



**HAL**  
open science

# Polarization, employment and the minimum wage: Evidence from European local labor markets

Paul Maarek, Elliot Moiteaux

► **To cite this version:**

Paul Maarek, Elliot Moiteaux. Polarization, employment and the minimum wage: Evidence from European local labor markets. *Labour Economics*, 2021, 73, pp.102076. 10.1016/j.labeco.2021.102076 . hal-04120471

**HAL Id: hal-04120471**

**<https://univ-panthéon-assas.hal.science/hal-04120471>**

Submitted on 22 Jul 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

# Polarization, employment and the minimum wage: Evidence from European local labor markets\*

Paul Maarek<sup>†</sup>

Elliot Moiteaux<sup>‡</sup>

First version: January 2018

This version: September 2021

## Abstract

The labor market is becoming increasingly polarized as routine jobs disappear. In the flexible US labor market, this has had a limited impact on employment due to the strong employment growth in low-paying manual occupations for workers who are not able to reallocate to high-paying abstract occupations. This may not be the case in some rigid wage European economies, which are capable of creating fewer low-paying manual jobs. We study the effect of a decrease in the proportion of routine jobs on employment and participation rates, conditionally on the level of the minimum wage, in European local labor markets. Our OLS and IV estimates show that the polarization process has a negative impact on employment and participation rates in high minimum wage countries only.

**Keywords:** polarization, employment, participation, minimum wage, ICT, routine occupations.

**JEL Codes:** J21, J23, J38

---

\*The usual disclaimers apply. We are grateful for the thoughtful comments from the seminar audience at the Université de Cergy-Pontoise. We also thank participants at the annual meetings of the European Economic Association, European Association of Labor Economists and Association Française de Science Economique for helpful comments. In particular, we received comments that improved the paper from Clément Bosquet, Thepthida Sopraseuth, Idriss Fontaine, Olivier Charlot, Régis Renault, Fabian Gouret, Medhi Senouci, Alexandra Fedorets, Martin Guzi and Gani Aldashev.

<sup>†</sup>Corresponding author: LEMMA, Université Panthéon Assas, Paris 2. E-mail: paul.maarek@u-paris2.fr

<sup>‡</sup>THEMA, CY Cergy Paris Université 33, boulevard du port 95000 Cergy, France. E-mail: elliot.moiteaux@cyu.fr

# 1 Introduction

The polarization of the labor market is now a well-documented phenomenon in the US (Autor et al. (2003) Autor et al. (2006)) and Europe (Goos and Manning (2007), Goos et al. (2014), Dustmann et al. (2009)), beginning in the mid-1980s and accelerating in the 1990s. It corresponds to a strong increase in the share of employment in high-paying abstract occupations and low-paying manual occupations, relative to the share of routine occupations in the middle of the wage distribution. Routine occupations are indeed easier to automate using information technologies, as they contain a large share of repetitive tasks. This has led researchers to reconsider the canonical model of skill-biased technological change toward a more subtle understanding of the labor in terms of tasks. Technology can substitute for workers in a subset of tasks (Acemoglu and Autor (2011)). This process has led to a dramatic deterioration of economic opportunities for low-skilled non-college-educated workers and particularly males (see Acemoglu and Autor (2011), Autor (2019) or Verdugo and Allègre (2020)). First, workers with low ability who lose their relatively well-paid routine occupations tend to reallocate to manual occupations that pay less on average, as they have no comparative advantage in abstract occupations (Cortes (2016) or Autor (2019)). Second, this creates a “displacement effect”, which lowers the demand for this factor and creates downward pressure on wages for both workers in the occupation that disappeared and occupations to which a share of the workers from the middling occupations reallocate. (Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2017)). We argue that, in a context in which labor market institutions do not allow wages to fully adjust, this process could lead to lower employment.

Surprisingly, the impact of this process in terms of aggregate employment has received limited attention (with some notable exceptions, however – see the literature review). The conventional wisdom is that this process has limited implications in terms of aggregate labor market performance. The destruction of routine occupations is accompanied by the massive creation of abstract occupations, mainly for high-skilled workers, and manual jobs for low-skilled workers, especially in the service sectors (Autor and Dorn (2013)). Autor et al. (2015) document an extremely limited impact of technology shocks implying routine job destruction on aggregate employment at the local labor market level in the US. Trade shocks have been argued to be much more costly in terms of aggregate employment (Autor and Dorn (2013)) but seem to be weakly related to polarization (see Goos et al. (2014) and Autor et al. (2015)). In the context of task-biased technological change, Acemoglu and Restrepo (2017) and Acemoglu and Restrepo (2020) provide a framework in which wages adjust, allowing the lower occupations to absorb the excess labor supply from the occupations (or tasks) that disappeared at the cost of a downward wage

adjustment. We argue that the polarization process could have had a very different impact from that in the US in certain European countries, given the higher minimum wage in place in the latter. In a rigid wage environment, wages do not necessarily adjust to clear the labor market, especially in the left tail of the wage distribution, where the minimum wage plays a crucial role in the wage determination process. This may prevent the creation of a sufficient number of low-paying jobs for low-skilled workers, who cannot reallocate to abstract occupations, to compensate for the destruction of routine jobs, which has been observed in every European country. The United States also has a national minimum wage, but relative to the median wage, it is much lower in many European countries. In France, for instance, in which a significant share of workers (approximately 13% in 2019 according to Garnero (2019)) are paid the minimum wage, Catherine et al. (2015) and Cahuc and Debonneuil (2004) document a strong deficit in manual job creation in the service sector relative to the US economy and relate this difference to the high minimum wage. We argue that, in such an environment, the destruction of routine jobs could have severe consequences in terms of aggregate employment, as routine jobs are often occupied by low-skilled workers, who cannot reallocate to abstract, high-paying jobs.

In this paper, we use the European Union Labor Force Survey (EULFS hereafter), which provides detailed information about the economic situation of a sample of workers from 1983 to 2014 at the subnational level (i.e., on local labor markets). The survey contains comprehensive information on occupations, allowing us to measure the polarization process (i.e., the evolution of the proportion of routine jobs) for each area within a country, which we define as a local labor market (Goos and Manning (2007) and Goos et al. (2014) use the same data). The cross-country dimension of the dataset, with important heterogeneity in minimum wage levels, enables us to measure the heterogeneity in the impact of the decrease in routine jobs on employment and participation rates in a particular local labor market within a country, depending on the level of the minimum wage. Retaining only countries with a national legal minimum wage (8 countries from the 15-country sample of Goos et al. (2014)), we ultimately have a panel of 86 local labor markets within our sample, as defined by the EULFS. There exists considerable heterogeneity in the levels of national minimum wages, ranging from 0.278 to 0.585 as a percentage of the mean wage of full-time workers. This allows us to identify the role of minimum wages in the impact of increasing job market polarization on labor market performance. Our identification relies on two sources of variation. First, we are able to compare the impacts of different degrees of routine job destruction within the same institutional setting. For instance, the local labor markets within a given country have not experienced the same degree of routine job destruction. Second, we are able to compare some local labor markets

with roughly similar degrees of routine job destruction located in different countries and subjected to different institutional settings. The EULFS also contains many socioeconomic characteristics that allow us to control for key variables that plausibly affect both the polarization process and the labor market outcome variable that we seek to explain (e.g., age structure, skill supply, industry composition). First, using fixed effects (local labor market and time) regressions in level, i.e. using within local labor markets variations over time, we show that the decrease in the number of routine jobs in a given local labor market has no impact, or a very limited positive one in a local labor market characterized by a low minimum wage, but it is strongly negatively correlated with the employment and participation rates in a local labor market characterized by a strong minimum wage. This outcome is consistent with Autor et al. (2015), who find a very weak effect of polarization on the employment rate for the US economy. This result holds for European countries characterized by a low minimum wage. The very modest increase observed in some specifications is consistent with the results of Verdugo and Allègre (2020), who show an increase in the participation rate of women associated with the polarization process, which they interpret as an intra-household response to the decreasing economic opportunities of men. For flexible wage labor markets, this effect should translate into an increase in the overall participation rate. For rigid wage labor markets, however, it is likely that the overall decrease in employment opportunities for males translates into a decrease in participation for this category of workers, which could more than compensate for the increase in women's participation.

We then provide more detailed evidence for the mechanisms. Consistent with our narrative, we show that a high minimum wage is associated with less creation of low-paying manual jobs following a decrease in the proportion of routine jobs, which we interpret as evidence of the mechanism that we have in mind to explain the effect of employment polarization in terms of aggregate labor market performance. Some of the workers who have no comparative advantage in abstract occupations and who suffer from the destruction of their routine jobs are unable to reallocate to manual occupations due to the presence of a high minimum wage that prevents the creation of low-paying occupations. We also include alternative labor market institutions, such as employment protection, and their interactions with the proportion of routine to understand whether the impact of minimum wage does not capture the effects of other labor market institutions, which may be correlated with the minimum wage. We show that labor market institutions are only weakly correlated with the level of the minimum wage in our sample. In addition, we find that, even when not controlling for minimum wage level, labor market institutions do not explain much of the dynamics in terms of employment in a context of routine job destruction.

We address the possible endogeneity of the proportion of routine jobs using an instrumental variable (IV) strategy. Despite our inclusion of numerous fixed effects and other controls, we cannot completely exclude the possibility of reverse causality, although the decrease in routine jobs is generally considered a demand shock (related to technology shocks). We follow the logic of the instrumental strategy of Karabarbounis and Neiman (2013) and use the shocks in ICT investment prices (from the KLEMS dataset) that occurred in the 1990s and that are recognized in the literature as having been among the major factors responsible for the decrease in the proportion of routine jobs (see Autor and Dorn (2013) or Michaels et al. (2014)). The massive adoption of computers and IT technologies substitute for workers (mostly low-skilled) in performing routine tasks—such as bookkeeping, clerical work, and repetitive production and monitoring activities—which are readily automatized because they follow precise and well-defined procedures. Specifically, to capture the extent to which a local labor market has been affected by a substantial decline in the price of new technology investments, we rely on a Bartik-type instrument and use the initial sector specialization of the local labor market and the initial ICT capital intensity of sectors, under the assumption that sectors (and local labor markets specialized in these sectors) that use ICT more intensively should be more affected by price shocks in ICT. This assumption allows us to construct the degree of exposure of each local labor market to the (exogenous) technological shocks, explaining the decrease in the proportion of routine jobs. These results are qualitatively similar to those obtained with OLS but are larger in magnitude.

Our results suggest that the impact of the minimum wage may depend on the economic context and, more particularly, the rates at which routine jobs are destroyed and the labor market is experiencing structural transformation. In such a context, more flexible institutional arrangements, such as minimum wages negotiated at the sector or firm level, could be much more efficient (as in countries such as Germany and Sweden). Another possibility that might lead to efficiency gains in such an environment is to fix the minimum wage at a sub-national level because local labor markets have very different exposures to global technology shocks.

We are not the first to question the impact of polarization on aggregate employment and participation rates. Autor et al. (2015) find little evidence that technology shocks that destroy routine jobs have a sizable aggregate impact on employment for the US economy. We show that this conclusion does not necessarily hold in countries with more rigid wages, due to their poor ability to create low-paying jobs. Two papers are very closely related to the mechanisms that we have in mind to explain the potential cost of routine job destruction in term of aggregate employment. First, Bock (2017) uses a calibrated

general equilibrium model and find that labor market polarization, by displacing unskilled workers from routine to manual jobs, could explain the strong decline in employment for this category of workers given its substantial labor costs. Using a similar calibration strategy, Albertini et al. (2016) compare the labor market performance of two economies with very different institutional settings (France and the US) in a context in which technology shocks destroy routine jobs. Nellas et al. (2011) also used a theoretical model to compare the employment consequences of the destruction of routine jobs between the US and the UK, which have flexible labor markets, and continental European countries. We directly use data at the local labor market level, which allows us to empirically compare the employment response to polarization across different institutional settings. Jaimovich and Siu (2020) show that the process of polarization may have been responsible for the jobless recovery after the Great Recession of 2008 in the US, given the acceleration of the destruction of routine jobs during this period, which did not recover following the recession. We focus on the long-term impact of labor market polarization on and the role of labor market institutions in this outcome.

Finally, in a very recent paper related to ours, Lordan and Neumark (2018) use the inflows and outflows of employment across the US states and show that workers who have lost their routine jobs are less likely to find a new job in states with a high minimum wage. Our results are in line with their findings, but our paper is distinct from theirs in several respects. First, we focus on aggregate equilibrium labor market performance instead of labor flows. Second, we analyze the effects on both employment and participation rates. Third, using data on European local labor markets allows us to compare very different institutional settings and heterogeneous minimum wage levels and to compare the impacts of very different labor market shocks within the same institutional setting. Finally, we use an IV strategy, which permits a causal interpretation of our results.

The remainder of this paper is organized as follows. We first present the data that we employ throughout the paper and some basic stylized facts. Then, we present our empirical strategy. Finally, we present our results and conclude the paper.

## 2 Data and stylized facts

In this section, we present the main data sources that we use in this paper. We first present the EULFS, from which we derive our main polarization variable and the control variables.

The EULFS contains data on 28 European countries at the national level.<sup>1</sup> One of the main advantages of this dataset is that it is available for many countries over a relatively long time period and has a large sample size of approximately 200,000 annual observations per country each year. We limit our analyses to the fifteen countries that composed the European Union before the 2004 enlargement as in Goos et al. (2014). These countries have the most complete datasets, and they should be very similar in terms of exposure to technology shocks, relative to the newest EU members. Of these fifteen countries, only 8 have a national minimum wage, making institutions and labor costs for low-skilled workers comparable across them. These countries are Belgium, Spain, France, Greece, Ireland, the Netherlands, Portugal and the United Kingdom. We ultimately have a total of 86 local labor markets within these 8 countries.<sup>2</sup> Occupations are coded using the two-digit 1988 International Standard Classification for Occupations (ISCO1988) and industries with the Nomenclature Statistique des Activités Economiques dans la Communauté Européenne (NACE) revision 1. These classifications include 39 occupations, 23 industries before 2008 and 22 industries after 2008.

