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The Earnings Distribution in Lithuania: The Role of the MinimumWage*

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ABSTRACT

In this paper, we investigate how the minimum wage has shaped the earnings distribution in Lithuania between 2010 and 2019. We rely on a distribution regression framework and detailed Social Security records to characterize the earnings distribution along with the minimum wage incidence at a monthly frequency. According to our preferred estimates, our results imply that minimum wage increases can explain about 32% (40%) of the decline in total (bottom-tail) earnings inequality and up to 20% of average earnings growth.

Keywords: Minimum wage, Earnings growth, Inequality

JEL codes: D31, J31, J38

1 Introduction

In recent decades, the Baltic States have experienced extraordinary economic growth, coupled with significant wage increases that have outpaced most European economies (Nickel et al., 2019; Garcia-Louzao and Jouvanceau, 2023) and a declining trend in wage inequality (Magda et al., 2021; Garcia-Louzao and Ruggieri, 2023). During the same period, minimum wage increases were the rule rather than the exception as the main policy tool to boost wages of workers at the bottom of the labor earnings distribution (Ferraro et al., 2018; Garcia-Louzao and Tarasonis, 2023).

In this paper, we investigate the role of the minimum wage in the observed wage trends in Lithuania between 2010 and 2019. Understanding how the minimum wage affects the earnings distribution is important to assess its relevance in addressing wage inequality. However, the impact of the minimum wage on the wage distribution is not only important from a distributional angle but also from a macroeconomic perspective. For example, minimum wage increases may spill over up the distribution, leading to wage increases for more workers than those directly affected. In such a case, minimum wage increases can play an important role in wage setting and ultimately in the average wage in the economy, with potential implications, for example, for competitiveness in international markets.

Our analysis is based on the distribution regression framework proposed by Fortin et al. (2021), implemented on a unique administrative dataset that tracks wages at a monthly frequency along with detailed information on workers and firms. This framework allows us to characterize the full density of labor earnings by estimating the probability that a worker belongs to a given point in the distribution as well as the position of the current minimum wage. We then use the model estimates and the composition of the sample at different points in time to perform a series of counterfactual exercises to quantify the contribution of the minimum wage to inequality and wage growth.

Our findings can be summarized as follows. First, we document that earnings inequality has been declining since 2010, and this dynamic has been the mirror image of the evolution of the minimum wage. Second, we show that there is a non-negligible mass of jobs at exactly the minimum wage level, but that this incidence has declined over time. Third, we show that in the absence of minimum wage increases, the distribution of earnings would have a noticeably different shape, with some workers whose jobs should be at the current minimum wage falling behind on the wage scale. Fourth, the impact of the minimum wage on the earnings distribution extends beyond its direct effect on the jobs for which it is binding, with substantial spillover effects. In particular, our preferred model estimates, which take into account labor productivity developments, imply that spillovers can reach up to the median of the monthly earnings distribution, which remains visible up to about the 75th percentile of the distribution. Based on these estimates, we quantify that the minimum wage can explain about 32% of the overall decline in earnings inequality and about 40% of the decline in bottom-tail inequality. In alternative counterfactuals based on different deflators, we find that the minimum wage can explain no more than 60% (74%) of the decline in total (bottom-tail) earnings inequality. Finally, minimum wage policy can explain up to 20% of the increase in average monthly earnings between 2010 and 2019.

Our paper connects to the revived and growing literature on the impact of the minimum wage on the shape of the wage distribution (e.g., Ferraro et al., 2018; Fortin et al., 2021; Gregory and Zierahn, 2022; Oliveira, 2023; Bossler and Schank, 2023; Choi et al., 2023; Giupponi et al., 2024). We add to this literature by quantifying the role of continuous minimum wage increases in an economy with double-digit annual wage growth. For instance, compared to papers using exactly the same methodology, our results suggest a much larger role of the minimum wage in wage inequality in Lithuania relative to the U.S. during a period when minimum wage policy was very mild (Fortin et al., 2021), but also a much smaller contribution compared to Portugal during a period when wage growth was quite anemic (Oliveira, 2023). In addition, we contribute to this literature by quantifying how minimum wage increases affect average wage dynamics.

Our paper also contributes to the literature on the role of the minimum wage in the dynamics of inequality in Central and Eastern Europe (e.g., Ferraro et al., 2018; Pereira and Galego, 2019; Laporšek et al., 2019; Magda et al., 2021; Dorjnyambuu and Galambosné Tiszberger, 2024). We complement these studies in several important ways. First, we examine a new country over a more recent period than most of the existing studies. Second, we use novel monthly administrative data that to implement a flexible semi-parametric modeling approach that allows us to characterize the wage distribution at a very granular level. Third, we quantify how *both* wage inequality and average wage dynamics would have evolved in the absence of minimum wage policy in a context of rapid economic and wage growth coupled with continuous minimum wage raises.

The rest of the paper is organized as follows. Section 2 discusses the institutional context and data. Section 3 presents stylized facts about the earnings distribution as well as the incidence of the minimum wage. Section 4 describes the econometric approach to characterize the role of the minimum wage in the earnings distribution, whereas Section 5 discusses how the minimum wage has affected wage dynamics. Section 6 concludes.

2 Data and institutional setting

2.1 The Lithuanian economy

The Lithuanian economy experienced over the period 2010-2019 substantial growth in output, productivity, and labor earnings. As summarized in Figure 1, the nominal gross domestic product grew by 80%, 60 percentage points faster than general prices. Employee average earnings also exhibit a substantial increase similar to that of the GDP. Although productivity growth likely contributed the most, the period was also marked by a tightening labor market, with employment rising 12% over the 10 years, leading to a historically low unemployment rate by 2019. In addition to the market forces underlying the strong growth in labor compensation, there were several increases in the minimum wage during this period, with a cumulative increase amounting to 75% in nominal terms (see Table 1).

2.2 Minimum wage legislation

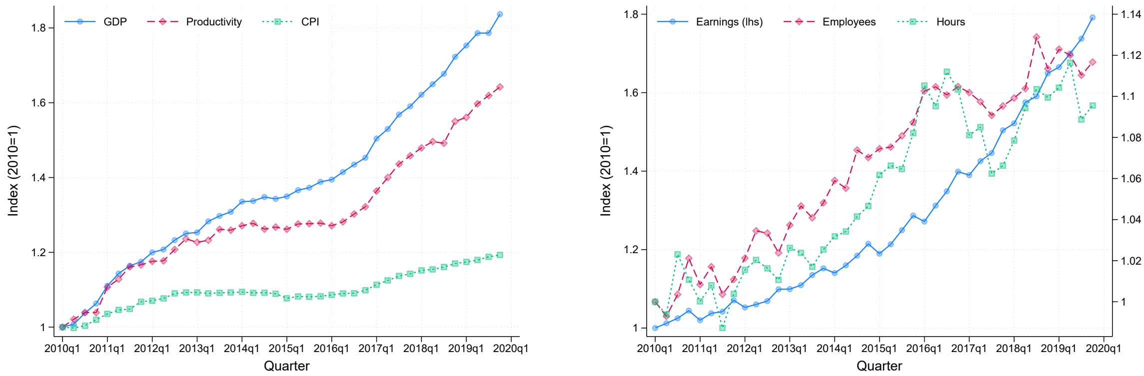
The minimum wage represents the main tool for setting the minimum monthly remuneration to which workers in Lithuania are legally entitled.[1] The minimum wage affects all salaried workers equally, both in the private and public sectors, and compliance with the law is supervised by the State Labor Inspectorate.[2] The monthly

[1]Unions or collective agreements play little role in wage determination, as they are not common. According to the OECD database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention, and Social Pacts (ICTWSS), in 2019 union density was just 7.4%, while the coverage of collective agreements was 7.9%.

[2]With the introduction of the *New Labor Code* in July 2017, the minimum wage can only be paid for unskilled work, i.e. work that does not require any special skills or professional experience, while skilled workers have to be compensated with a higher wage.

Figure 1: Macroeconomic performance, 2010-2019

A. GDP, productivity, and prices   **B.** Employees and compensation



Source: Statistics Lithuania and own calculations. Notes: GDP stands for gross domestic product, whereas CPI refers to the consumer price index. Productivity is value added per employee. Earnings refer to the average monthly labor income of employees in a quarter. Employees refer to the number of workers in each sector, whereas hours stand for the total hours worked by those employees. Monetary values are expressed in nominal terms.

minimum wage is decided following negotiations in the Tripartite Council (a national institution for social dialogue comprising labor unions, employers' associations, and the government) and is ultimately regulated by the Labor Code.[3] If no agreement is reached in the Tripartite Council negotiations, the decision on whether to increase the minimum wage will be the government's to make unilaterally.[4]

Table 1 offers a description of the Tripartite Council negotiations between 2010 and 2019, along with the nominal monthly minimum wage that came into effect after each discussion. During this period, negotiations lasted an average of 180 days, and in less than half of the cases, the Tripartite Council reached an agreement. Generally, the new minimum wage came into effect two months after the announcement made by the Government and it was increased by an average of 8% between 2010 and 2019, although with noticeable variation over the years.

[3] The minimum hourly wage, relevant for part-time workers, is the ratio of the monthly minimum wage to the *common* monthly hours of work. Therefore, unless there is a regulatory change in working hours, the minimum hourly wage is implicitly determined by the monthly minimum wage.

[4] In October 2017, the Tripartite Council reached an agreement to establish a formula for determining the minimum wage level each year and depoliticize its decision. Specifically, the national monthly minimum wage (i) must be between 45 and 50 percent of the average monthly labor income, excluding bonuses, allowances, and additional payments that are not paid each period, and (ii) cannot be lower than the average ratio of the EU countries in the top quartile of this measure over the last three years.

Table 1: National monthly minimum wage, 2010-2019

Negotiations					Minimum Wage	
Start	End	Agreement	Announcement	Enforcement	Euros	Growth (%)
17-Jun-2008	19-Jun-2012	No	20-Jun-2012	1-Aug-2012	317	6.0
18-Dec-2012	18-Dec-2012	Yes	19-Dec-2012	1-Jan-2013	373	17.7
25-Mar-2014	9-Sep-2014	No	24-Sep-2014	1-Oct-2014	387	3.5
27-Jan-2015	21-Apr-2015	Yes	27-Jun-2015	1-Jul-2015	419	8.5
27-Oct-2015	27-Oct-2015	Yes	2-Dec-2015	1-Jan-2016	451	7.6
3-May-2016	17-May-2016	No	22-Jun-2016	1-Jul-2016	490	8.6
23-May-2017	21-Sep-2017	Yes	11-Oct-2017	1-Jan-2018	516	5.3
18-May-2018	18-Sep-2018	No	16-Oct-2018	1-Jan-2019	555	7.6

Source: Tripartite Council meeting minutes. Notes: The start and end of negotiations are defined as the first and last dates of Tripartite Council meetings with the minimum wage issue on the agenda. As of January 1, 2019, the Social Security contribution rates paid by the employer and the employee were modified, which affects the way all salaries are declared as well as the minimum wage. The minimum wage is re-scaled by such rate change (1.289) before 2019 and expressed in nominal terms. Growth refers to the nominal growth rate in the national minimum wage (NMW) relative to its previous level.

