Labor Market Competition and Inequality*

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Abstract

We exploit a novel opportunity to study the joint dynamics of wage inequality and labor market competition in a growing economy. Our context is Lithuania, a country that went through several macroeconomic reforms, experienced sustained growth, and a large reduction in wage inequality in the past two decades. 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. Guided by a standard dynamic monopsony model, we then leverage variation across sectors and over time and document a negative co-movement between wage inequality and the elasticity of firm labor supply, akin to labor market competition. We finally provide suggestive evidence that the 2004 enlargement of the European Union could have acted as a potential driver of both trends.

Keywords: Wage inequality, Firm heterogeneity, Monopsony, Labor supply elasticity, Transition economy
JEL Classification: 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). 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 is a critical determinant of income gaps (Abowd et al., 1999; Card et al., 2013; Berlingieri et al., 2017; Song et al., 2019; Criscuolo et al., 2020).

Standard textbook models of monopsony predict that imperfect labor market competition allows firms to pay different wages to workers with similar skills: when labor supply curves are far from perfectly elastic, firms are enabled with market power and set wages below their competitive level (Manning, 2003). This might result in a degree of wage dispersion above the level predicted by a model of perfect competition. In this paper, we exploit a unique opportunity to study how changes in the dispersion of earnings among employees relate to changes in labor market competition among firms in a growing economy such as Lithuania.

The Lithuanian economy provides a useful laboratory for several reasons. First, Lithuania transitioned from being a low-income to a high-income country in about 20 years: GDP per capita increased by more than 120% in real terms. Second, in contrast to the experience of many other countries, wage inequality declined over the last three decades, i.e., approximately 20 log-points decrease in the variance of wages. Third, in 2004, the country joined the European Union, which contributed to a large influx of new businesses, driven by integration into the single market. At the same time, it triggered a dramatic decline in the working-age population due to the free movement of labor and new job opportunities for Lithuanian workers abroad, leading to a significant decline in the number of employees per firm.

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. More importantly, we quantify that the sharp decline observed in wage dispersion is mostly driven by the compression of firm fixed effects, which explains between 60 and 90% of the total decline. Moreover, we document that the compression of firm wage premia was not a consequence of structural change or minimum wage policy.

Guided by a standard dynamic monopsony model, we then estimate the elasticity of firm labor supply – akin to labor market competition. We do so by identifying the workers' elasticity of separations with respect to firm pay policies. Specifically, we take the estimated firm fixed effects and measure their impact on workers separations, conditional on workers' observables. Measuring how separation reacts to the firm pay policy is informative about the degree of firms' monopsony power: this is because it captures how the labor supply to the firm would respond to changes in the component of pay that is driven by arbitrary differences set by employers, instead of reflecting permanent differences in skills or transitory shocks to the job prospects of workers. We document that the elasticity of labor supply has increased over the past two decades by about 0.36 percentage points, corresponding to 25% of the baseline estimate. While the increase in competition mimics the reduction in employer market power as measured by firm-level wage markdowns from production function estimates, it is neither driven by changes in labor market concentration nor worker segmentation.

Finally, we leverage variation across sectors and over time to confirm that these two trends are correlated: increased labor market competition is negatively associated with the decline in the variance of firm-specific wage components, which implies 17% of the total fall in wage inequality. We then provide suggestive evidence that the 2004 EU accession may have spurred labor market competition among Lithuanian firms: by creating new job opportunities abroad, it increased the outside options of Lithuanian workers, and contributed to compress the wage distribution.

Our paper contributes to several strands of the literature. A large body of research highlights the role of firms in shaping the earnings distribution of 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., 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., 2023; Silva et al., 2022). With the increasing availability of linked employer-employee data around the world, new evidence suggests that firms tend to explain a larger share of wage dispersion in developing countries (Alvarez et al., 2018; Pérez Pérez and Nuno-Ledesma, 2023; Bassier, 2023). We contribute to this literature by looking at changes in firm-driven wage dispersion over different stages of a country's development, documenting a downward gradient in the contribution of firms to inequality.

Evidence on the contribution of firm-specific components to wage dispersion has sparked 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 declining 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. Autor et al. (2023) shows that labor market competition induced by the COVID-19 pandemic has boosted wage growth among low-wage workers, directly contributing to reducing inequality in the US. Bassier (2023) documents that the variance of firm-specific wage components explains a larger share of wage dispersion in South African local markets with low labor supply elasticity. Using a structural model of market power in both product and labor markets, Deb et al. (2024) shows that less competitive market structures are characterized by higher between-firm wage inequality and find that the decline in competition explains roughly 55% of the increase in wage inequality in the US. We complement this literature by documenting the joint dynamics of wage inequality and labor market competition during a period of economic growth and offer suggestive evidence that labor market tightening after European Union accession may have triggered the co-evolution of firm-driven inequality and labor market competition.

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 along a country's development path. Moreover, our evidence suggests that the 2004 EU enlargement has contributed to increased labor market competition and reduced overall wage inequality, providing a complementary explanation to 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 quantifies the contribution of worker and firm heterogeneity to changes in inequality, whereas Section 6 documents the dynamics of labor market competition. Section 7 discusses the relationship between wage inequality and labor market competition and the role of the 2004 EU enlargement. Section 8 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.[1]

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 adoption 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

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

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.

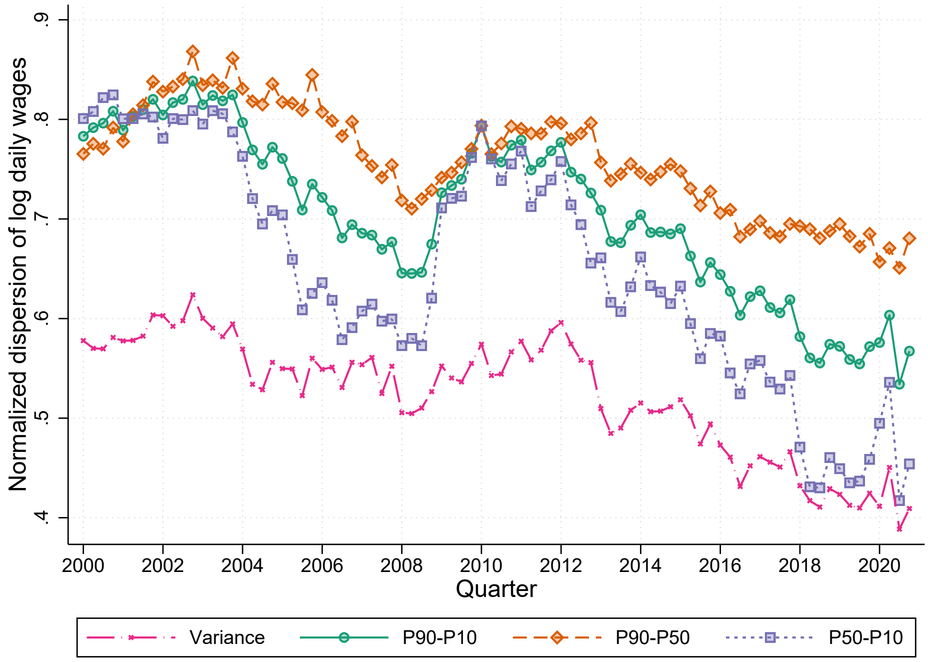
The EU accession also introduced free movements of capital and workers. While access to capital was critical to support economic growth, the right to live and work in other EU members led to a wave of mass emigration (Thaut, 2009; Klüsener et al., 2015): in 2020, Lithuanians living in EU countries represented the equivalent of 10% of Lithuania's population in that year. The size of emigration flows had significant consequences for the labor market (Zaiceva, 2014), leading to significant 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 to provide 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.[2] 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 (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]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.

Figure 1: 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., $\Phi^{-1}(\times) - \Phi^{-1}(\cdot)$.

2.2 Stylized facts about wage dispersion in Lithuania

Figure 1 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.[3] To simplify the comparison among ratios, we normalized the differences across percentiles by the corresponding percentile gaps from a standard normal distribution.[4] The evidence points to a substantial long-run 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. Notably, the decline in inequality was particularly pronounced at the lower end of the log wage distribution: while the P90-P50 ratio declined by only 10 log points, the P50-P10 ratio declined by nearly 40 log points.

To put these numbers in context, consider the case of Brazil. Wage inequality, as

[3]Figure A.7 in Appendix A shows separately the evolution of the 10th, 50th, and 90th percentiles of the quarterly daily log wage between 2000 and 2020.

[4]For instance, the normalized 50-10 percentile differences is the difference between percentiles 50th and 10th divided by 1.2815 ($\Phi^{-1}(0.5) - \Phi^{-1}(0.1)$, with $\Phi(\cdot)$ being the standard normal distribution).

measured by the variance of log wages, decreased 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). Conversely, from 1985 to 2009, Germany experienced an increase in the P80-P20 and P50-P20 ratios of about 16 and 18 log points, respectively (Card et al., 2013). Similar figures are found for the US, where the variance of log earnings increased by 19 log points between 1981 and 2013 (Song et al., 2019).

3 Decomposing the dynamics of wage inequality

What drove the decline in wage inequality documented in Section 2? Did firms play any role? In this section, we lay out an empirical framework that can be used to 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"

[5]A classic identification problem arises when estimating AKM models that include age, year, and cohort effects. Since cohort effects are loaded 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).

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 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).

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

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

of firm fixed effects and thus 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] 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 appearing 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, together with the firm where they are employed at a given time.[10] These individuals have been tracked every month since 2010. 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, lo-

[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 before 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).

[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 individuals in Social Security born in an odd month of each even 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.

cation of the firm's headquarters, and industry, as well as firm size and total payroll measured at the end of the year.[11]

The labor income variable refers to *all* work-related income subject to Social Security contributions, including base salary and non-regular payments such as bonuses, allowances, overtime pay, commissions, or severance payments.[12] 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.[13] To mitigate this issue, we employ daily wage, computed as quarterly income divided by days worked in the quarter and 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 workers aged 20 to 60 between 2000 and 2020 employed in the private sector.[14] Second, we only consider quarterly employment observations such that a person works at least 15 days and earns at least 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 a person has more than one job in a given quarter, 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

[11]Unfortunately, the database does not provide education information, and the occupation variable has only been available since 2012.

[12]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.

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

[14]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

	2000-2020		2000-2005		2015-2020	
	Cleaned data	Connected set	Cleaned data	Connected set	Cleaned data	Connected set
Wages						
Mean	2.905	2.909	2.525	2.539	3.252	3.278
Std.Dev.	0.779	0.777	0.764	0.759	0.679	0.667
Firms	143,461	137,783	64,509	56,698	78,103	62,387
Direct movers	296,159	295,942	124,873	124,425	124,595	123,530
Movers	391,670	391,229	173,540	172,827	165,418	163,837
Workers	532,495	526,536	330,161	320,625	333,238	314,337
Direct moves	815,911	815,539	218,456	217,821	233,805	232,016
Job changes	1,399,550	1,398,910	341,133	340,191	349,526	347,079
Worker-quarters	16,735,572	16,638,459	4,510,485	4,409,926	4,957,606	4,696,179

Notes: 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.

16,638,459 observations between 2000 and 2020.

Table 1 reports descriptive statistics for the cleaned data as well as the largest connected set. The figures show that the largest connected set captures virtually all 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 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 over the full sample period, i.e., the number of job changes divided by the total number of observations, is 8.4% (4.9% 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 9.7% rate for the US in Washington administrative data (Lachowska et al., 2020). This degree of mobility is an advantage of the long time dimension in the sample, as well as of the quarterly frequency of the data, and it improves identification when population data is not available (Andrews et al., 2012; Babet et al., 2023; Bonhomme et al., 2023).

5 Firms and workers in the variance of wages

Pooled estimates. We are now ready to discuss the role of firm and worker heterogeneity in the variance of wages in Lithuania. Table 2 reports the variance decomposition obtained using the estimates from the AKM model in equation (1), as well from the two alternative approaches, and 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 (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 of workers 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).

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.

Robustness checks. In Appendix B, we discuss the assumptions of the two-way fixed-effect approach and show that both exogenous mobility and additive separability are satisfied. 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 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. We find that restricting the sample to workers earning at least the minimum wage, or including the public sector, reduces the contribution of firms while increasing that of workers by the same proportion (Table C.2). In the first two columns of Table C.3, we allow firm fixed effects to shift every 5 years, in the spirit of dynamic wage policies (Engbom et al., 2023), while in the last two columns, we 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 compared to the baseline specification. This difference suggests the existence of some long-run trend 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. A key question is how the contribution has evolved 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., 2023). 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: Decomposition of the decrease in wage inequality

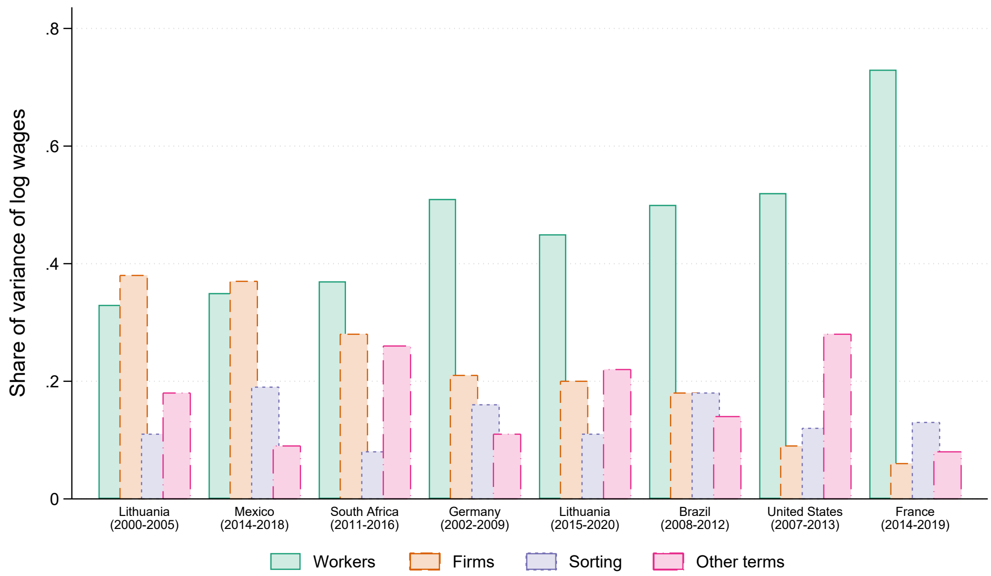
	2000-05 to 2015-20		
	AKM	KSS	BLM
Change in $Var(y)$	-0.131	-0.136	-0.123
Contribution			
$Var(\eta)$	-0.088	-0.043	-0.233
$Var(\psi)$	0.898	0.930	0.639
$Var(X\Omega)$	-0.067	-0.068	-0.148
$Var(\epsilon)$	0.058	0.059	0.096
$2 \times Cov(\eta, \psi)$	0.184	0.109	0.504
$2 \times Cov(\eta, X\Omega)$	0.036	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.

Table 3 reports the change in wage inequality from 2000-2005 to 2015-2020, together with the contribution of each component to such change.[15] 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 reduction 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

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

Figure 2: Comparison with existing estimates around the world



Source: Social Security records (Lithuania), Song et al. (2019) (United States), Babet et al. (2023) (France), Engbom and Moser (2022) (Brazil), Card et al. (2013) (Germany), Bassier (2023) (South Africa), and Pérez Pérez and Nuno-Ledesma (2023) (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.

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 it could explain more than 15% of the actual decline.

Cross-country comparison. We place the contribution of firm and worker wage components into perspective by comparing the experience of Lithuania with the outcomes of several countries. Figure 2 reveals that the Lithuanian economy in 2000-2005 exhibited the 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 (2014-2019), where the dispersion of firm fixed effects contributes less than 10% to the pay dispersion.

