure A.8: Inequality across selected countries and time



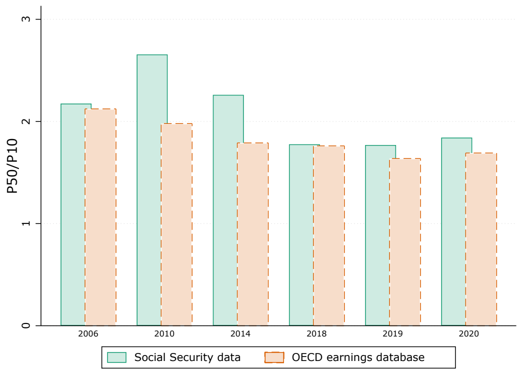
Source: OECD earnings database and own calculations.
Notes: The figure compares the evolution of gross earnings inequality across selected countries between 2005 and 2020. Inequality is measured as the ratio of the 90th percentile to the 10th percentile. Gross earnings refer to the labor income of full-time dependent employees.

Figure A.9: Inequality in Social Security data vs OECD earnings database

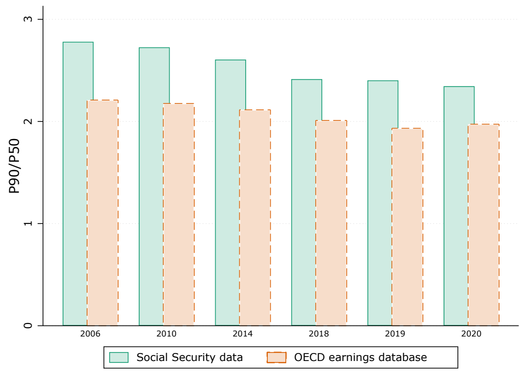
(A) Overall inequality



(B) Lower-tail inequality



(C) Upper-tail inequality



Source: Social Security records, OECD earnings database, and own calculations.
Notes: The figure shows the evolution of inequality in the Social Security data and in the OECD earnings database for the selected years for which information is available in the latter database. Labor income in the Social Security records corresponds to the insured income of workers between the ages of 20 and 60 whose primary job lasted at least 15 days and did not pay less than half the minimum wage in a quarter (see Section 4 for more details on the sample). Labor income in the OECD earnings database refers to the gross earnings of full-time dependent employees.

B Validation of the two-way fixed effects model

B.1 Exogenous mobility

One of the key assumptions for correct identification in AKM models and, in particular, of firm fixed effects implies that worker mobility among employers is exogenous, or uncorrelated with time-varying components of the residual in equation (1). Therefore, if the model specification is appropriate, workers moving from low-wage employers to high-wage employers should experience a wage increase and vice versa. More importantly, workers who move from firms with low fixed effects to firms with high fixed effects should obtain (on average) equal and opposite wage gains to workers who moved in the opposite (symmetric) direction. If, on the other hand, workers were to experience wage increases regardless of the type of job change, this would suggest the existence of specific worker-firm match effects, as workers are taking advantage of favorable specific job match opportunities.[24]

To assess the plausibility of this assumption, we follow the event study approach proposed by Card et al. (2013) to document how job mobility relates to employer switches and wage gains. More specifically, we focus on workers who change jobs in a given quarter but have held the previous job for at least two quarters prior to the job change and hold the new job for at least two quarters. For this group of workers, we classify their jobs according to the firm fixed effect estimated from the AKM model and track their wages over time before and after the job change.

Figure B.1 presents the results of this exercise, where we look at changes from the top to the bottom quartile of the firm fixed effects distribution. Firstly, the results suggest little evidence of transitory shocks prior to job change: wage trajectories are stable and parallel across workers, despite the expected level differences between workers employed in the highest paying firms and those working for employers at the bottom of the firm fixed effects distribution.[25] Secondly, workers who change firms but do not change employer type experience practically no wage variations. Thirdly, workers who move to high-wage firms experience (on average) wage increases, while those