The version of the EULFS that we use ranges from 1983 to 2013. As there is no information on the occupations of workers before 1992, we only use data from 1992 onward. Our baseline sample stops in 2007 to avoid the effect of the 2008 crisis on the labor market. Additionally, during this period, the NACE and ISCO classifications changed in 2008 and 2010, respectively, making use of the EULFS sample very difficult for years after 2010 (see below). Nevertheless, as a robustness test, we also consider a sample including post-crisis years until 2010.<sup>3</sup>

Table 1 displays some summary statistics for the variables that we use in this analysis. First, there is important variation in the proportion of routine occupations within and between local labor markets. We mostly use within variation in the proportion of routine occupations in our empirical analysis, as we

---

<sup>1</sup>Then, the data are processed centrally by Eurostat, which harmonizes them with the same set of characteristics for each country, common classifications and definitions.

<sup>2</sup>Using the 7 other countries with no national minimum wage using an alternative measure for possible downward rigidities would render comparisons difficult. For instance, in countries with no national minimum wage but an industry minimum wage, the lower bound for the wage can adjust more easily in industries with an excess supply of labor. We could consider the wage level of the lower wage decile compared to the mean wage in the population as an alternative measure for these countries. However, a high wage at the bottom of the wage distribution can be the result of a low supply of low-skilled workers, as in the Scandinavian countries, for instance. For these reasons, it seems preferable to retain only countries with a national minimum wage to measure properly the impact of such an institution.

<sup>3</sup>To address the change in the NACE classification in 2008, we use the methodology of Verdugo and Allègre (2020). They manually created a crosswalk to convert the classification from NCAE Rev. 1 to NACE Rev. 2, and to have consistent industries over time, they aggregated D (Electricity) with E (Water supply), H (Transportation) with J (Information) and L (Real Estate) and M (Professional activities) with N (Administrative and support service activities). Concerning the change in the ISCO classification in 2010, we use an existing crosswalk. The crosswalk was provided by the Institute for Structural Research and Faculty of Economics of the University of Warsaw. However, we observe a structural break in the data after using this crosswalk, so we do not use data from years after 2010, as argued in Breemersch et al. (2017). In our version of the EULFS, we had data until 2013, so we dropped 2011, 2012 and 2013. Note that our results are robust regardless of whether we consider data until 2007 or 2010 (see Tables A1 and A2).



Table 1: Summary statistics

	N	Mean	Min	Max	S.D.	Between S.D.	Within S.D.
Sh. of middling occ.	1137	0.422	0.230	0.602	0.060	0.055	0.029
Avg. minimum wage	1137	0.402	0.278	0.541	0.086	0.081	0.022
Sh. of low-skill	1134	0.533	0.230	0.890	0.141	0.145	0.051
Sh. of medium-skill	1134	0.297	0.073	0.476	0.102	0.103	0.027
Sh. of high-skill	1134	0.170	0.029	0.389	0.069	0.066	0.031
Sh. of male	1137	0.494	0.447	0.528	0.009	0.007	0.005
Sh. of $\leq 27$ y.o.	1137	0.268	0.131	0.378	0.031	0.027	0.017
Sh. of 28-37 y.o.	1137	0.196	0.128	0.291	0.017	0.013	0.011
Sh. of 38-47 y.o.	1137	0.185	0.123	0.225	0.015	0.010	0.011
Sh. of 48-57 y.o.	1137	0.155	0.106	0.241	0.020	0.013	0.016
Sh. of 58-67 y.o.	1137	0.136	0.093	0.233	0.022	0.019	0.011

Source: EULFS dataset for years 1992-2007. The descriptive statistics are calculated at the local labor market level. Sample includes 86 local labor markets spanning over 8 countries. We include all working individuals aged 17-72. "Between S.D." and "Within S.D." refer to the standard deviations calculated between and within local labor markets, respectively.

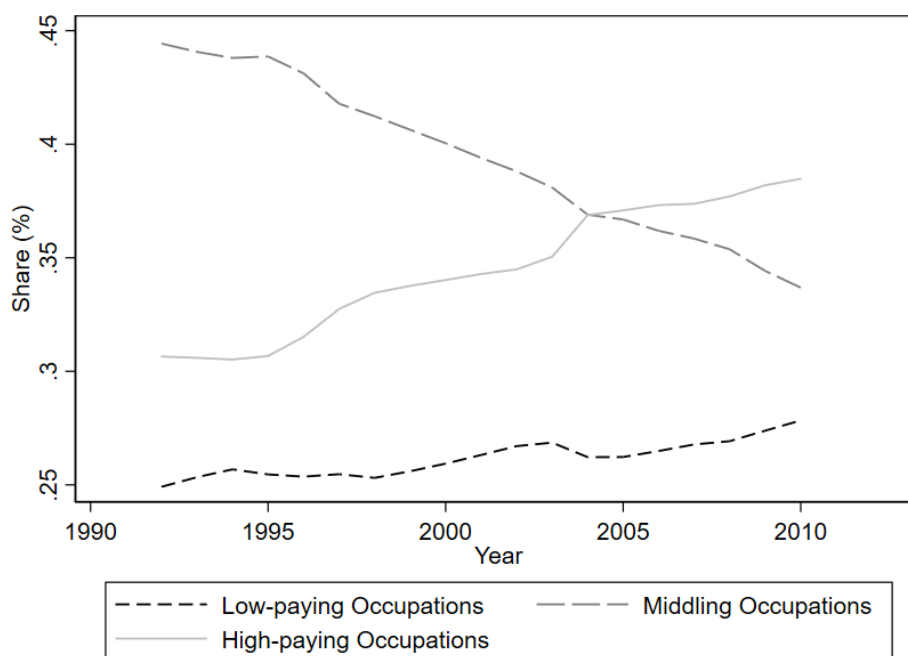
introduce local labor market fixed effects in most specifications. Moreover, the between-country standard deviation in the minimum wage is much greater than the within-country component, which means that the minimum wage is relatively stable in a given country and differs little relative to the institutional differences across countries.<sup>4</sup> The set of control variables displays standard values, giving us confidence in the representativeness of our sample.

#### Measure of routineness

To measure the evolution of middling occupations, we follow Verdugo and Allègre (2020) and Goos et al. (2014). There are several approaches in the literature to measuring labor market polarization. One approach is to consider the skill content of each occupation using the Dictionary of Occupational Titles (DOT, 1968) and classifying occupations according to their intensity in terms of routine tasks (see Autor et al. (2003), Autor and Dorn (2013) or Goos et al. (2014), specifically the second part of the paper). This approach has the merit of focusing directly on the skill content of each occupation. However, there are two main drawbacks of this approach. First, the US occupation classification differs substantially from the EULFS classification, and mapping occupations from the DOT to occupations in the EULFS necessitates the use of several correspondence tables with highly imperfect mapping at each step, requiring some random assignment (see Goos et al. (2014)). Second, the DOT provides a classification based on the task content of occupations in 1968, which may have evolved substantially since then (see Spitz-Oener (2006)).

<sup>4</sup>As we use interaction terms to measure the effect of within country variation in routine on employment outcomes conditionally on the level of the minimum wage, our heterogeneous effect should be driven mostly by the between country variation in the minimum wage. As explained later, we use the initial level of the minimum wage at the beginning of the period as the minimum wage could be affected by the variation in routine.

Figure 1: Evolution of occupations' shares



Source: EULFS dataset for years 1992-2010. The data used include all working individuals aged 17-72.

As a result, we prefer to use a more direct approach. We follow Verdugo and Allègre (2020), Acemoglu and Autor (2011) and Goos et al. (2014) in the first part of their paper by directly considering the occupations in the middle of the wage distribution (middling occupations). Goos et al. (2014) show that these occupations correspond to the routine occupations defined by Autor et al. (2003). We also define the corresponding categories for low-paying jobs (manual) and high-paying jobs (abstract).<sup>5</sup> We define the proportion of each category of occupations as its proportion of total employment. In the remainder of the paper, we refer to middling occupations rather than routine occupations as defined using the position of an occupation in the wage distribution. In addition, we refer to low-paying and high-paying occupations when considering manual and abstract occupations, respectively.

We can see in Figure 1 that the proportion of middling occupations clearly exhibits a sharp and continuous decrease over the period covered by our dataset. Conversely, we observe a clear increase in the proportion of high-paying jobs. However, the evidence is less clear-cut for the proportion of low-paying jobs. We observe an increase, but it seems to be much less important than that in the US labor market, as documented in the literature. We argue that at least part of this specific pattern could be related to European labor institutions, which may have prevented a massive creation of low-paying jobs at the

<sup>5</sup>Additional information about the classification of occupations available in Appendix.

expense of a decrease in employment and labor market participation.

### **Labor market outcomes**

The employment rate in a local labor market is defined as the ratio of the employed to the working age population. The participation rate is defined as the ratio of employed and unemployed to the working age population.<sup>6</sup>

### **Share of high-skilled and low-skilled workers**

Skill levels are coded using the information on education available in the dataset. The EULFS contains some detailed, harmonized data on educational attainment in the categories of low education, medium education and high education. These levels are defined following the International Standard Classification of Education of 1997 (ISCED 1997). In the EULFS, “low education” refers to lower secondary or the second stage of basic education (ISCED 0 to ISCED 2), “medium education” corresponds to upper secondary education (ISCED 3 and ISCED 4), and “high education” represents tertiary education or post-secondary education (ISCED 5 and ISCED 6). Throughout the paper, we approximate skill by education, so low-skill refers to low-education and high-skill to high-education.

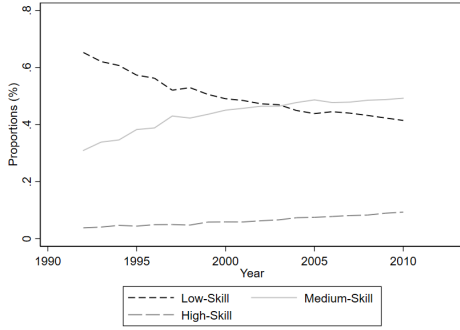
It is important to control for the educational attainment of the workforce in our regressions. Generally, the polarization process can be seen as driven by demand or supply factors. The most discussed factor in the literature is the introduction of new technologies (computers) that are substitutes for workers in some occupations and have modified labor demand. IT technologies are seen as the main driver behind the sharp decrease in the proportion of middling occupations. However, the polarization process can also be driven by supply shocks as a general increase in the skills of the labor force, making firms create more complex occupations with cognitive tasks. Generally, the literature regards polarization process as being driven by demand factors (see Autor et al. (2003), Autor and Dorn (2013), Goos et al. (2014), Acemoglu and Autor (2011) or Acemoglu and Restrepo (2020)), but we cannot exclude the possibility that part of it is driven by the global increase in skill supply observed in Europe in the 1990s, which could have also impacted labor market outcomes.

Regarding the skill composition of the workforce, we can derive several interesting patterns. First, we compute the proportion of low-paying and middling occupations that are occupied by low-skilled and medium-skilled workers, respectively. These results are displayed in Figure 2. We also compute the proportion of low-skilled and medium-skilled workers occupying low-paying and middling occupations.

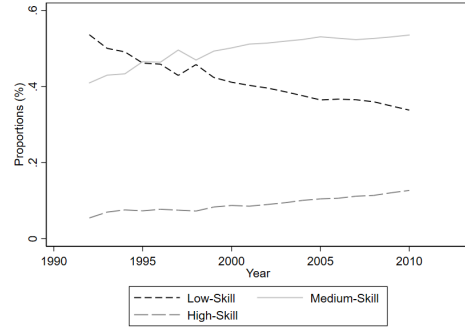
---

<sup>6</sup>In the EULFS, we do not have the exact age of each person; we only know to which 5-year age band an individual belongs (e.g., 0-4, 5-9). In our analysis, the working age population is defined as the number of individuals older than 17 and younger than 72. We also considered a lower threshold, i.e., younger than 67 years old, and our results are not affected by such a modification, mainly because we control for the age structure of the population.

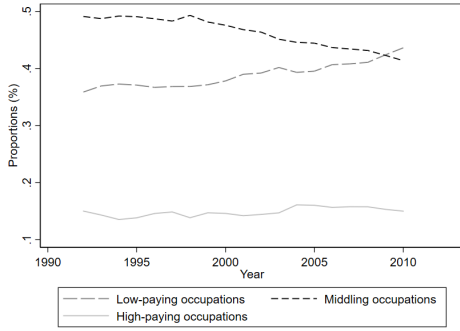
Figure 2: Evolution of labor market opportunities



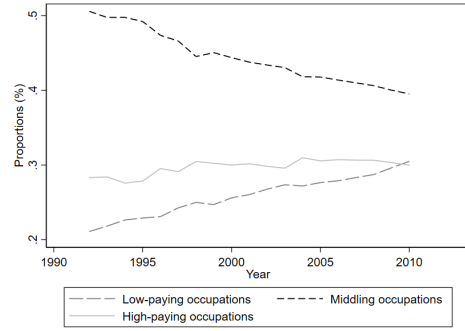
(a) Skill distribution for low-paying jobs



(b) Skill distribution for middling jobs



(c) Occupation distribution for low-skilled workers



(d) Occupation distribution for medium-skilled workers

Source: See Figure 1.

These results are also displayed in Figure 2.

Two important facts emerge. First, the proportion of low-skilled workers in low-paying and middling occupations tends to decrease sharply. The proportion of medium-skilled workers increased sharply not only in middling occupations but also in low-paying occupations. Second, the probability of a low-skilled worker having a low-paying occupation increased substantially over the period considered, consistent with Cortes (2016), who shows that workers with low ability move more often from routine (middling) to manual (low-paying) occupations relative to workers of higher ability. Moreover, there appears to be some skill downgrading: medium-skilled workers occupy less-qualified jobs than previously, given their increasing share among low-paying occupations. More generally, this is consistent with the “displacement effect” highlighted in Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2017), whereby part of the workers whose (middling) occupations have been destroyed are driven down in the occupational ladder and now compete with workers in occupations that have not been destroyed. Overall, this pattern is consistent with the view that labor market polarization has deteriorated the economic opportunities of low-skilled workers. The disappearance of middling occupations seems to be associated with an increase in

the proportion of low-skilled workers with low-paying occupations and a sharp decrease in the proportion of low-skilled workers who have a middling occupation. This sorting process does not favor low-skilled workers (and to some extent, medium-skilled workers) who cannot reallocate to high-paying, abstract jobs. The question that we ask is related to the ability of an economy to create a sufficient number of low-paying jobs for low-skilled workers, whose employment opportunities decreased sharply in middling occupations and cannot reallocate to high-paying occupations.