2.3 Social Security data

The main data source for the analysis comes from administrative records provided by the State Social Security Fund Board under the Ministry of Social Security and Labour, commonly known as SoDra. The dataset represents a "de facto random" sample of individuals registered in the Social Security system at any time between 2000 and 2020.[5] The dataset has a longitudinal design that allows for the tracking of individuals in the Social Security system at a monthly frequency.[6] For each sample member, we observe demographic information (e.g., sex, age), as well as we can determine whether they are employed or not. In addition, when they are employed with a labor contract, the observed labor income refers to all work-related income subject to Social Security contributions paid by the employer, including base salary, as well as payments such as bonuses, allowances, overtime, commissions, or severance payments. Moreover, the dataset includes information on job (e.g., seniority, occupation) and firm (e.g., location, sector) characteristics each month.[7] Thus, our data include all registered jobs held by each sampled individual, which allows the analysis to be conducted at the job level, where the minimum wage is binding.

[5]The sampling procedure is based on selecting all individuals registered with Social Security who were born in an odd-numbered month of each even-numbered year.

[6]Individuals are present in the system when they are paying contributions (e.g., salaried, self-employed) and those who receive some social benefits (e.g., unemployment insurance, child benefits, pension). However, for legal reasons, individuals do not appear in our sample until the age of 18, even if they were present in Social Security at an earlier age.

[7]Appendix A describes the aggregation of some of these characteristics to reduce the number of relevant groups.

For our analysis, we impose the following restrictions on the raw data. We exclude the year 2020 to avoid the influence of the COVID-19 pandemic on wages as well as observations with missing information. From this sample, we target workers aged 18 to 65 having jobs in both private and public sectors. Given we do not observe hours worked, we seek to address the influence of labor supply on our earnings metric as follows. On the one hand, we keep only job observations referring to monthly in which the individual works for the full month and earns no less than a fourth of the current monthly minimum wage. The idea is that under a full compliance assumption, full-time jobs who work the entire month must legally earn at least the minimum wage. Therefore, jobs with earnings below the monthly minimum wage are expected to refer mostly to part-time and we exclude those jobs with very few hours. On the other hand, we remove observations when workers are employed and receiving welfare benefits at the same time. This restriction is meant to avoid situations where employees do not actually work the whole month due to, for example, sick leave, or are simply in a bridge employment situation, e.g., working and receiving unemployment benefits. The resulting sample consists of 417,231 workers with 1,160,311 job spells over 27,058,892 monthly observations between January 2010 and December 2019.

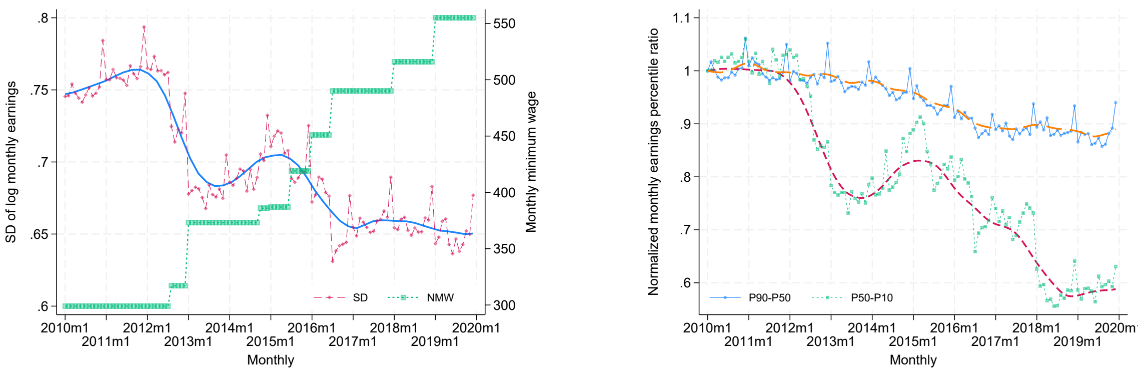
3 The earnings distribution and the minimum wage

Before turning to the econometric analysis, in this section, we provide an overview of the dynamics of the earnings distribution and the minimum wage.

Panel A of Figure 2 shows the evolution of the standard deviation of log (nominal) monthly earnings (and its smoothed series, solid line) between January 2010 and December 2019, along with the dynamics of the (nominal) monthly minimum wage. The figure shows a marked decline in inequality as measured by the standard deviation of log monthly income, which decreased by almost 10 log points. During the same period, the minimum wage was raised 8 times, with an average increase of roughly 8%. The evolution of earnings inequality seems to mirror the evolution of the minimum wage, with a correlation between both time series of -0.92 (-0.98 if the smoothed series is considered). Notably, looking at the monthly gross series, the largest declines in inequality appear to follow the most aggressive increases in the minimum wage, indicative of an important role of the minimum wage underlying the inequality dynamics. Panel B appears to support this view, as the sharpest decline arises from the compression at the lower end of the earnings distribution (50–10 percentile ratio), which falls by almost 40% from its value in January 2010, compared to a roughly 10% decline at the top end (90-50 percentile ratio).

Figure 2: Dynamics of earnings dispersion and the minimum wage, 2010-2019

A. Inequality and the minimum wage **B.** Top- and bottom-inequality

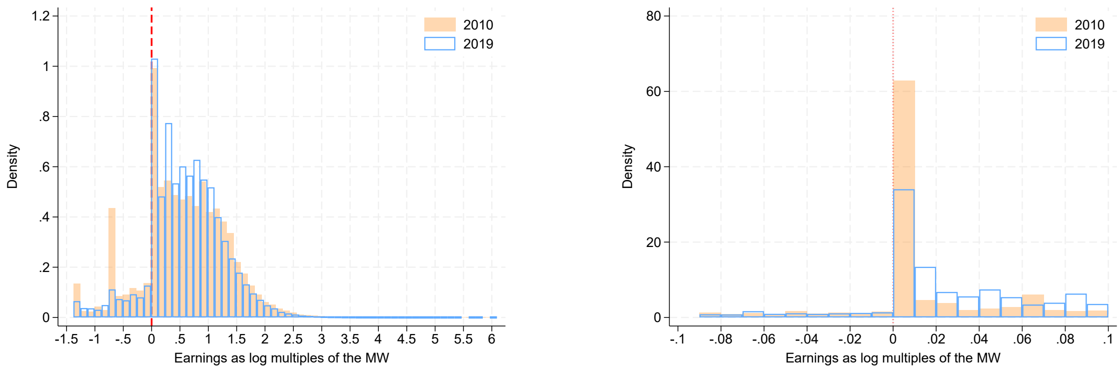


Notes: Panel A shows the dynamics of the standard deviation (SD) of log nominal monthly income together with the evolution of the nominal monthly minimum wage. Panel B shows the top (bottom) inequality calculated as the ratio between the 90th and 50th (50th and 10th) percentiles and normalized to its value in January 2010. Solid lines are smoothed series using a kernel-weighted local mean regression.

Figure 3 shows the distribution of log monthly earnings in 2010 and 2019. To make the two years comparable, we express earnings as multiples of the minimum wage in each year, so that zero corresponds to the minimum wage bin. Panel A shows that there is a significant mass of jobs at exactly the minimum wage in both periods. Interestingly, this bunching is also noticeable at half the current minimum wage in 2010, which may reflect a larger share of part-time jobs in that period. Panel B zooms in on the distribution to characterize jobs around a 10% window around the minimum wage. The numbers do not suggest much change in the share of jobs slightly below the minimum wage. However, the figure shows that the share of minimum wage jobs has become more spread out, as there is a smaller mass at exactly the minimum wage but a larger share of jobs slightly above it. This is in line with the de-facto change in minimum wage policy that followed the introduction of the new Labor Code in 2017. In addition, consistent with the time series dynamics of the (log) percentile ratios, the graph also highlights the compression of the (log) monthly earnings distribution. More specifically, a comparison between the densities in the first and last year of the data reveals that the distribution has become more skewed to the right at the end of the period. In other words, there is a larger mass of jobs in the left tail of the distribution, especially at and slightly above the prevailing minimum wage.

Figure 3: Earnings distribution around the minimum wage in 2010 and in 2019

A. Full distribution **B.** Distribution around the MW



Notes: Year-specific histograms are calculated from the distribution of monthly earnings by grouping all the months of a given year. Earnings are expressed as deviations from the prevailing minimum wage, i.e., $\ln(y_{it})$ - $\ln(\underline{w}_t)$. Panel A bars are based on 60 equally spaced bins. Panel B plots the distribution within 10% bands of the minimum wage with the bar width set at 0.01, representing approximately one-percent variations.

In Figure 4, we look at how binding the minimum wage is over time. Panel A shows the proportion of minimum wage jobs over time according to alternative definitions: (i) proportion of jobs with monthly earnings equal to the current monthly minimum wage, (ii) jobs with monthly earnings within a band of 10 percent of the current minimum wage, and (iii) jobs with monthly earnings equal to or below the current minimum wage.[8] Three main facts emerge from this figure. First, the share of workers affected by the minimum wage experienced a remarkable jump in 2013, when the largest relative increase in the minimum wage in Lithuanian history took place. Second, from that time onwards, the proportion of workers whose monthly income is exactly the minimum wage is around 10% of the working population until June 2017. With the introduction of the new Labor Code, which requires skilled workers to be paid above the minimum wage, this proportion decreased to 5% in July 2017 to remained stable thereafter.[9] When considering broader definitions of minimum wage jobs, the dynamics are similar. For instance, the figure reveals that about 20 to 25% of the workers had monthly earnings at or below the prevailing minimum wage and this

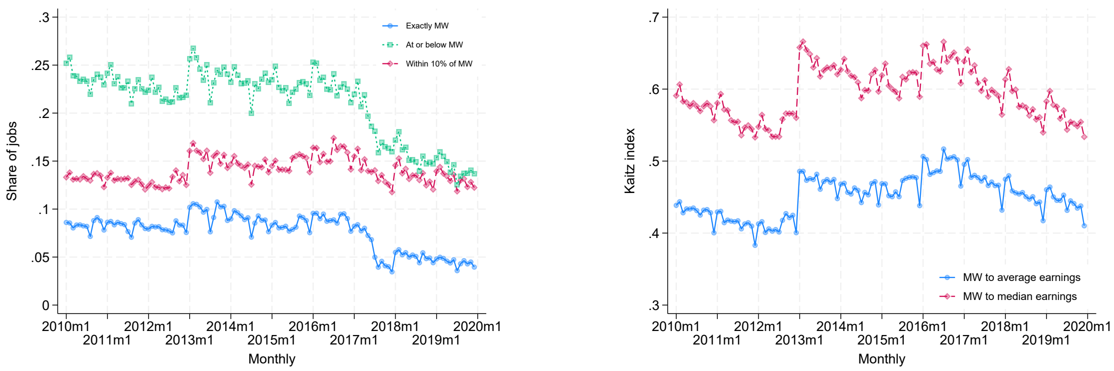
[8]Recall that, given the constraints imposed to select our sample, the lower limit of the earnings distribution corresponds to jobs whose reported monthly earnings are not less than one-fourth of the current minimum wage.