Structural change and labor reallocation. Between 2000 and 2020, Lithuania underwent a profound economic transformation, and the compression of the variance of firm fixed effects may simply be the result of labor reallocation to sectors with relatively lower wage dispersion. To assess to which extent compositional shifts in employment across sectors account for the overall reduction in the variance of firms' pay policies, we use a shift-share decomposition in the spirit of Foster et al. (2001).[16]

Table C.10 in Appendix C reports the contribution of between-sector and within-sector components to the total change in the variance of firms' fixed effects, both in levels and in percent, between 2000-2005 and 2015-2020. The decomposition shows that the total change in the dispersion of firms' pay policies over time can be fully explained by changes within sectors. Changes in employment across sectors have slowed wage compression: if the composition of employment across sectors had been fixed, the decline in the variance of firm pay policies across firms would have been between 0.6 and 1.6 percentage points higher.

Minimum wage and firm pay policies. Changes in the national minimum wage were significant over the last two decades and could have compressed the cross-firm wage distribution by raising wages at the bottom. Because the decline in the dispersion of firm pay policies has been realized within each sector, we now investigate the role of changes in the national minimum wage by constructing a sector-specific measure of minimum wage exposure for the period 2000-2005. This measure reflects the wage increase necessary to bring the wage of all workers in a sector up to the minimum wage (Dustmann et al., 2021). Then, we correlate the changes in the variance of firm fixed effects with the initial incidence of the minimum wage.

Figure C.3 in Appendix C shows that the decline in the dispersion of firm fixed effects was widespread and generally uncorrelated with minimum wage policy, as measured by the sectors that would be more exposed to increases in the MW.[17] In Figure C.5 we repeat the same exercise using the P90-P10 ratio, the P50-P10 ratio, and the P90-P50 ratio. The same result emerges: the decline in the percentile difference of the firm fixed effects occurred in almost every sector and is not correlated with sectoral

[16] Further details are reported in Appendix C.

[17] Figure C.4 shows that the lack of correlation holds for alternative measures of minimum wage incidence based on either the share of workers whose earnings are below the minimum wage or the share of firms for which the minimum wage is at least 75% of the average wage.

exposure to the minimum wage.

The lack of a clear link between minimum wage exposure and the compression of firm fixed effects should be understood in light of the observed wage dynamics: despite the significant increase, the growth in minimum wage did not outpace the economy-wide wage growth (see Figure A.6 in Appendix C).

6 Firms, inequality, and labor market competition

In the previous section, we have shown that the sharp decline in wage inequality observed in Lithuania over the last 20 years was almost entirely due to within-sector compression of firm-specific wage components and was not correlated with minimum wage policy. What can explain these dynamics? Guided by a textbook model of dynamic labor market monopsony, in this section, we argue that changes in labor market competition can be a plausible factor behind the observed trend in inequality.

6.1 Theoretical framework

We consider a parsimonious dynamic monopsony model for the labor supply to the firm, in the spirit of Manning (2003) and Langella and Manning (2021). While we do not explicitly estimate the model in this paper, the intuition of the effect of monopsony power on wage dispersion is central to our argument.

Time is discrete. The economy is populated by heterogeneous firms, differing in their productivity, z_{jt}, and producing a homogeneous good with a production function with decreasing marginal returns in labor L_{jt},[18]

$$y_{jt} = z_{jt} L_{jt}^{\alpha}, \quad \alpha \in (0, 1).$$

Let $\Pi(L_{jt-1})$ be the discounted value of future profits from date t onwards, and let $\beta \in (0, 1)$ be the discount rate. Each firm post wages w_{jt} to maximize $\Pi(L_{jt-1})$, defined recursively as follows:

$$\Pi(L_{jt-1}) = \max_{L_{jt}, w_{jt}} \quad z_{jt} L_{jt}^{\alpha} - w_{jt} L_{jt} + \beta \Pi(L_{jt}), \tag{3}$$

[18] Because of the limited role of worker fixed effects and sorting in explaining the change in inequality documented in Section 5, we follow Card et al. (2018) and abstract from modeling worker-level heterogeneity. See Lamadon et al. (2022) for a discussion on the role of worker sorting.

subject to the labor supply function for firm j, equal to

$$L_{jt} = R(w_{jt}) + [1 - s(w_{jt})]L_{jt-1}.$$

Here $R(w_{jt})$ and $s(w_{jt})$ denote the number of recruits and the separation rate, respectively, both defined as a function of wages w_{jt}. In what follows, we assume the following reduced-form for both recruits and the separation:

$$R(w_{jt}) = A_t w_{jt}^{\varepsilon_{Rt}} \quad \text{and} \quad s(w_{jt}) = B_t w_{jt}^{-\varepsilon_{sept}},$$

where ε_{Rt} and ε_{sept} denote the wage elasticities of recruits and separation, while A_t and B_t are common constant.[19] These two assumptions imply the following dynamics of employment:

$$L_{jt} = A_t w_{jt}^{\varepsilon_{Rt}} + [1 - B_t w_{jt}^{-\varepsilon_{sept}}]L_{jt-1}. \tag{4}$$

Taking the first-order condition with respect to wages, we get

$$\left[\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt} + \beta \frac{\partial \Pi(L_{jt})}{\partial L_{jt}}\right] \frac{\partial L_{jt}}{\partial w_{jt}} \frac{w_{jt}}{L_{jt}} = w_{jt}. \tag{5}$$

In a steady state with sufficient low future discounting (i.e., $\beta \approx 1$), equation (5) can be re-arranged to show that dispersion in wage is equal to[20]

$$\text{var}_t[\log w_{jt}] \approx \left(\frac{1}{1 + (1-\alpha)\varepsilon_{LSt}}\right)^2 \text{var}_t\left[\log z_{jt}\right], \tag{6}$$

where $\varepsilon_{LSt} = \varepsilon_{Rt} - \varepsilon_{sept}$ is the overall wage elasticity of labor supply.

Equation (6) states that the dispersion in firm pay negatively correlates with the degree of labor competition, as measured by the firm's labor supply elasticity.[21] Guided by this result, in the rest of this section we document how the labor supply elasticity has evolved between 2000 and 2020.

[19] Burdett and Mortensen (1998), or alternatively Manning (2003) provide with a micro-fundation of both functions in the context of a search and matching model.

[20] See Appendix D for a full derivation of the model solution.

[21] This prediction is valid as long as $\alpha \in (0, 1)$; that is, as long as there are decreasing returns to scale in production. We implicitly test this assumption in Section 7, where we estimate how wage dispersion and labor supply elasticity co-move across sectors and over time.

6.2 Estimation of the firm labor supply elasticity

To estimate the firm labor supply elasticity, ε_{LS}, 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,

$$P(s_{ijt} = 1) = \alpha + \beta \log w_{ijt} + X_{ijt}\Lambda + \xi_{ijt}, \tag{7}$$

where s_{ijt} stands for the separation of worker i from employer j at quarter t and w_{ijt} is the corresponding wage measure.[22] X_{ijt} is a vector of controls that includes *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.

Consistent with our theoretical framework, an estimate for the separation elasticity, ε_{sep}, can be obtained as

$$\varepsilon_{sep} = \frac{\hat{\beta}}{\overline{s_{ijt}}} \tag{8}$$

where $\overline{s_{ijt}}$ is the average separation rate in the period. A separation elasticity lower in magnitude, arising when separations are less sensitive to wage cuts, will reflect greater employers' labor market power. Following Manning (2003), we compute the firm labor supply elasticity as $\varepsilon_{LS} = \varepsilon_R - \varepsilon_{sep} \approx -2 \times \varepsilon_{sep}$.[23] 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 may not capture the full range of workers' outside options, especially following Lithuania's accession to the EU and the resulting free mobility of workers across countries. Therefore, we examine the elasticity of total separations and employer-to-employer transitions.

It is common in the literature to estimate these elasticities using workers' wages, 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

[22] In Table C.11 of Appendix C, we also report estimates of the separation elasticity using a complementary log-log hazard model as in Langella and Manning (2021).

[23] Monopsonistic employers set wages based on the labor supply elasticity, which is the sum of the quit and hire elasticities. In the steady state, this can be approximated as two times the value of the separation elasticity (Manning, 2003).

by Bassier et al. (2022) emphasizes that the relevant dimensions for workers' decisions to leave their current jobs are the firm- and match-specific components of wages. Thus, we also estimate the elasticity using the firm wage premia from the AKM model as the independent variable.[24] 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 using the firm's average wage as an instrument, which is 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 eliminate any mechanical correlation induced by the influence of worker mobility on the estimation of the firm's pay policy. This strategy resembles the splitting sample approach of Bassier et al. (2022), as the average wage used as an instrument is computed from a different pool of workers compared to the one used in the two-way fixed effect estimation.

6.3 The dynamics of labor market competition

Firm's labor supply elasticity. Table 4 reports the estimates of the quarterly elasticity of separation for the first and the last periods (2000-2005 and 2015-2020, respectively) together with the implied firm labor supply elasticity.[25] 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 a labor supply elasticity

[24] Although variation in firm fixed effects helps isolate the demand component of wages, this exercise may still underestimate elasticities because the separations may not fully reflect behavioral responses to firms' wage policies (Bassier et al., 2022). To the extent that the worker-specific propensity to move, which is correlated with the firm's wage policy, does not exhibit too much variability across periods, our results are still informative about changes in the elasticity over time.

[25] See Table C.12 in Appendix C for estimates for the 2005-2010 and 2015-2020 sub-periods.

of 1.03 and 0.98, respectively, values that are consistent with what Armangué-Jubert et al. (2024) document for low-income countries. Second, the estimates are significantly higher (1.38 and 1.69) when the wage measure is net of the worker-specific wage components and is instrumented by the average wage in the firm (Columns (5) and (6) of Panel A). 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. For example, comparing our estimates in Column (5) Panel A to those in Panel B of Table 4, we observe an increase in the labor supply elasticity of roughly 0.36 percentage points.[26]

Labor supply elasticity vs. wage markdowns. Changes in the frequency of job transitions over the period might bias the estimates of the labor supply elasticity if these were related to structural forces other than changes in labor market competition. If, as a result of economic transformation, workers responded less to wage changes at the beginning of the period, as opposed to the end, this would explain why the estimates of the separation elasticity are initially low and rise over time. However, in Appendix C Figure C.6, we show that, while the majority of transitions between jobs happened across 2-digit industries, there is no clear trend over the sample period.

To further address this concern, we rely on an alternative measure to describe labor market competition, i.e., firm-level wage markdown (Yeh et al., 2022). The optimality condition for the choice of labor input in equation (5) implies a negative relationship between the average wage markdown, ν_t, defined as the ratio of the marginal product of labor and wages, and the average elasticity of labor supply.

We test if this is the case in the data using estimates of firm-level wage markdowns provided by Ding et al. (2025).[27] We compare our two measures of labor market power

[26] In Appendix C, Table C.13, 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. While the magnitude of the estimates is slightly affected, the change between periods remains quantitatively the same.

[27] Ding et al. (2025) use Lithuanian firm balance sheet data to estimate a trans-log production function and obtain firm-level estimates of wage markdown as

$$\nu_{it} = \frac{e^{\ell}_{it}}{e^{c}_{it}} \frac{\alpha^{c}_{it}}{\alpha^{\ell}_{it}},$$

Table 4: Firms' 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)
β	-0.0601	-0.0250	-0.0485	-0.0220	-0.0800	-0.0433
	(0.0004)	(0.0003)	(0.0019)	(0.0010)	(0.0024)	(0.0014)
ε_{LS}	1.0329	0.9747	0.8327	0.8561	1.3746	1.6861
	(0.0068)	(0.0104)	(0.0083)	(0.0125)	(0.0417)	(0.0556)
First stage F-statistic					3,062.27	
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)
β	-0.0773	-0.0289	-0.0565	-0.0246	-0.0979	-0.0507
	(0.0005)	(0.0003)	(0.0015)	(0.0009)	(0.0023)	(0.0013)
ε_{LS}	1.3693	1.1145	1.0007	0.9478	1.7340	1.9514
	(0.0216)	(0.0220)	(0.0265)	(0.0125)	(0.0415)	(0.0519)
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 (8) 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 and 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. ε_{LS} refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

in Appendix E, and both suggest an increase in labor market competition: the increase in the firm's labor supply elasticity documented in Table (4) is met by a decline of more than 4% in the aggregate wage markdown. In addition, Figure E.1 compares sector-specific firm-labor supply elasticities with the sector-level average wage markdowns. Consistent with the theory, firms in sectors with higher labor supply elasticity, as estimated using Social Security data, charge lower wage markdowns, as estimated using firm balance sheet data.

Workers segmentation. Despite the limited role of worker heterogeneity in explaining the change in inequality over time, we cannot yet rule out increased labor market segmentation in terms of unobserved characteristics such as education and skills. If worker segmentation leads to more pronounced differences in job mobility or separa-

where e^{ℓ}_{it} is the estimated output elasticity of labour input, e^{c}_{it} is the estimated output elasticity of intermediates, α^{ℓ}_{it} is the labour share, and α^{c}_{it} is share of intermediate input costs in output.

tion behavior across labor market segments, we could observe a higher labor supply elasticity, even without changes in the underlying degree of labor market competition.

To address this concern, we replicate the estimates in Table 4 separately for high-skilled and low-skilled workers. We use the estimated AKM worker fixed effects to label workers as low- or high-skilled depending on whether they are below or above the median fixed effects, respectively. The estimates indicate that the overall dynamics of labor market competition are similar across skill types: between 2000 and 2020, the labor supply elasticity based on all separations (job-to-job transitions) has increased by about 0.37 (0.34) percentage points for low-skilled workers and 0.30 (0.21) percentage points for high-skilled workers — see Columns (5) and (6) of Tables C.14 and C.15 in Appendix C.

Firm granularity. The model proposed in Section 6.1 features atomistic firms in the spirit of Card et al. (2016) and Lamadon et al. (2022). In this framework, the labor supply elasticity is constant, and it does not depend on the degree of market concentration. In contrast, when firms are granular, as in Berger et al. (2022), changes in the labor supply elasticities could reflect changes in the market structure.

To understand the role of granularity, Figure C.7 in Appendix C scatters changes in the firm's labor supply elasticity against changes in wage-bill Herfindahl index across sectors over the sample period. Overall, sectors with a larger increase in the labor supply elasticity did not experience a (larger) decline in industry concentration, suggesting market structure had a limited role in explaining changes in labor market competition.[28]

7 The joint dynamics of inequality and competition

The model predicts that the variation in firm wage premia, $\text{var}_t[\log w_j]$, which maps one to one into the variance of the firms' indicator terms, $\text{var}_t[\psi_j]$, is driven by firm productivity dispersion, $\text{var}_t\left[\log z_j\right]$, and by the labor supply elasticity ε_{LSt}. Because $\text{var}_t[\log z_j]$ is strictly positive, the model implies a negative correlation between changes in labor supply elasticity and changes in wage dispersion across firms.

[28] When firms are granular, an increase in minimum wage could also increase the average labor supply elasticity by reducing markdowns of low-paying firms. Figures C.8 and C.9 in Appendix C show there is no direct relation between the incidence of minimum wage across sectors and the relative change in the firm's labor supply elasticity.