### **Local labor markets**

Local labor markets are coded using the Nomenclature des Unités Territoriales Statistiques at the two-digit level (NUTS). The NUTS data in the EULFS have a different geographical granularity depending on the country: we have only one region for the Netherlands, i.e., the entire country, while we have 22 regions for France.<sup>7</sup>

### **The minimum wage**

To obtain information on the national minimum wage in each country, we use a dataset from the OECD. Here, the minimum wage is expressed as the proportion of the average wages of full-time workers. Only 8 countries are available in this dataset: Belgium, Spain, France, Greece, Ireland, the Netherlands, Portugal and the United Kingdom. This is explained by the fact that many countries, such as Germany, do not have a national minimum wage but several sectoral minimum wages. As a consequence, our analysis of the impact of the national minimum wage on the shape of the polarization of the labor market is restricted to countries that have a national minimum wage to ensure that labor market institutions and minimum wage levels are comparable across countries.

Table 2 displays the first year of data on the national minimum wage in each country, its initial level and its mean over the period. First, we observe substantial heterogeneity in the levels of the minimum wage between countries, and as a result, we should have sufficient variation to identify the role of the minimum wage in the impact of polarization on the labor market. However, one caveat is that our panel is unbalanced: we only have five countries since the beginning of our sample in 1992, due to the absence, at this time, of a national minimum wage in the other three countries. In Appendix Figure A1, we also provide a graph displaying the evolution of the minimum wage for each country of the sample.

---

<sup>7</sup>Moreover, to perform our analysis, we must have a consistent definition of a local labor market over time. However, there are several changes in classification for some countries over time. To address this problem, we retain only those regions that are comparable over time. In essence, we aggregate areas when necessary and drop areas when they disappear from the classification to ensure that the definition of a given local labor market is the same throughout the period considered. Further details are available in the Appendix. Our results are not sensitive to this modification in the classification of local labor markets or to the exclusion of the Netherlands.

<sup>8</sup>For Ireland, we decided to use the minimum wage in 2001 instead of 2000, as its level changed from 0.59 to 0.44 in 2001 and didn't change much afterwards. This choice doesn't affect our results and our results are unaffected by using the minimum wage level of 2000.

Table 2: Summary statistics: Minimum Wage

Country	Available since	Initial level	Mean
Belgium	1992	0.490	0.460
France	1992	0.492	0.505
Greece	1992	0.420	0.369
Ireland	2000	0.441 <sup>8</sup>	0.459
Netherlands	1992	0.498	0.455
Portugal	1998	0.313	0.328
Spain	1992	0.321	0.301
United-Kingdom	1999	0.356	0.358

Note: OECD dataset on minimum wages. Ratio of the minimum wage over the mean wage. Column "Initial level" corresponds to the first observation for the minimum wage in each country over the period we consider and the column "Mean" corresponds to the mean value of the minimum wage ratio over the period 1992-2007.

As an illustration, we document how the minimum wage became more constraining over time for wage determination, especially for low-paying occupations, focusing on France, a high minimum wage country.

Consistent with the mechanism that we have in mind, we should observe more individuals paid at the minimum wage at the bottom of the wage distribution, in low-paying occupations. As middling occupations disappear, workers reallocate from middling to low-paying occupations, creating a downward wage pressure in occupations in which workers are displaced. The proportion of individuals paid at the minimum wage at the bottom of the wage distribution should increase as a result.<sup>9</sup>

We use the Enquête Emploi en Continue (the French labor force survey).<sup>10</sup> One caveat of this dataset is that the wage data are very noisy, especially when considering hourly wage data.<sup>11</sup>

Looking at Figure 3, we can see that the share of workers earning the minimum wage among the low-paying occupations is growing over time, going from approximately 10% at the beginning of the 1990s to nearly 20% at the beginning of the 2000s. Looking at Figure 4, we observe the same dynamic for workers occupying middling occupations. Although fewer workers are paid the minimum wage in these occupations, the share goes from 6% at the beginning of the 1990s to nearly 12% at the beginning of the 2000s.<sup>12</sup> This pattern should not be related to institutional change since the minimum wage as a proportion of the mean wage was quite stable over this period in France, going from 0.492 in 1992 to 0.510

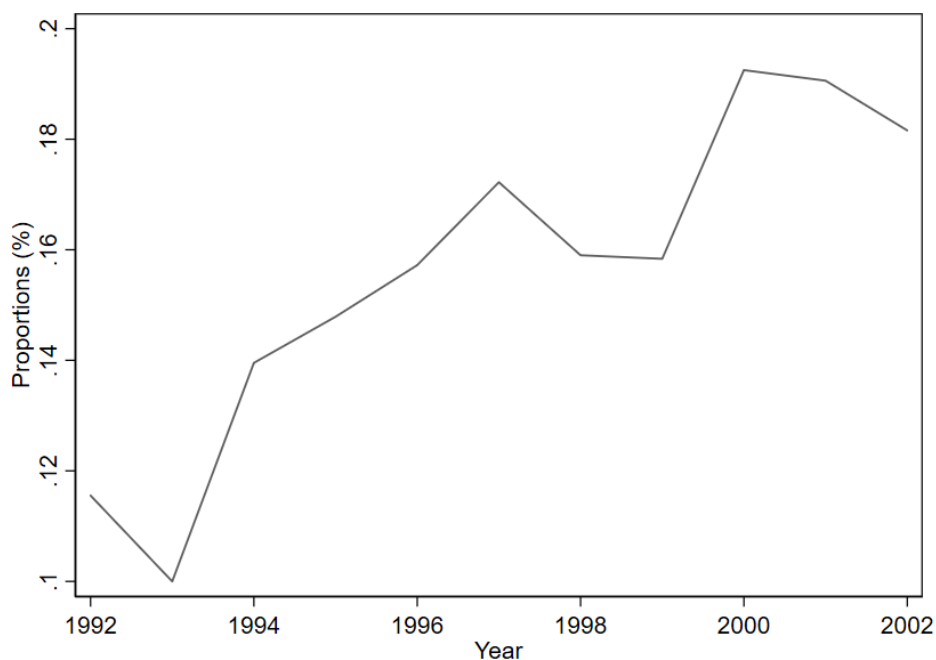
<sup>9</sup>This should also be observed to a lesser extent on middling occupations. We will show that a significant proportion of individuals in middling occupation are paid the minimum wage, but this proportion remains substantially smaller than in manual occupations. The displacement effect should exert downward pressure on middling occupations too and increase the proportion of individuals paid the minimum wage as a result.

<sup>10</sup>Wages are not available in the European Labor Force Survey

<sup>11</sup>To identify workers paid the minimum wage, we consider a 10% halo around the value of the minimum wage. Indeed, there are many observations in which the hourly wage is less than the minimum wage. Observations with an hourly wage inferior to 90% of the minimum wage are dropped. In addition, there is a structural break in the data in 2003, so we only use data from 1992 to 2002. However, there is no reason to expect that the dynamic drastically change after 2002. We are confident in the relevance of our strategy to identify workers paid the minimum wage since our numbers correspond to proportions estimated by Garnero (2019)

<sup>12</sup>This pattern is also observed when considering different halo sizes, ranging from 1 to 10%.

Figure 3: Evolution of minimum wage workers' shares, low-paying occupations only



Source: Enquête Emploi en Continu (EEC) from 1992 to 2002. Share of workers paid at the minimum wage calculated using a 10% halo around the minimum wage value due to data limitations.

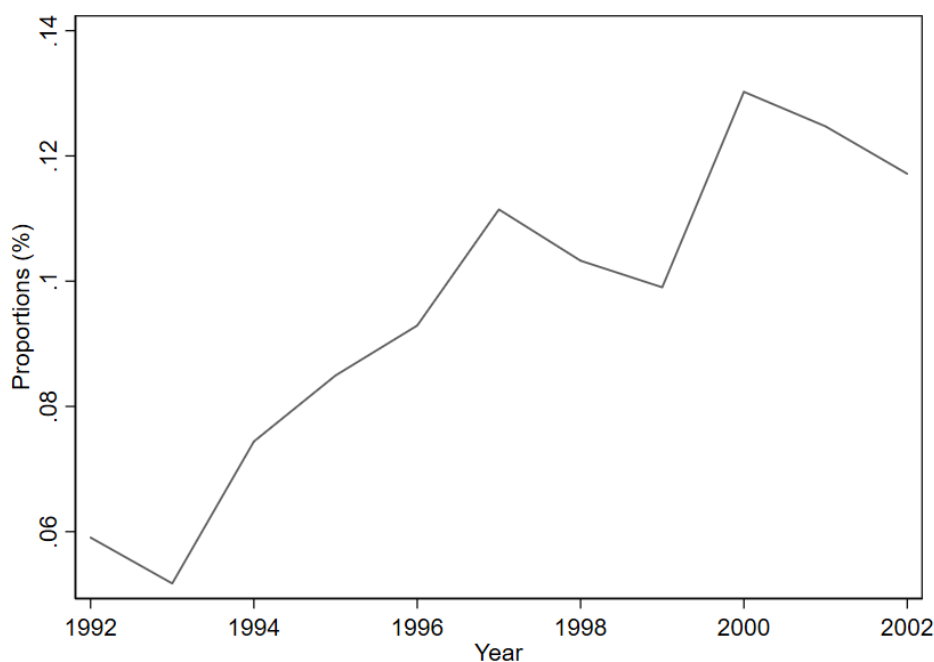
in 2002. This pattern is consistent with the displacement effect in an environment in which wages at the lower bound of the distribution are rigid. Displaced workers create a downward wage pressure such that more workers meet the minimum wage threshold. The effect is also observed for middling occupations since a significant share of workers (but fewer than for low-paying occupations) are paid the minimum wage. This displacement effect should also concern these occupations.

#### **Additional controls**

In addition to skill levels, we control for other characteristics in our regressions. These controls are the proportion of males in the working age population of the local labor market, the age structure of the population using detailed age categories and the industry shares in terms of employment (13 industries).<sup>13</sup> These controls are necessary to control for the heterogeneity of the labor force since these populations have different job opportunities, and these characteristics may affect the shape of labor market polarization. For instance, the age structure of the population is likely to influence the rate of destruction of middling occupations (Autor and Dorn (2009)). Also, structural change, such as the decrease in manufacturing, may affect the degree of job market polarization, as shown by Barany and Siegel (2018), and could also

<sup>13</sup>Younger than or 27 years old, between 28 and 37, between 38 and 47, between 48 and 57 and finally between 58 and 67

Figure 4: Evolution of minimum wage workers' shares, middling occupations only



Source: Enquête Emploi en Continu (EEC) from 1992 to 2002. Share of workers paid at the minimum wage calculated using a 10% halo around the minimum wage value due to data limitations.

affect labor market outcomes.

### **ICT investment price data and technology shocks**

In order to construct our shift share instrument, we use the price index of ICT capital and the ICT capital stock for the US, which are available at the sector level (NACE Rev. 1) in the KLEMS dataset.<sup>14</sup> As described later, ICT capital stock at the sector level and sector shares allow to obtain the initial ICT intensity of each local labor market and the price index of ICT capital is the (exogenous) shock that will affect each local labor market according to their initial period ICT intensity. For the exclusion restriction to be satisfied, the price shock variable should not affect the labor market outcomes through channels other than the destruction of middling occupations.<sup>15</sup> The price shock variable should affect labor market outcomes only through the destruction of middling occupations. We believe that this should be the case. In the recent literature, it is now widely accepted that ICT, such as the massive diffusion of computers

<sup>14</sup>Sectors in the KLEMS dataset are defined according to the NACE Rev. 2 classification. As we have regrouped the sectors in the EULFS to have consistent sector definitions over the period considered, we must do the same for the KLEMS dataset. When sectors are merged in the KLEMS dataset to match those in the EULFS, they are weighted by their relative GDP.

<sup>15</sup>We use US capital stock and prices, as they should better satisfy the exogeneity conditions with respect to the evolution in European labor markets.



in many industries, is task-biased rather than skill-biased and is the main factor behind the massive destruction of middling occupations (Autor et al. (2003), Acemoglu and Autor (2011), Autor and Dorn (2013)).

### 3 Empirical strategy

#### Baseline specifications

We first estimate an OLS specification to highlight the relationship between the variation in the share of middling occupations (MSH) and our labor market outcome (LMO) variables, which correspond to the employment rate and the participation rate, respectively. Formally, we estimate for each outcome:

$$LMO_{a,t} = \alpha_1 MSH_{a,t-1} + \alpha_2 (MSH \times \overline{MW})_{a,t-1} + \beta X_{a,t-1} + \gamma_a + \delta_t + u_{a,t} \quad (1)$$

where  $\gamma_a$ ,  $\delta_t$ , and  $u_{a,t}$  correspond to a local labor market fixed-effect, a time fixed-effect and the error term that captures all other factors not correlated with our controls, respectively, which may also explain our  $MSH_{a,t-1}$  variable and the  $LMO_{a,t}$  variables, with  $E(u_{a,t}) = 0$ . In Equation 1,  $X_{a,t-1}$  is a vector of the control variables described above.  $\overline{MW}_a$  corresponds to the initial minimum wage in local labor market  $a$ . Our  $MSH_{a,t-1}$  variable is interacted with the initial level of the minimum wage at the beginning of the period. The impact of the share of middling jobs on labor market outcomes corresponds to  $\alpha_1 + \alpha_2 \times MW$ ; thus, it is conditional on the level of the minimum wage. In OLS estimates, all of the variables are one period lagged. Using a fixed level of the minimum wage in the interaction seems preferable since the minimum wage policy could react to labor market outcomes or the destruction rate of middling jobs.