[9]An alternative explanation for this decline could be related to better tax enforcement, which could have led to a reduction in the envelope wage or, more generally, in the shadow economy. However, existing evidence on the size of the shadow economy in Lithuania does not suggest that it has significantly changed during the period under study (Sauka and Putniņš, 2023).

share markedly decreased after July 2017 to be 15%. Panel B of Figure 4 depicts an alternative measure of the bindingness of the minimum wage based on the Kaitz index. The index summarizes the bite of the minimum wage on the earnings distribution by taking the ratio of the monthly minimum wage to market monthly earnings, either the average or the median. The minimum wage has significantly impacted earnings, making up over 60% of the median earnings since 2013. The Kaitz index, based on average earnings, also indicates a noticeable shift, though of a smaller scale. The substantial rise in the Kaitz index tied to the median aligns with the compression of the lower end of the earnings distribution documented above.

Figure 4: Bindingness of the minimum wage, 2010-2019

A. Minimum wage jobs **B.** Bite of the minimum wage



Notes: Each line in Panel A represents the proportion of workers earning exactly the minimum wage, those having earnings less than or equal to the minimum wage, and the share whose earnings are within a 10% band around the minimum wage. Panel B depicts the ratio of the minimum wage to either average or median monthly earnings.

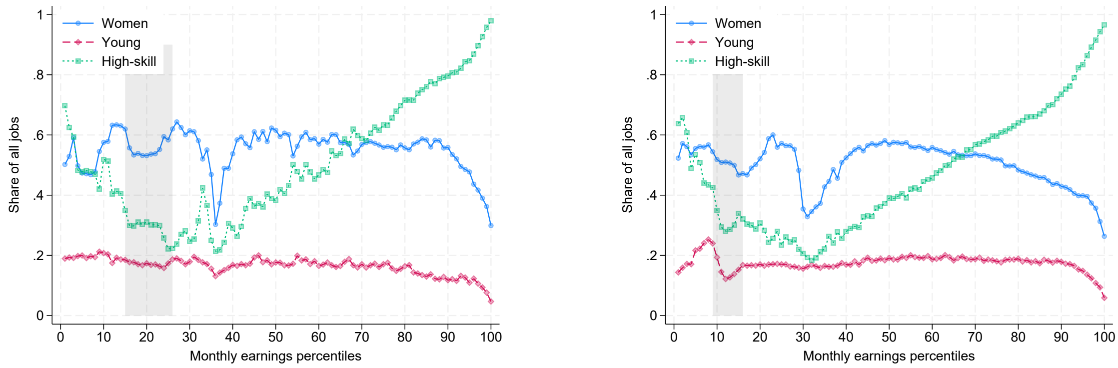
Figure 5 characterizes the types of workers who hold jobs at different points in the earnings distribution in 2010 (Panel A) and 2019 (Panel B). The figure reveals that, in 2010, women accounted for about 60% of workers with jobs up to the 90th percentile and their share declined sharply thereafter to about 25% at the top of the earnings distribution. In 2019, some notable changes emerged. Jobs held by women account for less than 60% of jobs within the top 60th percentile, with a sharp decline at around the 30th percentile, where their share falls below 40%.[10] Compared to 2010, however, the share of jobs held by women begins to decline at a lower point in the distribution, as the share of women drops steadily from the 60th percentile to account for less than 20% at the top of the earnings distribution. Notably, between 2010 and 2019, the share

[10]The substantial drop in the share of women around the 30th percentile is due to the over-representation of male-dominated activities, wholesale, transport, and storage activities, in that point of the distribution (see Figure B.1 in Appendix B).

of jobs held by women declined from nearly 55% to 50%. In terms of age composition, young workers, those under age 30, consistently occupied about 16% (17%) of jobs across the earnings distribution in 2010 (2019), and their share only began to decline at the 95th percentile. The evidence also reveals two interesting facts about high-skill jobs. On the one hand, the share of high-skill occupations has declined from about 51% of all jobs in 2010 to only 47% in 2019, as can be seen from the downward shift of the profile curve. On the other hand, the share of high-skill jobs shows a U-shaped pattern in both periods: they account for more than 40% of workers with jobs at the bottom 10th percentile, about 20-25% of workers with jobs at the 20th and 30th percentiles, and their share increases steadily as one moves up the income distribution until they account for all workers at the top. This high share of high-skilled jobs at the lower end of the distribution is related to a peculiarity of the Lithuanian labor market, where a non-negligible share of highly skilled people have multiple jobs in a given month, where they are paid by the hour as consultants, managers, or similar positions, but also where company owners hire themselves as minimum-wage workers in their company for Social Security coverage purposes.[11]

Figure 5: Worker characteristics along the earnings distribution in 2010 and in 2019

A. 2010 **B.** 2019



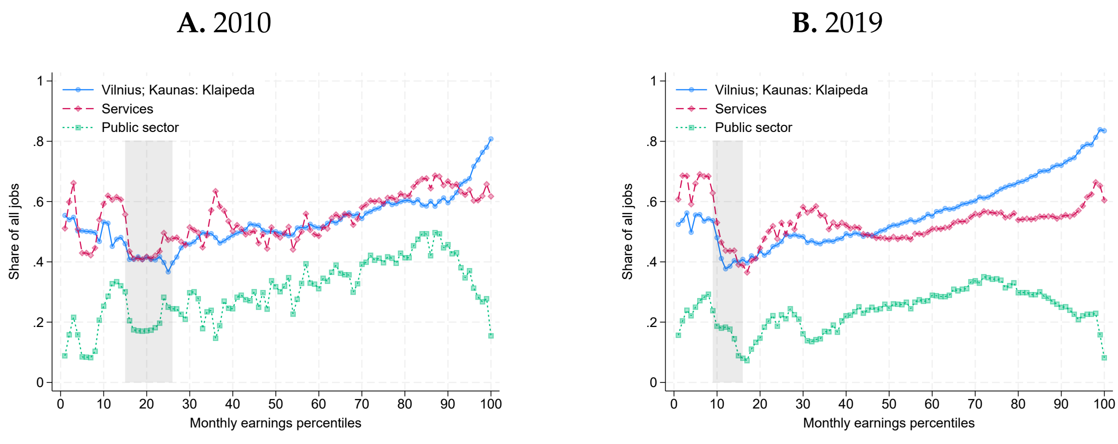
Notes: Each line portrays the share of workers of a given type within an earnings percentile. Young refers to workers younger than 30 years old. High-skill is defined as a function of the complexity and range of tasks and duties to be performed in an occupation under ISCO-08 classification referring to 1-digit groups 1 to 3. Earnings percentiles are created by ranking workers in a given month based on the current earnings and averaging their rank within the specific year: 2010 or 2019. The shaded area corresponds to the percentiles of the distribution where minimum wage jobs lie.

Figure 6 examines firm characteristics. The data reveal that the share of jobs in the three largest municipalities is U-shaped in both periods, accounting for almost the

[11] In Appendix B.1, Figure B.2 reports the average number of employers per month along the earnings distribution and by skill categories in 2010 and 2019. Figure B.3 shows that the incidence of minimum wage workers in the distribution of high-skill jobs only appears in the private sector.

60th percentile of jobs at the top end and from the 10th percentile onwards increasing steadily to increase across the income distribution to account for a staggering 80th percentile at the 95th percentile. Importantly, the average share of jobs in the largest municipalities increased between 2010 and 2019, from 53 to 56% of total jobs. In terms of sector of activity, the data indicate that service sector jobs are overrepresented at the lower end of the monthly earnings distribution, accounting for about 60% of jobs, even more so in 2019. Their share rises steadily from the 30th percentile to represent just under 60% of jobs at the high end of the distribution. The average composition of jobs by sector slightly declined between 2010 and 2019, from accounting for almost 55% of jobs to around 53%. Finally, the figures indicate a somewhat hump-shaped profile of public sector jobs across the income distribution that lost large weight in the economy: in 2010 (2019) they account for about 30% (24%) of total jobs within the bottom 20th percentile, steadily increasing their share up to the 85th (75th) percentile, where they account for about 45% (38%) of jobs, and begin to decline from there until they fall below constituting about 25% (15%) of jobs at the top of the distribution. This notably lower share of public sector jobs at the top of the distribution is related to different state laws that regulate the compensation of public sector employees and set limits on maximum compensation for top officials.

Figure 6: Firm characteristics along the earnings distribution in 2010 and in 2019

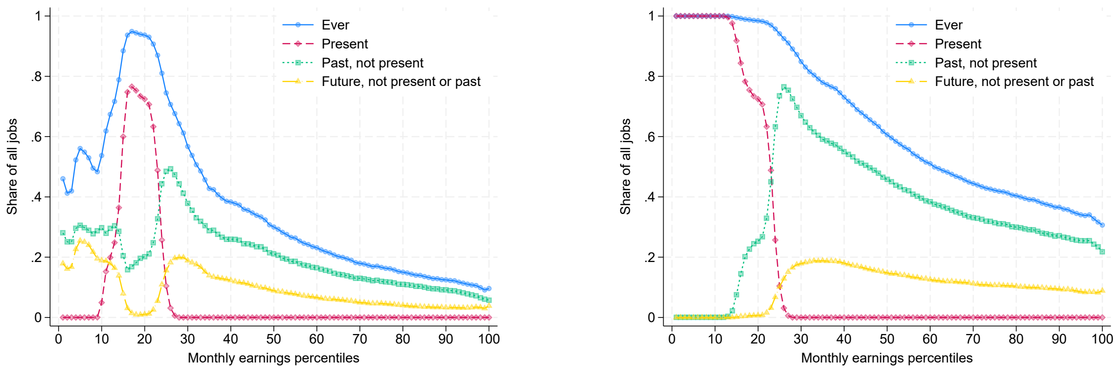


Notes: Each line portrays the share of firms of a given type within an earnings percentile. Vilnius, Kaunas, and Klaipeda are the three biggest municipalities in Lithuania. Services correspond to tertiary sector activities defined using NACE2 2009 classification including 2-digit groups 48 to 96 Public sector refers to both public administration entities as well as bodies of any level of the government. Earnings percentiles are created by ranking workers in a given month based on the current earnings and averaging their rank within the specific year: 2010 or 2019. The shaded area corresponds to the percentiles of the distribution where minimum wage jobs lie.