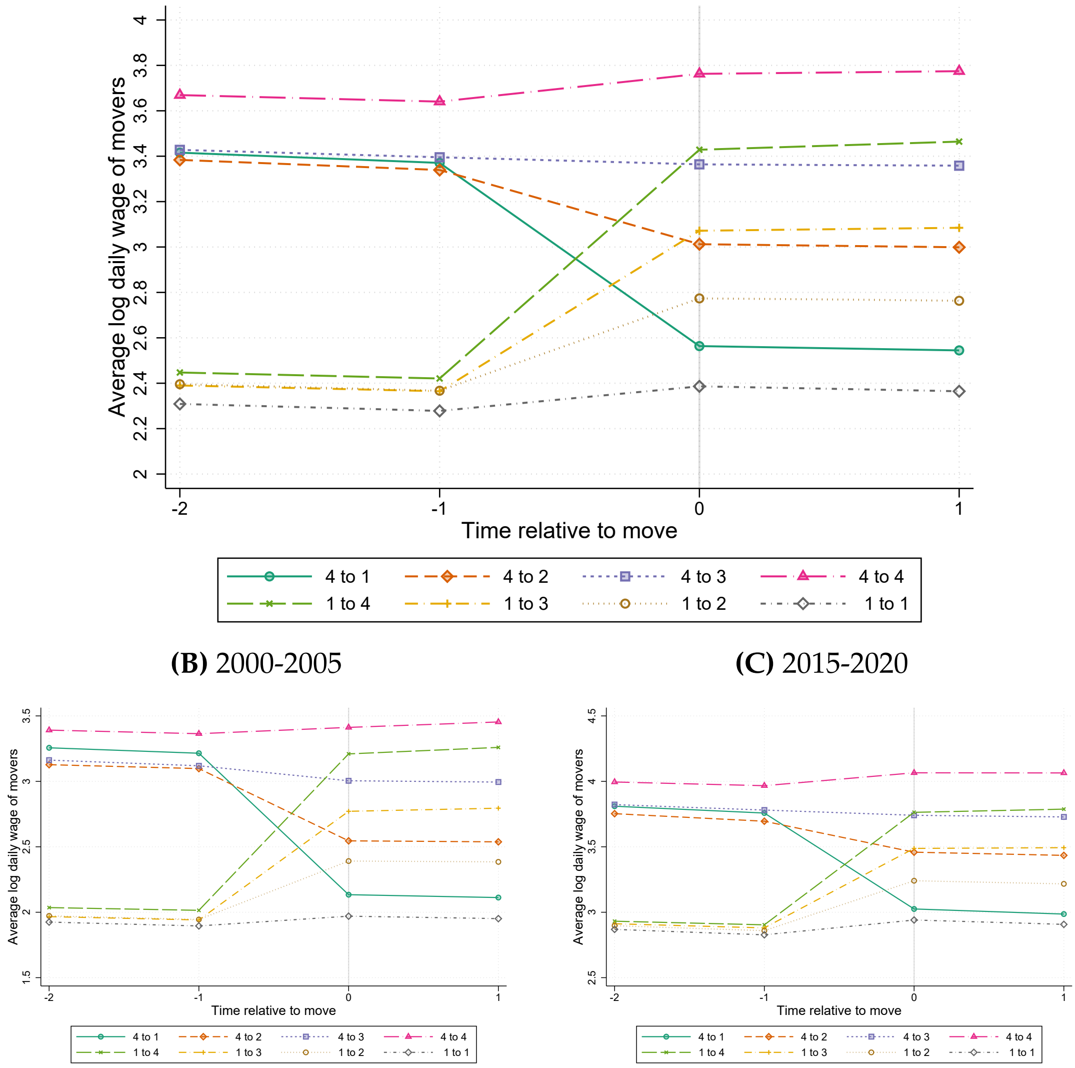
[24]The existence of match effects is just one example of a possible violation of the exogenous mobility assumption. Card et al. (2018) provide extensive discussion and examples of situations where the exogenous mobility assumption may be violated.

[25]If worker mobility were due to a progressive learning curve on the part of employers, one would expect wage changes to precede movements between groups of firms and these changes should be correlated with the type of movement (Lange, 2007).

who fall to the bottom of the job ladder exhibit wage losses, and these wage changes are almost symmetric (see Figure B.2). Therefore, the absence of an overall mobility premium for workers who remain in the same firm fixed effect quartile, along with wages moving in (nearly symmetric) opposite directions for workers who move along the firms' ladder, suggests that job mobility is not driven by idiosyncratic worker-firm match effects and that firm pay premiums seem to be additively separable.

