

THEMA Working Paper n°2018-02 Université de Cergy-Pontoise, France

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

Paul Maarek, Elliot Moiteaux





January 2018

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

Paul Maarek<sup>†</sup>

Elliot Moiteaux<sup>‡</sup>

THEMA, University of Cergy-Pontoise

THEMA, University of Cergy-Pontoise

January 2018

#### Abstract

Since 1980, labor markets became increasingly polarized: occupations in the middle of the wage distribution (routine occupations) tend to disappear, and are replaced by low-wage occupations (manual occupations) and high-wage occupations (abstract occupations). In the US flexible labor market, the decrease of routine occupations has been compensated by massive creation of low-paying occupations, and polarization only had a very limited impact on employment levels. This is not necessarily the case in rigid wage European countries in which the creation of such low-paying jobs is more difficult, given the institutional environment. We study the effect of the reduction of the proportion of routine jobs on the employment rate and the participation rate, conditionally on the value of the minimum wage, using local labor markets from the European Union Labor Force Survey on 8 countries which have a national minimum wage. Our OLS and IV estimates indicate that the disappearance of routine jobs has a negative impact on labor market outcomes in high-minimum wage countries due to an insufficient creation of low-paid occupations. Impact on participation is positive for low minimum wage countries, as labor supply may increase in order to compensate the deterioration of labor market opportunities.

Keywords: Polarization, employment, participation, minimum wage, ICT, routine occupations.

**JEL Codes:** J23, J24, J38

<sup>\*</sup>The usual disclaimer applies. We thank Clément Bosquet, Thepthida Sopraseuth, Idriss Fontaine, Olivier Charlot, Regis Renault, Fabian Gouret and Gani Aldashev for their precious suggestions.

 $<sup>^\</sup>dagger \rm Corresponding author$  : University of Cergy Pontoise, 33 boulevard du Port 95000 Cergy, France. E-mail : paul.maarek@u-cergy.fr

<sup>&</sup>lt;sup>‡</sup>THEMA, University of Cergy-Pontoise 33, boulevard du port 95000 Cergy, France. E-mail : elliot.moiteaux@u-cergy.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)) or in Europe (Goos and Manning (2007), Goos et al. (2014), Dustmann et al, 2009). It started in the mid-eighties and accelerated in the nineties. 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 automatize using information technologies or offshoring. This led researchers to reconsider the canonical model of skill-biased technological change to a more subtle view of the labor in terms of tasks. In this model, information technologies and offshoring can replace a subset of tasks which was previously mostly performed by medium and low-skilled workers (Acemoglu and Autor (2011)). This process led to a dramatic deterioration of economic opportunities for low-skilled and particularly males (see Acemoglu and Autor (2011) or Verdugo and Allègre (2017)) as well as for some medium-skilled who now perform some tasks previously performed by low-skilled. More specifically, workers with lower ability who lose their routine occupation, tend to relocate in manual occupations, given that they have no comparative advantage in abstract occupations (Cortes (2017)). This creates a "displacement effect" which lowers the demand for that factor (Acemoglu and Restrepo (2017b), Acemoglu and Restrepo (2017a))

Surprisingly, the impact of this process in terms of aggregate employment has received only little attention (with some notable exceptions however - see literature review). The conventional wisdom is that this process has only little implications in terms of aggregate labor market performances. The destruction of routine occupations goes together with a massive creation of abstract occupations, mainly for high-skilled workers, and manual jobs for low-skilled workers, especially in the service sectors Autor et al. (2013). Acemoglu et al. (2014) document a very limited impact of technology shocks implying routine job destruction on aggregate employment at the local labor market level in the US. However, Acemoglu and Autor (2011) argue this process is consistent with the strong real earnings decrease for low-skilled (especially male) workers during the last four decades as they switch from middling occupations, which are relatively well-paid, to low-paid occupations. Trade shocks have been argued to be much more costly in terms of aggregate employment (Autor et al. (2013)) but seems to be weakly related to polarization (see Goos et al. (2014) and Acemoglu et al. (2014)). We argue that the polarization process could have had a very different impact on European countries, given strong labor market institutions and minimum wage in place. This may prevent a sufficient creation of low-paid jobs for low-skilled workers, in order to compensate the destruction of routine jobs, observed in every European countries. In France for instance,

Catherine et al. (2015) or Cahuc and Debonneuil (2004) document a strong deficit in manual job creation in the service sector as compared to the US economy and relate it to the strong labor market institutions. We argue that in such an environment, destruction of routine jobs could have some strong consequences in terms of aggregate employment given that routine jobs are often occupied by low-skilled workers which cannot reallocate in abstract high-paid jobs.