7.1 Did they comove?

To assess whether firm-driven inequality and labor market competition occurred together over time, we exploit the variation across sectors in changes in the dispersion of firm fixed effects and elasticities to estimate the following reduced-form equation

$$\Delta \text{var}_{st+1}[\psi_j] = \alpha + \beta \Delta \varepsilon_{st+1} + X_{st+1}\Omega + v_{st+1}, \tag{9}$$

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.[29,30] X_{st+1} refers to two sets of controls. The first set includes model-based controls, as equation (6) suggests after some manipulation.[31] These are the level of the labor supply elasticity in the last period and the change in the dispersion of employers' (log) size to control for variation in firm-level productivity dispersion. The second set of controls includes sector-level changes in the wage bill HH index and the sector-level incidence of the minimum wage in the initial period. The former accounts for the evolution of labor market concentration and its relationship to wage dispersion across firms (Deb et al., 2024), whereas the latter captures the heterogeneous effect of the sustained minimum wage increases that took place in the last 20 years in Lithuania and that could have influenced firm-wage inequality and competition (Dustmann et al., 2021).[32]

To estimate equation (9), we first re-estimate the labor supply elasticity with respect to firm-specific wages 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 premia between these two periods, exploiting differences across sectors.[33] We complement the OLS estimates with the *obviously related instrumental*

[29]We use the elasticity based on all separations and with respect to firm-specific wages as our preferred measure, as discussed in Section 6. In Table C.17, we find quantitatively similar results when using the elasticity based on job-to-job transitions.

[30]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.

[31]See Appendix D for a full derivation.

[32]While product market power is not explicitly controlled for, we show in Appendix E that its exclusion might lead to a downward bias for the OLS estimate of β. This is because changes in industry-level markups and markdowns are negatively correlated (see Figure E.3).

[33]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

variables (ORIV) approach proposed by Griliches and Hausman (1986) to address the attenuation bias induced by measurement error in the estimated regressor. Formally, we instrument the change in the firm's labor supply elasticity between 2000-2005 and 2015-2020, with its change observed between 2005-2010 and 2010-2015.[34]

We report the estimates in columns (1) to (3) of Table 5. Consistent with our theory, we document a negative correlation between changes in the firm labor supply elasticity and changes in the variance of the firm fixed effects. Using our preferred estimate in Column (3), a 10 percentage point increase in labor market competition is associated with a 3.8 percentage point decrease in the variance of the firm's fixed effects. This estimate, along with the observed change in the labor supply elasticity, allows us to calculate the decline in wage dispersion had inequality and competition been uncorrelated.[35] All else equal, the overall decline in wage inequality would be 16.9% lower.[36] Columns (4) to (6) of Table 5 report alternative estimates of equation (9), where we replace the dependent variable with sector-specific changes in percentile ratios of firm fixed effects. Changes in labor supply elasticity negatively correlate only with inequality at the bottom of the pay distribution, in line with the prediction of the canonical model of labor market monoposony (Autor et al., 2023).

Note that changes in wage dispersion may also have been driven by changes in the dispersion of firm productivity (Criscuolo et al., 2021). In Figure F.1 in Appendix F, we show that the dispersion of firm-level TFP estimates from Ding et al. (2025) has declined from 0.70 to 0.65 over the last two decades. On the other hand, the observed changes in productivity dispersion, evaluated at the initial level of labor supply elasticity (i.e., 1.375 — see Column (5) in Table 4), through the lens of equation (6), contributed to a -0.1 decline in firm wage inequality, or about 10% of the total decline. We find similar results using changes in firm size dispersion as they evolve in parallel (Figure F.2). Thus, controlling for employer size dispersion in our regression alleviates concerns about unobserved variable bias arising from ignoring the role of productivity

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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 due to non-zero correlation is very small.

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

[35]The change of wage inequality implied by the increase in competition is computed as $0.9 \times \sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta} \Delta \varepsilon_{st+1} \times (\sum_{s=1}^{S} \frac{L_{st}}{L_t} \Delta \text{var}_{st+1}[\psi_{jt+1}])^{-1} \times 100$, 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)

[36]The contribution increases to 20.6% when we consider elasticities based on the job-to-job transitions. See Table C.17 in Appendix C.

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

	Δ var$_{st+1}[\psi]$			ΔP90P10	ΔP50P10	ΔP90P50
	OLS	OLS	ORIV	ORIV	ORIV	ORIV
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ \varepsilon_{st+1}$	-0.0128	-0.0137	-0.0379	-0.1714	-0.1371	-0.0343
	(0.0047)	(0.0047)	(0.0175)	(0.0047)	(0.0741)	(0.0577)
Implied %Δ var$[y]$	5.7	6.1	16.9	-	-	-
Model-based controls	✓					
Full set of controls		✓	✓	✓	✓	✓
No. sectors	74	74	74	74	74	74

Notes: The dependent variable in the specifications of columns (1) to (3) is the sector-specific change in the variance of the AKM firm fixed effects between the periods 2000-2005 and 2015-2020. The dependent variable in the specifications of columns (4) to (6) is the sector-specific change in the specified percentile difference of firm fixed effects. The change in the firm labor supply elasticity (LSE) refers to the sector-specific change between the periods 2000-2005 and 2015-2020. The elasticities are estimated using all types of separations as Table 4 of Columns (5). ORIV 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. Model-based controls refer to sector-specific changes in the variance of the log firm size and the sector-specific elasticity in the final period, 2015-2020. The full set of controls includes the model-based controls plus the sector-specific changes in the wage bill HH index and the sector-specific minimum wage incidence in the initial period, 2000-2005. Only sectors with at least 20 firms are included. The change of wage inequality explained by the increase in competition is computed as $0.9 \times \sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta} \Delta\varepsilon_{st+1} \times (\sum_{s=1}^{S} \frac{L_{st}}{L_t} \Delta \text{var}_{st+1}[\psi_{jt+1}])^{-1} \times 100$. Robust standard errors are in parentheses.

dispersion.

Importantly, we abstract from worker heterogeneity in our model. This is because changes in the dispersion of worker fixed effects or the covariance of worker and firm fixed effects played little role in the decline in overall wage inequality. If labor market competition were genuinely behind changes in inequality through its *sole* effect on firm-specific wage components, we should find no correlation between changes in the labor supply elasticity and the variance of the worker-specific components of wages or sorting between workers and firms over time and across industries. Table C.16 in Appendix C shows this is the case: when sector-specific changes in the variance of worker fixed effects (Panel A) or the covariance of worker and firm fixed effects (Panel B) are used as the dependent variable in equation (9), there is no meaningful relationship between either measure and changes in labor market competition.

Taken together, the evidence suggests that changes in labor market competition occurred jointly with a compression in the dispersion of firms' wage premia and wage inequality overall. Despite the robustness of our results, the estimates in Table 5 should still be understood as suggestive correlation, because of possible omitted variable bias or reverse causality. In the next section, we discuss how the 2004 EU accession could have acted as a potential driver of both trends.

7.2 Accession to the EU as a catalyst for labor market competition

We conclude our analysis by arguing that the 2004 EU accession could plausibly have operated as a catalyst for labor market competition among Lithuanian firms.

In 2020, Lithuanians working abroad amounted to more than 15% of Lithuania's population in that year, and two-thirds of them were in EU countries. This mass emigration, which accelerated with EU accession in 2004 and led to a tightening of the Lithuanian labor market, is likely to have contributed to the decline in domestic wage inequality by expanding the range of job opportunities for Lithuanian workers.[37]

Through the lens of a standard dynamic search model, more and better job opportunities (e.g., due to access to new labor markets) would lead to an increase in workers' reservation wages, as workers could use the option of migrating as a credible threat when negotiating their wages (Burdett and Mortensen, 1998). In this context, expanded job opportunities can induce wage compression among firms operating in a monopsonistic labor market by fostering job shopping and reducing job stickiness (Autor et al., 2023).[38]

To shed light on this potential channel, we compute a proxy of employment outside options for Lithuanian workers in EU countries that opened up their labor markets after 2004. In the spirit of Caldwell and Harmon (2019), for each sector s and country c already in the EU before 2004, we first calculate the increase in labor demand as the (log) change in either total hours worked (Δh_{cst+1}) or total real labor compensation (Δw_{cst+1}) between 2000 and 2020.[39,40] Each of these variables is then weighted by the share of Lithuanians who were residing in those countries in 2000, μ_{c2000}, relying on the idea that, i) individuals often learn about jobs through the network of workers who already migrated abroad, and ii) migration decision is often influenced by the existence of networks of migrants in the destination abroad (Card, 2001).[41]

[37] For example, Elsner (2013) quantifies that a 1% increase in the emigration rate of Lithuanians towards Ireland was associated with a 0.66% increase in the wages of those who stayed in Lithuania.

[38] Amior and Stuhler (2022) formulate a model of labor market monopsony where immigration induces firms to undercut native labor in destination countries when migrant labor can be purchased more cheaply.

[39] Labor compensation and hours worked are sourced from EU-KLEMS. Labor compensation is deflated using domestic CPI from FRED. Using EU-KLEMS output deflator does not alter our results. See Table C.19 in Appendix C.

[40] While changes in total hours proxy for the expansion of labor demand across sectors in EU destination countries, changes in total labor compensation further capture skill composition and wage heterogeneity, thus reflecting both quantity *and* quality changes of labor demand.

[41] Consistent with this, Figure C.10 in Appendix C shows that the share of Lithuanians in 2000 across

Formally, this shift-share variable is defined as

$$\Delta x_{st+1} = \sum_{c \in \mathcal{C}} \mu_{c2000} \Delta x_{cst+1}$$

where x refers to either total labor compensation or hours worked. This measure is meant to capture favorable sector-level developments in the EU labor markets, giving more weight to the EU countries with a large presence of Lithuanian workers prior to 2004.

Table 6: Inequality, competition, and opportunities abroad

	$\Delta\ \varepsilon_{st+1}$		$\Delta\text{var}_{st+1}[\psi_j]$	
	(1)	(2)	(3)	(4)
Δw_{st+1}	0.913		-0.053	
	(0.405)		(0.024)	
Δh_{st+1}		0.763		-0.051
		(0.449)		(0.024)
No. sectors	74	74	74	74

Notes: The dependent variable in the specifications of columns (1) and (2) is the sector-specific change in the firm labor supply elasticity (LSE) between the periods 2000-2005 and 2015-2020. The elasticities are estimated using all types of separations as Table 4 of Columns (5). The dependent variable in the specifications of columns (3) and (4) is the sector-specific change in the variance of the AKM firm fixed effects between the periods 2000-2005 and 2015-2020. Δw_{st+1} refers to the shift-share measure of sector-specific (log) changes in total labor real compensation averaged across EU destination countries, c, between 2000 and 2020. Labor compensation is deflated using national CPI. Δh_{st+1} refers to the shift-share measure of sector-specific (log) changes in total hours worked averaged across EU destination countries, c, between 2000 and 2020. Robust standard errors are in parenthesis.

We provide suggestive evidence of this channel in Table 6, where we report the OLS estimates from regressing changes in elasticities and changes in firms' pay inequality, $\Delta\varepsilon_{st+1}$ and $\Delta\text{var}_{st+1}[\psi_j]$, on either of the two shift-share measures plausibly capturing workers' outside options in pre-2004 EU countries. In line with our argument, the estimates in Table 6 suggest a positive (negative) correlation between changes in labor supply elasticity (firm wage dispersion) and changes in labor market opportunities abroad.[42] In other words, sectors in EU countries that faced the largest

countries who joined the EU before 2004 strongly correlates with where most Lithuanians who reside abroad are 20 years later.

[42]Estimates in Columns (1) and (2) of Table 6 refer to elasticities of labor supply computed using

expansions in their labor demand, measured either by growth in total hours worked or in total compensation, are, on average, exactly the same sectors that experienced the largest increases in labor supply elasticities and the strongest compression of firm pay inequality in Lithuania. Through the lens of a canonical monopsony model, EU accession in 2004 plausibly contributed to the decline in wage inequality by increasing (decreasing) the elasticity of labor supply to firms (employer market power).

8 Conclusions

Standard models of monopsonistic competition predict that increases in labor market competition would reduce firm-driven wage dispersion. In this paper, we characterize the joint dynamics of firm-driven wage dispersion and labor market competition using Social Security data for Lithuania, covering two decades of high economic growth and declining wage inequality.

We first quantify 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. Finally, we document a negative correlation between labor market competition and firm-driven wage inequality, along with suggestive evidence that EU accession in 2004 may have been a potential driver of both trends.

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 increasing worker mobility or strengthening worker bargaining power can help address firm-driven wage inequality.

all types of separation. In Table C.18, Appendix C, we report estimates based on elasticities computed using only job-to-job separation.

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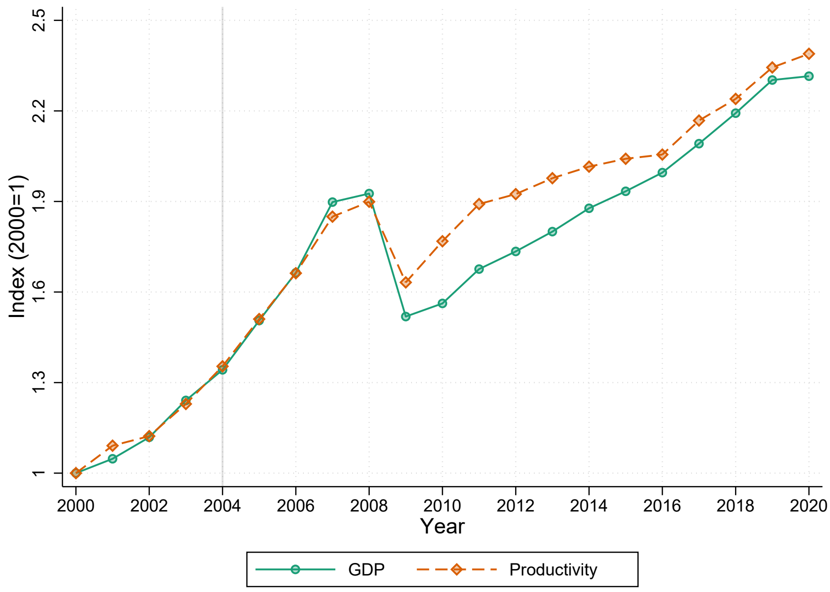
Online Appendix (not intended for publication)

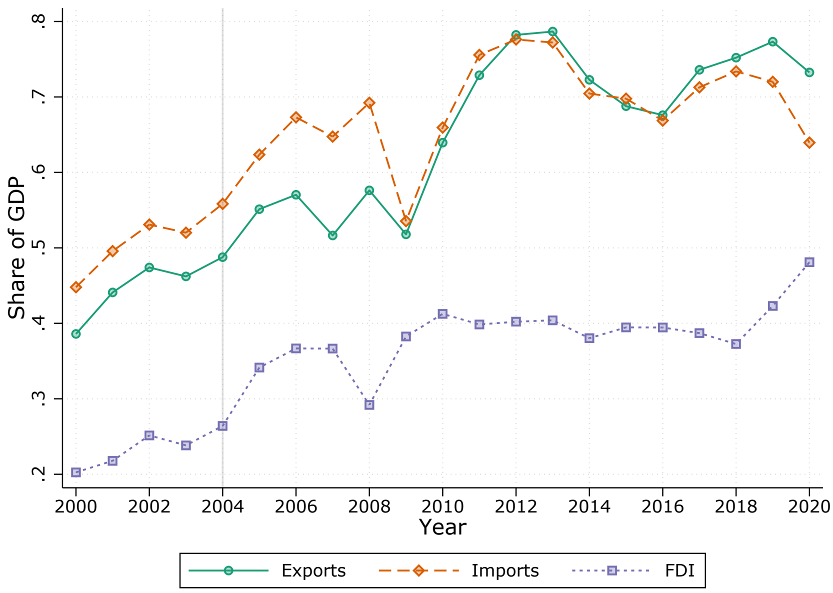
A Institutional background: Graphical evidence

Figure A.1: Economic growth



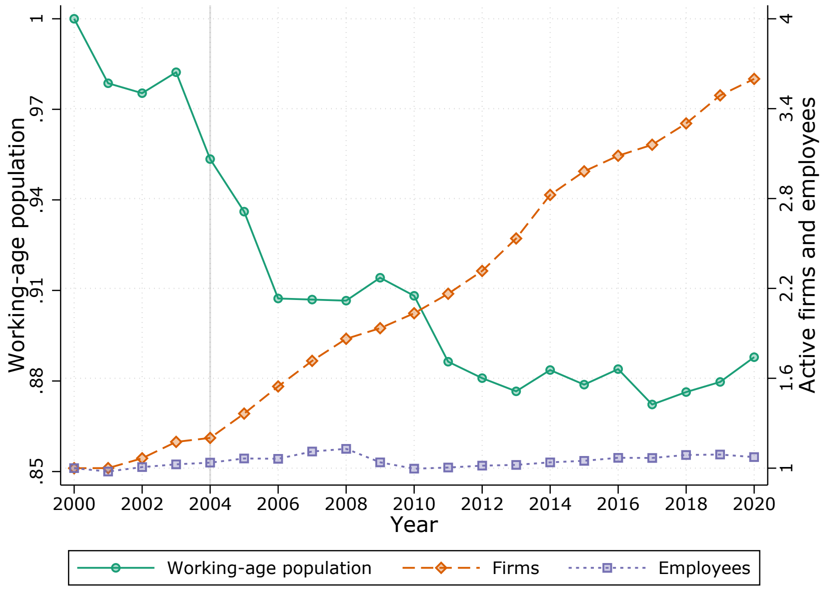
Source: Statistics Lithuania and own calculations.
Notes: The figure shows Lithuania's economic growth between 2000 and 2020, measured by gross domestic product (GDP) and gross value added per worker (productivity). The series are normalized to their value in 2000.