Figure B.1: Average wages of switchers by quartile of firm fixed effects

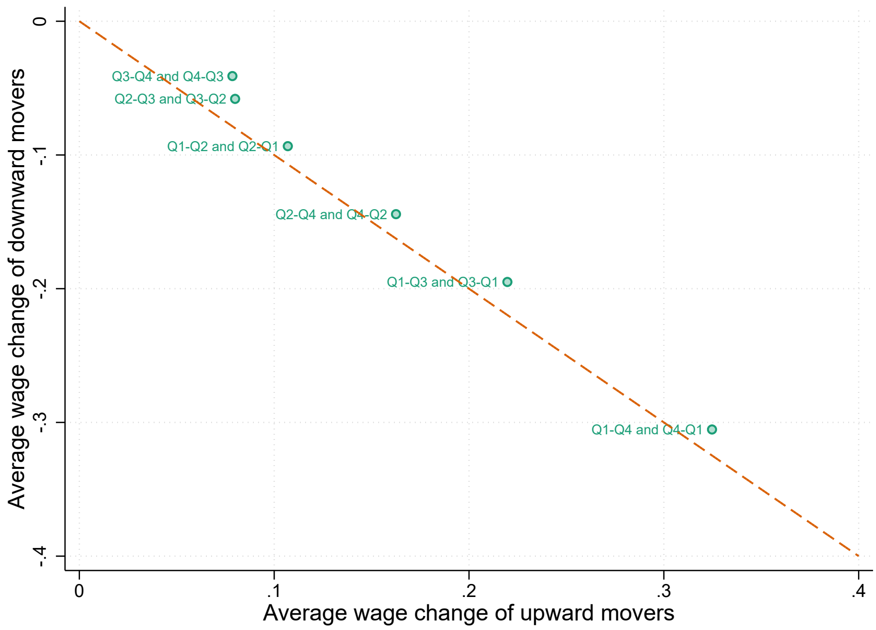
(A) 2000-2020



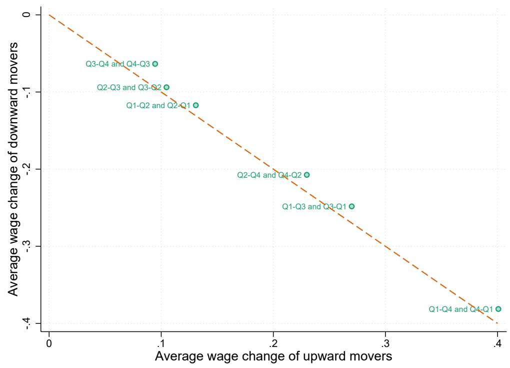
Source: Social Security records and own calculations.
Notes: Panel A shows the average daily wage of workers observed between 2000 and 2020 who changed jobs and held the old job for two or more quarters and the new job for two or more quarters, while Panel B and C report the wage dynamics of movers by sub-periods. Firms are grouped into quartiles according to period-specific AKM fixed effects estimated from the equation (1). Log daily wages are net of the time effects by removing the time-varying AKM observable component from each observation. The vertical line represents the quarter when the new job starts.

Figure B.2: Average wage change of switchers by quartile of firm fixed effects

(A) 2000-2020



(B) 2000-2005



(C) 2015-2020

Source: Social Security records and own calculations.
Notes: Panel A shows regression-adjusted average wage changes over a 4-quarter interval for workers who switch jobs and move between the listed quartiles of firm fixed effects over the entire sample period, while Panel B and C report such average wage changes by sub-periods. Regression-adjusted average wage changes for job switchers are obtained as deviations from the actual 4-quarter interval average wage change and the predicted value using the coefficients of a model of estimated wage changes in a sample of those remaining in the same job over a given 4-quarter interval, as in Card et al. (2016). Firms are grouped into quartiles according to period-specific AKM fixed effects estimated from the equation (1).