In this paper, we make use of the European Union Labor Force Survey (EULFS hereafter) which provides detailed information on the economic situation of a sample of workers from 1983 to 2014 with information available at the subcountry geographical level (local labor market). The survey contains comprehensive information on occupations which allows to measure the polarization process (the evolution of the proportion of routine jobs) for each area within a country (Goos and Manning (2007) and Goos et al. (2014) use the same data). The cross-country dimension of the dataset enables us to measure the heterogeneity in the impact of the decrease in routine jobs on employment and participation rates, depending on the level of the minimum wage. Keeping only countries with a national legal minimum wage (8 countries over the 14 countries sample of Goos et al. (2014)) we end up with a panel of 86 employment area as defined by the EULFS. There exists a very strong heterogeneity in terms of the level of legal nationwide minimum wage which goes from .278 to .585 as measured as a percentage of the mean wage. This allows to identify the effect of minimum wage in a context of increasing job polarization. Our identification relies on two sources of variation. First, we are able to compare the impact of different degrees of routine job destruction within the same institutional setting. Second, we are able to compare some areas with a roughly similar degree of job market polarization but very different institutional settings. The EULFS also contains many socioeconomic characteristics which allow to control for key variables, which plausibly affect both the polarization process and the labor market outcome variable we seek to explain (demography, skill supply, etc.). First, using some fixed-effects (area and time) regressions, we show that the decrease in the number of routine jobs in a given area do not has any impact (or sometimes slightly positive) in area characterized by a low minimum wage but has a strong pervasive impact in terms of employment rate in area characterized by a strong minimum wage. This is consistent with Autor et al (2014) who find a very weak effect of polarization on employment rate for the US economy. This result holds for European countries characterized by a low minimum wage. For the participation rate, results are mixed. Polarized local markets have exhibited an increase in the participation rate in countries characterized by a low minimum wage but a decrease in countries characterized by a high minimum wage. This is consistent with the results of Verdugo and Allègre (2017) who show an increase in the participation rate of women associated with the polarization process, which they interpret as a response of the decreasing economic opportunities of men in the the household. For flexible wage labor markets, this effect should translate in 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 translate into a decrease in participation for this category of workers, which could overcompensate the increase in the participation of women. Also we show that a high minimum wage is associated with a lower creation of low-paying jobs following a decrease in the proportion of routine jobs which we interpret as an evidence of the mechanism we have in mind, to explain the effect of employment polarization in terms of aggregate labor market performances. Part of the workers that have no comparative advantage in abstract occupations and that suffer from the destruction of their routine jobs, are unable to relocate to manual occupations, due to the presence of a high-minimum wage that prevents the creation of low-paying occupations.

We then tackle the endogeneity issue using an instrumental variable strategy. Even controlling for a bunch of fixed-effects and other controls, we cannot completely rule out the possibility of reverse causality for instance, despite the decrease of routine jobs is generally considered as a demand shock (related to technology shocks). We follow the logic of the instrumental strategy of Karabarbounis and Neiman (2013) and make use of shocks in ICT investment price (from the KLEMS dataset) which have occurred in the nineties and which is recognized in the literature to have been one of the major factor behind the decrease in the proportion of routine jobs. More precisely, in order to capture to which extent a local labor market has been affected by the strong decrease in investment price in new technologies, we use the initial sector specialization of the area and the initial capital ICT intensity of sectors, having in mind that sectors (and areas specialized in those sector) that use more intensively ICT should be more affected by price shocks. Results are qualitatively similar to those obtained with OLS but are higher in magnitude.