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



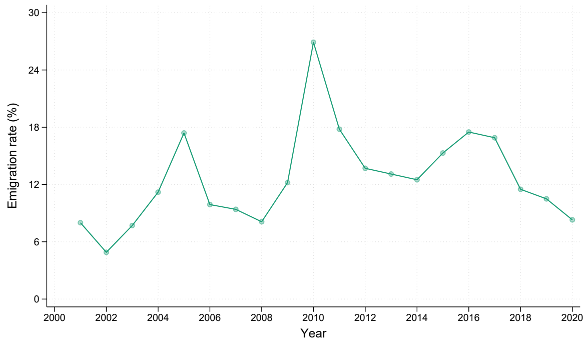
Source: Statistics Lithuania and own calculations. Notes: The figure shows the evolution of the working-age population together with the number of active enterprises and employees (rhs) in the Lithuanian economy between 2000 and 2020. The series are normalized relative to their value in 2000.

Figure A.4: Labor supply and demand

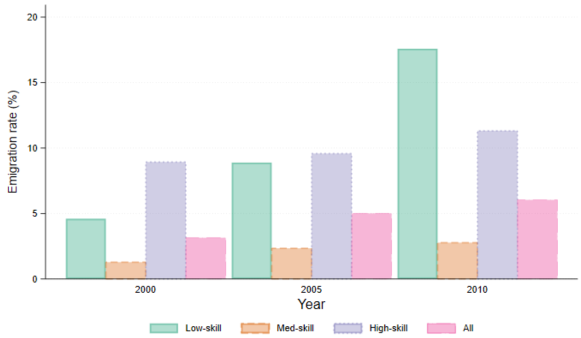
Source: Statistics Lithuania and own calculations.
Notes: The figure shows the labor supply (nonemployment and unemployment) and labor demand (job vacancies) in Lithuania between 2000 and 2020. Nonemployment is the share of the total working-age population without a job. Unemployment refers to the ratio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

Figure A.5: Emigration rate over time and skill levels

(A) Emigration rate

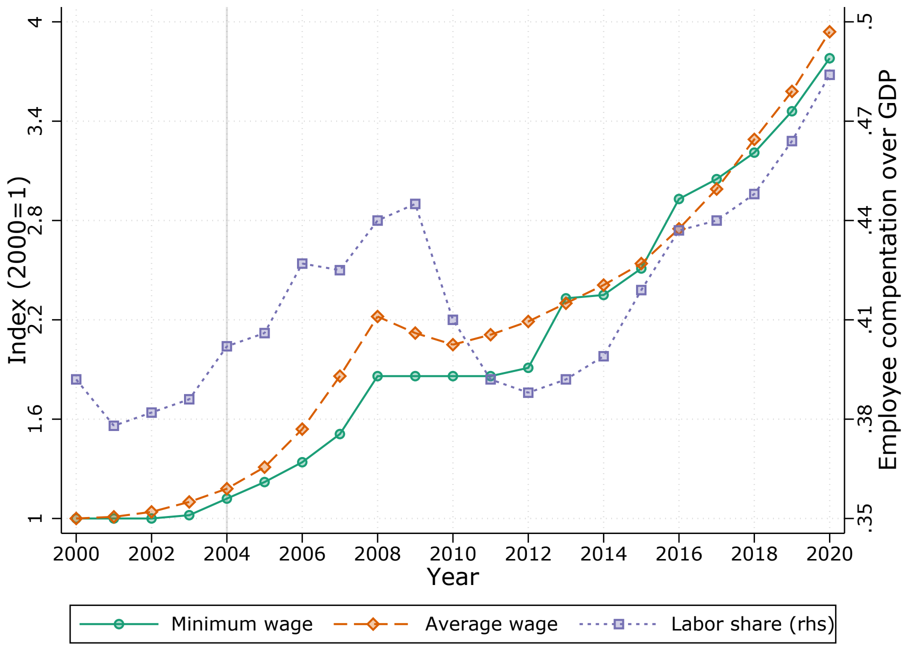


(B) Stock of emigrants by skill



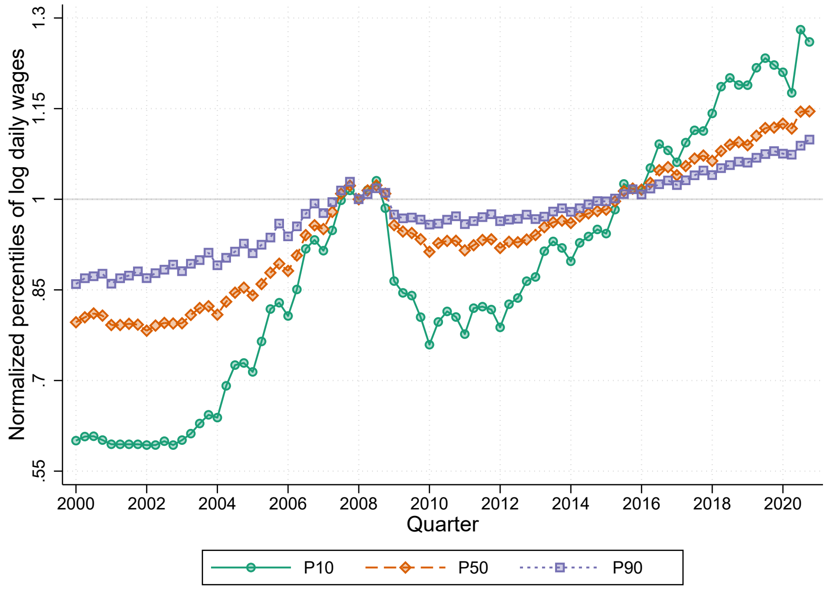
Source: Statistics Lithuania, IAB Brain Drain Data, and own calculations.
Notes: Emigration rate is the number of emigrants at the end of the year as a percentage of the Lithuanian population at the beginning of the corresponding year. Stock of emigrants by skill refers to the number of Lithuanians aged 25 and over living in Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom or the United States in a given year as a percentage of the pre-migration population in the destination countries of the same educational level and age in the corresponding year.

Figure A.6: 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.7: Dynamics of selected wage percentiles

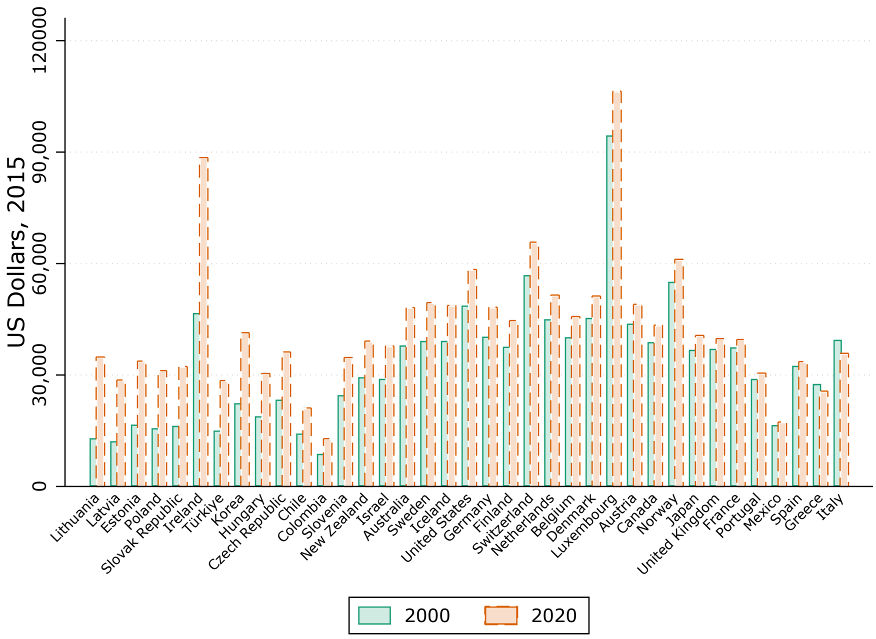


Source: Social Security records and own calculations.
Notes: The graph shows the evolution of selected percentiles of the private sector wage distribution for workers aged 20 to 60 between 2000 and 2020. Daily wages refer to quarterly income divided by days worked in a given quarter and are expressed 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 A.8: Wage vs disposable income inequality

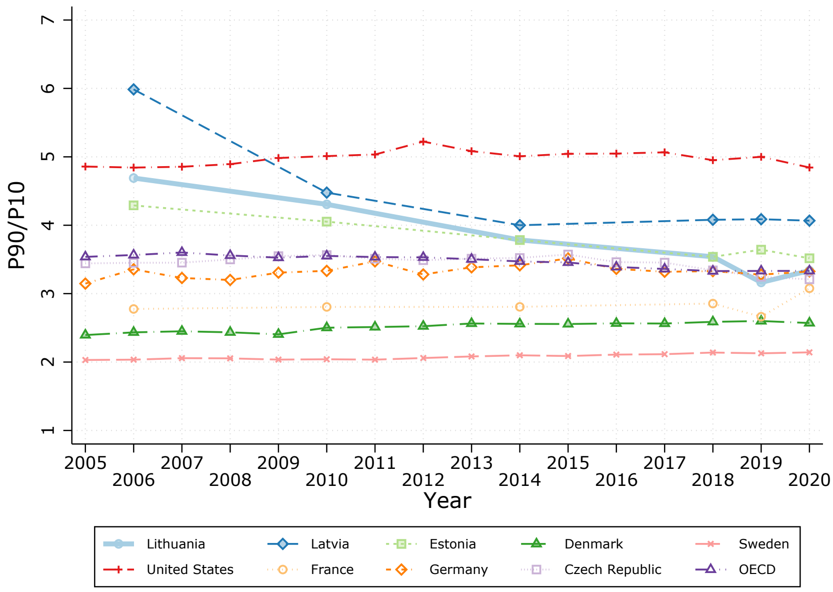
Source: Social Security records, OECD, and own calculations.
Notes: The figure compares the evolution of wage inequality and disposable income inequality. Wages refers to labor income divided by days, where labor income in the Social Security records corresponds to the insured income of workers between 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.9: 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.

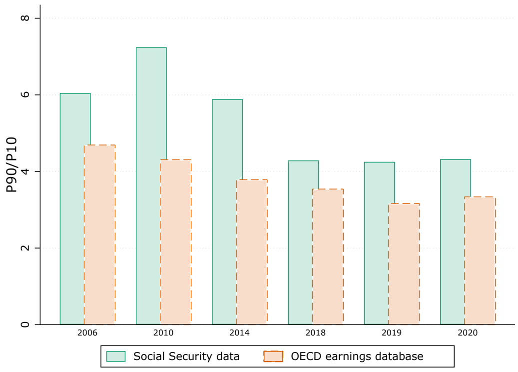
Figure A.10: Inequality across selected countries and time



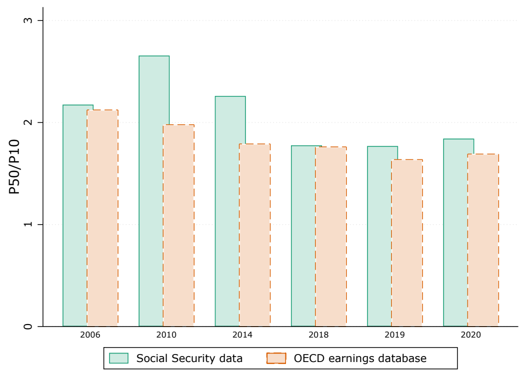
Source: OECD earnings database and own calculations.
Notes: The figure compares the evolution of gross earnings inequality across selected countries between 2005 and 2020. Inequality is measured as the ratio of the 90th percentile to the 10th percentile. Gross earnings refer to the labor income of full-time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

Figure A.11: Inequality in Social Security data vs OECD earnings database

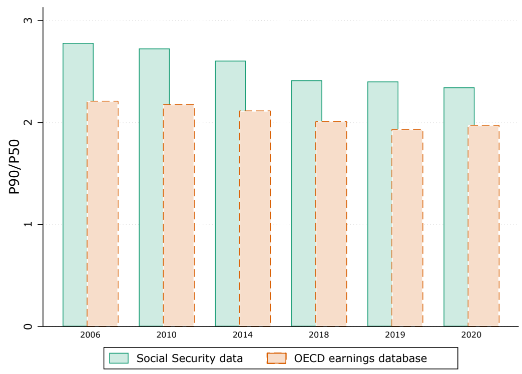
(A) Overall inequality



(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.[43]

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.[44] 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

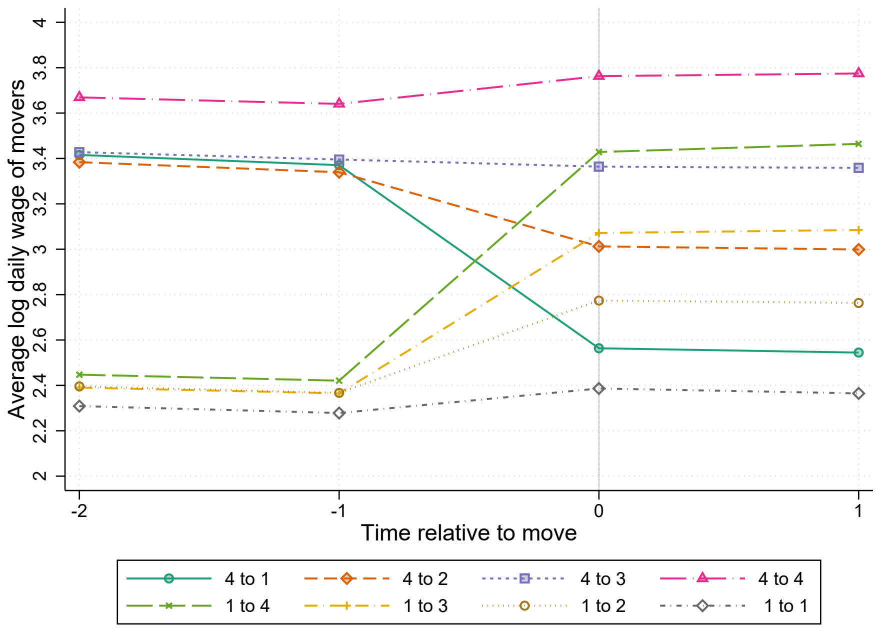
[43]The existence of match effects is just one example of a possible violation of the exogenous mobility assumption. Card et al. (2018) provide extensive discussion and examples of situations where the exogenous mobility assumption may be violated.