To further characterize the distribution of monthly earnings along with the incidence of the minimum wage among workers, in Figure 7, we pool all years together to decompose the proportion of workers who have ever earned the minimum wage in a job into those earning the minimum wage in the present, in the past, and in the future between January 2010 and 2019. Despite the relatively low proportion of workers earning the minimum wage described above, Panel A reveals that all workers in the economy between 2010 and 2019 have ever earned the minimum wage. For example, while 80% of workers at the 20th percentile (around the minimum wage point in the distribution) have ever earned the minimum wage, approximately 10% of those at the 90th percentile did so at some point. Surprisingly, when we use a broader definition of minimum wage incidence, i.e., the proportion of workers who have ever had earnings at or below the minimum wage, the incidence of low wages across all workers throughout the distribution is more substantial. For example, 20% of workers at the high end of the distribution have had a low-wage job at some point in the past, which is explained by the high proportion of high-skill jobs we observe at the bottom of the earnings distribution.

Figure 7: Minimum wage incidence along the earnings distribution, 2010-2019

A. Minimum wage incidence **B.** Low-wage incidence



Notes: Each line portrays the share of workers of a given type within an earnings percentile. Minimum wage (low-wage) incidence stands for workers whose earnings in a given month are exactly (at or below) the current minimum wage. Each line represents the share of workers who have ever earned (present, past, or future) exactly the minimum wage at the current earnings percentile. Earnings percentiles are created by ranking workers in a given month based on the current earnings and averaging their rank over all the years between 2010 and 2019.

Taken together, the descriptive analysis in this section uncovers several futures about the earnings distribution and the incidence of the minimum wage. Earnings inequality has declined since 2010, but the compression of the distribution has been more acute in the bottom tail. The dynamics of inequality appear to mirror the evolution of the minimum wage, which affected a non-negligible share of jobs at the beginning of the period. However, the incidence of the minimum wage might have weakened over time as the New Labor Code introduced in July 2017 limited the type of jobs for which the minimum wage can be paid. In addition, the composition of workers and firm types along the earnings distribution shows considerable cross-sectional heterogeneity but has also changed over time. Interestingly, a substantial share of workers have ever held at least one minimum wage job between 2010 and 2019, regardless of their current position in the earnings distribution. In the next section, we examine how the minimum wage has contributed to the dynamics of inequality, taking into account potential spillover effects as well as compositional differences in the incidence of low-wage jobs across workers and firms.

4 Estimating the role of the minimum wage

To estimate the contribution of the minimum wage to the earnings distribution, we use a distribution regression framework following Fortin et al. (2021). The approach consists of characterizing the entire earnings distribution and the effects of the minimum wage at different points in the distribution. Intuitively, the approach exploits peaks across earnings intervals containing the minimum wage and identifies the time in which the distribution shifts along with changes in the minimum wage. The point estimates from the model can then be used to generate counterfactual scenarios that abstract from the effect of minimum wage increases on job destruction.[12]

Econometric model. The starting point is to model the probability that the reported income in job i at time t, Y_{it}, is above (or below) a given cutoff point of the unconditional (real) earnings distribution, y_k, as a function of a set of fixed and time-varying characteristics, X_{it}. Formally, the unrestricted probability model can be represented as

$$Pr(Y_{it} \geq y_k) = \Phi\left(X_{it}\beta_k\right), \text{for } k = 1, 2, ..., K \tag{1}$$

where Φ is the standard normal CDF, so Equation (1) represents a Probit model. X_{it}

[12]The model relies on the observed distribution to characterize the probabilities of a worker falling into a particular point in it. Thus, any effect of the minimum wage on job losses in the lower tail of the distribution, which would directly reduce inequality by eliminating the lowest-paying jobs, is not accounted for. Existing quasi-experimental evidence for the largest minimum wage increase in Lithuania suggests small disemployment effects (Garcia-Louzao and Jouvanceau, 2023), which together with the continuous employment growth in the country over the period suggests that this margin may not be critical in our context.

is the set of controls included in the model to account for shifts in the likelihood of Y_{it} exceeding a given earnings threshold, y_k. The model can be made as flexible as possible, allowing β_k to vary over any earnings bin of the distribution, and the cutoffs to be as fine as desired. Unfortunately, the computational burden increases with the degree of flexibility introduced in the model as well as with the sample size. Moreover, flexibility may also introduce identification problems, as some counterfactual probabilities may be negative (see Fortin et al., 2021, for a detailed discussion) and, these identification challenges become more salient when analyzing the role of the minimum wage along the distribution (Firpo et al., 2009). For example, if time effects are included to account for business cycle fluctuations and are allowed to vary fully along the earnings distribution, the minimum wage effects will not be identified because they would be confounded with the time effects.

To deal with the cost of flexibility, we adopt a more parametric version of the model. More precisely, we restrict the β coefficients to vary smoothly over the earnings distribution following the rank regression model proposed by Fortin and Lemieux (1998) such that the observed earnings are a monotonic, $g(\cdot)$, transformation of the latent earnings, $Y^*_{it} = X_{it}\beta + \epsilon_{it},\ \epsilon_{it} \sim N(0,1)$. In this framework, we can model the earnings distribution using a standard ordered probit model

$$Pr(y_k \leq Y_{it} < y_{k+1}) = \Phi\left(X_{it}\beta - c_k\right) - \Phi\left(X_{it}\beta - c_{k+1}\right) \tag{2}$$

which represents the probability of observing monthly earnings belonging to a given category $[y_k, y_{k+1}]$, with $c_k = g^{-1}(y_k)$. This model is more restricted than the distribution framework outlined in Equation (1) and assumes a homoskedastic error term, which is considered to be a strong assumption when analyzing (log) earnings data (Lemieux, 2006). We introduce some degree of flexibility in Equation 2 by allowing some of the effects of the covariates to vary linearly over the earnings distribution, such that they drift at every cut-off point, y_k. The ordered probit can be expressed as follows

$$Pr(y_k \leq Y_{it} < y_{k+1}) = \Phi\left(X_{it}\beta + y_k X_{it}\Omega - c_k\right) - \Phi\left(X_{it}\beta + y_{k+1} X_{it}\Omega - c_{k+1}\right) \tag{3}$$

where Ω quantifies the bin-specific effects of some of the covariates included in the model, i.e., groups that one might expect to have a different mean and variance.

To introduce the effects of the minimum wage, MW_t, we extend Equation (3) by adding a set of indicator variables that characterize the incidence of the minimum wage at different cutoffs of the distribution. More precisely, we introduce dummies of the form $D_{kt}^m = 1[y_{k-m} \leq MW_t], m \in \{M_{min}, M_{max}\}$ that identify the distance, m, of a given income bin to the current monthly minimum wage. For example, $D_{kt}^0 = 1[y_k \leq MW_t]$ would reflect the bunching at exactly the level of the MW. Thus, the ordered probit that includes minimum wage effects takes the following form

$$Pr(Y_{it} \geq y_k) = \Phi\left(X_{it}\beta + y_k X_{it}\Omega + \sum_m D_{kt}^m \varphi_m - c_{k+1}\right) \tag{4}$$

with parameters φ_0 quantifies the bunching of MW jobs, $\varphi_m, m > 0$ quantifying spillover effects of the MW, and $\varphi_m, m < 0$ helps to account for jobs below the minimum wage due to, for example, non-compliance (Fortin and Lemieux, 1998; Oliveira, 2023). Equation (4) allows us to estimate the effect of the minimum wage over the earnings distribution and we can use the point estimates to build counterfactual distributions

Practical implementation. Estimating Equation (4) requires some practical choices to keep the estimation procedure tractable since implementing the model empirically requires jointly fitting K stacked Probit models in our large dataset. This implies that each observation in the data is replicated K times, with the outcome variable in each observation reflecting whether the earnings are not higher than a given y_k, i.e., taking the value 1 if $Y_{it} \geq y_k$ and 0 otherwise. Thus, the sample size explodes when the data is expanded, because the final number of observations would be $K \times$27,058,892 over the entire period.[13]

To deal with the large dimension of the expanded dataset, we choose the number of cutoff points, y_k, to produce a sufficiently fine grid of the earnings distribution to meaningfully locate jobs and the minimum wage in the distribution, while keeping the number of K bins manageable for the estimation. Thus, we partition the (log) monthly earnings distribution into $K - 2$ bins of 0.07 log points (approximately the average percent increase in the minimum wage over our sample period), plus the first and last percentiles of the distribution. Given the chosen bin size, the resulting number of bins is 52. We then estimate the model using a 15% sample clustered by each month

[13]Note that for all observations in the data, $Pr(Y_{it} \geq y_1) = 1$, and thus this observation is not relevant for identification.

between January 2010 and December 2019. The resulting estimation sample contains a total of 211,059,524 (52×4,058,837) observations.

Concerning the covariates, the vector of controls, X_{it}, includes dummies for female, young workers, high-skill jobs, public sector, firm-size categories, region, industry, and earnings bins. We also include month dummies to capture seasonal effects and year indicators to account for macroeconomic fluctuations. In addition, we allow the effects of female, young, public sector, rural areas, service sector, and year to vary smoothly across the earnings distribution by interacting these effects with a linear transformation of the earnings cutoffs.[14] Therefore, we allow for heterogeneous effects along the earnings distribution related to labor supply and demand characteristics as well as economy-wide shocks.

For the minimum wage effects, φ_m, we include indicators to identify (i) the bunching of jobs whose monthly earnings are exactly at the minimum wage, (ii) the potential effects below the current monthly minimum wage due to imperfect compliance, measurement error, or sub-minimum wage jobs, and (iii) the spike in the distribution at exactly half the minimum wage, as documented in Figure 3. In terms of spillover effects, we consider indicators for jobs above the minimum wage until they represent jobs whose earnings are at most at the 90th percentile of the distribution, which, given the log size of each income bin, implies including 20 parameters. This approach avoids having to make ad hoc decisions about the number of indicators based on their statistical significance when adding an additional indicator, as in the previous literature (Fortin et al., 2021; Oliveira, 2023). The chosen number of parameters would at most capture the size of spillovers equal to the largest reported in recent studies of the distributional effects of minimum wage increases (Gregory and Zierahn, 2022; Choi et al., 2023). Therefore, we estimate a total of 23 minimum wage parameters.