This specification relies on the between variation only to estimate a conditional effect.<sup>16</sup> Note that the between variation of the minimum wage is much greater than the within variation of the minimum wage. Alternatively we also estimate a dynamic specification including the lag of  $LMO_{a,t}$  as a regressor. Labor market adjustments can take time, and a dynamic specification could capture this process more accurately.<sup>17</sup>

<sup>16</sup>In Appendix Tables A3 and A4, we also estimate a model using the time-varying level of the minimum wage in the interaction and also as a regressor. The results are unchanged, suggesting that the between component of the minimum wage is the key driver of our identification of heterogenous effects of the proportion of middling jobs. In addition, in Tables A5 and A6, we also estimate a model using the mean minimum wage level over the period, and our results are also unchanged

<sup>17</sup>Estimating a dynamic model with a lagged dependent variable as a regressor may suffer from the so-called dynamic panel bias (Nickell (1981)). We note, however, that the size of the bias ( $1/T$ ) decreases with T (Judson and Owen (1999)) and should not be a first-order concern given the time period that we consider.

Also, instead of using a continuous variable for the minimum wage in the interaction, we also estimate specification using dummies for high and low minimum wage countries. The high minimum wage countries are France (0.50), Belgium (0.46), Ireland (0.45) and the Netherlands (0.46), and the low minimum wage countries are Greece (0.37), the United-Kingdom (0.36), Portugal (0.33) and Spain (0.30).

### **Instrumental Variable Strategy**

We then turn to the IV strategy. The correlation that we observe may be due to an omitted variable that is correlated with both labor market outcomes and the occupational composition of the workforce. We cannot exclude this possibility despite all of the controls and fixed effects that we introduce in our regressions.<sup>18</sup> Second, poor labor market conditions and economic outcomes could affect the decision to destroy middling occupations and thus accelerate the diffusion of technologies. Our estimates could capture such reverse causality. In our IV strategy, we thus attempt to isolate a technology shock that will affect labor demand through its impact on the destruction of middling jobs using a shift-share setting. The disappearance of middling occupations is explained primarily by the diffusion of information technologies (see Goos et al. (2014) or Autor and Dorn (2013)). In the spirit of Karabarbounis and Neiman (2013), we use the investment price of ICT capital, which decreased sharply over the period that we study and explains the massive diffusion of ICT capital, such as computers in the economy. To identify how each local labor market has been exposed to such a price shock, we use the initial industrial specialization of each local labor market and the ICT capital use intensity of each sector at the national level from KLEMS.<sup>19</sup> Our regression sample is smaller in IV than in OLS because ICT data are only available since 1998 in the KLEMS dataset. More formally, our instrument for  $MSH_{a,t-1}$  is written as:

$$Exposure_{at} = \sum_s \left( \frac{L_{s,a,2000}}{L_{a,2000}} \times P_{s,t}^{ICT} \times \frac{K_{s,2000}^{ICT}}{L_{s,2000}} \right) \quad (2)$$

where  $s$ ,  $a$  and  $t$  correspond to sector, local labor market and year, respectively.  $P_{s,t}^{ICT}$  corresponds to the price of ICT capital for sector  $s$  in year  $t$  in the US economy.  $K_{s,2000}^{ICT}$  and  $L_{s,2000}$  correspond to ICT capital stock and employment, respectively, in sector  $s$  in the year 2000.  $L_{s,a,2000}$  and  $L_{a,2000}$  correspond to employment in sector  $s$  in local labor market  $a$  and to employment in area  $a$ , respectively. In this

<sup>18</sup>For instance, polarization could be related to a global increase in skill supply, which will affect the occupational composition of the workforce but does not correspond to a shock affecting labor demand, which is what we assume is at work. We control for the most obvious factors, such as the skill supply, demographic factors, industry composition and area and time fixed-effects, to account for unobserved heterogeneity, but some omitted variables may nevertheless bias our estimates.

<sup>19</sup>The instrument's construction follows the same Bartik logic of Autor and Dorn (2013) for trade shocks, exploiting nationwide variation in trade at the sector level (ICT prices in our case) with the initial specialization of the area or Acemoglu and Restrepo (2020) for robots.

equation,  $(L_{s,a,2000}/L_{a,2000})$  is the industrial specialization in 2000, and  $(K_{s,2000}^{ICT}/L_{s,2000})$  corresponds to the ICT capital stock per worker in sector  $s$  in the US in 2000. Here, the idea is that the exposure of a local labor market to price shocks in ICT should depend on its intensity of ICT capital use, which is defined as each sector’s share of total employment times the ICT capital stock per worker in 2000 in this sector. We use 2000 as a reference year because data are available for all local labor markets on this date. In other words, our instrument is local labor market specific, given that the intensity of ICT use  $(\frac{L_{s,a,2000}}{L_{a,2000}} \times \frac{K_{s,2000}^{ICT}}{L_{s,2000}})$  is local labor market specific. Our instrument varies over time due to our ICT price variable, which is industry-year specific.

We instrument our interaction term  $MSH_{a,t} \times \overline{MW}_a$  using the interaction of our instrument with the initial level of the minimum wage  $Exposure_{a,t-1} \times \overline{MW}_a$  as Woolridge (2000) suggests for estimating a model with interaction terms in which one regressor is endogenous.

An important literature on the shift-share Bartik instrument emerged recently. Goldsmith-Pinkham et al. (2020) discuss the identification assumption underlying Bartik instruments and the conditions under which the instruments should be valid. An important question is whether the identification relies on industry share (in our case, initial industry composition multiplied by initial ICT capital intensity of each industry) or shocks (in our case, ICT capital price in each sector). In most papers reviewed in Goldsmith-Pinkham et al. (2020), identification mostly relies on shares rather than shocks. Our setting makes no exception. Appendix Figure A2 shows the evolution of ICT capital prices in each sector, and we can see that they evolve very similarly across all sectors. This outcome suggests that changes in ICT prices are a global shock that cheapened ICT capital for all sectors of the economy. The heterogeneity of the exposure of each local labor market is due to differences in initial specialization (and sector-specific intensity in ICT use, rather than heterogenous shocks across sectors.<sup>20</sup> When identification relies on industry shares, it is important to ensure that initial industry shares are exogenous to local labor market future developments and do not affect labor market outcomes through other channels than destruction of middling jobs (i.e., the exclusion restrictions are satisfied). We control for many factors in our regressions, which could be affected by the initial industry shares in a local labor market and which could affect labor market outcomes. An important factor to control, which is recommended by Goldsmith-Pinkham et al. (2020), is the current industry share at time  $t$ . It is quite plausible that initial industry shares determine the evolution of industry shares in a local labor market, which could affect labor market outcomes in many ways. For instance, an important initial manufacturing sector is a good predictor of the future

<sup>20</sup>Goldsmith-Pinkham et al. (2020) developed a methodology based on the Rotemberg weights to understand the part of the identification for the IV coefficient that is related to shocks and the part that is related to industry shares. Unfortunately, the methodology that they developed allows for only one endogenous regressor.

decrease in the manufacturing sector share over time in a local labor market. Autor and Dorn (2013) control for the manufacturing sector share. We control for broad industry shares (i.e., primary, secondary and tertiary sectors), but we also use the more detailed classification NACE rev 1, which we use for the Bartik instrument.

### **Investigation of Mechanisms**

We finally provide a preliminary investigation of the mechanisms for the role of the minimum wage in shaping the relationship between destruction of middling jobs and employment. We estimate the impact of the variation in the proportion of middling occupations on the proportion of low-paying manual jobs in a local labor market. The mechanism we have in mind is that the presence of a strong minimum wage prevents the creation of low-paid jobs at the bottom of the wage distribution to provide sufficient jobs for low-skilled workers who lost their middling occupations and cannot reallocate to high-paying occupations due to skill mismatch. As a result, in the presence of a high minimum wage, we should observe a smaller increase in the proportion of low-paying occupations following a decrease in the proportion of middling occupations.

We will finally investigate the role of other labor market institutions that may be correlated with the level of minimum wage. We include an interaction between our *MSH* variable and other labor market institutions, such as the EPL from OECD, in the regression, with and without controlling for the interaction with the minimum wage. We expect a null coefficient for other labor market institutions, which would suggest a specific role for the minimum wage.

## **4 Baseline Results**

This section presents the results for our OLS and IV specifications.

### **4.1 Labor market outcomes**

The estimated coefficients of Equation 1 are presented in Table 3 panel A considering the employment rate and in Table 4 panel A considering the participation rate as the LMO variables. Both tables have the same presentation: the first two columns display simple regressions of the proportion of middling occupations in a local labor market on the outcome variable. The second columns include our standard set of control variables: gender, skill and age composition of the population, as defined previously. Columns 3 and 4 reproduce columns 1 and 2, respectively, including lag of  $LMO_{a,t}$  (which are also included in columns

5 and 6). In columns 5 and 6, we estimate specifications using dummies for high and low minimum wage countries instead of the continuous minimum wage variable (with and without our set of controls). Finally, column 7 provides a robustness of column 2 based on the IV sample. Local labor market and time fixed effects are included in all regressions. Standard errors are clustered at the local labor market level. For regressions in columns 1 to 4 and 7, we compute the threshold value of the minimum wage such that the marginal effect of  $MSH$  equals zero ( $\alpha_1 + \alpha_2 \times MW = 0$ ). If  $\alpha_1 < 0$  and  $\alpha_2 > 0$ , as we expect, the marginal impact of a decrease in  $MSH$  is negative for values of the minimum wage higher than this threshold.

Focusing first on Table 3 panel A, the coefficients are significant in all specifications. The threshold values for the minimum wage decrease as we add control variables. In the most complete specification using the level of the minimum wage in column 4, the threshold value is equal to 0.367, meaning that, when the national minimum wage level, calculated as a fraction of the average wages of full-time workers, exceeds 0.367, a reduction in the proportion of middling occupations has a negative effect on employment according to our estimation (i.e., the marginal impact of  $MSH$   $\alpha_1 + \alpha_2 \times MW$  is positive). Then, looking at columns 5 and 6, we can see that a decrease in  $MSH$  has a negative impact on labor market outcomes only for high minimum wage countries and no impact for low minimum wage countries. Indeed, in columns 5 and 6, the coefficient associated with the share of middling is statistically insignificant, indicating that the average effect when considering the bottom half of the minimum wage distribution is null.

If we consider the impact on the participation rate in Table 4 panel A, the results are almost identical. When considering columns 1 to 4, all of the coefficients are significant, and the threshold value decreases as we add controls, although it is slightly lower than for the previous estimates for the employment rate. When the minimum wage becomes sufficiently high, the diminution of the proportion of middling occupations decreases the participation rate. When looking at the specifications using minimum wage dummies (column 5 and 6), the results are also similar to the previous ones: the minimum wages level plays a role in the labor market impacts of the polarization only in high minimum wage countries.

Figure 5 provides a visualization of the conditional marginal effects estimated in column 2 of Tables 3 and 4, i.e., on the employment rate and participation rate, respectively. The plotted line shows on the right axis the effect of a marginal one percentage point increase in the proportion of middling occupations on the labor market outcomes according to the initial value of the minimum wage in a local labor market ( $\alpha_1 + \alpha_2 \times MW$ ). The plot is superimposed over a histogram of the distribution of initial minimum wage levels over local labor markets of our sample, represented on the left axis, in order to provide a sense of

Table 3: OLS and IV regressions: Employment rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
	Std. Sample				IV Sample		
Sh. middling <sub>-1</sub>	-1.885*** (0.275)	-0.953*** (0.194)	-0.499*** (0.081)	-0.488*** (0.088)	-0.008 (0.032)	0.003 (0.026)	-0.419 (0.276)
- X Minimum Wage <sub>0</sub>	4.347*** (0.644)	2.454*** (0.448)	1.274*** (0.186)	1.330*** (0.219)			1.237** (0.620)
- X Up. half MW <sub>0</sub>					0.091*** (0.033)	0.146*** (0.036)	
Sh. male <sub>-1</sub>		0.084 (0.248)		-0.038 (0.121)		-0.035 (0.124)	0.115 (0.222)
Sh. high-skill <sub>-1</sub>		0.538*** (0.083)		0.173*** (0.038)		0.195*** (0.039)	0.475*** (0.082)
Sh. low-skill <sub>-1</sub>		0.057 (0.059)		0.037 (0.026)		0.040 (0.026)	0.099* (0.056)
Emp. rate <sub>-1</sub>			0.820*** (0.026)	0.727*** (0.029)	0.856*** (0.027)	0.744*** (0.027)	
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes	yes
R <sup>2</sup>	0.91	0.95	0.97	0.97	0.97	0.97	0.95
Observations	1111	1111	1111	1111	1111	1111	823
Threshold value	.434	.389	.392	.367	-	-	.339
Panel B: IV							
Sh. middling	-3.195*** (0.973)	-3.719*** (0.855)	-2.417*** (0.646)	-0.630* (0.377)	-1.121*** (0.417)	-1.185*** (0.397)	-1.097*** (0.401)
- X Minimum Wage <sub>0</sub>	6.505*** (1.672)	7.479*** (1.648)	5.336*** (1.325)	1.420** (0.625)	2.658*** (0.799)	2.523*** (0.763)	2.470*** (0.794)
Sh. male <sub>-1</sub>		-0.068 (0.221)	-0.112 (0.218)		-0.204 (0.182)	-0.153 (0.154)	-0.221 (0.185)
Sh. high-skill <sub>-1</sub>		0.302*** (0.084)	0.350*** (0.081)		0.107* (0.059)	0.123** (0.055)	0.125 (0.078)
Sh. low-skill <sub>-1</sub>		0.164*** (0.059)	0.035 (0.056)		0.099* (0.051)	0.092* (0.052)	0.056 (0.035)
Emp. rate <sub>-1</sub>				0.722*** (0.037)	0.684*** (0.052)	0.658*** (0.056)	0.629*** (0.052)
Sh. age cat. <sub>-1</sub>	no	yes	yes	no	yes	yes	yes
Sh. ind. <sub>-1</sub>	no	no	16 posts	no	no	3 posts	16 posts
Observations	823	823	823	823	823	823	823
F	12	12	12	12	11	8	8
F K-P	9	10	8	9	9	10	8
A-R Wald $\chi^2$ (p-value)	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Threshold value	.491	.497	.453	.444	.422	.47	.444