Our results suggest that the impact of minimum wage may depend on the economic context and more particularly, the rate at which routine jobs are destroyed and labor market is experiencing structural transformations. In such a context, more flexible institutional arrangements such as minimum wages negotiated at the sector level or at the firm level could be much more efficient (as in countries like Germany or Sweden). Another possibility which may lead to efficiency gain in such an environment, is that the minimum wage is fixed at the subnational level given that local labor markets are exposed very differently to global technology shocks.

We are not the first to question the impact of polarization on aggregate employment and participation

rates. Autor et al (2014) find only little evidence that technology shocks which destroy routine jobs have a sizeable aggregate impact on employment. We show that this conclusion do not necessarily hold in more rigid wage countries due to their poor ability to create low-paying jobs. Two papers are very close to the mechanisms we have in mind to explain the potential cost of routine jobs destruction in term of aggregate employment. First, Bock (2017) uses a calibrated general equilibrium model and finds that labor market polarization, by displacing unskilled workers from routine to manual jobs, may explain the strong decrease in employment for this category of workers given its strong labor costs. Using a similar calibration strategy, Albertini et al. (2016) compare labor market performances of two economies with very different institutional settings (France and US) in a context in which technology shocks destroy routine jobs. Nellas et al. (2011) also 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 in a theoretical model. We directly use data at the local labor market level which allow to empirically compare the employment response of polarization across different institutional settings. Jaimovich and Siu (2012) 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 have not recover following the recession. We focus in the long run impact of labor market polarization and the role of labor market institutions in this outcome.

Our paper is also very related to another strand of literature. Some authors have questioned the existence of job market polarization in Europe. Menes and Oesch (2010), Nellas et al. (2011) or Salvatori (2015) show that in Europe the decrease in the proportion of routine jobs do not seem to be clearly associated with a massive increase in the proportion of low-paying manual jobs contrary to the US where it is clearly the case. Menes and Oesch (2010) even qualify this process as skill upgrading rather than polarization. We empirically show that this European specificity may be related to labor market institutions which prevent the creation of those low-paying jobs which in turn affects the shape of the polarization of the labor market. Finally, in a very recent paper related to ours, Lordan and Neumark (2017) use the flows in and out of employment across the US states and show that workers who have lost their job in routine have a lower probability to find a job in states characterized by a high minimum wage. We make several contributions with respect to their findings. First, we focus on aggregate equilibrium labor market performances instead of labor flows. Second, we analyse the effects on both employment and participation rates. Third, using data on European local labor market allows us to compare very different institutional settings and to compare the impact of very different labor market shocks within

the same institutional setting. Finally, we use an instrumental variable strategy which allows a causal interpretation of our results.

The rest of the paper is organized as follows. We first present the data we use all along the paper and some basic stylized facts. Then we present our empirical strategy. Finally we present our result and conclude the paper.

## 2 Data and stylized facts

## 2.1 Data

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

The European Union Labour Force Survey (EULFS) contains data for 28 European countries. Data are collected on a national level. Then, data are processed centrally by Eurostat which makes the data harmonized with a same set of characteristics for each country, common classifications and definitions. One of the main advantage of this dataset is that it is available for many countries over a relatively long time period and that it 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 previous to the 2004 enlargement as in Goos et al. (2014) These countries are the ones with the most complete datasets and they should be very similar in terms of exposition to technology shocks as compared to the newest EU members. Over these fifteen countries, only 8 have a national minimum wage which makes institutions and labor costs for low-skill comparable across them. Those countries are Belgium, Spain, France, Greece, Ireland, Netherlands, Portugal and the United-Kingdom. We end up with a total of 86 local labor markets. 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.

The version of the EULFS we use goes from 1983 to 2013. As there is no information on the occupation of workers before 1993, we only use years from 1993 onwards. Our baseline sample stops in 2007, in order to avoid the effect of the 2008 crisis on the labor market. Nevertheless, as a robustness test, we have also a sample including post-crisis years until 2010. However, during this period, the NACE and the ISCO classifications changed, respectively in 2008 and 2010. This makes the use of the EULFS sample for years after 2010 very difficult (see below).