5 The distributional consequences of the minimum wage

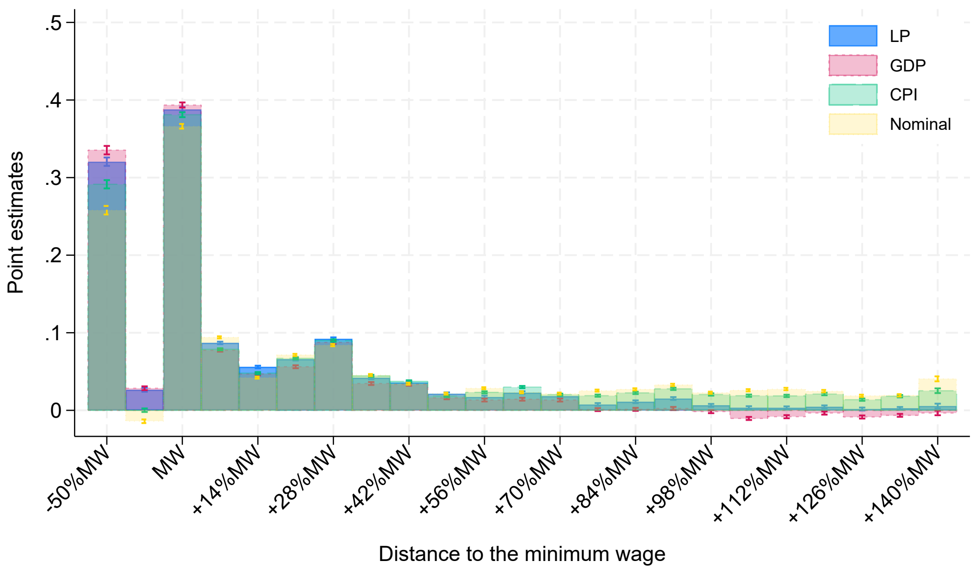
5.1 Estimation results

Point estimates. We start discussing the results from the estimation of the Probit model. The estimates of the minimum wage effects are reported in Figure 8; while they do not provide a meaningful interpretation, the cross-deflator comparison is useful

[14] The linear transformation of the cutoffs is simply $y_k - 1$.

to assess the importance of making the distributions comparable in a setting where earnings growth outpaced the increase of any other macroeconomic variable. The figure shows the clustering of jobs created by the minimum wage, as indicated by jobs with earnings at the minimum wage (MW) or half the minimum wage ($-50\%MW$). In both cases, the point estimates are large and significant regardless of the deflator used. The effects for the dummy that captures potential noncompliance or measurement error, i.e. the indicator for the mass of all jobs below the minimum wage, tend to be small but significant using labor productivity (LP) or GDP as deflators, while they are zero or slightly negative using CPI-deflated earnings or in nominal terms. The figure also shows differences in the size of spillover effects depending on the deflator (or the absence of it) used in the estimation. While spillover effects are present regardless of deflator up to jobs with earnings of about +70% of the current minimum wage, they converge to zero when earnings are deflated by LP or GDP, but remain at similar levels and do not decrease when CPI or non-deflated earnings are used.

Figure 8: Point estimates of the minimum wage indicators, 2010-2019



Notes: Each bar represents the point estimates of the φ parameters from the model in Equation (4) along with 95% confidence intervals using alternative variables to deflate earnings and the minimum wage, i.e., labor productivity (LP), gross domestic product (GDP), and the consumer price index (CPI), as well as nominal monthly earnings. Standard errors are clustered at the job level.

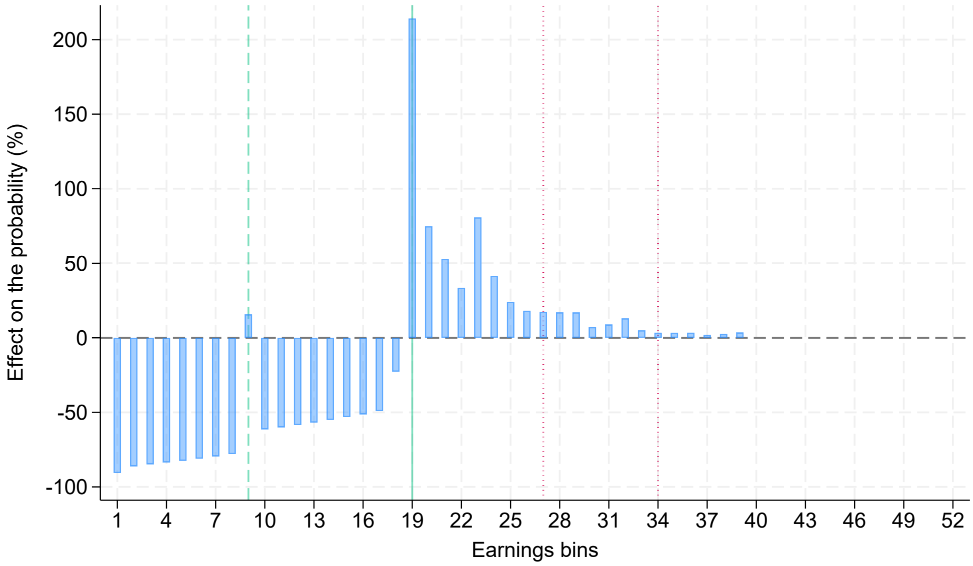
The similarity in the size of the spillover effects between the results of the model based on nominal earnings and the model using CPI-deflated earnings suggests that the CPI together with our set of controls does not fully capture the large increase in wages that took place in Lithuania between 2010 and 2019, as shown in Figure 1.[15] This is important because when pooling the data, as the econometric approach assumes that the probability of a worker falling into a particular category depends on observed factors as well as minimum wage effects. Failure to properly deflate earnings would violate this assumption due to scale effects (Barth and Kallapur, 1996; Wu and Xu, 2008), resulting in artificially large spillovers. Therefore, in the remainder of the paper, we focus on the estimates from LP-deflated earnings, since it falls between the other two deflators (GDP and CPI), but discuss the results from all deflators when quantifying the contribution of the minimum wage to wage growth and inequality, thereby adding lower and upper bounds.

Marginal effects. To provide an alternative visualization of the regression results, we transform the point estimates into marginal, calculated as the difference between the predicted probabilities with and without the minimum wage (Fortin et al., 2021). The predicted probability *with minimum wage* is based on the median value of the minimum wage observed between 2010 and 2019, while for the predicted probability *without minimum wage* we simply set the minimum wage indicators to zero. In terms of covariates, both predicted probabilities use the observed characteristics referring to the average job in the economy over the sample period. Comparing these two probabilities provides insights into how the existence of a minimum wage affects the location of jobs along the earnings distribution.

Figure 9 reports the marginal effects of the minimum wage along the earnings distribution based on the Probit estimates obtained using the LP-deflated earnings. The results indicate that the marginal effects corresponding to the presence of a minimum wage are substantially large: the increase in the probability that a job pays exactly the minimum wage, if it exists, is over 200%, at the expense of the mass of jobs below the minimum wage level that disappear. The marginal effect of being paid half the minimum wage is positive but quite small. Interestingly, the figure shows that the spillover effects are substantial up to 4 earnings bins above the minimum wage (or at +28% above the median level of the minimum wage) and still sizable up to around the median of the earnings distribution while decaying to zero before reaching the 75th

[15] This is because prices barely change compared to the evolution of GDP and LP, and therefore seem to be disconnected from the evolution of wages (see Garcia-Louzao and Jouvanceau (2023) for a decomposition of wage growth between 2008 and 2020).

Figure 9: Marginal effects of the minimum wage, 2010-2019



Notes: Marginal effects refer to the difference in the predicted probability of a job falling into a particular earnings bin when there is a minimum wage relative to when there is no minimum wage. Marginal effects are calculated using probit estimates based on LP-deflated earnings. The dashed and solid vertical lines represent the earnings bins in which the median value of half the minimum wage and the minimum wage fall between 2010 and 2019. The dotted vertical lines correspond to the median and 75th percentile of the pooled earnings distribution over the sample period.

percentile of the earnings distribution. The evidence on the marginal effects reveals how the existence of a minimum wage leads to a bunching of jobs exactly at its level in the earnings distribution, but they also show that the minimum wage matters further up in the distribution. The next section examines the role of the minimum wage in shaping the earnings distribution and quantifies how much it can explain the earnings dynamics in Lithuania between 2010 and 2019.

5.2 The shape of the distribution and the minimum wage

To characterize the role of the minimum wage in shaping the earnings distribution, we follow the reweighting approach of DiNardo et al. (1996) to generate a series of alternative scenarios using the *full* estimation sample. These counterfactuals are obtained by varying the distribution of the minimum wage effect parameters using the estimates we obtain from the Probit model. For example, one can create a new set of indicators, D^m_{kt}, that relate the distance of a given income bin to the minimum wage, but using the 2010 minimum wage level for all t. Using the Probit estimates, $[\hat{\beta}, \hat{\Omega}, \hat{\varphi}_m]$, along with the distribution of the covariates, X_{it}, and the new minimum wage indicators, D^m_{k2010}, we can predict the counterfactual cumulative probabilities, $\hat{P}_{k2010}$, following Equation (4). Similarly, we can obtain the actual predicted probability, $\hat{P}_{kt}$, using the actual minimum wage effect indicators, D^m_{kt}, and compute the interval predicted probability, $\hat{Q}_k = \hat{P}_k - \hat{P}_{k+1}$, i.e., the probability an individual belongs to a given income bin. The reweighting factor, $\hat{\psi}_k = \frac{\hat{Q}_{k2010}}{\hat{Q}_k}$, is the ratio of the interval predicted probability while keeping the minimum wage at its level in 2010, $\hat{Q}_{k2010}$, and the actual interval predicted probability, $\hat{Q}_k$. Using the reweighting factor, we can similarly calculate counterfactual statistics as propensity score methods (Fortin et al., 2011).

Constant minimum wage. Our first counterfactual experiment seeks to characterize how the shape of the earnings distribution would have evolved if the minimum wage had not changed. To do so, In Panel A of Figure 10, we follow Fortin et al. (2021) and fix the minimum wage location in the distribution at their level in 2010.[16] In other words, we use the value of the minimum wage in 2010 deflated to be expressed in 2019 terms using average labor productivity to create the minimum wage distance indicators, D^m_{k2010}.[17] Then, we use these new indicators to obtain the reweighting factor and generate the counterfactual earnings density that would result at the end of the period if the minimum wage had remained constant in real terms. In Panel B of Figure 10, we modify the approach and instead of fixing the position of the minimum wage in the distribution at the 2010 level, we fix the minimum wage at its 2010 current value (299 euros) and allow its location in the distribution to fall over time.[18] In other words, we calculate the reweighting factor for 2019 based on the *nominal* value of the minimum wage. While this alternative exercise is not useful for quantification, it does allow us to visualize the distributions in nominal terms, thus providing a snapshot of the actual distributions in 2010 and 2019, and what the latter would look like if the minimum wage had lost purchasing power in an economy where wages have more than doubled.[19]

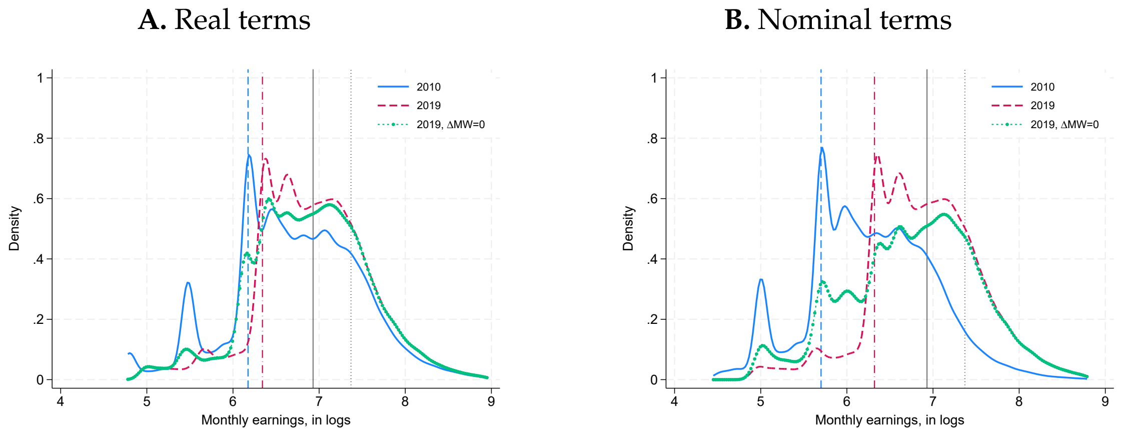
[16]The minimum wage in 2010 belonged to earnings bracket 18, while half of it was in earnings bracket 8.