[44]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).

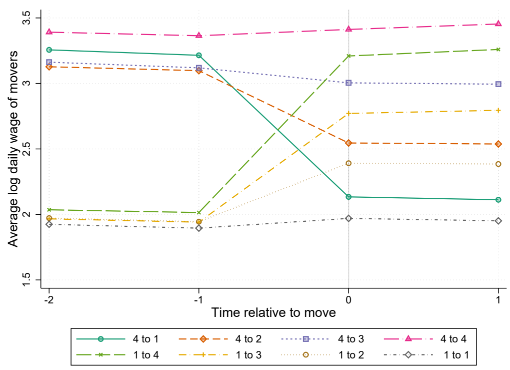
who fall to the bottom of the job ladder exhibit wage losses, and these wage changes are almost symmetric (see Figure B.2). Therefore, the absence of an overall mobility premium for workers who remain in the same firm fixed effect quartile, along with wages moving in (nearly symmetric) opposite directions 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 premia seem to be additively separable.

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

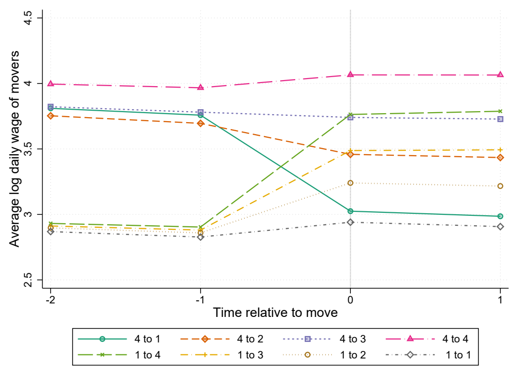
(A) 2000-2020



(B) 2000-2005



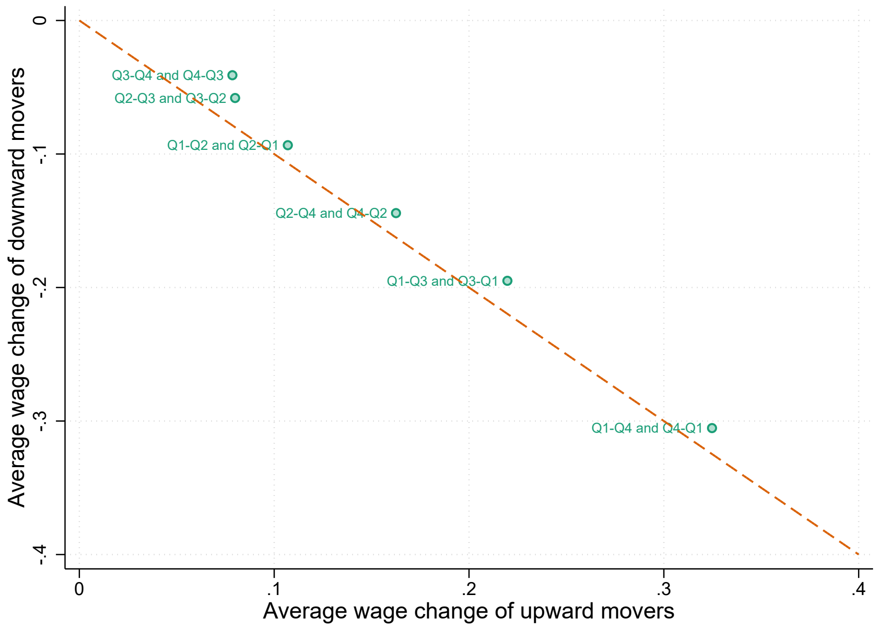
(C) 2015-2020



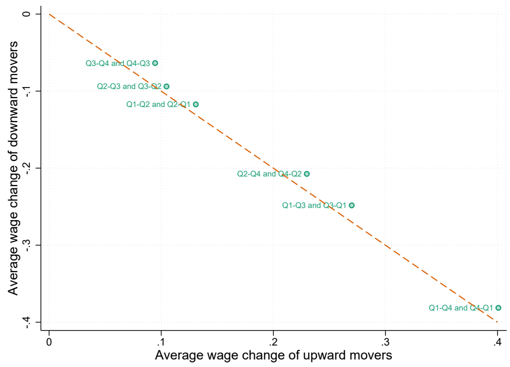
Source: Social Security records and own calculations.
Notes: Panel A shows the average daily wage of workers observed between 2000 and 2020 who changed jobs and held the old job for two or more quarters and the new job for two or more quarters, while Panel B and C report the wage dynamics of movers by 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

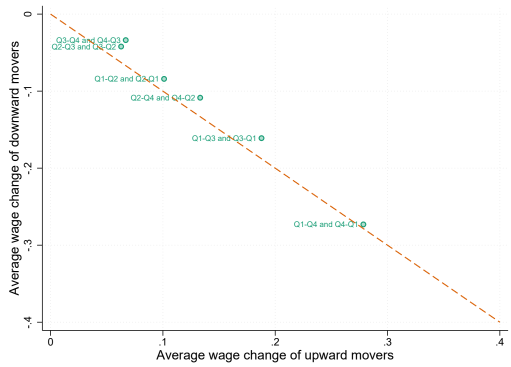
(A) 2000-2020



(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).

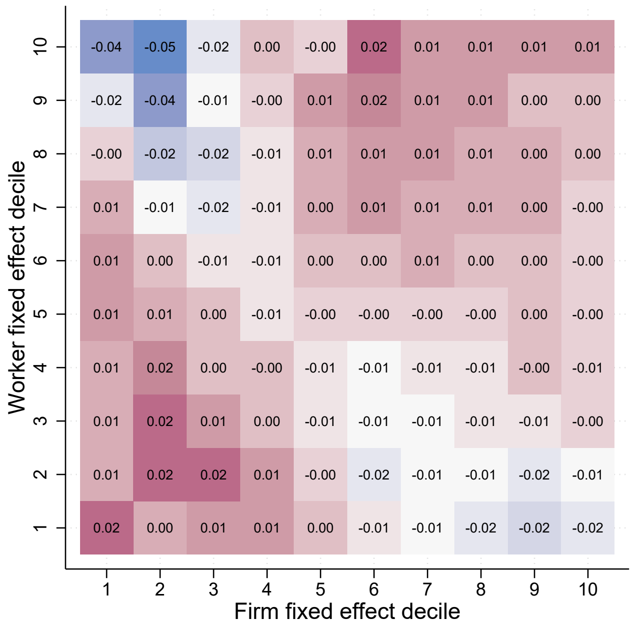
B.2 Additive separability

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.

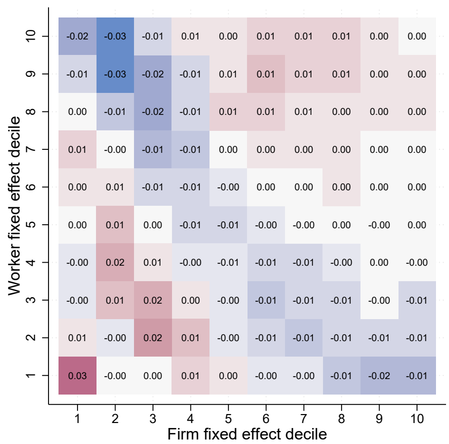
To explore the assumption of additive separability more thoroughly, we estimate the CHK match effects model (Card et al., 2013), which allows us to assess the relevance of idiosyncratic worker-firm matches in explaining the variance of wages relative to the AKM model. The idea is that if match effects 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

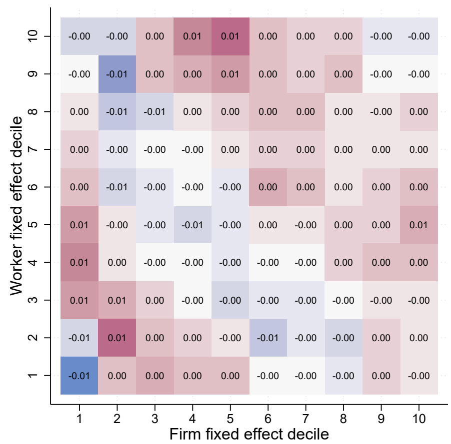
(A) 2000-2020



(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

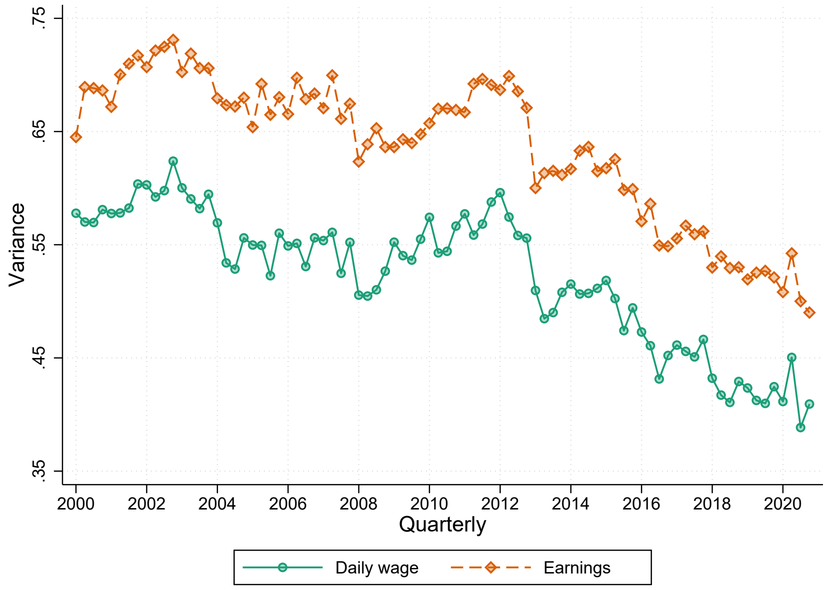
	2000-2020		2000-2005		2015-2020	
	AKM	CHK	AKM	CHK	AKM	CHK
Adj. R-squared	0.792	0.849	0.846	0.878	0.820	0.852
RMSE	0.354	0.302	0.298	0.267	0.283	0.262

Notes: AKM refers to model specification in equation (1). CHK is a match effects model where worker and firm 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

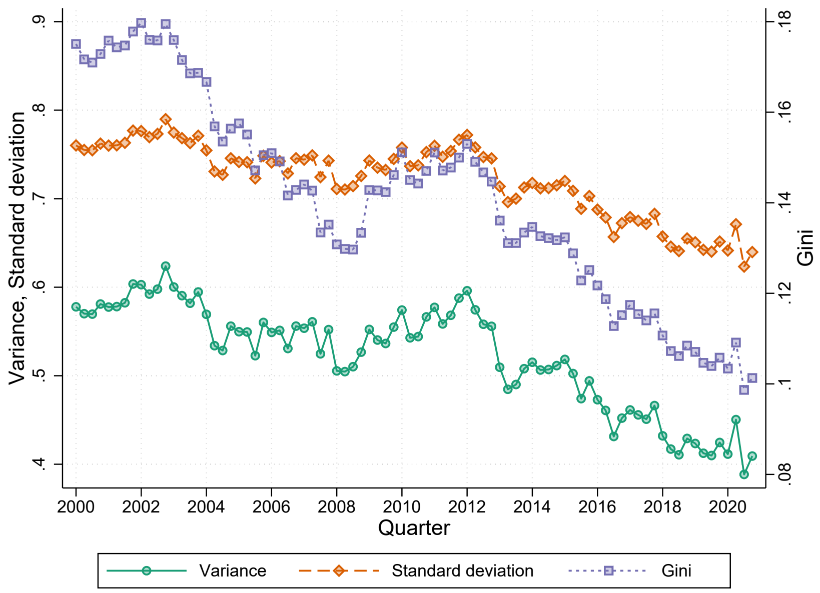
C.1 Inequality trends in the estimation sample

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.

C.2 Firm-driven inequality

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 column allow age profiles and year effects to vary between men and women. Wages-centered column uses as a dependent variable the deviation of individuals' wages from the average wage in a given quarter. Residual wages column relies 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×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, 600, and 6000 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 indicators 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.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).

C.3 Shift-share decomposition

We follow Foster et al. (2001) and decompose the aggregate change in the variance of ψ_j, $\Delta\text{var}_{t+1}[\psi_j]$ as:

$$\Delta\text{var}_{t+1}[\psi_j] = \sum_{s\in\mathcal{S}} \Delta n_{st+1}\text{var}_{st}[\psi_j] + \sum_{s\in\mathcal{S}} n_{st+1}\Delta\text{var}_{st+1}[\psi_j]$$

where n_{st+1} denote the employment share of sector s at time $t+1$, $\text{var}_{st}[\psi_j]$ is the variance of the firm pay policies in sector s at time t, Δn_{st+1} is the change in employment share of sector s over time, and $\Delta\text{var}_{st+1}[\psi_j]$ is the change in the variance of the firm pay policies in sector s over time. The first term represents a *between-sector* component that reflects changing employment shares, weighted by the variance in the *initial* period. The second term represents a *within-sector* component based on the change in variance for a given sector s between the two periods, weighted by the *final* employment shares of that sector.

Notice that the second term can broken into two separate pieces, i.e.,

$$\sum_{s\in\mathcal{S}} n_{st+1}\Delta\text{var}_{st+1}[\psi_j] = \sum_{s\in\mathcal{S}} n_{st}\Delta\text{var}_{st+1}[\psi_j] + \sum_{s\in\mathcal{S}} \Delta n_{st+1}\Delta\text{var}_{st+1}[\psi_j]$$

where the *within-sector* component is now weighted by the *initial* employment shares of each sector, while the second term represents a *cross-term* that relates changes in employment shares to changes in variance. Table C.10 reports the contributions of each term to the change in the variance of the AKM and BLM firms' fixed effects.

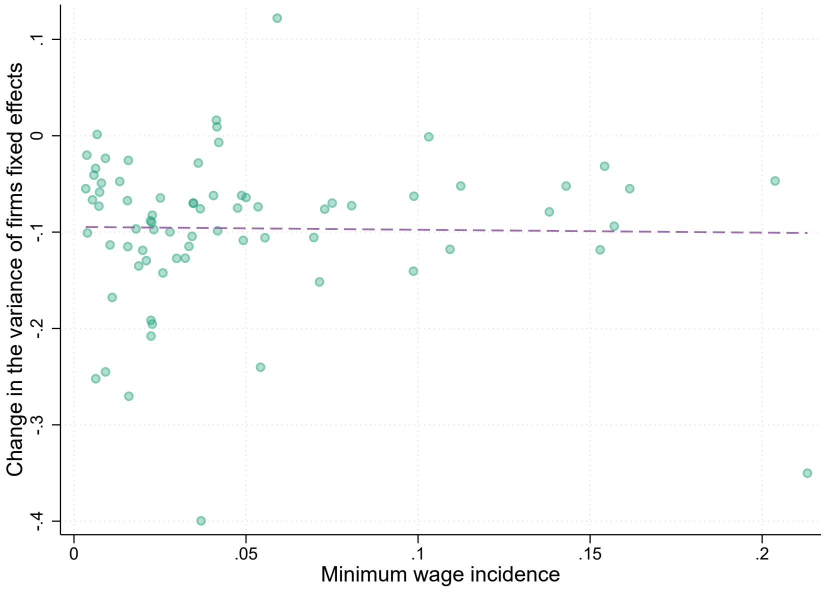
Table C.10: Sectoral decomposition

	AKM		BLM	
	Estimate	Contribution (%)	Estimate	Contribution (%)
	(1)	(2)	(3)	(4)
Change in $Var(y)$	-0.131	-	-0.136	-
Change in $Var(\psi)$	-0.118	89.8	-0.127	93.0
Within-sector	-0.084	71.2	-0.061	48.0
Between-sector	0.016	-13.5	0.006	-4.7
Cross-term	-0.050	42.3	-0.072	56.7

Notes: Column (1) reports the observed change in wage dispersion between 2000-2005 and 2015-2020, the estimated change in AKM firm-pay policies, and its decomposition in within- and between-sector components following Foster et al. (2001). Column (2) reports the % contribution of each component.