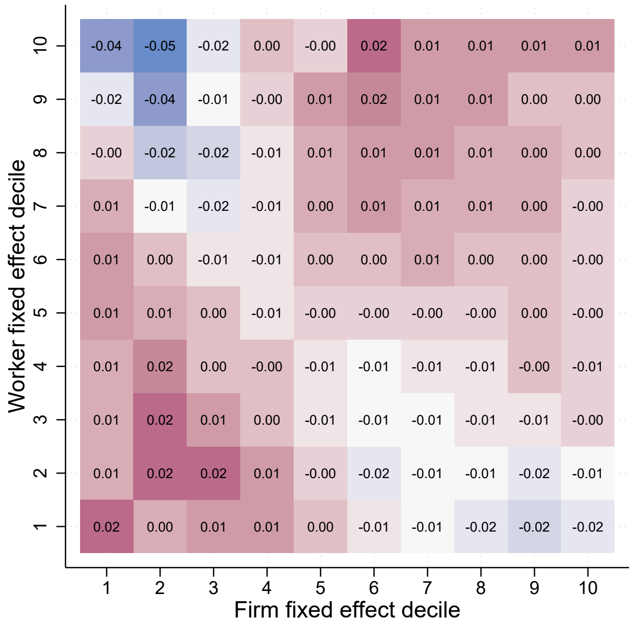
B.2 Additive separability

The second key assumption relates to the additive separability of worker and firm effects or, in other words, the absence of match effects. Therefore, if the additive separability assumption of firm and worker permanent heterogeneity is not met, we should observe systematic differences in the residuals within the pairs defined by worker and firm fixed effects cells. To assess whether additive separability holds, in Figure B.3, we classify workers and firms into 10 groups according to their estimated fixed effects and plot the distribution of residuals across these 100 pairs. A couple of points emerge from this exercise. On the one hand, there is some evidence of misspecification for workers with the lowest value of fixed effects, as the residuals are systematically higher compared to other workers when they work in firms at the bottom of the distribution, while they are negative when they work in firms at the top. On the other hand, for firms at the bottom of the fixed effect distribution, high fixed effect workers exhibit systematically negative residuals, while the opposite is true for low fixed effect individuals. This poor fit at the bottom of both firm and worker fixed effect distribution has been found in other studies and is consistent with the existence of binding minimum wages (e.g., Alvarez et al., 2018; Card et al., 2018; Bassier, 2023). However, the magnitude of the errors is generally small, especially when compared to the wage gains from mobility described in Figure B.1, suggesting that there are no large deviations from the assumption of additive separability.

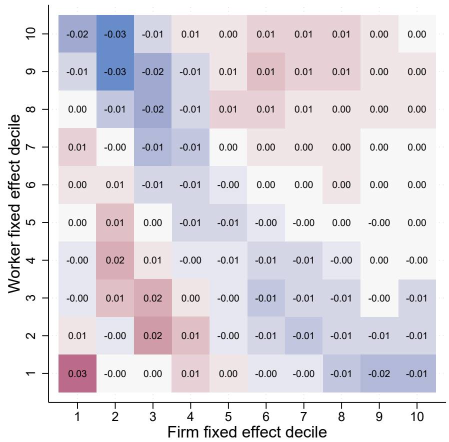
To explore the assumption of additive separability more thoroughly, we estimate the CHK match effects model (Card et al., 2013), which allows us to assess the relevance of idiosyncratic worker-firm matches in explaining the variance of wages relative to the AKM model. The idea is that if match effects are relevant, a model that features a distinct dummy variable for each worker-firm pair should fit the data much better than the AKM specification. Therefore, we estimate the equation (1) but instead of having separate fixed effects for workers and firms, we introduce a fixed effect for each pair. Table B.1 captures the results of this comparison and indicates that, although the fit of the CHK matching effects model is slightly better. However, the approximately 0.065 (0.03) increase in the adjusted R-squared of the CHK model compared to the fit of the AKM model in the full sample (in the sub-periods) suggests that the AKM model's specification of earnings as the sum of worker and firm fixed effects does not appear to be critical.

Figure B.3: Average residuals by deciles of worker and firm fixed effects

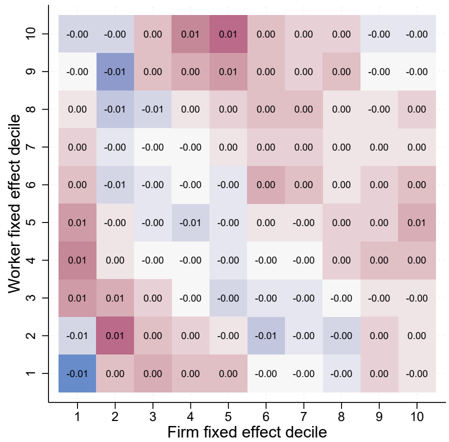
(A) 2000-2020



(B) 2000-2005



(C) 2015-2020



Source: Social Security records and own calculations.
Notes: Panel A shows the average of residuals by cells defined by deciles of the estimated worker and firm fixed effects from the AKM model in equation (1) using the entire sample period. Panel B and C show the average of residuals separately by sub-periods.

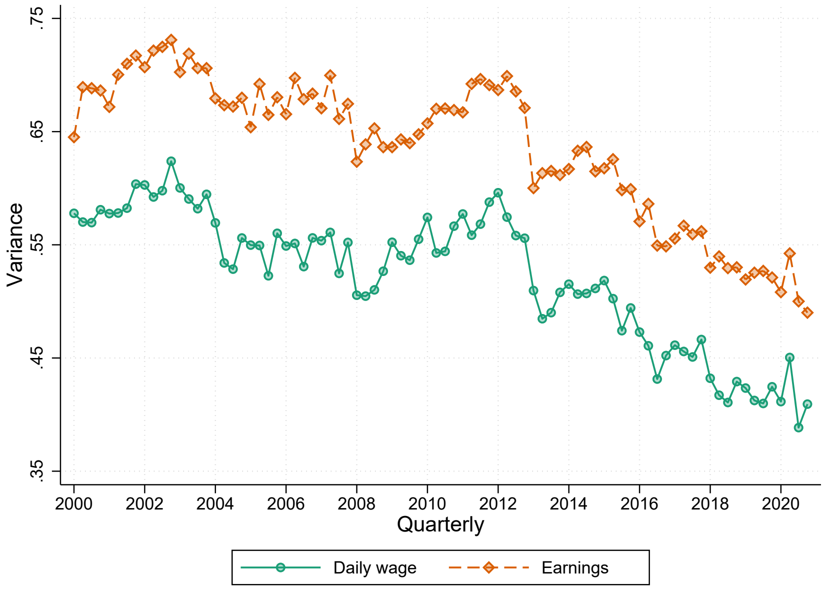
Table B.1: Additive separability vs match effects