[17]Given that labor productivity (LP) deflated point estimates lie in between those resulting from using either the GDP or the CPI as deflators, in the following, we mostly focus on the LP-deflated earnings Probit estimates to characterize the distributional effects of the minimum wage and refer to Appendix B.2 for results using alternative deflators.

[18]If the value of the minimum wage (half of it) remains unchanged, its position in the earnings distribution falls between 2010 and 2019 from earnings interval 18 (8) to 12 (2).

[19]This exercise is not useful for quantifying the earnings dynamics that can be attributed to the minimum wage, because using the nominal value of the minimum wage to create the reweighting factor in 2019 means that the minimum wage is forced to lag behind its distributional level in real terms, and thus would mechanically attribute to the minimum wage all of the nominal shift in the actual and

Figure 10: Actual and counterfactual distribution with 2010 minimum wage



Notes: Panel A shows actual distributions expressed in real terms using labor productivity as the deflator, and the counterfactual distribution from keeping the minimum wage at its 2010 income bin. Panel B shows the actual distribution re-scaled by the deflator to be in nominal terms, while the counterfactual distribution keeps the minimum wage at its 2010 value. The solid and dashed lines correspond to the density function of the earnings distribution in 2010 and 2019, respectively. The connected line represents the density function in 2019 but with the minimum wage level equal to that of 2010, i.e., 299 euros. The vertical dashed lines correspond to the (log) minimum wage level each year. The vertical solid line is the (log) median earnings in 2019, while the dotted vertical line is the 75th percentile. The plotted densities are truncated at values below 0.95 of the 1st percentile and values above 1.05 of the 99th percentile.

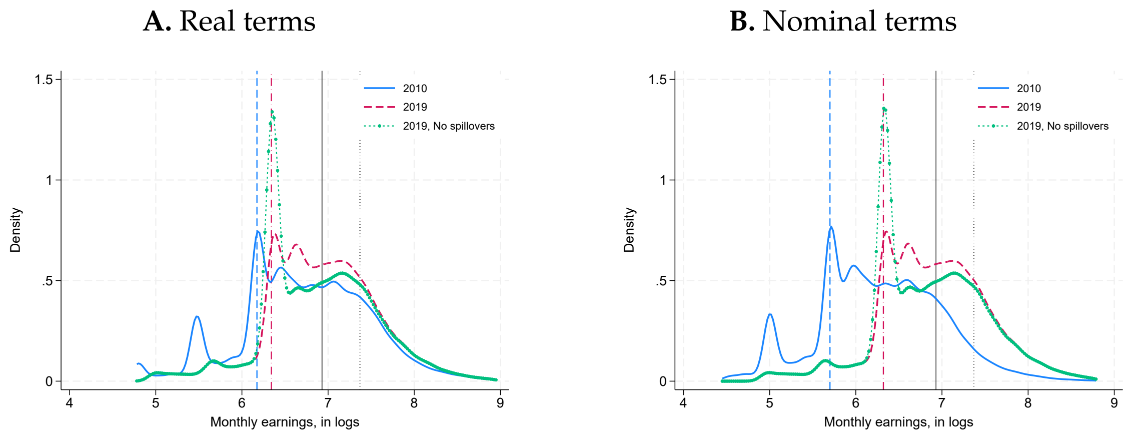
The figures show that the minimum wage has played an important role in shaping the distribution of earnings by contributing to the compression of its bottom tail, as illustrated by comparing the empirical densities in 2010 and 2019. When looking at the counterfactual distributions, the main message that emerges from both exercises is that if the minimum wage had not changed, a non-negligible fraction of jobs with earnings at the minimum wage in 2019 would have lower earnings. This can be seen more clearly when comparing the densities in the nominal exercise, as the gap in the distributions is more apparent due to the high increase in earnings. In both cases, however, the underlying story is that half of the jobs that were exactly at the minimum wage in 2019 would have fallen behind the wage scale to the level in 2010.

No spillover effects. Our second counterfactual exercise characterizes the role of spillovers even in the presence of minimum wage changes, i.e., we do not allow for any effects beyond the directly affected jobs. To do this, we use the reweighting factors from the two counterfactual exercises above to express the distributions in both real and nominal terms. Figure 11 shows that spillovers have also played a noticeable role in shaping the evolution of the earnings distribution between 2010 and 2019. Namely,

counterfactual distributions in 2019.

in the absence of such effects, the mass of jobs at exactly the minimum wage would be significantly larger, as several jobs would have been reallocated to the minimum wage level in 2019. The magnitude of this reallocation of jobs, and hence of the spillovers, is substantial up to about the median of the distribution (solid vertical line). However, minimum wage spillovers appear to affect wage setting up to about the 75th percentile of the distribution in 2019. Taken together, these results suggest that the minimum wage has affected the earnings distribution not only by increasing earnings in low-skilled jobs for which the minimum wage is binding but also by increasing earnings in jobs higher up the distribution.

Figure 11: Actual and counterfactual distribution without spillover effects



Notes: Panel A shows actual distributions expressed in real terms using labor productivity as the deflator, and the counterfactual distribution from keeping the minimum wage at its 2010 income bin. Panel B shows the actual distribution re-scaled by the deflator to be in nominal terms, while the counterfactual distribution keeps the minimum wage at its 2010 value. The solid and dashed lines correspond to the density function of the earnings distribution in 2010 and 2019, respectively. The connected line represents the density function in 2019 removing spillover effects of the minimum wage. The vertical dashed lines correspond to the (log) minimum wage level in each year. The vertical solid line is the (log) median earnings in 2019, while the dotted vertical line is the 75th percentile. The plotted densities are truncated at values below 0.95 of the 1st percentile and at values above 1.05 of the 99th percentile.

5.3 The contribution of the minimum wage to earnings dynamics

The previous section suggests that minimum wage increases affected the dynamics of monthly earnings between 2010 and 2019. The most important question, however, is how much it mattered. Therefore, we now turn to quantifying the role of the minimum wage in several selected statistics. To do so, we use the reweighting factor that would result if the minimum wage remained at its distributional value in 2010 to compute the counterfactual values of our objects of interest. We report the results using alternative deflators because they play a key role in generating the weighting factor, as suggested by the point estimates reported in Figure 8. Thus, we rely on the three deflators to provide a broad picture and bounds on the minimum and maximum contribution of the minimum wage.

Table 2: The contribution of minimum wage changes to inequality

	SD	P90-P10	P90-P50	P50-P10
A. Observed inequality				
2010	0.751	1.940	0.920	1.020
2019	0.650	1.410	0.810	0.600
Actual change	-0.101	-0.530	-0.110	-0.420
B. LP-deflated counterfactual				
2019, ΔMW=0	0.682	1.600	0.830	0.770
Change	-0.068	-0.340	-0.090	-0.250
Change due to MW	0.033	0.190	0.020	0.170
Contribution (%)	-32.27	-35.85	-18.18	-40.48
C. GDP-deflated counterfactual				
2019, ΔMW=0	0.675	1.530	0.820	0.710
Change	-0.076	-0.410	-0.100	-0.310
Change due to MW	0.025	0.120	0.010	0.110
Contribution (%)	-24.64	-22.64	-9.09	-26.19
D. CPI-deflated counterfactual				
2019, ΔMW=0	0.712	1.770	0.870	0.900
Change	-0.039	-0.170	-0.060	-0.110
Change due to MW	0.062	0.370	0.060	0.310
Contribution (%)	-61.15	-68.52	-50.00	-73.81

Notes: SD stands for standard deviation, P90-P10, P90-P50, and P50-P10 are log-percentile differences of monthly earnings. Panel A reports actual levels of inequality in 2010 and 2019 along with its change. Panel B to D report counterfactual inequality statistics under different deflators, labor productivity (LP), gross domestic product (GDP), and consumer price index (CPI)., when estimating Equation (4). Within each counterfactual panel: 2019, ΔMW=0 refers to the value of that statistics without MW changes; Change refers to the change in a given statistic between 2010 and 2019 if the MW had remained at its distribution level in 2010; Change due to MW is the difference in a given statistic between the counterfactual and actual change; Contribution is the percent contribution of the change due to MW to the actual change in a given statistic.

Inequality. Table 2 reports the results quantifying the contribution of the minimum wage on the dynamics of earnings inequality. The evidence highlights the sharp decline in earnings inequality observed between 2010 and 2019, whether measured by the standard deviation of (log) monthly earnings or the difference between the (log) 90th and 10th percentiles. Moreover, the P50-P10 column shows that the decline was particularly large when looking at the lower tail of the distribution, where minimum wage increases bite. The counterfactual change shows a significant but milder decline in inequality, regardless of the deflator. Importantly, the decline in bottom-tail inequality would be substantially reduced if the minimum wage had remained constant.

In terms of the magnitude of the minimum wage's contribution, the numbers vary depending on the deflator used to normalize the earnings distribution over time and then calculate the predicted distributions with the model estimates for the reweighting factor. Specifically, our results show that when earnings are deflated to capture average labor productivity growth, 32% of the decline in overall earnings inequality and 40% of the decline in bottom-tail inequality can be attributed to the minimum wage. These figures are 25% (61%) for overall earnings dispersion when the deflator used in the estimation of the Probit model is the GDP (CPI) and 26% (74%) for bottom-tail inequality.

To put these numbers in context, Fortin et al. (2021) documents that the minimum wage can explain 15% (21%) of the evolution of male (female) wage inequality in the US between 1979 and 2017, but the magnitude of the effect was higher between 1979 and 1988, when the policy was particularly active, with minimum wage raises explaining about 40% of the evolution of wage inequality. However, the contribution of the minimum wage to wage inequality appears to be higher in Europe. For example, Bossler and Schank (2023) finds that the introduction of the German minimum wage helped reduce inequality, as between 41 and 57% of the decline in wage dispersion can be explained by the minimum wage. Oliveira (2023) shows that in Portugal the contribution of the minimum wage to the dynamics of wage inequality was about 85% between 2006 and 2019, when minimum wage hikes were common. However, he finds that in periods when the minimum wage did not change much, the contribution to inequality was at most 33%.