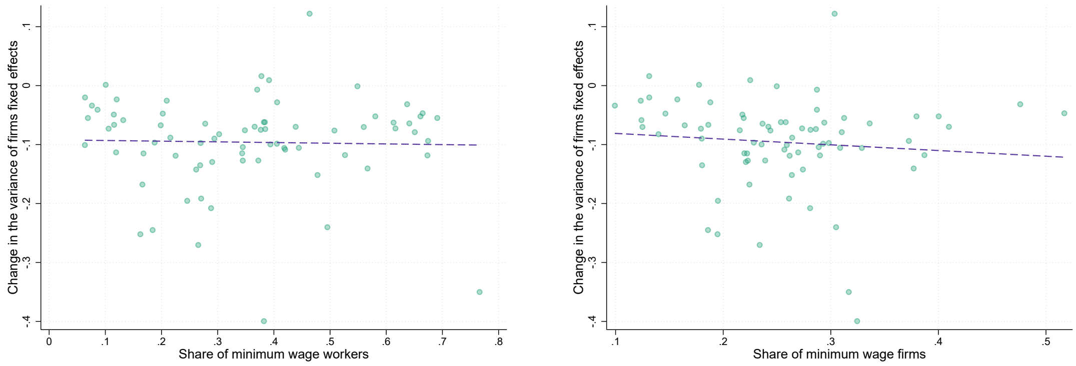
C.4 Role of minimum wage

Figure C.3: Changes in the variance of firm fixed effects and minimum wage incidence



Source: Social Security records and own calculations.
Notes: Changes in the variance of firm fixed effects is the difference between the sector-specific variance of firm fixed effects in 2015-2020 and that in 2000-2005. Minimum wage incidence refers to the bite of the minimum wage across sectors in the initial period, 2000-2005. For each sector s, the minimum wage incidence is computed as $\frac{\sum_{i\in s}\max\{0, MW - w_{it}\}}{\sum_{i\in s} w_{it}}$ where MW is the prevailing daily minimum wage, w_{it} refers to the daily income of worker i at time t. Only sectors with at least 20 firms are included for a total of 74 sectors.

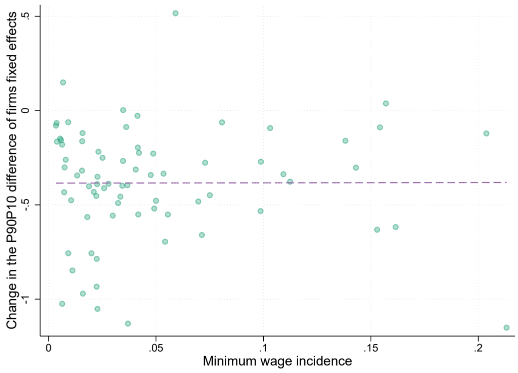
Figure C.4: Changes in the variance of firm fixed effects and the minimum wage



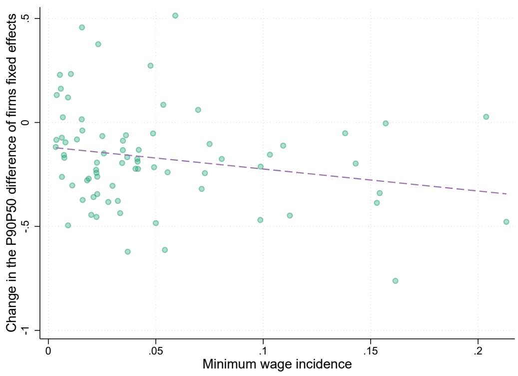
Source: Social Security records and own calculations.
Notes: Changes in the variance of firm fixed effects is the difference between the sector-specific variance of firm fixed effects in 2015-2020 and that in 2000-2005. Minimum wage incidence refers to the bite of the minimum wage across sectors in the initial period. In Panel A, the share of minimum wage workers is the sector-specific share of workers whose earnings are at or below the current minimum wage. In Panel B, the share of minimum wage firms is the sector-specific share of firms where the minimum wage is at least 75% of the firm's average wage. Only sectors with at least 20 firms are included for a total of 74 sectors.

Figure C.5: Changes in the percentile difference of firm fixed effects and the minimum wage

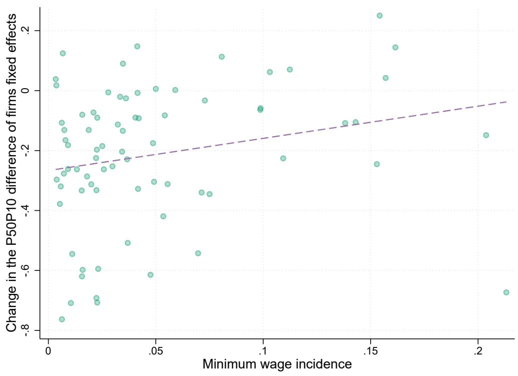
(A) P90-P10



(B) P90-P50



(C) P50-P10

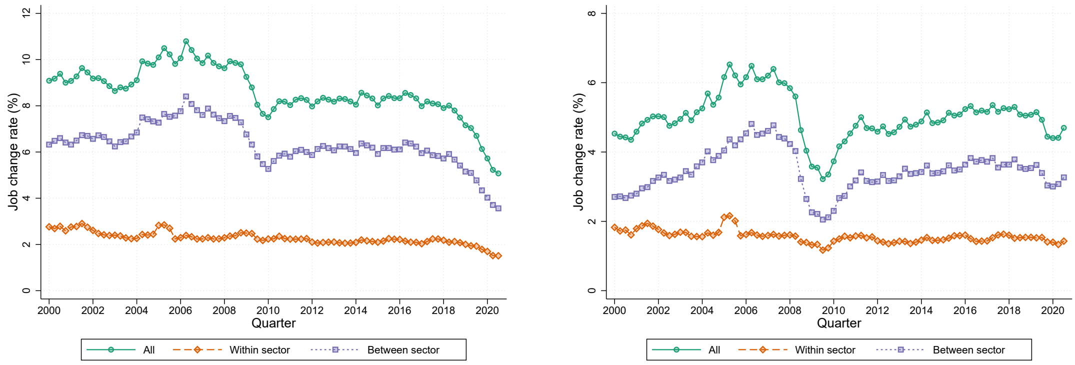


Source: Social Security records and own calculations.
Notes: Changes in the percentile differences of firm fixed effects refer to the difference between the sector-specific percentiles of firm fixed effects in 2015-2020 and that in 2000-2005. Minimum wage incidence refers to the bite of the minimum wage across sectors in the initial period, 2000-2005. For each sector s, the minimum wage incidence is computed as $\frac{\sum_{i \in s} \max\{0, MW - w_{it}\}}{\sum_{i \in s} w_{it}}$ where MW is the prevailing daily minimum wage, w_{it} refers to the daily income of worker i at time t. Only sectors with at least 20 firms are included for a total of 74 sectors.

C.5 Firm's labor supply elasticity

Figure C.6: Job changes between and within sectors, 2000-2020

(A) All job changes **(B)** Direct job changes



Source: Social Security records and own calculations.
Notes: All job changes in Panel A include all individuals who changed jobs between 2000 and 2020. Direct job changes in Panel B refer to individuals who changed within two consecutive quarters. Within sector represents job changes that did not involve a change in the 2-digit industry, while between sector captures individuals who change jobs *and* 2-digit industries.

Table C.11: 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 the independent variable. In the IV-firm fixed effects, we follow 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, time effects, and 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.12: Firm labor supply elasticity, 2005-2010 and 2010-2015

A. 2005-2010	Worker wage		Firm fixed effect		IV-Firm fixed effect	
	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep
	(1)	(2)	(3)	(4)	(5)	(6)
β	-0.0675	-0.0246	-0.0494	-0.0199	-0.0680	-0.0352
	(0.0004)	(0.0003)	(0.0014)	(0.0008)	(0.0021)	(0.0011)
ϵ_{LS}	1.1104	0.9268	0.8139	0.7528	1.1184	1.3281
	(0.0177)	(0.0195)	(0.0238)	(0.0297)	(0.0347)	(0.0399)
First stage F-statistic					10,105.15	
Observations	4,561,130	4,561,130	4,561,130	4,561,130	4,561,130	4,561,130

B. 2010-2015	Worker wage		Firm fixed effect		IV-Firm fixed effect	
	Sep	EE Sep	Sep	EE Sep	Sep	EE Sep
	(1)	(2)	(3)	(4)	(5)	(6)
β	-0.0694	-0.0274	-0.0570	-0.0257	-0.0852	-0.0458
	(0.0004)	(0.0003)	(0.0015)	(0.0009)	(0.0022)	(0.0012)
ϵ_{LS}	1.2788	1.1370	1.0510	1.0654	1.5703	1.9003
	(0.0234)	(0.0259)	(0.0278)	(0.0378)	(0.0406)	(0.0485)
First stage F-statistic					12,205.60	
Observations	4,181,332	4,181,332	4,181,332	4,181,332	4,181,332	4,181,332

Notes: Panel A and B estimate period-specific linear probability models as specified Equation (8) 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. ε_{LS} refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

Table C.13: Separation semi-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
β	-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
B. 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
β	-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 (8) 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.14: Firm labor supply elasticity: Workers with AKM FE below median

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)
β	-0.0674	-0.0235	-0.0552	-0.0241	-0.0856	-0.0451
	(0.0007)	(0.0004)	(0.0029)	(0.0013)	(0.0036)	(0.0018)
ϵ_{LS}	0.9520	0.8651	0.7798	0.8872	1.2093	1.6626
	(0.0092)	(0.0148)	(0.0413)	(0.0462)	(0.0514)	(0.0665)
First stage F-statistic					2,328.86	
Observations	2,074,976	2,074,976	2,074,976	2,074,976	2,074,976	2,074,976
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)
β	-0.0875	-0.0271	-0.0730	-0.0299	-0.1036	-0.0538
	(0.0007)	(0.0005)	(0.0021)	(0.0011)	(0.0036)	(0.0019)
ϵ_{LS}	1.3317	1.0121	1.1122	1.1173	1.5776	2.0090
	(0.0112)	(0.0178)	(0.0317)	(0.0428)	(0.0550)	(0.0695)
First stage F-statistic					9,975.29	
Observations	2,202,037	2,202,037	2,202,037	2,202,037	2,202,037	2,202,037

Notes: Panel A and B estimate period-specific linear probability models as specified Equation (8) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. The models are estimated in the sample of workers with AKM worker FE at or below the median of the period-specific distribution. 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. ε_{LS} refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

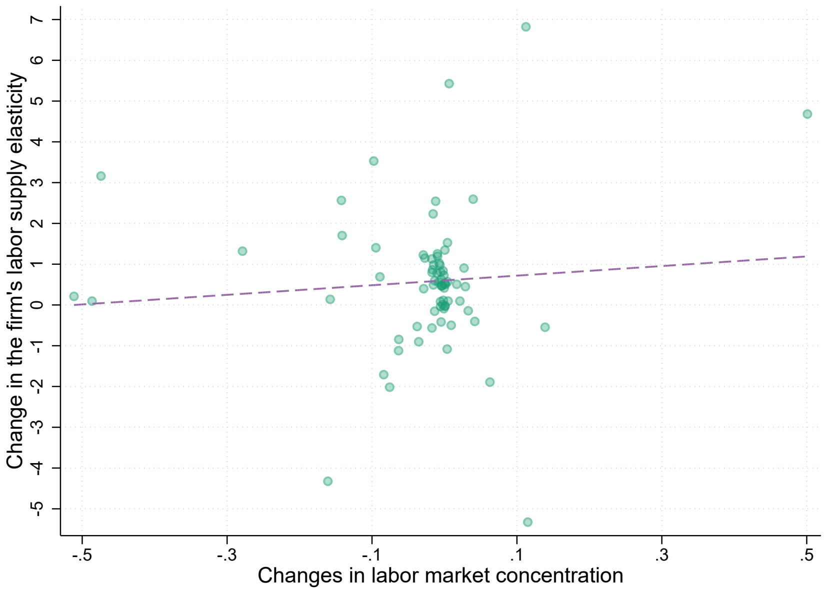
Table C.15: Firm labor supply elasticity: Workers with AKM FE above median

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)
β	-0.0526	-0.0249	-0.0403	-0.0185	-0.0742	-0.0405
	(0.0005)	(0.0004)	(0.0015)	(0.0010)	(0.0020)	(0.0014)
ϵ_{LS}	1.1529	1.0236	0.8842	0.7613	1.6261	1.6690
	(0.0108)	(0.0148)	(0.0332)	(0.0425)	(0.0430)	(0.0570)
First stage F-statistic					3,576.39	
Observations	2,074,947	2,074,947	2,074,947	2,074,947	2,074,947	2,074,947
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)
β	-0.0668	-0.0293	-0.0417	-0.0193	-0.0910	-0.0474
	(0.0006)	(0.0004)	(0.0014)	(0.0010)	(0.0021)	(0.0014)
ϵ_{LS}	1.4158	1.1625	0.8840	0.7665	1.9285	1.8814
	(0.0134)	(0.0175)	(0.0301)	(0.0394)	(0.0449)	(0.0562)
First stage F-statistic					10,122.45	
Observations	2,202,027	2,202,027	2,202,027	2,202,027	2,202,027	2,202,027

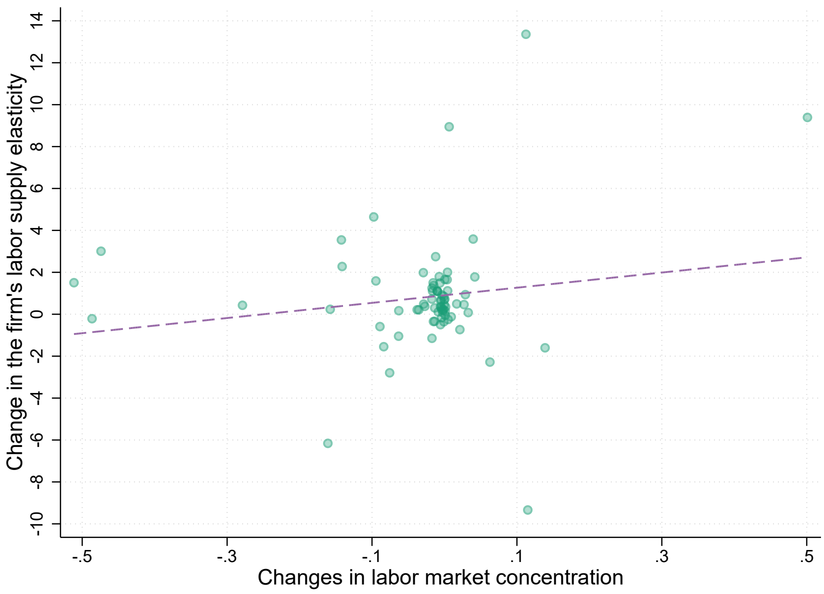
Notes: Panel A and B estimate period-specific linear probability models as specified Equation (8) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. The models are estimated in the sample of workers with AKM worker FE above the median of the period-specific distribution. 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. ε_{LS} refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

Figure C.7: Changes in the firm's labor supply elasticity and industry concentration

(A) All separations



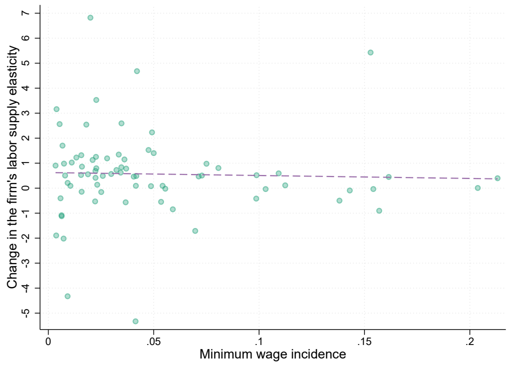
(B) Job-to-job



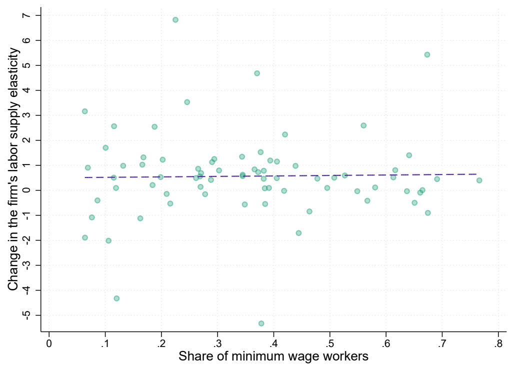
Source: Social Security records and own calculations.
Notes: Changes in the firm's labor supply elasticity are the difference in the sector-specific firm's labor supply elasticity in 2015-2020 and that in 2000-2005. Changes in industry concentration refer to differences in sector-specific wage-bill Herfindahl index between 2015-2020 and 2000-2005. Panel A relies on all separations to estimate the elasticity, whereas Panel B exploits only job-to-job transitions. There are 74 sectors.