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries. IV sample begins in 1998.

the empirical relevance of the range of minimum wage levels for which the effect of the reduction in the proportion of middling occupations is statistically significant. The left panel of Figure 5 shows that the marginal effect of a decrease in the proportion of middling occupations on the employment rate is negative and significant ( $\alpha_1 + \alpha_2 \times MW > 0$ ) for sufficiently high values of the minimum wage (above 0.43) and very marginally positive and significant ( $\alpha_1 + \alpha_2 \times MW < 0$ ) for sufficiently low values of the minimum wage (below 0.33). The impact of the polarization phenomenon is thus negative on employment when

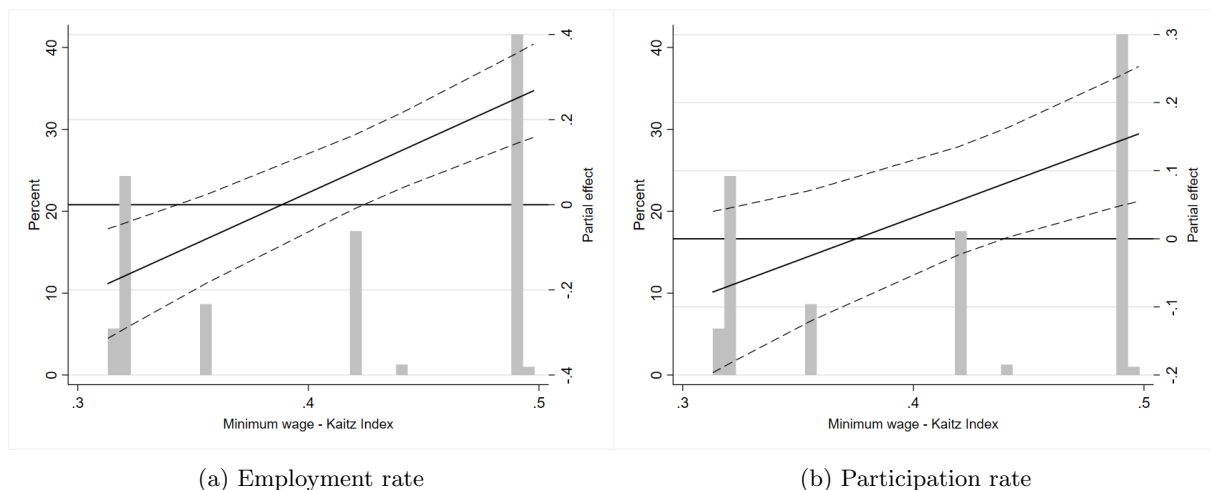
Table 4: OLS and IV regressions: Participation rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
	Std. Sample				IV Sample		
Sh. middling <sub>-1</sub>	-0.996*** (0.191)	-0.472*** (0.177)	-0.400*** (0.090)	-0.284** (0.111)	0.011 (0.037)	0.035 (0.037)	-0.613** (0.242)
- X Minimum Wage <sub>0</sub>	2.400*** (0.436)	1.257*** (0.407)	1.098*** (0.205)	0.870*** (0.264)			1.598*** (0.543)
- X Up. half MW <sub>0</sub>					0.099*** (0.036)	0.102** (0.046)	
Sh. male <sub>-1</sub>		0.289* (0.164)		0.148 (0.102)		0.148 (0.105)	0.164 (0.172)
Sh. high-skill <sub>-1</sub>		0.243*** (0.058)		0.093** (0.040)		0.111*** (0.039)	0.321*** (0.066)
Sh. low-skill <sub>-1</sub>		0.017 (0.052)		0.007 (0.033)		0.010 (0.033)	0.092* (0.051)
Part. rate <sub>-1</sub>			0.648*** (0.042)	0.590*** (0.037)	0.676*** (0.046)	0.600*** (0.038)	
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes	yes
R <sup>2</sup>	0.92	0.94	0.95	0.96	0.95	0.95	0.93
Observations	1111	1111	1111	1111	1111	1111	823
Threshold value	.415	.375	.364	.326	-	-	.384
Panel B: IV							
Sh. middling	-2.117*** (0.770)	-2.555*** (0.618)	-1.266*** (0.466)	-0.979** (0.431)	-1.454*** (0.388)	-1.183*** (0.330)	-0.897** (0.372)
- X Minimum Wage <sub>0</sub>	4.541*** (1.272)	5.259*** (1.250)	3.303*** (0.881)	2.175*** (0.692)	3.349*** (0.790)	2.902*** (0.724)	2.430*** (0.689)
Sh. male <sub>-1</sub>		0.041 (0.181)	0.016 (0.196)		-0.058 (0.135)	-0.029 (0.136)	-0.079 (0.168)
Sh. high-skill <sub>-1</sub>		0.205*** (0.072)	0.231*** (0.055)		0.094** (0.047)	0.118** (0.047)	0.113** (0.053)
Sh. low-skill <sub>-1</sub>		0.134** (0.056)	0.039 (0.048)		0.102** (0.043)	0.086 (0.052)	0.043 (0.039)
Part. rate <sub>-1</sub>				0.569*** (0.040)	0.514*** (0.049)	0.498*** (0.049)	0.455*** (0.044)
Sh. age cat. <sub>-1</sub>	no	yes	yes	no	yes	yes	yes
Sh. ind. <sub>-1</sub>	no	no	16 posts	no	no	3 posts	16 posts
Observations	823	823	823	823	823	823	823
F	12	12	12	13	11	8	8
F K-P	9	10	8	9	10	10	8
A-R Wald $\chi^2$ (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Threshold value	.466	.486	.383	.45	.434	.408	.369

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries. IV sample begins in 1998.

the minimum wage is high, which we interpret as the poor ability of such economies to create a sufficient number of low-paying occupations for workers who do not reallocate to abstract, high-paying occupations. The right panel of Figure 5 demonstrates that the marginal effect of a decrease in the proportion of middling occupations on the participation rate is negative and significant ( $\alpha_1 + \alpha_2 \times MW > 0$ ) for high levels of the minimum wage (above 0.43) and positive but never significant ( $\alpha_1 + \alpha_2 \times MW < 0$ ) for low values (less than 0.37). This finding is consistent with our findings on the employment rate. When the

Figure 5: Marginal effect of the proportion of routine occupations on labor market outcomes, conditional on the value of the minimum wage.



Notes: This figure plots, on the right axis, the marginal effect of a one percentage point variation in the proportion of middling occupations on labour market outcomes, conditionally on the initial level of the minimum wage (i.e.  $\alpha_1 + \alpha_2 \times MW$ ) represented by the dark line. The coefficients are obtained from regression estimates from column 2 of Tables 3 and 4. Dashed lines represent 95% confidence intervals. The histogram plots, on the left axis, the proportion of each local labor market in the estimation sample according to their initial minimum wage level.

minimum wage is high, the decrease in employment rate translates into a decrease in participation. Many people exit the labor market due to skill mismatch and poor employment prospects. When the minimum wage is low, the economy is able to create a number of low-paying jobs in the service sector, translating into an increase in the participation rate. Over the period of 1992-2010, the proportion of middling occupations decreased by approximately ten percentage points, and this shock had a heterogeneous impact. According to our estimates (Table 3 and Table 4, panel A column 2), the employment rate decreases by 2.49 percentage points in France, which is characterized by a high-level minimum wage over the period considered (0.49). In contrast, over the same period in the United Kingdom, a country with a low minimum wage of 0.36, it triggered a 0.69 percentage point increase in the employment rate. However, the effect is not significant. Concerning the participation rate, when the proportion of middling occupations declines by 10 percentage points, polarization leads to a 1.43 percentage point decrease in France. For the United Kingdom, it leads to a 0.19 percentage point increase in the participation rate, but here again, the effect is not significant. These effects are economically sizable for high minimum wage countries. Several robustness checks are provided in the Appendix: using data until 2010 instead of 2007 in Tables A1 and A2, using the time-varying minimum wage in Tables A3 and A4, using the mean minimum wage over the period in Tables A5 and A6, including controls for 3 industry shares in Tables A7 and A8, including controls for 16 industry shares in Tables A9 and A10 and finally using a jackknife



estimator in Tables A11 and A12.

We now present our IV results. To address the endogeneity issue mentioned above, we re-estimate Equation 1 using an IV strategy. Results concerning employment and participation rates are respectively displayed in Tables 3 and 4, panel B. As we cluster standard errors at the local labor market level, we provide the cluster-robust Kleibergen-Paap Wald rk F-statistic to determine whether our instrument is strong. We also display the standard F-statistic.<sup>21</sup> All IV estimations contain local labor market and time fixed effects.<sup>22</sup>

It is worth noting that the F-statistics in our specifications are around the rule-of-thumb threshold of 10 but are sometime slightly less than this threshold. However, as noted in Andrews et al. (2019), the fact that instruments are weak is not a problem in itself since it may “unnecessarily eliminates specifications of potential economic interest”. As a consequence and as they recommend, we also evaluate the joint significance of the instrumented endogenous variables in the second stage regression with the p-value of the Anderson-Rubin Wald statistic, which provides valid inference when instrument are weak.

We also provide some more tests to convince the reader that the instrument is exogenous and that the exclusion restrictions are likely to be satisfied. First, as explained earlier, in columns 3, 6 and 7, following the recommendations of Goldsmith-Pinkham et al. (2020), we include industry shares as a control (aggregated 3 industries and more detailed 16 industries classifications). In addition, we show in Appendix Table A15 that the past share of middling occupations does not predict future values of the instrument (conditional on past values of the instrument).<sup>23</sup> In all specifications of Tables 3 and 4 panel B, we observe that all of the coefficients are statistically significant. The Anderson-Rubin Wald statistics indicate that, for all specifications, the endogenous regressors are jointly significant. Threshold values and the magnitudes of the coefficients are higher than in OLS specifications, but our results remain qualitatively unchanged. The minimum wage level plays a role in the impact of the destruction of middling occupations on labor market outcomes.

---

<sup>21</sup>Andrews et al. (2019) argue that there is “no theoretical justification for the use of either the standard or cluster robust F-statistic to gauge instrument strength in non-homoskedastic settings”. We thus report both to provide all of the information to the reader.

<sup>22</sup>First-stage results are available in the Appendix Tables A13 and A14.

<sup>23</sup>More specifically, we regress the value of the instrument on the one year lagged value of the instrument and the one year lagged share of middling occupation, including all of the controls of the IV estimates. We expect that the past value of middling occupation does not explain contemporaneous values of our instrument.

## 4.2 The number of low-paying occupations

We now examine more specifically the mechanism that we have in mind by which the minimum wage prevents the creation of sufficient low-paying jobs to compensate for the decrease in the number of middling occupations and thus reduces the employment rate when the number of middling occupations decreases. We slightly modify Equation 1: instead of focusing on one of our LMO variables, we now estimate the effect of the proportion of middling occupations on the number of low-paying occupations.<sup>24</sup> The results are displayed in Table 5. In columns 1 and 2, we estimate our standard specification with the continuous minimum wage variable, while in columns 3 and 4, we use dummies for minimum wage groups as in our baseline OLS specifications in Tables 3 and 4. Controls for industry shares are included in all regressions.

Table 5: OLS regressions: Low-paying in numbers (log)

	(1)	(2)	(3)	(4)
Sh. middling <sub>-1</sub>	-9.713*** (2.823)	-7.358** (3.353)	-2.427*** (0.846)	-1.890** (0.946)
- X Minimum Wage <sub>0</sub>	21.640*** (6.714)	16.629** (7.679)		
- X Up. half MW <sub>0</sub>			3.600*** (1.035)	3.183*** (1.140)
Sh. male <sub>-1</sub>		-2.005 (3.601)		-1.921 (3.593)
Sh. high-skill <sub>-1</sub>		2.010 (1.641)		2.246 (1.605)
Sh. low-skill <sub>-1</sub>		0.505 (1.077)		0.675 (1.096)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes
R <sup>2</sup>	0.87	0.88	0.87	0.88
Observations	1111	1111	1111	1111
Threshold value	.449	.442	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects and control for 16 industry shares. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

The mechanism that we have previously highlighted seems to be confirmed. All of the coefficients are highly significant. When the proportion of middling occupations decreases, the number of low-paying occupation occupations increases, but this increase is conditional on the level of the minimum wage; the higher that the minimum wage is, the smaller that the resulting increase in the proportion of manual low-paying occupations is.

According to the estimates in column 2, in a low minimum wage country, such as the United Kingdom, a 1 percentage point decrease in the share of middling occupations increases by 1.38% the number of low-paying jobs compared to other local labor markets. In contrast, for a high minimum wage country

<sup>24</sup>We express the number of low-paying jobs in log to prevent the largest local labor markets from driving all of our results.

such as France, a 1 percentage point decrease in the share of middling occupations decreases by 0.78% the number of low-paying jobs compared to other local labor markets. Our results show that the impact of the decrease in the proportion of middling occupations on employment in low-paying occupations is thus very different across low and high minimum wage countries.

## 5 The role of other labor market institutions

One concern that could arise regarding the preceding analysis is the role played by other labor market institutions. It is possible that, through the level of the national minimum wage, we are capturing the impact of other labor market institutions because a high minimum wage is often correlated with strong labor market institutions. Note, however, that this assumption is not systematically true, as we will see. As a consequence of possible correlation between the minimum wage and other labor market institutions, our interaction coefficient  $((MSH \times MW)_{a,t})$  could capture some other institutional factors, leading to incorrect inferences about the role of the minimum wage in driving the shape of polarization and its impact on labor market outcomes. Specifically, the other labor market institutions could create frictions at the bottom of the wage distribution that inhibit the creation of manual low-paying jobs and, as a consequence, negatively affect labor market outcomes in the context of the destruction of middling occupations. More generally, strong labor market institutions provide workers with some bargaining power and affect the wage determination process. However, in our opinion, labor market institutions and the level of the minimum wage do not affect wages in the same way. The national minimum wage acts as a lower bound on wages, creating important downward nominal wage rigidity for lower wages. This increases the wages of workers in low-paying occupations relative to other workers. Conversely, labor market institutions give bargaining power to all workers, but the bargaining power of low-paid workers should not increase much, mainly because they are easily substitutable in a context of high unemployment and because they often have temporary jobs, which offer less protection. As a result, other labor market institutions, unlike the minimum wage, should not increase the relative wages of low-paid workers. The mechanism that we have in mind to explain the impact of the massive destruction of middling occupations on employment is thus specific to the minimum wage.