Wage growth. To illustrate how minimum wage hikes can feed through to economy-wide wage developments, Table 3 reports the evolution of average earnings between 2010 and 2019 and how much the minimum wage has contributed to its growth. The results show that the magnitude of the increase in earnings differs substantially depending on the deflator used, as the average increase based on CPI-deflated earnings was almost 50%, while the average increase based on the GDP was only 10%. The counterfactual change, on the other hand, suggests that earnings would still have increased by between 8 and 40% in the absence of minimum wage increases. Comparing actual and counterfactual average earnings growth, our estimates imply that the minimum wage can explain up to 20% of the observed growth between 2010 and 2019.[20]

For comparison, Ferraro et al. (2018) finds that in Estonia between 2001 and 2014, a 1 euro increase in the minimum wage led to an 11 cents rise in average wages. In our case, we can use our results on the change in average wage growth due to the minimum wage in Table 3 to obtain a back-of-the-envelope elasticity comparable to that of Ferraro et al. (2018). This exercise indicates that a 1 euro increase in the minimum wage leads to an increase in the average wage of between 19 and 32 cents.

Table 3: The contribution of minimum wage changes to average earnings growth

	LP-deflated	GDP-deflated	CPI-deflated
2010	6.728	6.837	6.434
2019	6.935	6.937	6.921
2019, ΔMW=0	6.897	6.918	6.834
Actual change	0.207	0.100	0.487
Counterfactual change	0.169	0.080	0.400
Change due to MW	-0.038	-0.020	-0.087
Contribution (%)	-18.17	-19.79	-17.94

Notes: Each panel uses point estimates from Equation (4) using alternative deflators: labor productivity (LP), gross domestic product (GDP), and consumer price index (CPI). Rows 2010 and 2019 refer to the value of average earnings in the specific year, whereas in 2019, ΔMW=0 refers to the value of those statistics without MW changes. Actual change represents the observed average earnings growth between 2010 and 2019. Counterfactual change is the average earnings growth between 2010 and 2019 if the MW had remained at its distribution level in 2010. Change due to MW is the difference in average earnings growth between the counterfactual change and the actual change. Contribution is the percent contribution of the change due to MW to actual average earnings growth.

6 Conclusions

Using detailed monthly Social Security records, this paper quantifies the effect of the minimum wage on the earnings distribution in Lithuania between 2010 and 2019. Our analysis indicates that the minimum wage played a critical role in shaping earnings dynamics by not only boosting the earnings of workers in jobs directly affected by the minimum wage but also by having economically meaningful spillovers up to about

[20] Using estimates from a model in which earnings are not deflated and spillovers are the largest, as documented in Figure 8, we find that the minimum wage cannot explain more than 27% of the nominal growth in average earnings.

the median of the distribution of real monthly earnings.

Based on our preferred estimates that account for increases in labor productivity when deflating earnings, we quantify that minimum wage increases can explain 32% of the decline in overall earnings inequality and 40% of the fall in bottom-tail inequality between 2010 and 2019. In addition, we document that up to 20% of the average earnings growth above and beyond the average increase in labor productivity can be attributed to minimum wage changes.

Our analysis underscores the role of minimum wage policy in lowering income inequality in the context of a growing and initially highly unequal economy. However, it is important to emphasize that the extent to which the minimum wage can reduce overall disposable income inequality ultimately depends on who the minimum wage workers are and their employment prospects (Redmond et al., 2021; Giupponi et al., 2024). Our results also carry a note of caution, as minimum wage increases may spill over into the earnings distribution and affect wage setting in jobs further away from the minimum wage, plausibly putting upward pressure on economy-wide earnings dynamics.

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Appendix

A Data transformation

Skill categories. We create three job-skill categories by grouping information on occupations based on ISCO-08 classification as follows: (i) *low-skill* jobs refer to ISCO-08 codes 91 to 96, (ii) *medium-skill* jobs correspond to codes 41 to 81, and (iii) *high-skill* jobs are codes 11 to 35. More information on ISCO-08 classification and aggregation guidelines can be found here: `https://isco-ilo.netlify.app/en/isco-08/`

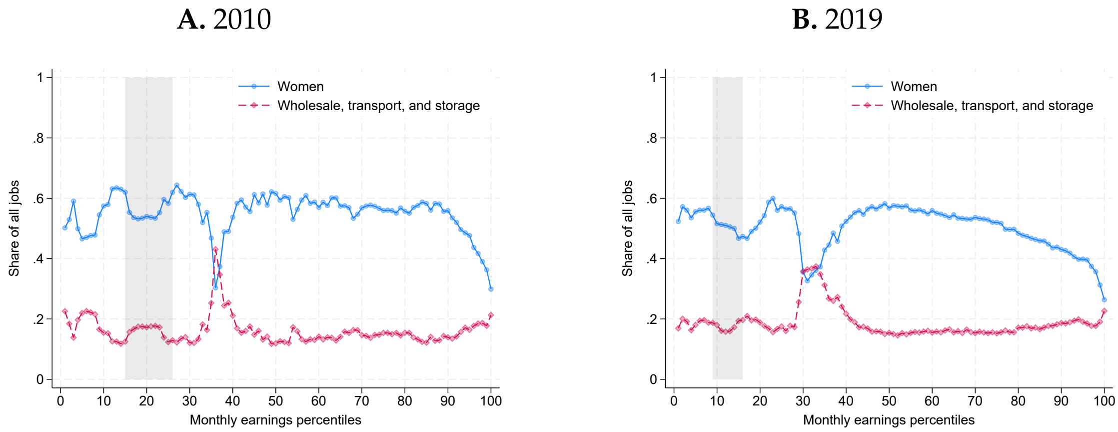
Sector of activity. Detailed 2-digit NACE2 economic activities are grouped into ten broad sectors of activities: (i) *primary sector* correspond to NACE2 codes 1 to 9, (ii) *industry* are coded 10 to 39, (iii) *construction* 40 to 43, (iv) *wholesale, transport, and storage* are 45 to 46 and 49 to 53, (v) *retail, accommodation, and restaurants* codes 47 and 55 to 56, (vi) *IT and finance* groups 58 to 66, (vii) *professional activities* are 69 to 75, (viii) *real estate, and other admin activities* 55 to 56, 68, and 77 to 82, (ix) *public administration, education, and health* 84 to 88 and 99, and (x) *other activities* are 90 to 98. More information on ISCO-08 classification and aggregation guidelines can be found here: `https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF`

Firm location. The 60 municipalities are aggregated into broader administrative regions (counties) to create ten locations referring to *Vilnius*, *Kaunas*, *Klaipėda*, *Šiauliai*, *Panevėžys*, *Alytus*, *Marijampolė*, *Tauragė*, *Utena*, and *Telšiai*. Detailed information on the administrative division of Lithuanian can be found here: `https://osp.stat.gov.lt/lietuvos-regionai-2022/lietuvos-suskirstymas`

B Supplementary figures and tables

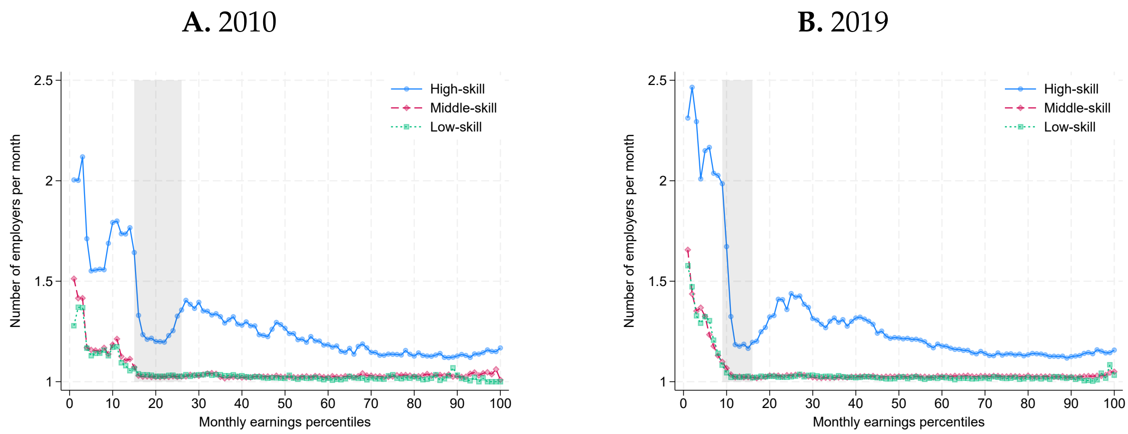
B.1 Additional summary statistics

Figure B.1: Women and wholesale, transport, and storage along the earnings distribution in 2010 and in 2019



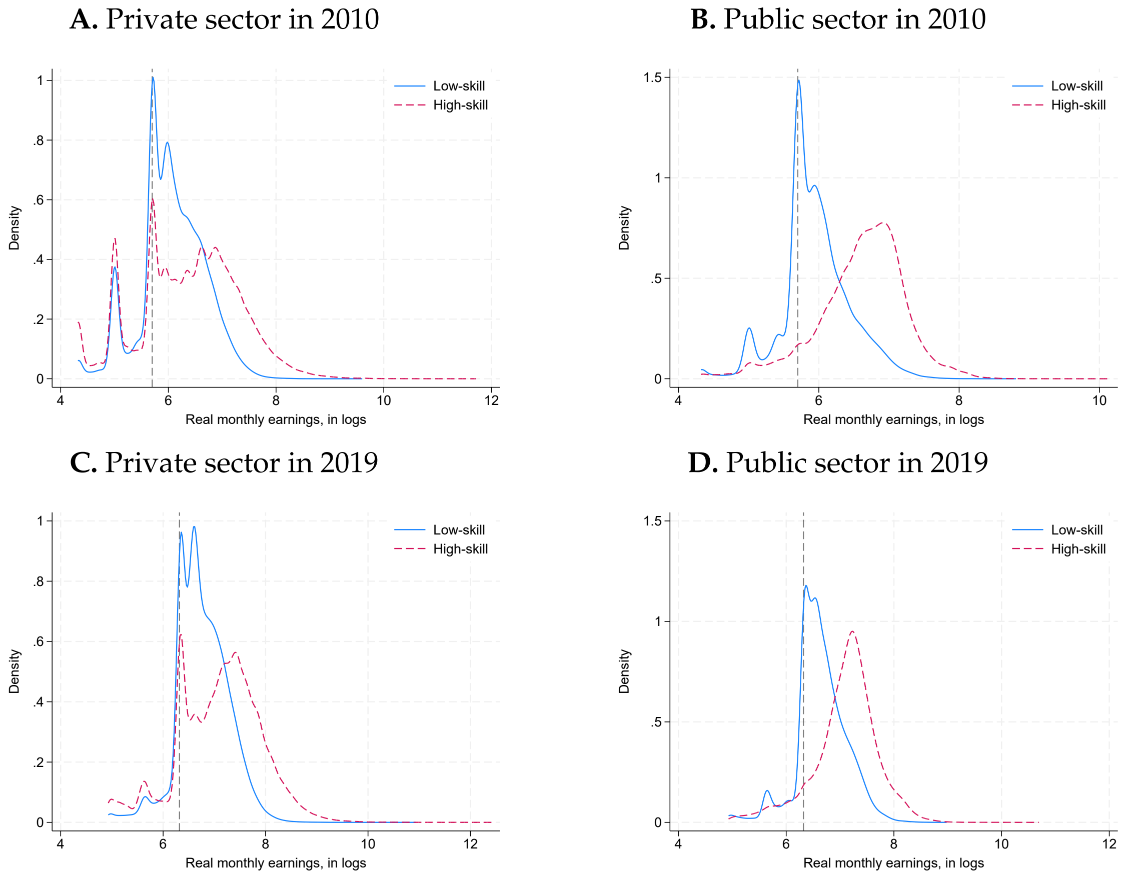
Notes: Each line portrays the share of females as well as the percentage of jobs in wholesale, transport, and storage activities. Earnings percentiles are created by ranking workers in a given month based on the current earnings and averaging their rank within the specific year: 2010 or 2019. The shaded area corresponds to the percentiles of the distribution where minimum wage jobs lie.