Figure C.8: Changes in the firm's labor supply elasticity (all separations) and the minimum wage

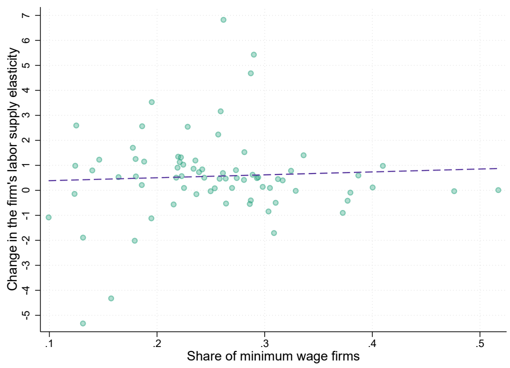
(A) MW incidence



(B) MW workers



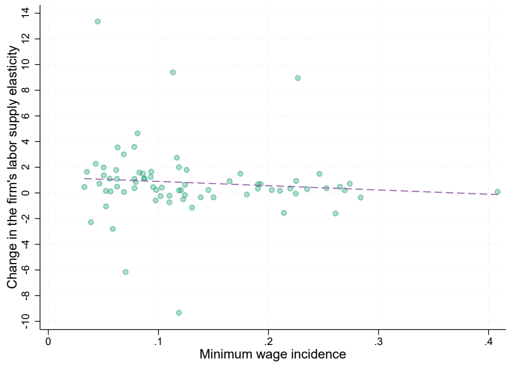
(C) MW firms



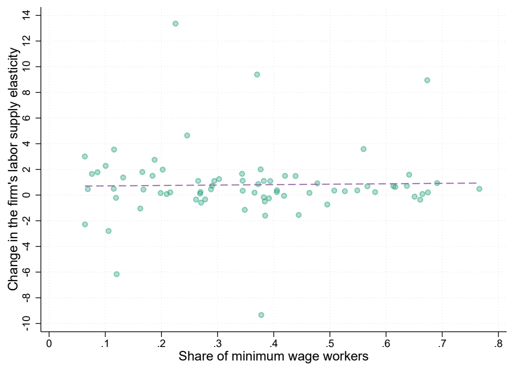
Source: Social Security records and own calculations.
Notes: Changes in the firm's labor supply elasticity are the difference in the sector-specific firm's labor supply elasticity in 2015-2020 and that in 2000-2005. The elasticity is estimated using all types of separations. In Panel A, for each sector s, the minimum wage incidence is computed as $\frac{\sum_{i \in s} max\{0, MW - w_{is}\}}{\sum_{i \in s} w_{is}}$ where MW is the prevailing daily minimum wage, w_{is} refers to the daily income of worker i in sector s. In Panel B, the share of minimum wage workers is the sector-specific share of workers whose earnings are at or below the current minimum wage. In Panel C, the share of minimum wage firms is the sector-specific share of firms where the minimum wage is at least 75% of the firm's average wage. There are 74 sectors.

Figure C.9: Changes in the firm's labor supply elasticity (job-to-job transitions) and the minimum wage

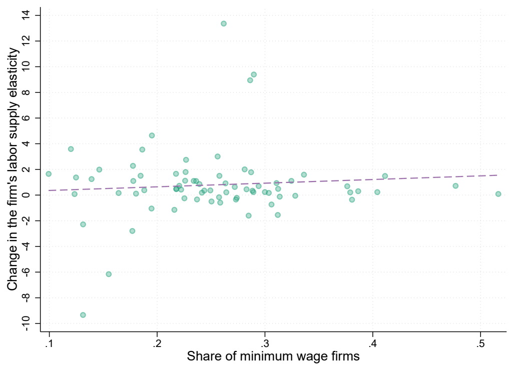
(A) MW incidence



(B) MW workers



(C) MW firms



Source: Social Security records and own calculations.
Notes: Changes in the firm's labor supply elasticity are the difference in the sector-specific firm's labor supply elasticity in 2015-2020 and that in 2000-2005. The elasticity is estimated using job-to-job transitions. In Panel A, for each sector s, the minimum wage incidence is computed as $\frac{\sum_{i \in s} max\{0, MW - w_{is}\}}{\sum_{i \in s} w_{is}}$ where MW is the prevailing daily minimum wage, w_{is} refers to the daily income of worker i in sector s. In Panel B, the share of minimum wage workers is the sector-specific share of workers whose earnings are at or below the current minimum wage. In Panel C, the share of minimum wage firms is the sector-specific share of firms where the minimum wage is at least 75% of the firm's average wage. There are 74 sectors.

C.6 Co-movement of inequality and competition

Table C.16: Variance of workers fixed effects, Covariance worker and firm fixed effects, and firm's labor supply elasticity

A. $\Delta \text{var}_{st+1}[\eta]$	All separations		Job-to-job	
	OLS	ORIV	OLS	ORIV
	(1)	(2)	(3)	(4)
$\Delta\ \varepsilon_{st+1}$	-0.0094	-0.0097	-0.0056	0.0051
	(0.0045)	(0.0089)	(0.0029)	(0.0154)
B. $\Delta \text{cov}_{st+1}[\psi, \eta]$	All separations		Job-to-job	
	OLS	ORIV	OLS	ORIV
	(1)	(2)	(3)	(4)
$\Delta\ \varepsilon_{st+1}$	-0.0000	0.0198	-0.0006	0.0125
	(0.0034)	(0.0170)	(0.0024)	(0.0205)
Full set of controls	✓	✓	✓	✓
No. sectors	74	74	74	74

Notes: The dependent variable in Panel A (Panel B) is the sector-specific change in the variance (covariance) of the AKM worker (firm and worker) fixed effects between the periods 2000-2005 and 2015-2020. The change in the firm labor supply elasticity (LSE) refers to the sector-specific change between the periods 2000-2005 and 2015-2020. The elasticities are estimated as Table 4 Columns (5) for all separations and (6) for job-to-job transitions. ORIV 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. The full set of controls includes sector-specific changes in the variance of the log firm size, the sector-specific elasticity in the final period 2015-2020, the sector-specific changes in the wage bill HH index, and the sector-specific incidence of the minimum wage in the initial period, 2000-2005. Only sectors with at least 20 firms are included. Robust standard errors are in parentheses.

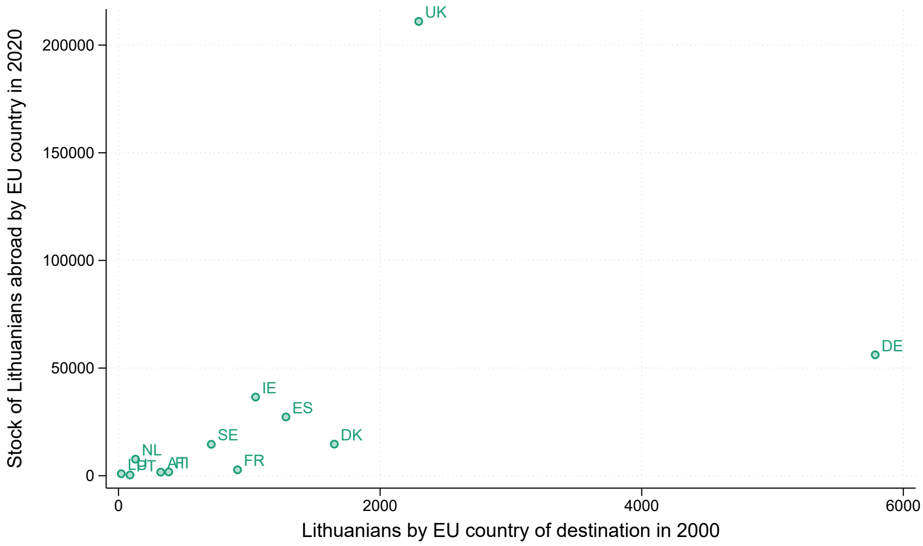
Table C.17: Dispersion of firm fixed effects and firm's labor supply elasticity (job-to-job)

	Δ var$_{st+1}[\psi_j]$			ΔP90P10	ΔP50P10	ΔP90P50
	OLS	OLS	ORIV	ORIV	ORIV	ORIV
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ \varepsilon_{st+1}$	-0.0126	-0.0146	-0.0422	-0.1769	-0.1790	0.0021
	(0.0038)	(0.0038)	(0.0287)	(0.1214)	(0.1388)	(0.0759)
Implied %Δ var[y]	6.2	7.1	20.6	-	-	-
Model-based controls	✓					
Full set of controls		✓	✓	✓	✓	✓
No. sectors	74	74	74	74	74	74

Notes: The dependent variable in the specifications of columns (1) to (3) is the sector-specific change in the variance of the AKM firm fixed effects between the periods 2000-2005 and 2015-2020. The dependent variable in the specifications of columns (4) to (6) is the sector-specific change in the specified percentile difference of firm fixed effects. The change in the firm labor supply elasticity (LSE) refers to the sector-specific change between the periods 2000-2005 and 2015-2020. The elasticities are estimated using only job-to-job transitions as in Columns (6) of Table 4. ORIV 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. Model-based controls refer to sector-specific changes in the variance of the log firm size and the sector-specific elasticity in the final period, 2015-2020. The full set of controls includes the model-based controls plus the sector-specific changes in the wage bill HH index and the sector-specific minimum wage incidence in the initial period, 2000-2005. Only sectors with at least 20 firms are included. The change of wage inequality explained by the increase in competition is computed as $0.9 \times \sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta} \Delta\varepsilon_{st+1} \times (\sum_{s=1}^{S} \frac{L_{st}}{L_t} \Delta \text{var}_{st+1}[\psi_{jt+1}])^{-1} \times 100$. Robust standard errors are in parentheses.

C.7 2004 EU accession

Figure C.10: Lithuanians in pre-2004 EU countries



Source: Statistics Lithuania, IAB Brain Drain dataset, and own calculations.
Notes: Selected EU countries refer to economies that were part of the European Union before the 2004 enlargement with available data on both foreign-born populations and EU-KLEMS.

Table C.18: Competition and opportunities abroad - Job-to-job elasticity

	$\Delta\ \varepsilon_{st+1}$	
	(1)	(2)
Δw_{st+1}	0.835	
	(0.598)	
Δh_{st+1}		0.722
		(0.644)
No. sectors	74	74

Notes: The dependent variable is the sector-specific change in the firm labor supply elasticity (LSE) between the periods 2000-2005 and 2015-2020. The elasticities are estimated using job-to-job separations as Table 4 of Columns (6). Δw_{st+1} refers to the shift-share measure of sector-specific (log) changes in total labor real compensation averaged across EU destination countries, c, between 2000 and 2020. Labor compensation is deflated using the final output deflator. Δh_{st+1} refers to the shift-share measure of sector-specific (log) changes in total hours worked averaged across EU destination countries, c, between 2000 and 2020. Robust standard errors are in parenthesis.

Table C.19: Inequality, competition, and opportunities abroad - Output deflator

	$\Delta\ \varepsilon_{st+1}$	$\Delta \text{var}_{st+1}[\psi_j]$
	(1)	(2)
Δw_{st+1}	1.051	-0.124
	(0.623)	(0.041)
No. sectors	74	74

Notes: The dependent variable in the specification of columns (1) is the sector-specific change in the firm labor supply elasticity (LSE) between the periods 2000-2005 and 2015-2020. The elasticity is estimated using all types of separations as Table 4 of Columns (5). The dependent variable in the specification of columns (2) is the sector-specific change in the variance of the AKM firm fixed effects between the periods 2000-2005 and 2015-2020. Δw_{st+1} refers to the shift-share measure of sector-specific (log) changes in total labor real compensation averaged across EU destination countries, c, between 2000 and 2020. Labor compensation is deflated using final output deflator. Robust standard errors are in parenthesis.

D Model derivation

We start from the first-order condition with respect to wages, which is equal to

$$\left[\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt} + \beta \frac{\partial \Pi(L_{jt})}{\partial L_{jt}}\right] \frac{\partial L_{jt}}{\partial w_{jt}} \frac{w_{jt}}{L_{jt}} = w_{jt},$$

and it corresponds to equation (5) in the main text. Differentiating the firm value function in equation (3) of the main text with respect to employment, we obtain that

$$\frac{\partial \Pi(L_{jt-1})}{\partial L_{jt-1}} = \left[\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt} + \beta \frac{\partial \Pi(L_{jt})}{\partial L_{jt}}\right] \frac{\partial L_{jt}}{\partial L_{jt-1}}.$$

Using the envelope condition in steady state, we can solve for $\frac{\partial \Pi(L_{jt})}{\partial L_{jt}}$

$$\frac{\partial \Pi(L_{jt})}{\partial L_{jt}} = \frac{\left[\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}\right] \frac{\partial L_{jt}}{\partial L_{jt-1}}}{1 - \beta \frac{\partial L_{jt}}{\partial L_{jt-1}}}.$$

Substituting it back to the first order condition (5), we get

$$\left[\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}\right] \left(1 + \frac{\beta \frac{\partial L_{jt}}{\partial L_{jt-1}}}{1 - \beta \frac{\partial L_{jt}}{\partial L_{jt-1}}}\right) \frac{\partial L_{jt}}{\partial w_{jt}} \frac{w_{jt}}{L_{jt}} = w_{jt},$$

which simplifies to

$$\frac{\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}}{w_{jt}} = \left(1 - \beta \frac{\partial L_{jt}}{\partial L_{jt-1}}\right) \frac{1}{B_t w_{jt}^{-\varepsilon_{sept}} [\varepsilon_{Rt} - \varepsilon_{sept}]},$$

where we used the fact that

$$\left(\frac{\partial L_{jt}}{\partial w_{jt}} \frac{w_{jt}}{L_{jt}}\right) = B_t w_{jt}^{-\varepsilon_{sept}} [\varepsilon_{Rt} - \varepsilon_{sept}].$$

From the law of motion of employment (equation (4)), we know that

$$\frac{\partial L_{jt}}{\partial L_{jt-1}} = 1 - B_t w_{jt}^{-\varepsilon_{sept}},$$

which implies that

$$\frac{\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}}{w_{jt}} = (1 - \beta + \beta B_t w_{jt}^{-\varepsilon_{sept}}) \frac{1}{\left(B_t w_{jt}^{-\varepsilon_{sept}} [\varepsilon_{Rt} - \varepsilon_{sept}]\right)}.$$