To capture the other labor market institutions, we use several indicators. Most of these indicators come from the OECD Indicators of Employment Protection Legislation (EPL) dataset. First, we employ the most aggregated indicator of labor market institutions, the EPRC index, which captures regulations on “Regular contracts, including additional provision for collective dismissals”. This indicator consists

of several variables representing the numerous dimensions of labor market institutions. In addition, we consider the EPT index, which reflects regulations on "Temporary employment". Finally, we also use the Gross Replacement Rate (GRR), also provided by the OECD. Those variables should allow us to capture the various dimensions of the labor market institutions in each country that are different from the minimum wage.

Table 6: Correlation table: Minimum wage and EPL indexes

	Minimum Wage	EPRC	EPT	GRR
Minimum Wage	1.00			
EPRC	-0.31	1.00		
EPT	-0.04	0.31	1.00	
GRR	0.38	0.26	-0.25	1.00

Notes: Data from OECD Employment Protection Legislation, OECD minimum wage and OECD Gross replacement rate for years 1992-2007. Correlations calculated at the country×year level (N=90).

We first display in Table 6 correlations between the minimum wage and the various labor market institutions variables mentioned before at the country and year level. The correlations are computed over the 90 country×year level observations. We can see that, for our sample of countries, the level of the minimum wage is not strongly correlated with either the aggregated indicators of employment protection or the gross replacement rate. This suggests that the minimum wage should not systematically capture the effect of other labor market institutions, but it plays a specific role by making the wages of low-paying occupations difficult to adjust after the displacement effect generated by labor market polarization. In the Appendix Table A16, we also provide the average of these variables for each country of our sample. As we can see, in Spain, for example, many strong labor market institutions (regarding regular and temporary contracts, for instance) coexist with a very low minimum wage. We then perform a statistical analysis to confirm the specific role of the minimum wage. To do so, we estimate the same specification as in the rest of the paper, and we simply sequentially add several labor market institution variables and their interactions with the level of middling occupations at the local labor market level. Given the weak correlation between the minimum wage and other labor market institutions shown in Table 6, this outcome should allow for estimating the specific role of both types of institutions. Specifically, we estimate the following equation for each outcome:

$$LMO_{a,t} = \alpha_1 MSH_{a,t} + \alpha_2 (MSH \times MW)_{a,t} + \alpha_3 (MSH \times LMI)_{a,t}$$

$$+\beta X_{a,t} + \gamma_a + \delta_t + u_{a,t} \quad (3)$$

All of the variables in this equation are the same as before except for LMI, which stands for “labor market institutions”. Similar to the minimum wage, we fix the LMI variables to their initial levels since changes in labor market institutions may be correlated with the polarization of the labor market. If the mechanism we have in mind is the one at work, most of the effect will go through the minimum wage variable, and the labor market institutions, interacted with the level of middling occupations, should not have a significant, positive impact on labor market outcomes.

Alternatively, we also estimate a slightly different specification, in which we only include the other labor market institutions and their interactions with *MSH* without the minimum wage.

These specifications are available in the Appendix in Table A17. We do not expect the coefficient related to LMI and its interaction with *MSH* to be significant and positive. Such an outcome would confirm the specific role of the minimum wage, rather than other labor market institutions.

Table 7: OLS regressions: EPL

	Employment rate				Participation rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh. middling <sub>-1</sub>	-0.953*** (0.194)	-1.348*** (0.289)	-0.930*** (0.190)	-0.821*** (0.178)	-0.472*** (0.177)	-0.347 (0.221)	-0.407** (0.156)	-0.345** (0.163)
- X Minimum Wage <sub>0</sub>	2.454*** (0.448)	2.936*** (0.442)	2.668*** (0.487)	2.804*** (0.518)	1.257*** (0.407)	1.105*** (0.406)	1.862*** (0.412)	1.592*** (0.416)
- X EPRCv1 <sub>0</sub>		0.076 (0.060)				-0.024 (0.036)		
- X EPTv1 <sub>0</sub>			-0.030 (0.022)				-0.084*** (0.021)	
- X GRR APW <sub>0</sub>				-0.900** (0.365)				-0.862*** (0.308)
Sh. male <sub>-1</sub>	0.084 (0.248)	0.061 (0.256)	0.087 (0.245)	0.098 (0.235)	0.289* (0.164)	0.297* (0.163)	0.298* (0.160)	0.302* (0.155)
Sh. high-skill <sub>-1</sub>	0.538*** (0.083)	0.552*** (0.084)	0.530*** (0.084)	0.486*** (0.086)	0.243*** (0.058)	0.238*** (0.057)	0.221*** (0.057)	0.194*** (0.057)
Sh. low-skill <sub>-1</sub>	0.057 (0.059)	0.057 (0.060)	0.061 (0.059)	0.034 (0.057)	0.017 (0.052)	0.017 (0.052)	0.029 (0.049)	-0.005 (0.049)
R <sup>2</sup>	0.95	0.95	0.95	0.95	0.94	0.94	0.94	0.94
Observations	1111	1111	1111	1111	1111	1111	1111	1111

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects and share of age categories. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

The estimated coefficients of Equation 3 are presented in Table 7 for both the employment and participation rates. Local labor market and time fixed effects are included in all of the regressions. As before, standard errors are clustered at the local labor market level. In columns 1 and 5, we display the coefficients from our baseline specification for both the employment and the participation rates from Tables 3 and 3, column 2, to ease the comparison.

Looking at Table 7, we can see that the interaction coefficient  $(MSH \times MW)_{a,t}$  for the minimum wage is still positive and highly significant in all specifications. The magnitude of the coefficients does not significantly change when controlling more broadly for many dimensions of labor market institutions, which are distinct from the minimum wage. We observe that the coefficients associated with the labor market institutions, interacted with the proportion of middling occupations in a local labor market, are not significant or are statistically significant but negative. This finding confirms that our effect works only through the minimum wage level and its specific impact on the degree of wage rigidity at the bottom of the wage distribution, and it does not capture the effect of other labor market institutions. <sup>25</sup>

## 6 Conclusion

In recent years, a growing body of literature has focused on the causes of labor market polarization, but little attention has been paid to its possible impact on labor market outcomes. Our hypothesis is that the minimum wage level changed the shape taken by polarization by preventing the creation of low-paying jobs at the bottom of the skill distribution, thereby affecting the participation and employment rates. Using the European Union Labor Force Survey, we estimated the impact of a reduction in the proportion of middling occupations on labor market outcomes, such as participation and employment rates. Our estimates show that the minimum wage level plays a crucial role in the impact of the destruction of routine occupations on labor market outcomes: economies characterized by high minimum wages saw their employment decrease as the proportion of middling occupations decreased, while no impact was observed for low minimum wage countries. In addition, we demonstrated that these results are consistent with our preferred explanation: a high minimum wage seems to prevent the creation of low-paying jobs. Our estimates indicate that the proportion of manual jobs does not increase in response to the reduction in middling occupations when the minimum wage is high.

Our results suggest that the costs of the minimum wage could be magnified in an environment in which middling occupations are destroyed. These jobs provided good wage opportunities for low-skilled (and some medium-skilled) workers, and employment opportunities for this category of workers deteriorated as a result. In this environment, in which many low-skilled workers cannot reallocate to abstract, well-paid occupations, the ability of an economy to create manual low-paying jobs is necessary to main-

---

<sup>25</sup>Appendix Table A17 displays results when we do not include the minimum wage and its interaction. We observe that the coefficient associated with  $MSH_{a,t}$  is positive, and the interaction with the labor market institutions is negative or insignificant, providing additional evidence for the mechanism that we have in mind. Other labor market institutions do not seem to play a similar role and do not capture the impact of the minimum wage. Those results are in line with the results in Table 7, and they can be seen as a falsification test.

tain a constant employment rate. This ability could be limited in high minimum wage countries, and the displacement effect documented theoretically in Acemoglu and Restrepo (2017) should generate a decrease in employment in such an environment. Given the higher cost of a nationwide minimum wage in the context of rapid, task-biased technological change that destroys middling occupations at a rapid rate, alternative policy interventions could be attractive to prevent such a pervasive impact on local labor markets affected by polarization shocks. For instance, employment subsidies could be a credible alternative because they do not modify the relative labor costs of low- and high-skilled workers. Another alternative for such countries would be to allow the minimum wage to be set at the sector level (as in Sweden and Germany, for example) or even at the local labor market level, to make labor market institutions more flexible in response to technological shocks, which have heterogeneous impacts across local labor markets.

## References

- Acemoglu, D., Autor, D.H., 2011. Skills, tasks and technologies: Implications for employment and earnings, in: *Handbook of Labor Economics*, Volume 4. Amsterdam: Elsevier-North, pp. 1043–1171.
- Acemoglu, D., Restrepo, P., 2017. Low-skill and high-skill automation. *Journal of Human Capital* .
- Acemoglu, D., Restrepo, P., 2018. The race between man and machine: Implications of technology for growth, factor shares and employment. *American Economic Review* 108, 1488–1542.
- Acemoglu, D., Restrepo, P., 2020. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128, 2188–2244.
- Albertini, J., Hairault, J.O., Langot, F., Sopraseuth, T., 2016. How do product and labor market regulations affect aggregate employment, inequalities and job polarization? a general equilibrium approach. Working paper or preprint.
- Andrews, I., Stock, J.H., Sun, L., 2019. Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics* 11, 727–753.
- Autor, D.H., 2019. Work of the past, work of the future. *American Economic Association Papers and Proceedings* 109, 1–32.
- Autor, D.H., Dorn, D., 2009. This job is “getting old”: Measuring changes in job opportunities using occupational age structure. *American Economic Review* 99, 45–51.

- Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103, 1553–1597.
- Autor, D.H., Dorn, D., Hanson, G.H., 2015. Untangling trade and technology: Evidence from local labour markets. *The Economic Journal* 125, 621–646.
- Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the u.s. labor market. *American Economic Review* 96, 189–194.
- Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118, 1279–1333.
- Barany, Z., Siegel, C., 2018. Job polarization and structural change. *American Economic Journal: Macroeconomics* 10, 57–89.
- Bock, S., 2017. Job Polarization and Unskilled Employment Losses in France. Working paper or preprint.
- Breemersch, K., Damijan, J.P., Konings, J., 2017. Labour market polarization in advanced countries .
- Cahuc, P., Debonneuil, M., 2004. Productivite et emploi dans le tertiaire. *La Documentation francaise* .
- Catherine, S., Landier, A., Thesmar, D., 2015. Marche du travail : la grande fracture. Institut Montaigne .
- Cortes, G.M., 2016. Where have the middle-wage workers gone? A study of polarization using panel data. *Journal of Labor Economics* 34, 63–105.
- Dustmann, C., Ludsteck, J., Schönberg, U., 2009. Revisiting the German wage structure. *Quarterly Journal of Economics* 124, 843–881.
- Garnero, A., 2019. Les salariés rémunérés au salaire minimum : une minorité le reste durablement. DARES - Publications .
- Goldsmith-Pinkham, P., Sorkin, I., Swift, H., 2020. Bartik instruments: What, when, why, and how. *American Economic Review* 110, 2586–2624.
- Goos, M., Manning, A., 2007. Lousy and lovely jobs: The rising polarization of work in Britain. *Review of Economics and Statistics* 89, 118–133.
- Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104, 2509–2526.



- Jaimovich, N., Siu, H.E., 2020. The trend is the cycle: Job polarization and jobless recoveries. *The Review of Economics and Statistics* 102, 129–147.
- Judson, R.A., Owen, A.L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. *Economics Letters* 65, 9–15.
- Karabarbounis, L., Neiman, B., 2013. The global decline of the labor share. *Quarterly Journal of Economics* .
- Lordan, G., Neumark, D., 2018. People versus machines: The impact of minimum wages on automatable jobs. *Labour Economics* 52, 40–53.
- Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics* 96, 60–77.
- Nellas, V., Olivieri, E., Bentivogli, C., Casadio, P., Corsini, L., Friebel, G., Nannicini, T., Onofri, P., Zanella, G., 2011. Job polarization and labor market institution.
- Nickell, S., 1981. Biases in dynamic models with fixed effects. *Econometrica* 49, 1417.
- Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics* 24, 235–270.
- Verdugo, G., Allègre, G., 2020. Labour force participation and job polarization: Evidence from europe during the great recession. *Labour Economics* 66, 101881.
- Woolridge, J.M., 2000. *Econometric analysis of cross section and panel data* .