Figure B.2: Number of employers along the earnings distribution by skill category in 2010 and in 2019



Notes: Each line portrays the average number of employers in a given month within an earnings percentile by skill category. Earnings percentiles are created by ranking workers in a given month based on the current earnings and averaging their rank within the specific year: 2010 or 2019. The shaded area corresponds to the percentiles of the distribution where minimum wage jobs lie.

Figure B.3: Earnings distribution by skill type in public and private sectors in 2010 and 2019

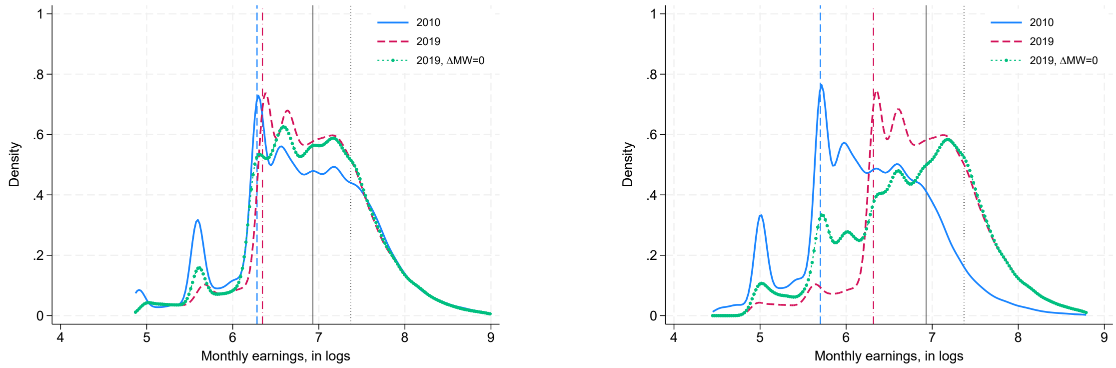


Notes: The figure shows the empirical (log) nominal monthly earnings for low- and high-skill jobs in 2010 and 2019 differentiating between the private and the public sector. The dashed vertical line represents the (log) nominal monthly minimum wage.

B.2 The impact of the minimum wage on the earnings distribution under different deflators

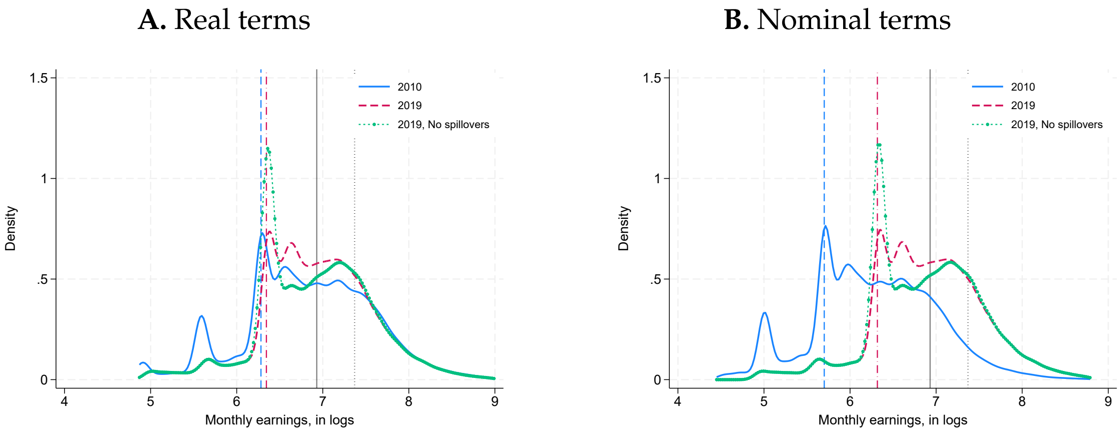
Figure B.4: Actual and counterfactual distribution with 2010 minimum wage: GDP

A. Real terms **B.** Nominal terms



Notes: Panel A shows actual distributions expressed in real terms using the GDP as the deflator, and the counterfactual distribution from keeping the minimum wage at its 2010 income bin. Panel B shows the actual distribution re-scaled by the deflator to be in nominal terms, while the counterfactual distribution keeps the minimum wage at its 2010 value. The solid and dashed lines correspond to the density function of the earnings distribution in 2010 and 2019, respectively. The connected line represents the density function in 2019 but with the minimum wage level equal to that of 2010, i.e., 299 euros. The vertical dashed lines correspond to the (log) minimum wage level each year. The vertical solid line is the (log) median earnings in 2019, while the dotted vertical line is the 75th percentile. The plotted densities are truncated at values below 0.95 of the 1st percentile and values above 1.05 of the 99th percentile.

Figure B.5: Actual and counterfactual distribution without spillover effects: GDP

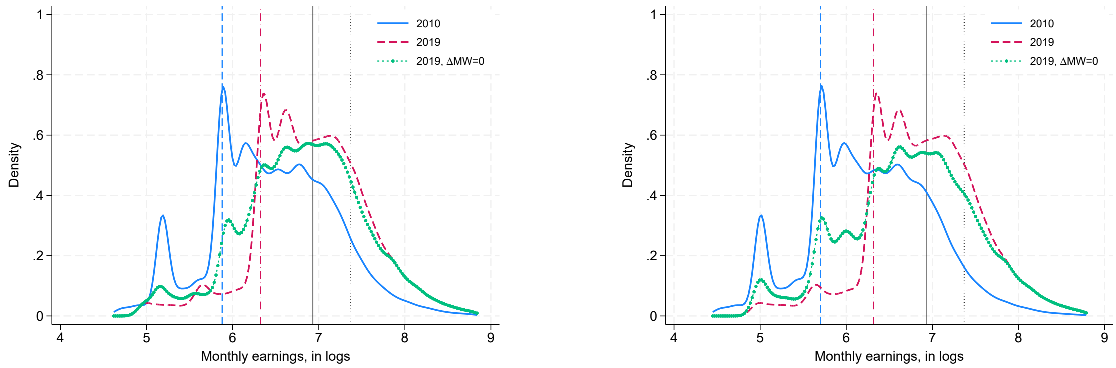


Notes: Panel A shows actual distributions expressed in real terms using the GDP as the deflator, and the counterfactual distribution from keeping the minimum wage at its 2010 income bin. Panel B shows the actual distribution re-scaled by the deflator to be in nominal terms, while the counterfactual distribution keeps the minimum wage at its 2010 value. The solid and dashed lines correspond to the density function of the earnings distribution in 2010 and 2019, respectively. The connected line represents the density function in 2019 removing spillover effects of the minimum wage. The vertical dashed lines correspond to the (log) minimum wage level each year. The vertical solid line is the (log) median earnings in 2019, while the dotted vertical line is the 75th percentile. The plotted densities are truncated at values below 0.95 of the 1st percentile and values above 1.05 of the 99th percentile.

Figure B.6: Actual and counterfactual distribution with 2010 minimum wage: CPI

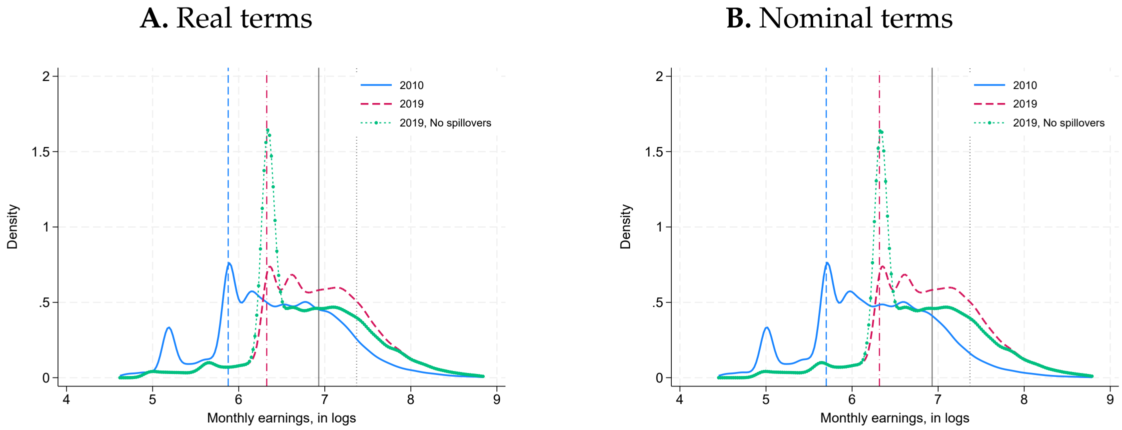
A. Real terms

B. Nominal terms



Notes: Panel A shows actual distributions expressed in real terms using the CPI as the deflator, and the counterfactual distribution from keeping the minimum wage at its 2010 income bin. Panel B shows the actual distribution re-scaled by the deflator to be in nominal terms, while the counterfactual distribution keeps the minimum wage at its 2010 value. The solid and dashed lines correspond to the density function of the earnings distribution in 2010 and 2019, respectively. The connected line represents the density function in 2019 but with the minimum wage level equal to that of 2010, i.e., 299 euros. The vertical dashed lines correspond to the (log) minimum wage level each year. The vertical solid line is the (log) median earnings in 2019, while the dotted vertical line is the 75th percentile. The plotted densities are truncated at values below 0.95 of the 1st percentile and values above 1.05 of the 99th percentile.

Figure B.7: Actual and counterfactual distribution without spillover effects: CPI



Notes: Panel A shows actual distributions expressed in real terms using the CPI as the deflator, and the counterfactual distribution from keeping the minimum wage at its 2010 income bin. Panel B shows the actual distribution re-scaled by the deflator to be in nominal terms, while the counterfactual distribution keeps the minimum wage at its 2010 value. The solid and dashed lines correspond to the density function of the earnings distribution in 2010 and 2019, respectively. The connected line represents the density function in 2019 removing spillover effects of the minimum wage. The vertical dashed lines correspond to the (log) minimum wage level each year. The vertical solid line is the (log) median earnings in 2019, while the dotted vertical line is the 75th percentile. The plotted densities are truncated at values below 0.95 of the 1st percentile and values above 1.05 of the 99th percentile.