	2000-2020		2000-2005		2015-2020	
	AKM	CHK	AKM	CHK	AKM	CHK
Adj. R-squared	0.792	0.849	0.846	0.878	0.820	0.852
RMSE	0.354	0.302	0.298	0.267	0.283	0.262

Notes: AKM refers to model specification in equation (1). CHK is a match effects model where worker and firm fixed effects are assumed not to be separable and, hence, are introduced as pair fixed effects as in Card et al. (2013). Models are estimated separately by each period.

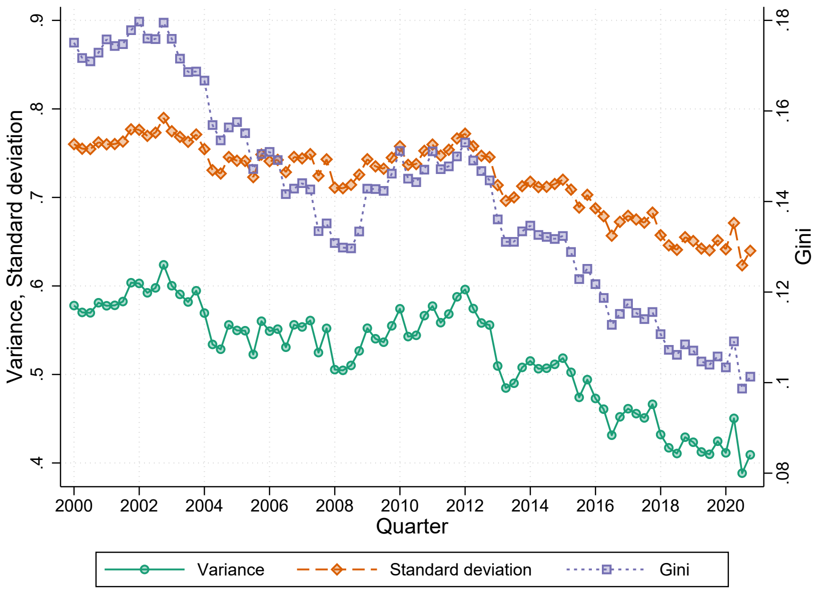
C Sensitivity tests and additional results

Figure C.1: Dispersion of daily wages vs quarterly earnings



Source: Social Security records and own calculations.
Notes: The figure compares the evolution of inequality expressed in terms of the variance of (log) daily wages and total quarterly earnings.

Figure C.2: Wage inequality under alternative measures



Source: Social Security records and own calculations.
Notes: The figure compares the evolution of inequality using alternative indices to measure the dispersion of (log) daily wages.

Table C.1: Variance decomposition of log daily wages for alternative AKM specifications

	Sex-specific time effects		Wages centered		Residual wages	
	Component	Share	Component	Share	Component	Share
$Var(y)$	0.604	-	0.518	-	0.511	-
$Var(\eta)$	0.169	0.280	0.164	0.317	0.163	0.318
$Var(\psi)$	0.189	0.313	0.190	0.366	0.188	0.367
$Var(X\Omega)$	0.090	0.149	0.007	0.013	-	-
$Var(\epsilon)$	0.120	0.199	0.121	0.234	0.121	0.238
$2 \times Cov(\eta, \psi)$	0.041	0.069	0.041	0.079	0.039	0.076
$2 \times Cov(\eta, X\Omega)$	-0.007	-0.011	-0.003	-0.007	-	-
$2 \times Cov(\psi, X\Omega)$	0.001	0.001	-0.001	-0.002	-	-

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the AKM methodology. Sex-specific time effects allow age profiles and year effects to vary between men and women. Wages-centered uses as a dependent variable the deviation of individuals' wages from the average wage in a given quarter. Residual wages rely on wages net of age and time effects as dependent variables.