In order to deal with the change of the NACE classification, we use the methodology of Verdugo and Allègre (2017). They manually created a crosswalk to convert the classification from Nace 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), M (Professional activities) with N (Administrative and support service activities). Concerning the change of the ISCO classification in 2010, we have used an existing crosswalk.<sup>1</sup>. However, we have observed a structural break in the data after using this crosswalk, so we won't use years after 2010 as argued in Breemersch et al. (2017). It is worth noting that our OLS results are robust, whether we consider until 2007 or 2010 (see online appendix).

#### Measure of routineness

To measure the evolution of middling occupations, we follow Verdugo and Allègre (2017) and Goos et al. (2014). There exist several approaches in the literature to measure the polarization of the labor market. The most common approach is to refer as the skill content of each occupation using the Dictionary of Occupational Title (DOT, 1968) and classify occupations according to their intensity in term of routine tasks (Autor et al. (2003), Autor et al. (2013) or Goos et al. (2014) for the second part of their paper). This approach has the merit of focusing directly on the skill content of each occupation. On the other hand, there are two main drawbacks with this approach. First, the US occupation classification differs substantially from the EULFS classification and mapping occupations from the DOT to occupations of the EULFS necessitate the use of several correspondence table with at each step a very imperfect mapping which requires some random assignments (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 this year (see Spitz-Oener (2006)) As a result we prefer to use a more direct approach. We follow Verdugo and Allègre (2017) and Goos et al. (2014) in the first part of their paper by looking directly at the occupations at the middle of the wage distribution (middling occupations). Goos et al. (2014) show that those occupations correspond to the routine occupations as defined by Autor et al. (2003). We also define the corresponding categories for low-paying jobs (manual) and high paid jobs (abstract). More precisely, as in Goos et al. (2014, Table 1, p. 2512 and Appendix Table A3), low-paid occupations includes occupations 93, 51, 52 and 91. Middling occupations includes 81, 72, 83, 73, 71, 42, 82, 74. High-paying occupations include 12, 21, 22, 24, 13, 31, 34 and 32. We define the proportion of each category of occupations as its proportion over the total employment.

<sup>1.</sup> The crosswalk has been provided by the Institute for Structural Research and Faculty of Economics of the University of Warsaw



Figure 1 – Evolution of the proportion of occupations by type

We can see on 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-paid jobs. However the evidence is less clear-cut for the proportion of low-paid jobs. We can see an increase but it seems to be much less important than 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-paid jobs at the expense of a decrease in employment and labor market participation.

#### Labor market outcomes

The employment rate in an area is defined as the ratio of the employed over the working age population. The participation rate is defined as the ratio of employed and unemployed over the working age population. In our version of the EULFS, we don't have the exact age of each person, we only know to which 5-year age bands he belongs (0-4, 5-9 etc.). In our analysis, the working age population is defined as the number of individuals over the age of 15 and below the age of 72. We also tried using the lower threshold, i.e. below 67 years old, and our results are not affected by such a modification.

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

Skill-levels are coded using the available information about education in the database. The EULFS contains some detailed harmonized data on educational attainment with low education, medium education and high education. Those levels are defined thanks to the International Standard Classification of Education of 1997 (ISCED 1997).

In the EULFS, "low" education refers to lower secondary or 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).

It is important to control for educational attainment of the workforce in our regressions. Generally, the polarization process can be seen as driven by demand factors or supply factors. The most discussed in the literature is the introduction of new technologies (computers) that are substitute to workers in some occupations and which have modified the labor demand. But it can also be driven by supply shocks, as a general increase in the skills of the labor force. Generally the polarization process is seen in the literature as being driven by demand factors (see Autor et al. (2003), Autor et al. (2013), Goos et al. (2014) or Acemoglu and Autor (2011)) but we cannot exclude that part of it is driven by the global increase in skill supply observed in Europe in the nineties and which could have also impacted labor market outcomes. We will also tackle this issue by employing an instrumental variable strategy, which isolates a negative demand shock for routine tasks.