## A Data

### A.1 NUTS Classification

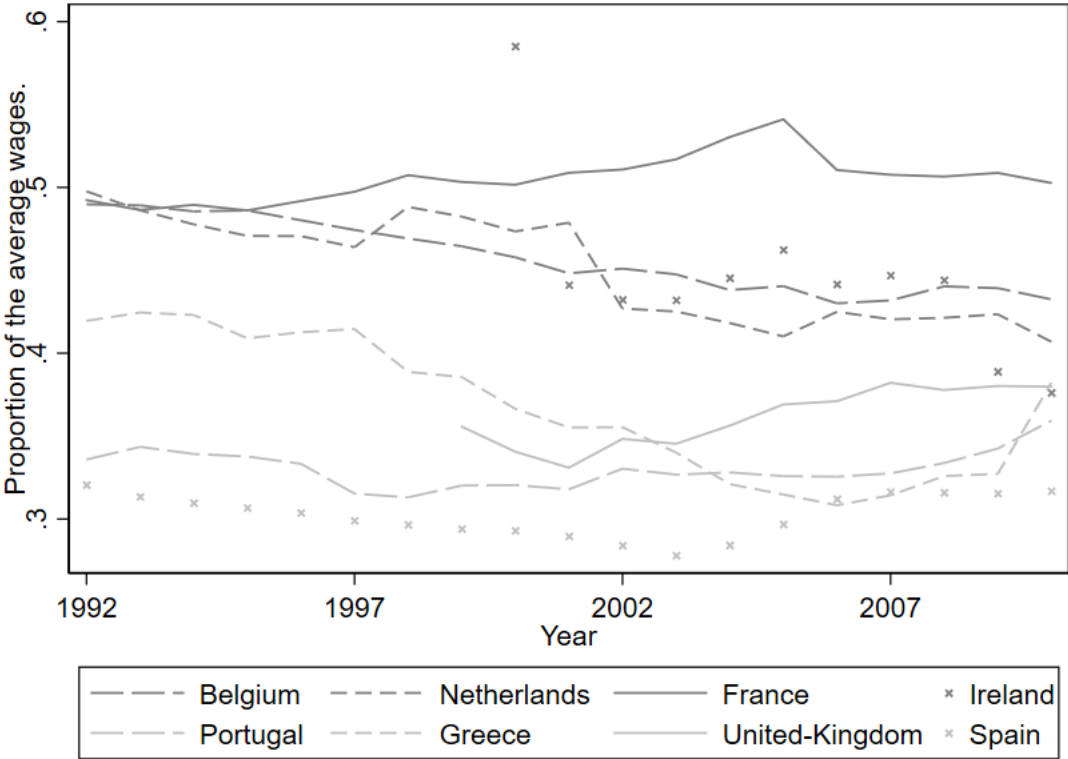
As mentioned before, we had to delete and modify some areas in the EULFS in order to have a consistent coding over time. Here, we will detail those modifications. Concerning Belgium, for years prior to 1996, we have deleted area "BE12", and modified the code of "BE11" to "BE21", "BE24" to "BE33", "BE13" to "BE24", "BE22" to "BE31", "BE15" to "BE22", "BE19" to "BE25", "BE23" to "BE32", "BE18" to "BE23", "BE26" to "BE34", "BE27" to "BE35" and "BE30" to "BE10". For Spain, we only had to recode one area, from "ES64" to "ES63". Concerning Portugal and Ireland, we had to drop years before 1998, as the classification completely change afterwards for those two countries. Finally, we had to drop all the years before 1997, for the same reason as before, classification completely change and information is too aggregated to use a crosswalk.

### A.2 Occupational classification

We follow Goos et al. (2014, Table 1, p. 2512 and Appendix Table A3) in order to define our occupation categories. Here, low-paying occupations include the occupations "51: Personal and protective service workers", "52: Models, salespersons, and demonstrators", "91: Sales and service elementary occupations" and "93: Laborers in mining, construction, manufacturing, and transport". Middling occupations include "42: Customer service clerks", "71: Extraction and building trades workers", "72: Metal, machinery, and related trade work", "73: Precision, handicraft, craft printing, and related trade workers", "74: Other craft and related trade workers", "81: Stationary plant and related operators", "82: Machine operators and assemblers", and "83: Drivers and mobile plant operators." Finally, high-paying occupations include "12: Corporate managers", "13: Managers of small enterprises", "21: Physical, mathematical, and engineering professionals", "22: Life science and health professionals", "24: Other professionals", "31: Physical, mathematical, and engineering associate", "32: Life science and health associate professionals" and "34: Other associate professionals".

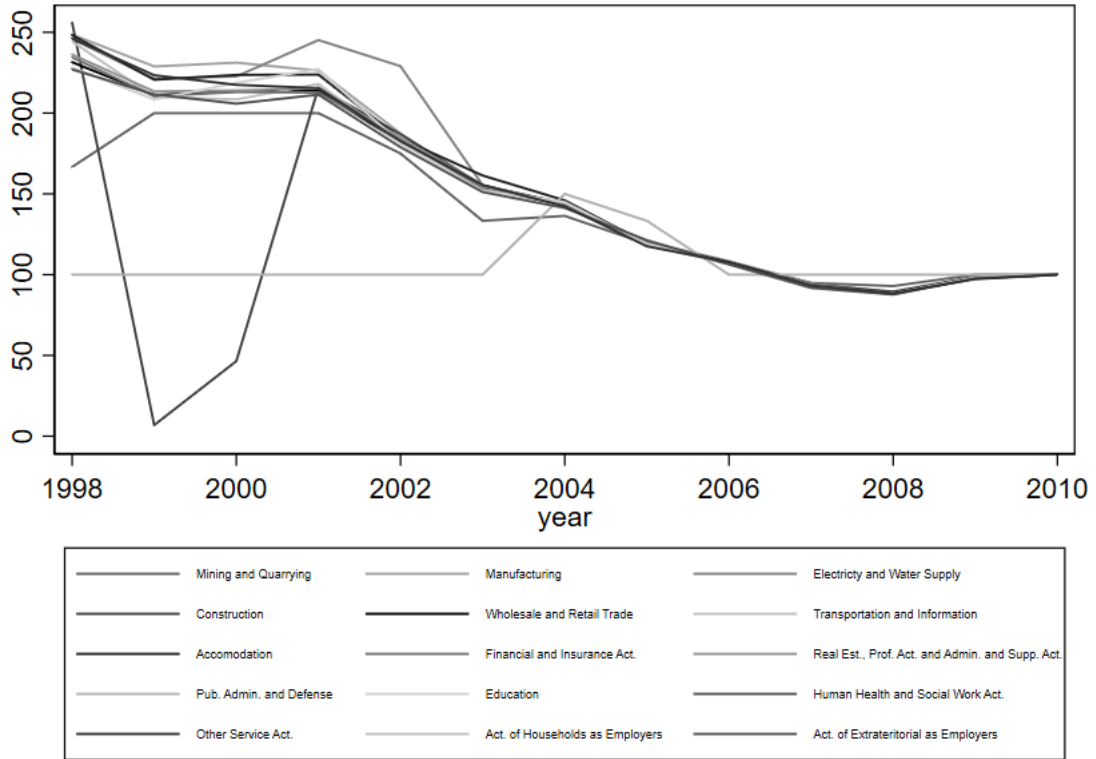
# B Additional graphs

Figure A1: Evolution of the levels of the minimum wage



Source: OECD dataset on minimum wages.

Figure A2: Evolution of the price indices of ICT Capital per industry in the US



Source: Klems dataset. Merged industries weighted by their relative GDP.

## C Robustness

### C.1 OLS until 2010

Table A1: OLS regressions: Employment rate, *with sample stopping in 2010 instead of 2007*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-1.387*** (0.240)	-0.610*** (0.189)	-0.136** (0.062)	-0.227*** (0.067)	0.027 (0.026)	0.035 (0.023)
- X Minimum Wage <sub>0</sub>	3.129*** (0.545)	1.646*** (0.422)	0.394*** (0.137)	0.706*** (0.162)		
- X Up. half MW <sub>0</sub>					0.004 (0.023)	0.072** (0.028)
Sh. male <sub>-1</sub>		0.113 (0.183)		-0.047 (0.081)		-0.043 (0.082)
Sh. high-skill <sub>-1</sub>		0.560*** (0.087)		0.134*** (0.039)		0.147*** (0.039)
Sh. low-skill <sub>-1</sub>		0.029 (0.052)		0.035 (0.023)		0.037 (0.023)
Emp. rate <sub>-1</sub>			0.802*** (0.019)	0.790*** (0.025)	0.818*** (0.020)	0.797*** (0.025)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.90	0.93	0.97	0.97	0.97	0.97
Observations	1369	1369	1369	1369	1369	1369
Threshold value	.443	.371	.346	.321	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2010 and includes 86 local labor markets spanning over 8 countries.

Table A2: OLS regressions: Participation rate, *with sample stopping in 2010 instead of 2007*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-1.138*** (0.179)	-0.515*** (0.160)	-0.331*** (0.075)	-0.242** (0.097)	0.017 (0.031)	0.043 (0.030)
- X Minimum Wage <sub>0</sub>	2.739*** (0.415)	1.382*** (0.377)	0.940*** (0.177)	0.784*** (0.244)		
- X Up. half MW <sub>0</sub>					0.090*** (0.029)	0.095** (0.041)
Sh. male <sub>-1</sub>		0.313** (0.135)		0.157* (0.080)		0.157* (0.081)
Sh. high-skill <sub>-1</sub>		0.241*** (0.055)		0.081** (0.036)		0.097*** (0.035)
Sh. low-skill <sub>-1</sub>		-0.007 (0.043)		-0.003 (0.024)		0.001 (0.024)
Part. rate <sub>-1</sub>			0.691*** (0.039)	0.626*** (0.035)	0.723*** (0.041)	0.637*** (0.035)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.91	0.94	0.96	0.96	0.95	0.96
Observations	1369	1369	1369	1369	1369	1369
Threshold value	.416	.373	.352	.309	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2010 and includes 86 local labor markets spanning over 8 countries.

## C.2 Time-varying minimum wage

Table A3: OLS regressions *using time-varying minimum wage*: Employment rate

	(1)	(2)	(3)	(4)
Sh. middling <sub>-1</sub>	-1.772*** (0.234)	-0.731*** (0.159)	-0.484*** (0.086)	-0.370*** (0.082)
- X Minimum Wage <sub>-1</sub>	4.296*** (0.583)	1.986*** (0.373)	1.292*** (0.199)	1.076*** (0.196)
Minimum Wage <sub>-1</sub>	-1.509*** (0.235)	-0.615*** (0.166)	-0.467*** (0.086)	-0.414*** (0.089)
Sh. male <sub>-1</sub>		0.170 (0.249)		-0.009 (0.127)
Sh. high-skill <sub>-1</sub>		0.491*** (0.078)		0.161*** (0.038)
Sh. low-skill <sub>-1</sub>		-0.015 (0.052)		0.018 (0.026)
Emp. rate <sub>-1</sub>			0.794*** (0.025)	0.725*** (0.030)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes
R <sup>2</sup>	0.92	0.95	0.97	0.97
Observations	1111	1111	1111	1111
Threshold value	.412	.368	.374	.344

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

Table A4: OLS regressions *using time-varying minimum wage*: Participation rate

	(1)	(2)	(3)	(4)
Sh. middling <sub>-1</sub>	-0.975*** (0.160)	-0.458*** (0.130)	-0.420*** (0.078)	-0.290*** (0.087)
- X Minimum Wage <sub>-1</sub>	2.455*** (0.375)	1.258*** (0.296)	1.198*** (0.175)	0.906*** (0.197)
Minimum Wage <sub>-1</sub>	-0.937*** (0.150)	-0.438*** (0.130)	-0.438*** (0.072)	-0.337*** (0.089)
Sh. male <sub>-1</sub>		0.326** (0.163)		0.171 (0.104)
Sh. high-skill <sub>-1</sub>		0.213*** (0.056)		0.076* (0.040)
Sh. low-skill <sub>-1</sub>		-0.013 (0.048)		-0.009 (0.032)
Part. rate <sub>-1</sub>			0.628*** (0.037)	0.582*** (0.036)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes
R <sup>2</sup>	0.92	0.94	0.95	0.96
Observations	1111	1111	1111	1111
Threshold value	.397	.364	.35	.32

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

### C.3 Mean minimum wage over the period considered

Table A5: OLS regressions *using mean minimum wage*: Employment rate

	(1)	(2)	(3)	(4)
Sh. middling <sub>-1</sub>	-1.557*** (0.251)	-0.855*** (0.161)	-0.378*** (0.076)	-0.442*** (0.076)
- X Mean Minimum Wage	3.696*** (0.612)	2.317*** (0.378)	1.024*** (0.173)	1.272*** (0.190)
Sh. male <sub>-1</sub>		0.067 (0.254)		-0.048 (0.125)
Sh. high-skill <sub>-1</sub>		0.548*** (0.084)		0.178*** (0.038)
Sh. low-skill <sub>-1</sub>		0.068 (0.060)		0.043 (0.026)
Emp. rate <sub>-1</sub>			0.830*** (0.026)	0.728*** (0.028)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes
R <sup>2</sup>	0.91	0.95	0.97	0.97
Observations	1111	1111	1111	1111
Threshold value	.421	.369	.369	.347

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

Table A6: OLS regressions *using mean minimum wage*: Participation rate

	(1)	(2)	(3)	(4)
Sh. middling <sub>-1</sub>	-0.901*** (0.168)	-0.504*** (0.155)	-0.353*** (0.082)	-0.312*** (0.103)
- X Mean Minimum Wage	2.256*** (0.391)	1.393*** (0.363)	1.023*** (0.184)	0.977*** (0.251)
Sh. male <sub>-1</sub>		0.274 (0.167)		0.138 (0.105)
Sh. high-skill <sub>-1</sub>		0.244*** (0.058)		0.095** (0.039)
Sh. low-skill <sub>-1</sub>		0.026 (0.051)		0.014 (0.033)
Part. rate <sub>-1</sub>			0.647*** (0.044)	0.585*** (0.038)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes
R <sup>2</sup>	0.92	0.94	0.95	0.96
Observations	1111	1111	1111	1111
Threshold value	.399	.362	.345	.319

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

## C.4 Including controls for industry share

### C.4.1 3 industries

Table A7: OLS regressions: Employment rate, *controlling for 3 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-1.924*** (0.256)	-0.864*** (0.173)	-0.531*** (0.090)	-0.482*** (0.085)	-0.040 (0.032)	-0.024 (0.027)
- X Minimum Wage <sub>0</sub>	4.401*** (0.605)	2.085*** (0.412)	1.303*** (0.212)	1.249*** (0.214)		
- X Up. half MW <sub>0</sub>					0.102*** (0.036)	0.137*** (0.034)
Sh. male <sub>-1</sub>		0.258 (0.215)		-0.016 (0.127)		-0.006 (0.128)
Sh. high-skill <sub>-1</sub>		0.481*** (0.079)		0.179*** (0.038)		0.200*** (0.039)
Sh. low-skill <sub>-1</sub>		-0.025 (0.053)		0.034 (0.029)		0.035 (0.029)
Emp. rate <sub>-1</sub>			0.801*** (0.024)	0.713*** (0.036)	0.836*** (0.024)	0.724*** (0.034)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.93	0.95	0.97	0.97	0.97	0.97
Observations	1111	1111	1111	1111	1111	1111
Threshold value	.437	.414	.408	.386	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects and control for 3 industry shares. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

Table A8: OLS regressions: Participation rate, *controlling for 3 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-1.027*** (0.177)	-0.430** (0.170)	-0.425*** (0.093)	-0.281** (0.113)	-0.001 (0.038)	0.027 (0.036)
- X Minimum Wage <sub>0</sub>	2.547*** (0.420)	1.154*** (0.393)	1.167*** (0.229)	0.853*** (0.280)		
- X Up. half MW <sub>0</sub>					0.123*** (0.037)	0.103** (0.046)
Sh. male <sub>-1</sub>		0.390** (0.163)		0.177* (0.106)		0.182* (0.107)
Sh. high-skill <sub>-1</sub>		0.202*** (0.057)		0.090** (0.041)		0.106*** (0.040)
Sh. low-skill <sub>-1</sub>		-0.042 (0.046)		-0.006 (0.032)		-0.005 (0.032)
Part. rate <sub>-1</sub>			0.631*** (0.038)	0.568*** (0.037)	0.655*** (0.040)	0.574*** (0.037)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.92	0.94	0.95	0.96	0.95	0.95
Observations	1111	1111	1111	1111	1111	1111
Threshold value	.403	.373	.364	.329	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects and control for 3 industry shares. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.