Table C.2: Variance decomposition of log daily wages for alternative AKM samples

	LM attachment		MW		Public sector		No welfare benefits	
	Component	Share	Component	Share	Component	Share	Component	Share
$Var(y)$	0.617	-	0.395	-	0.564	-	0.608	-
$Var(\eta)$	0.178	0.289	0.146	0.368	0.183	0.324	0.169	0.300
$Var(\psi)$	0.205	0.332	0.102	0.257	0.149	0.264	0.205	0.364
$Var(X\Omega)$	0.088	0.143	0.077	0.194	0.088	0.156	0.100	0.178
$Var(\epsilon)$	0.117	0.189	0.068	0.171	0.115	0.203	0.099	0.175
$2 \times Cov(\eta, \psi)$	0.031	0.050	0.018	0.044	0.034	0.060	0.040	0.072
$2 \times Cov(\eta, X\Omega)$	-0.002	-0.004	-0.005	-0.013	-0.007	-0.012	-0.004	-0.007
$2 \times Cov(\psi, X\Omega)$	0.000	0.001	-0.009	-0.022	0.002	0.004	-0.002	-0.003

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the AKM methodology. LM attachment column considers only worker-quarter observations such that individuals work at least 75% of the quarter. MW column includes only worker-quarter observations such that individuals earn no less than the current minimum wage. Public sector column adds to the estimation sample of public administration. No welfare benefits column removes from the benchmark estimation sample worker-quarter observations when the individual collects some type of welfare benefits (e.g., sickness benefits).

Table C.3: Variance decomposition of log daily wages for AKM model with dynamic effects

	Dynamic firm effects		Dynamic worker&firm effects	
	Component	Share	Component	Share
$Var(y)$	0.604	-	0.604	-
$Var(\eta)$	0.162	0.269	0.323	0.536
$Var(\psi)$	0.282	0.467	0.179	0.297
$Var(X\Omega)$	0.020	0.032	0.026	0.043
$Var(\epsilon)$	0.105	0.175	0.077	0.128
$2 \times Cov(\eta, \psi)$	0.042	0.069	0.015	0.025
$2 \times Cov(\eta, X\Omega)$	-0.006	-0.010	-0.018	-0.029
$2 \times Cov(\psi, X\Omega)$	-0.001	-0.002	0.001	0.001

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the AKM methodology. Dynamic firm (worker&firm) effects allow firm (worker and firm) fixed effects to shift every 5 years. In these cases, identification comes from workers moving across firm$\times$5-year units.

Table C.4: Variance decomposition of log daily wages for alternative KSS leave-out-units

	Leave-out-observations		Leave-out-workers	
	Component	Share	Component	Share
$Var(y)$	0.598	-	0.594	-
$Var(\eta)$	0.157	0.263	0.156	0.263
$Var(\psi)$	0.177	0.295	0.171	0.287
$Var(X\Omega)$	0.089	0.148	0.089	0.149
$Var(\epsilon)$	0.121	0.202	0.121	0.204
$2 \times Cov(\eta, \psi)$	0.050	0.084	0.052	0.088
$2 \times Cov(\eta, X\Omega)$	-0.003	-0.004	-0.003	-0.005
$2 \times Cov(\psi, X\Omega)$	0.002	0.004	0.003	0.004

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the KSS estimator proposed by Kline et al. (2020). Leave-out observations column excludes in each iteration a given worker-quarter observation to estimate the bias, while leave-out-workers column removes the entire worker history in each iteration to estimate the bias.

Table C.5: Variance decomposition of log daily wages for alternative firm clusters

	BLM 150		BLM 600		BLM 6000	
	Component	Share	Component	Share	Component	Share
$Var(y)$	0.606	-	0.606	-	0.606	-
$Var(\eta)$	0.212	0.350	0.205	0.337	0.193	0.318
$Var(\psi)$	0.088	0.144	0.091	0.151	0.108	0.178
$Var(X\Omega)$	0.068	0.112	0.067	0.110	0.069	0.113
$Var(\epsilon)$	0.150	0.247	0.149	0.245	0.144	0.238
$2 \times Cov(\eta, \psi)$	0.074	0.121	0.078	0.129	0.077	0.126
$2 \times Cov(\eta, X\Omega)$	-0.007	-0.012	-0.007	-0.012	-0.006	-0.011
$2 \times Cov(\psi, X\Omega)$	0.023	0.038	0.024	0.040	0.022	0.037

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020. BLM stands for two-way fixed effect estimates from the firm-clustering approach of Bonhomme et al. (2019) using three different numbers of firm clusters, i.e., 150, 500, and 2500 firm types.

Table C.6: Variance decomposition of log daily wages for alternative wage definitions for clustering

	BLM w/ worker variables		BLM w/ firm variables	
	Component	Share	Component	Share
$Var(y)$	0.607	-	0.607	-
$Var(\eta)$	0.195	0.322	0.251	0.415
$Var(\psi)$	0.103	0.170	0.074	0.122
$Var(X\Omega)$	0.082	0.136	0.083	0.137
$Var(\epsilon)$	0.145	0.238	0.153	0.252
$2 \times Cov(\eta, \psi)$	0.078	0.128	0.044	0.072
$2 \times Cov(\eta, X\Omega)$	-0.004	-0.007	-0.007	-0.011
$2 \times Cov(\psi, X\Omega)$	0.008	0.013	0.009	0.015

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020. BLM stands for two-way fixed effect estimates from the firm-clustering approach of Bonhomme et al. (2019). BLM w/ worker characteristics column regresses (log) wages on time, age, nationality, and sex indicatoes and uses the residuals to classify firms. BLM w/ job-firm variables column regresses (log) wages on time, tenure, sector, and location indicators, and uses the residuals to classify firms.