For low enough future discounting (i.e., $\beta \approx 1$), the condition above can be written as follows

$$\frac{\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}}{w_{jt}} \approx \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}.$$

The degree of monopsony power is then given by the elasticity of the labor supply curve facing the firm. Re-arranging terms, we get:

$$w_{jt} \approx \frac{1}{\left(1 + \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}\right)} \alpha z_{jt} L_{jt}^{\alpha-1}.$$

Taking logs,

$$\log w_{jt} \approx \log z_{jt} - (1-\alpha) \log L_{jt} - \log \left(1 + \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}\right) + \log \alpha.$$

Since, in a steady state, firm-level employment is equal to

$$L_{jt} = \frac{R(w_{jt})}{s(w_{jt})} = \frac{A_t}{B_t} w_{jt}^{\varepsilon_{Rt} - \varepsilon_{sept}},$$

then the equation for log wages becomes

$$\log w_{jt} \approx \log z_{jt} - (1-\alpha)[\varepsilon_{Rt} - \varepsilon_{sept}] \log (w_{jt}) + C_t,$$

where C is a market constant, possibly time-varying, and equal to:

$$C_t = (1-\alpha) \log \left(\frac{A_t}{B_t}\right) - \log \left(1 + \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}\right) + \log \alpha.$$

The equation above allows us to solve for log wages and to compute log wage dispersion equal to

$$
\begin{aligned}
\text{var}_t[\log w_{jt}] &\approx \left(\frac{1}{1+(1-\alpha)[\varepsilon_{Rt}-\varepsilon_{sept}]}\right)^2 \text{var}_t\left[\log z_{jt}\right] \\
&\approx \left(\frac{1}{1+(1-\alpha)\varepsilon_{LSt}}\right)^2 \text{var}_t\left[\log z_{jt}\right] \qquad (10)
\end{aligned}
$$

which is the equation (6) in the main text. Taking changes between two different periods, and using a linear approximation around $\varepsilon_{LSt} = 1$, we can write:

$$
\begin{aligned}
&\Delta\text{var}_{t+1}[\log w_{jt}] = \left(\frac{1}{1+(1-\alpha)\varepsilon_{LSt+1}}\right)^2 \text{var}_{t+1}\left[\log z_{jt}\right] - \left(\frac{1}{1+(1-\alpha)\varepsilon_{LSt}}\right)^2 \text{var}_t\left[\log z_{jt}\right] \\
&\approx \frac{1}{2}\Delta\text{var}_{t+1}\left[\log z_{jt}\right] - \frac{1}{4}(1-\alpha)\varepsilon_{LSt+1}\Delta\text{var}_{t+1}\left[\log z_{jt}\right] - \frac{1}{4}(1-\alpha)\text{var}_t\left[\log z_{jt}\right]\Delta\varepsilon_{LSt+1}, \qquad (11)
\end{aligned}
$$

where $\frac{1}{4}(1-\alpha)\text{var}_t\left[\log z_{jt}\right] > 0$ as long as $\alpha \in (0,1)$.

E Market power evidence from firm-level data

In this section, we present supporting evidence on the dynamics of market power in Lithuania based on balance sheet data for the period 2004 and 2018. The dataset covers the population of private limited liability companies, 30-40% of all employers in Lithuania. The dataset allows us to implement a production function approach to recover firm-level price markups and wage markdowns for the set of industries covered in the dataset. We rely on estimates from Ding et al. (2025), who estimate translog production functions for firms with at least 2 employees with positive revenues and operating with variable inputs, labor, and capital. The estimation is done separately for each of those industries in the data that have at least 10 firms in each year (a total of 54 sectors). Using the estimated output elasticities along with firm-level information on inputs and sales, they derive theory-based sector-level markups and markdowns for each of the sectors as well as their economy-wide counterparts.

E.1 Elasticity of labor supply vs wage markdown

Consider now the profit maximization problem proposed in Section 6.1. The optimality condition for the choice of the labor input implies the following relationship between the marginal product of labor MRPL_j and the inverse elasticity of residual labor supply facing the firm, ϵ_t^{-1}:

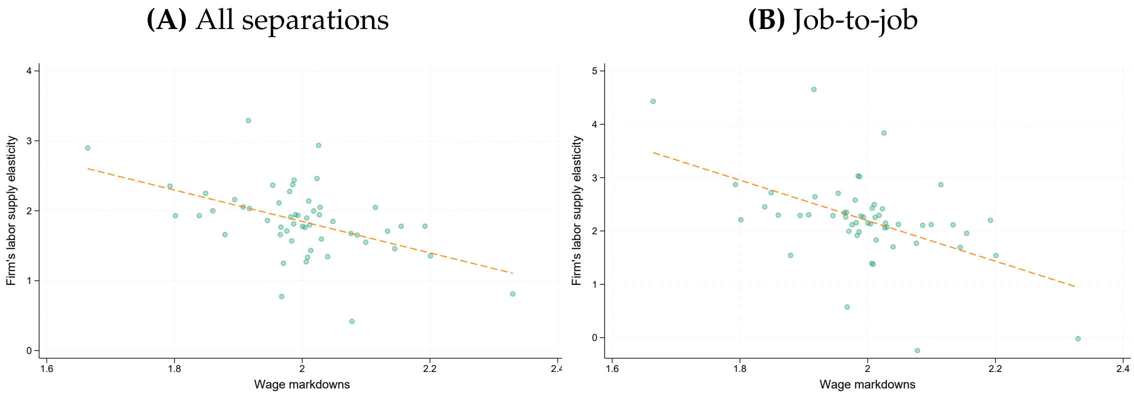
$$\frac{\text{MRPL}_{jt} - w_{jt}}{w_{jt}} = \frac{1}{\epsilon_{LSt}}$$

where $\epsilon_{LSt} = \epsilon_{Rt} - \epsilon_{sept}$. Re-arranging terms, we can obtain an expression that links the average wage markdown ν_t, defined as the ratio between the marginal product of labor and wages, to the inverse elasticity of labor supply, ϵ_{LSt}^{-1},

$$\frac{\text{MRPL}_{jt}}{w_{jt}} \equiv \nu_t = \left(1 + \epsilon_{LSt}^{-1}\right)$$

Figure E.1 shows the negative correlation between the sector-level firm labor supply elasticity estimated from Social Security data using initial and final periods and the sector-level wage markdown estimated using balance sheet data for 2004 and 2018, controlling for period and sector fixed effects.

Figure E.1: Firm's labor supply elasticity and wage markdowns

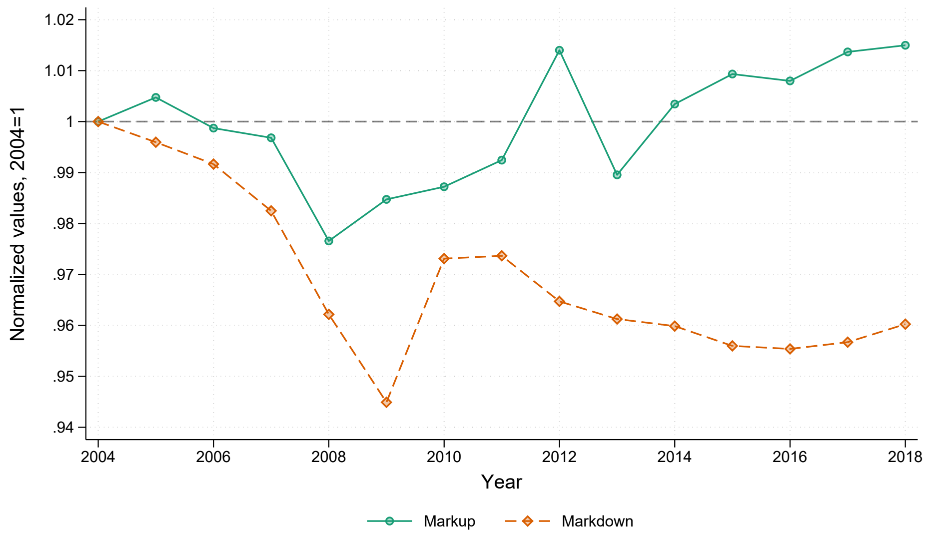


Notes: The figure shows the correlation between sector-level firm labor supply elasticity and sector-level wage markdowns, controlling for period and sector fixed effects. Firm's labor supply elasticity is based on equation (8) estimated separately by sector for the periods 2000-05 and 2015-20 using the Social Security data described in Section 4. Panel A uses all separations to estimate the elasticity, while Panel B exploits only job-to-job transitions. Markdowns refer to sector-level (log) wage markdowns calculated using firm-level estimates for 2004 and 2018. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

E.2 Product markups vs wage markdown

Figure E.2 shows the dynamics of aggregate markup and markdown between 2004 and 2018 in Lithuania. The data show rather opposite dynamics: while aggregate markup increased by almost 2%, aggregate markdown decreased by more than 4%.

Figure E.2: Aggregate markup and markdown, 2004-2018



Notes: Markups and markdowns refer to aggregate price markups and wage markdowns calculated using firm-level estimates for 2004 and 2018. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

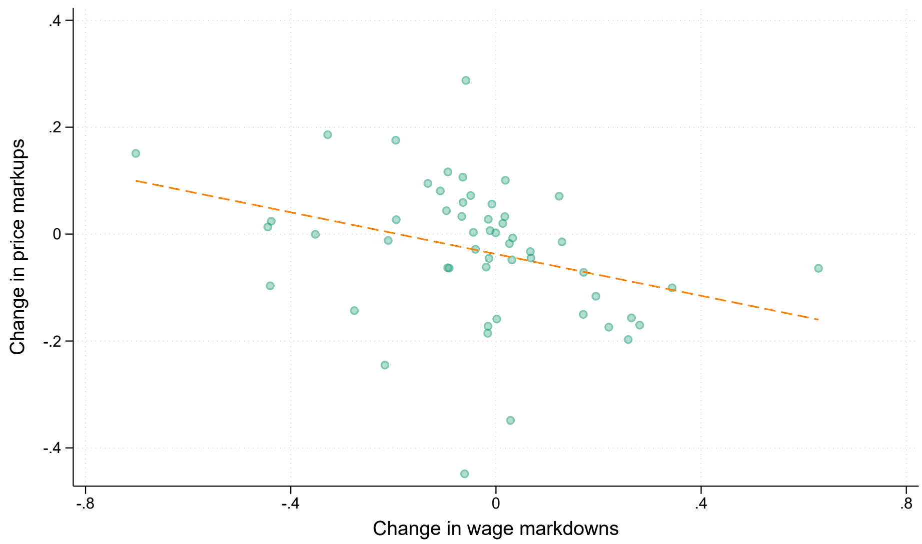
Despite the divergent dynamics over time, differences in labor market power across sectors might still correlate with differences in product market power, invalidating our inference. If this were the case, the error term in equation (9) would contain the sectoral change in product market power, ϵ^P_{st+1}, i.e.

$$\Delta v_{st+1} = \gamma_0 + \gamma_1 \Delta\epsilon^P_{st+1} + \tilde{v}_{st+1}$$

which might lead to a bias in the estimate of β_1, where bias$[\beta_1] \propto \gamma_1 \text{cov}[\Delta\epsilon_{st+1}, \Delta\epsilon^P_{st+1}]$.

Figure E.3 scatters the changes in industry-level markups and industry-level markdowns between 2004 and 2018. During this period, sectors experiencing a decrease in the average wage markdown have witnessed an increase in price markups, suggesting a slightly negative correlation. This implies $\text{cov}[\Delta\epsilon_{st+1}, \Delta\epsilon^P_{st+1}] \neq 0$. Given the positive correlation between price markups on wage dispersion (Kaplan and Zoch, 2020), i.e., $\gamma_1 > 0$, the OLS estimates of β_1 reported in Table (5) are likely to be downward biased, and the effect of labor market competition on wage dispersion to be underestimated.

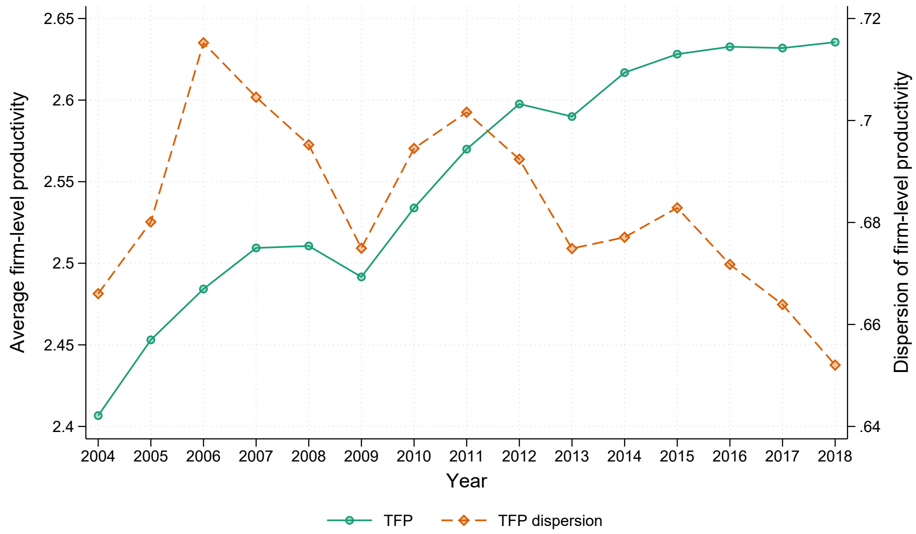
Figure E.3: Changes in industry-level markups and markdowns



Notes: Markups and markdowns refer to sector-level price markups and wage markdowns calculated using firm-level estimates for 2004 and 2018. The change refers to the log change in these statistics between 2004 and 2018. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

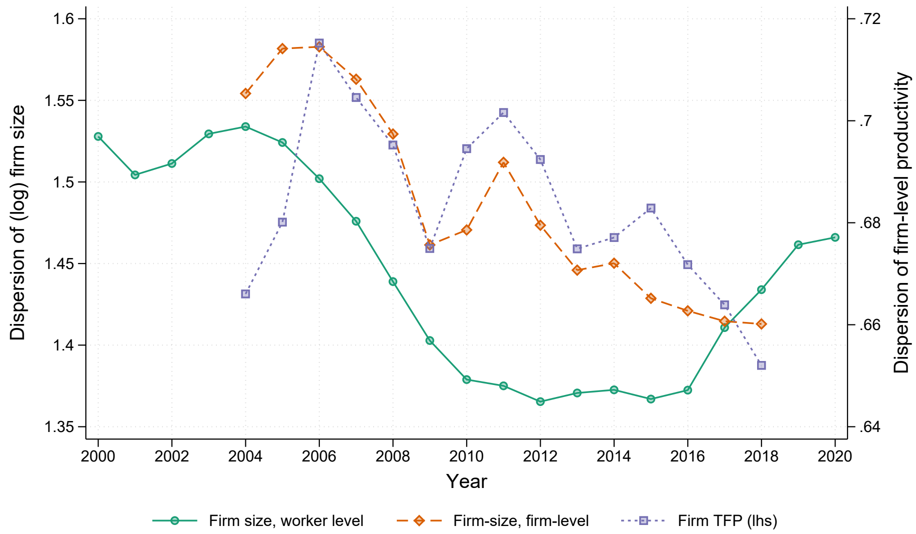
F Dynamics of firm-level productivity

Figure F.1: Firm-level productivity, 2004-2018



Notes: The figure shows the evolution of the average firm-level productivity as well as the dispersion of firm-level productivity. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

Figure F.2: Dispersion of firm-level productivity and firm size



Notes: The figure shows the evolution of the dispersion of firm size computed both from Social Security data (worker-level) and balance sheet data firm-level together with the dispersion firm-level productivity. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).