### C.4.2 16 industries

Table A9: OLS regressions: Employment rate, *controlling for 16 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-1.597*** (0.241)	-0.651*** (0.166)	-0.491*** (0.086)	-0.421*** (0.084)	-0.045 (0.027)	-0.020 (0.027)
- X Minimum Wage <sub>0</sub>	3.684*** (0.563)	1.645*** (0.394)	1.193*** (0.210)	1.101*** (0.211)		
- X Up. half MW <sub>0</sub>					0.102*** (0.034)	0.123*** (0.033)
Sh. male <sub>-1</sub>		0.158 (0.195)		-0.044 (0.132)		-0.035 (0.131)
Sh. high-skill <sub>-1</sub>		0.489*** (0.070)		0.174*** (0.048)		0.188*** (0.048)
Sh. low-skill <sub>-1</sub>		-0.087* (0.048)		0.007 (0.028)		0.009 (0.028)
Emp. rate <sub>-1</sub>			0.756*** (0.029)	0.669*** (0.039)	0.780*** (0.030)	0.676*** (0.037)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.94	0.96	0.97	0.97	0.97	0.97
Observations	1111	1111	1111	1111	1111	1111
Threshold value	.433	.396	.412	.382	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects and control for 16 industry shares. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

Table A10: OLS regressions: Participation rate, *controlling for 16 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-0.810*** (0.155)	-0.259 (0.156)	-0.316*** (0.099)	-0.167 (0.114)	0.022 (0.037)	0.053 (0.042)
- X Minimum Wage <sub>0</sub>	2.112*** (0.375)	0.822** (0.350)	0.941*** (0.241)	0.611** (0.264)		
- X Up. half MW <sub>0</sub>					0.108*** (0.040)	0.074* (0.044)
Sh. male <sub>-1</sub>		0.377** (0.149)		0.196* (0.102)		0.201* (0.102)
Sh. high-skill <sub>-1</sub>		0.180*** (0.050)		0.079* (0.041)		0.088** (0.040)
Sh. low-skill <sub>-1</sub>		-0.080 (0.050)		-0.023 (0.034)		-0.022 (0.033)
Part. rate <sub>-1</sub>			0.592*** (0.041)	0.524*** (0.034)	0.604*** (0.042)	0.527*** (0.034)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.93	0.95	0.95	0.96	0.95	0.96
Observations	1111	1111	1111	1111	1111	1111
Threshold value	.383	.315	.336	.273	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects and control for 16 industry shares. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

## C.5 Jackknife resampling

Table A11: OLS regressions: Employment rate, *jackknife resampling*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-1.885*** (0.287)	-0.953*** (0.207)	-0.499*** (0.083)	-0.488*** (0.093)	-0.008 (0.033)	0.003 (0.027)
- X Minimum Wage <sub>0</sub>	4.347*** (0.669)	2.454*** (0.481)	1.274*** (0.192)	1.330*** (0.233)		
- X Up. half MW <sub>0</sub>					0.091*** (0.035)	0.146*** (0.038)
Sh. male <sub>-1</sub>		0.084 (0.294)		-0.038 (0.134)		-0.035 (0.139)
Sh. high-skill <sub>-1</sub>		0.538*** (0.089)		0.173*** (0.040)		0.195*** (0.041)
Sh. low-skill <sub>-1</sub>		0.057 (0.067)		0.037 (0.028)		0.040 (0.028)
Emp. rate <sub>-1</sub>			0.820*** (0.027)	0.727*** (0.030)	0.856*** (0.028)	0.744*** (0.028)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.66	0.80	0.88	0.89	0.88	0.89
Observations	1111	1111	1111	1111	1111	1111
Threshold value	.434	.389	.392	.367	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

Table A12: OLS regressions: Participation rate, *jackknife resampling*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling <sub>-1</sub>	-0.996*** (0.201)	-0.472** (0.192)	-0.218 (0.149)	-0.191 (0.179)	0.027 (0.051)	0.027 (0.055)
- X Minimum Wage <sub>0</sub>	2.400*** (0.457)	1.257*** (0.446)	0.676** (0.305)	0.578 (0.385)		
- X Up. half MW <sub>0</sub>					0.079* (0.042)	0.055 (0.060)
Sh. male <sub>-1</sub>		0.289 (0.189)		0.215* (0.119)		0.218* (0.120)
Sh. high-skill <sub>-1</sub>		0.243*** (0.063)		0.023 (0.045)		0.032 (0.045)
Sh. low-skill <sub>-1</sub>		0.017 (0.061)		0.005 (0.039)		0.005 (0.039)
Emp. rate <sub>-1</sub>			0.460*** (0.035)	0.439*** (0.040)	0.475*** (0.035)	0.447*** (0.039)
Sh. age cat. <sub>-1</sub>	no	yes	no	yes	no	yes
R <sup>2</sup>	0.65	0.73	0.78	0.80	0.78	0.79
Observations	1111	1111	1111	1111	1111	1111
Threshold value	.415	.375	.322	.33	-	-

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

## C.6 Instrumental Variables - First-Stage

Those two tables present the first-stage regressions from Table 3 and Table 4 panel B. The first three columns of each table corresponds to the first three columns of Table 3 and 4. Columns 4 to 7 corresponds to columns 4 to 7 of Table 3 and columns 8 to 11 corresponds to columns 4 to 7 of Table 4.

Table A13: First-stage regressions from Table 3 and Table 4 panel B: share of middling occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Instrument <sub>-1</sub>	0.004 (0.003)	0.005* (0.003)	0.006** (0.003)	0.002 (0.003)	0.004 (0.003)	0.006* (0.003)	0.005 (0.003)	0.003 (0.003)	0.004* (0.003)	0.007** (0.003)	0.006** (0.003)
- <b>X</b> Minimum Wage <sub>0</sub>	0.011** (0.004)	0.009* (0.005)	0.007 (0.005)	0.014*** (0.004)	0.010* (0.006)	0.009 (0.005)	0.009 (0.006)	0.013*** (0.004)	0.009* (0.005)	0.007 (0.005)	0.007 (0.005)
Sh. male <sub>-1</sub>		0.204 (0.222)	0.184 (0.231)		0.217 (0.216)	0.274 (0.218)	0.204 (0.225)		0.212 (0.217)	0.262 (0.221)	0.193 (0.228)
Sh. high-skill <sub>-1</sub>		-0.074 (0.064)	-0.072 (0.069)		-0.053 (0.070)	-0.021 (0.072)	-0.040 (0.070)		-0.061 (0.067)	-0.038 (0.068)	-0.063 (0.066)
Sh. low-skill <sub>-1</sub>		-0.039 (0.075)	-0.052 (0.063)		-0.035 (0.077)	-0.059 (0.074)	-0.055 (0.062)		-0.036 (0.077)	-0.060 (0.075)	-0.052 (0.063)
Emp. rate <sub>-1</sub>				-0.092 (0.058)	-0.055 (0.074)	-0.099 (0.077)	-0.079 (0.077)				
Part. rate <sub>-1</sub>								-0.081 (0.059)	-0.047 (0.072)	-0.079 (0.075)	-0.032 (0.080)
Sh. age cat. <sub>-1</sub>	no	yes	yes	no	yes	yes	yes	no	yes	yes	yes
R <sup>2</sup>	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
Sh. ind. <sub>-1</sub>	no	no	no	no	no	3 posts	16 posts	no	no	3 posts	16 posts
Observations	823	823	823	823	823	823	823	823	823	823	823

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

Table A14: First-stage regressions from Table 3 and Table 4 panel B: share of middling occupations interacted with initial minimum wage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Instrument <sub>-1</sub>	-0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.002 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
- X Minimum Wage <sub>0</sub>	0.011*** (0.002)	0.009*** (0.002)	0.008*** (0.002)	0.012*** (0.002)	0.010*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.011*** (0.002)	0.009*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
Sh. male <sub>-1</sub>		0.114 (0.098)	0.102 (0.103)		0.122 (0.096)	0.144 (0.097)	0.112 (0.101)		0.117 (0.097)	0.136 (0.098)	0.104 (0.102)
Sh. high-skill <sub>-1</sub>		-0.025 (0.028)	-0.024 (0.030)		-0.012 (0.031)	-0.000 (0.032)	-0.007 (0.030)		-0.021 (0.029)	-0.012 (0.030)	-0.022 (0.029)
Sh. low-skill <sub>-1</sub>		-0.023 (0.035)	-0.025 (0.027)		-0.020 (0.035)	-0.030 (0.035)	-0.026 (0.027)		-0.022 (0.035)	-0.031 (0.035)	-0.025 (0.027)
Emp. rate <sub>-1</sub>				-0.046** (0.023)	-0.034 (0.030)	-0.051 (0.032)	-0.041 (0.032)				
Part. rate <sub>-1</sub>								-0.033 (0.022)	-0.017 (0.029)	-0.029 (0.030)	-0.008 (0.034)
Sh. age cat. <sub>-1</sub>	no	yes	yes	no	yes	yes	yes	no	yes	yes	yes
R <sup>2</sup>	0.96	0.96	0.97	0.96	0.96	0.96	0.97	0.96	0.96	0.96	0.97
Sh. ind. <sub>-1</sub>	no	no	no	no	no	3 posts	16 posts	no	no	3 posts	16 posts
Observations	823	823	823	823	823	823	823	823	823	823	823

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

## D Additional result: Serial correlation

Table A15: OLS Regressions: Share of middling occupations, controlling for 16 industry shares

	(1)	(2)	(3)	(4)
Instrument <sub>-1</sub>	0.842*** (0.024)	0.838*** (0.024)	0.815*** (0.025)	0.816*** (0.027)
Sh. middling <sub>-1</sub>	0.523 (0.419)	0.521 (0.419)	0.344 (0.403)	0.360 (1.607)
Sh. male <sub>-1</sub>		-4.923*** (1.546)	-5.115*** (1.199)	-4.898*** (1.335)
Sh. high-skill <sub>-1</sub>		-0.742 (0.468)	-1.731*** (0.560)	-1.634** (0.633)
Sh. low-skill <sub>-1</sub>		-0.680 (0.447)	-0.984** (0.448)	-0.795 (0.700)
- X Minimum Wage <sub>0</sub>				-0.026 (3.399)
Sh. age cat. <sub>-1</sub>	no	no	yes	yes
R <sup>2</sup>	1.00	1.00	1.00	1.00
Observations	851	837	837	823

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.

## E Additional result: The role of other labor market institutions

Table A16: Summary statistics: Average minimum wage and EPL Indexes by country

Country	Minimum wage	GRR	EPRC	EPT
Belgium	0.46	1.87	3.13	0.40
France	0.51	2.38	3.63	0.39
Greece	0.37	2.80	4.25	0.14
Ireland	0.46	1.39	0.44	0.31
Netherlands	0.46	2.89	1.13	0.51
Portugal	0.32	4.52	2.71	0.41
Spain	0.30	2.58	3.33	0.35
United-Kingdom	0.36	1.24	0.32	0.16

Notes: Data from OECD Employment Protection Legislation, OECD minimum wage and OECD Gross replacement rate for years 1992-2007.

Table A17: OLS regressions: EPL, without minimum wage

	Employment rate				Participation rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh. middling <sub>-1</sub>	-0.953*** (0.194)	0.341** (0.145)	-0.125 (0.092)	0.140 (0.097)	-0.472*** (0.177)	0.289*** (0.103)	0.155* (0.081)	0.201** (0.086)
- X Minimum Wage <sub>0</sub>	2.454*** (0.448)				1.257*** (0.407)			
- X EPRCv1 <sub>0</sub>		-0.103* (0.057)				-0.091** (0.038)		
- X EPTv1 <sub>0</sub>			0.054*** (0.020)				-0.025 (0.017)	
- X GRR APW <sub>0</sub>				-0.190 (0.287)				-0.458* (0.241)
Sh. male <sub>-1</sub>	0.084 (0.248)	0.156 (0.242)	0.124 (0.257)	0.142 (0.253)	0.289* (0.164)	0.333** (0.157)	0.323* (0.165)	0.327** (0.162)
Sh. high-skill <sub>-1</sub>	0.538*** (0.083)	0.565*** (0.091)	0.605*** (0.090)	0.592*** (0.089)	0.243*** (0.058)	0.243*** (0.058)	0.273*** (0.062)	0.254*** (0.059)
Sh. low-skill <sub>-1</sub>	0.057 (0.059)	0.033 (0.061)	0.022 (0.062)	0.018 (0.060)	0.017 (0.052)	0.008 (0.051)	0.001 (0.053)	-0.014 (0.051)
R <sup>2</sup>	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.94
Observations	1111	1111	1111	1111	1111	1111	1111	1111

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. All regressions include local labor market and year fixed effects. Robust standard errors clustered at the local labor market level are in parentheses. Sample covers the period 1992-2007 and includes 86 local labor markets spanning over 8 countries.