Table C.10: Separation elasticity under complementary log-log model

A. 2000-2005	Worker wage		IV-Firm fixed effect	
	Sep	EE Sep	Sep	EE Sep
ε_{sep}	-0.5550	-0.4747	-0.6712	-0.7611
	(0.0034)	(0.0046)	(0.0366)	(0.0481)
Observations	4,149,923	4,149,923	4,149,923	4,149,923
B. 2015-2020	**Worker wage**		**IV-Firm fixed effect**	
	Sep	EE Sep	Sep	EE Sep
ε_{sep}	-0.6692	-0.5086	-0.8459	-0.8666
	(0.0037)	(0.0050)	(0.0203)	(0.0224)
Observations	4,404,064	4,404,064	4,404,064	4,404,064

Notes: Panel A and B estimate period-specific complementary log-log models for the binary outcome of having any type of separation (Sep) and an employer-to-employer transition (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as independent variable. IV-firm fixed effects follows a two-stage approach to instrument the period-specific AKM firm fixed effects retrieved from estimating equation (1). In the first stage, we regress the firm's FE on the (log) average firm wage together with indicators for age group, sex, 2-digit industry, and time effects as well as the estimated AKM worker fixed effects. In the second stage, the complementary log-log model is estimated using the value predicted in the first stage as the wage measure. All specifications control for estimated AKM worker fixed effects along with indicators for age groups, sex, 2-digit industries, and time effects.

Table C.7: Variance decomposition of log daily wages by sub-periods: AKM

	2000-2005		2005-2010		2010-2015		2015-2020	
	Component	Share	Component	Share	Component	Share	Component	Share
$Var(y)$	0.577	-	0.549	-	0.524	-	0.445	-
$Var(\eta)$	0.208	0.360	0.224	0.409	0.236	0.450	0.219	0.493
$Var(\psi)$	0.241	0.418	0.196	0.357	0.192	0.367	0.123	0.276
$Var(X\Omega)$	0.025	0.044	0.032	0.058	0.028	0.053	0.034	0.077
$Var(\epsilon)$	0.081	0.141	0.094	0.172	0.074	0.142	0.074	0.166
$2 \times Cov(\eta, \psi)$	0.037	0.064	0.019	0.035	0.012	0.024	0.013	0.028
$2 \times Cov(\eta, X\Omega)$	-0.015	-0.026	-0.016	-0.029	-0.020	-0.038	-0.020	-0.044
$2 \times Cov(\psi, X\Omega)$	-0.001	-0.001	-0.001	-0.002	0.001	0.002	0.002	0.005
Adj. R-squared	0.846		0.813		0.845		0.820	
RMSE	0.298		0.321		0.285		0.283	
N	4,409,926		4,807,353		4,448,801		4,696,179	

Notes: Variance decomposition of (log) daily wages based on equation (2) using the AKM estimates from each sub-period. AKM stands for two-way fixed effect estimates from equation (1).

Table C.8: Variance decomposition of log daily wages by sub-periods: KSS

	2000-2005		2005-2010		2010-2015		2015-2020	
	Component	Share	Component	Share	Component	Share	Component	Share
$Var(y)$	0.564	-	0.534	-	0.503	-	0.429	-
$Var(\eta)$	0.187	0.331	0.199	0.373	0.205	0.408	0.195	0.453
$Var(\psi)$	0.215	0.380	0.163	0.306	0.149	0.297	0.088	0.206
$Var(X\Omega)$	0.026	0.046	0.033	0.061	0.029	0.057	0.035	0.081
$Var(\epsilon)$	0.082	0.145	0.095	0.178	0.075	0.149	0.075	0.174
$2 \times Cov(\eta, \psi)$	0.062	0.111	0.052	0.097	0.055	0.110	0.048	0.111
$2 \times Cov(\eta, X\Omega)$	-0.015	-0.027	-0.017	-0.031	-0.021	-0.041	-0.021	-0.048
$2 \times Cov(\psi, X\Omega)$	0.000	-0.001	-0.001	-0.001	0.002	0.004	0.003	0.007
Observations	4,510,485		4,940,511		4,677,094		4,957,606	

Notes: Variance decomposition of (log) daily wages based on equation (2) using the KSS estimates from each sub-period. KSS refers to the leave-one-out estimator proposed by Kline et al. (2020).

Table C.9: Variance decomposition of log daily wages by sub-periods: BLM

	2000-2005		2005-2010		2010-2015		2015-2020	
	Component	Share	Component	Share	Component	Share	Component	Share
$Var(y)$	0.583	-	0.558	-	0.540	-	0.460	-
$Var(\eta)$	0.249	0.427	0.258	0.461	0.279	0.517	0.277	0.603
$Var(\psi)$	0.112	0.192	0.086	0.154	0.074	0.136	0.033	0.072
$Var(X\Omega)$	0.022	0.037	0.032	0.058	0.030	0.055	0.040	0.087
$Var(\epsilon)$	0.101	0.172	0.114	0.204	0.091	0.169	0.089	0.193
$2 \times Cov(\eta, \psi)$	0.112	0.192	0.088	0.157	0.091	0.169	0.050	0.109
$2 \times Cov(\eta, X\Omega)$	-0.015	-0.027	-0.019	-0.034	-0.025	-0.047	-0.030	-0.066
$2 \times Cov(\psi, X\Omega)$	0.004	0.007	0.000	-0.001	0.001	0.002	0.001	0.003
Observations	4,506,950		4,939,701		4,674,446		4,955,309	

Notes: Variance decomposition of (log) daily wages based on equation (2) using the BLM estimates from each sub-period. BLM stands for two-way fixed effect estimates from the firm-clustering approach of Bonhomme et al. (2019).

Table C.11: Separation elasticity with different set of controls

A. 2000-2005	Worker wage								IV-Firm fixed effect							
	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep
ε_{sep}	-0.0475	-0.0209	-0.0622	-0.0269	-0.0598	-0.0249	-0.0647	-0.0191	-0.0627	-0.0379	-0.0815	-0.0472	-0.0794	-0.0431	-0.0989	-0.0460
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0022)	(0.0014)	(0.0023)	(0.0015)	(0.0024)	(0.0014)	(0.0024)	(0.0014)
Observations	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,923	4,149,876	4,149,876	4,149,923	4,149,923	4,149,923	4,149,923
A. 2015-2020	Worker wage								IV-Firm fixed effect							
	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep
ε_{sep}	-0.0684	-0.0254	-0.0795	-0.0298	-0.0766	-0.0288	-0.0750	-0.0222	-0.0851	-0.0457	-0.1062	-0.0666	-0.0969	-0.0503	-0.1394	-0.0601
	(0.0004)	(0.0003)	(0.0005)	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0021)	(0.0013)	(0.0025)	(0.0015)	(0.0023)	(0.0013)	(0.0026)	(0.0015)
Observations	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,064	4,404,024	4,404,024	4,404,064	4,404,064	4,404,064	4,404,064
Tenure FE	Y	Y	N	N	N	N	N	N	Y	Y	N	N	N	N	N	N
Sector×Municipality FE	N	N	Y	Y	N	N	N	N	N	N	Y	Y	N	N	N	N
Family controls	N	N	N	N	Y	Y	N	N	N	N	N	N	Y	Y	N	N
AKM worker type	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	N	N

Notes: Panel A and B estimate period-specific linear probability models as specified Equation (4) for all separations (Sep) and employer-to-employer separations (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as the independent variable. IV-firm fixed effects columns instrument period-specific AKM firm fixed effects with the (log) of firms' average wage in that period. Tenure is a set of indicators for each year of tenure with the current employer. Sector×Municipality FE are pair fixed effects for each combination of sector and firm headquarters location. Family controls include indicators for marital status (single, married, divorced) and whether the individual has children or not. AKM worker refers to worker permanent heterogeneity estimated from model (1). All specifications control for age, sex, and 2-digit industry fixed effects.

Table C.12: Variance of firm fixed effects and firm's labor supply elasticity: IV Validity

	Worker wage	Firm fixed effect
	(1)	(2)
Δ Firm LSE	-0.027	-0.079
	0.013	0.038
ORIV	-0.021	-0.095
	0.014	0.089
Controls	✓	✓
No. sectors	74	74

Notes: The dependent variable in all specifications is the sector-specific change in the variance of the AKM firm fixed effects between the periods 2000-2005 and 2015-2020. Each column corresponds to a different specification for estimating the firm's labor supply elasticity. Worker wage elasticities are based on individual wages, while the firm fixed effect uses AKM firm fixed effects instrumented by the average wage of the firm to compute the elasticity. Firm labor supply elasticities are based on all separations. ORIV refers to the change in the firm labor supply elasticity between 2005-2010 and 2010-2015, used as an instrumental variable for the change in the firm labor supply elasticity between 2015-2020 and 2005-2000. Controls include sector-specific time changes in the variance of the log firm size and the elasticity of the labor supply in the final period. Only sectors with at least 20 firms are included.