Using the skill composition of the workforce, we can derive several interesting patterns. First, we compute the proportion of low-paid and middling occupations which are occupied respectively by low-skilled and medium skilled workers. Results are displayed in figure 2. We also compute the proportion low-skilled and medium skilled that occupies low-paying and middling occupations. 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-skill workers increased sharply in medium skills occupations but also in low-paying occupations. Second, the probability for a low-skill worker to have a low-paid occupation increased substantially over the period. This is consistent with Cortes (2017) who shows that workers with low ability move more often from routine to manual occupations relative to workers of higher ability. Also it seems there is some skill downgrading: medium skills occupied less qualified jobs than previously, given their increase in low-paying occupations. More generally, this is consistent with the "displacement effect" highlighted in (Acemoglu and Restrepo (2017b), Acemoglu and Restrepo (2017a)) Overall this pattern is consistent with the view that job market polarization has deteriorated the economic opportunities of low-skilled. The disappearance of routine jobs seems to be associated with an increase in the proportion of low-skilled who occupy a manual occupation and a sharp decrease of low-skilled that occupied a routine occupation. This sorting process do not favor low-skilled who cannot reallocate in high paid abstract jobs. The question we ask is related to the ability



(c) Occupation distribution for low-skilled workers
(d) Occupation distribution for medium-skilled workers
Figure 2 – Evolution of labor market opportunities

of an economy to create a sufficient amount of low-paid jobs for low-skilled workers whose employment opportunities decreased sharply in routine occupations and which cannot reallocate in high-paid ones.

#### Local labor market

Local labor markets are coded using the Nomenclature des Unités Territoriales Statistiques at the twodigit level (NUTS). The NUTS data in the EULFS is incomplete; we only have one region for Netherlands, i.e. the full country while we have 22 regions for France. Moreover, in order to perform our analysis, we need to have a consistent definition of a local labor market over time. However, there are several changes of classification for some countries. To deal with this problem, we have only kept regions that are comparable over time. Basically, we have aggregated areas when needed, and dropped areas when they disappear in the classification so that the definition of a given local labor market is the same over the period. More details are available in the appendix. Our results are not sensible to this modification in the classification of local labor markets, nor to the exclusion of Netherlands.

### The minimum wage

In order to have information about the national minimum wage level in each country, we have used

the database of 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 database: Belgium, Spain, France, Greece, Ireland, Netherlands, Portugal and the United-Kingdom. This is explained by the fact that some countries like Germany don't 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 so that labor market institutions are made comparable across countries.

#### Additional control

Besides skill levels, we have controlled for other characteristics in our regressions. Those controls are the proportion of male in the working age population of the local labor market, the proportion of young, defined as the number of persons aged between 15 and 27 years old, and the proportion of elderly, defined as the number of persons aged between 67 and 72 years old. Those controls are necessary, in order to control for the heterogeneity of the labor force, as they have different job opportunities. Also those characteristics may affect the shape of labor market polarization. For instance, the age structure of the population is likely to have an impact on the rate of destruction of routine jobs (Autor and Dorn (2009)).

### ICT investment price data and technology shocks

We use the price index of ICT capital for the US, which is available at the sector level (NACE rev 1) in the KLEMS dataset. For the exclusion restriction to be satisfied, the price shock variable should not affect the labor market outcomes through other channel than the destruction of routine occupations. We think this should be the case. In the recent literature, it is now widely accepted that the ITC and other related IA technologies are task-biased rather than skill-biased. We thus believe that impact on labor market outcomes should translate mainly through this channel, i.e. the destruction of specific occupations which are intensive in routine tasks. Of course, it is still possible that our price shock variable affects labor market outcomes through other channels. For instance, technology shocks could modify the skill composition of the workforce in a specific local labor market which is more intensive in ICT sectors than other areas. This could in turn affect agregate labor market performances. Thus, by controling our IV regressions for skill composition and demographic characteristics, we should make our exclusion restriction more likely to be satisfied.

Sectors in the KLEMS database are defined according to the Nace Rev.2 classification. As we have regrouped sectors in the EULFS in order to have consistent sector definition over the period, the same thing needs to be done in the KLEMS dataset. When sectors were merged in the KLEMS dataset in order to match those of the EULFS, they were weighted by their relative GDP.

## 3 Empirical strategy

We first estimate OLS specification to highlight the correlation between the variation of the proportion of routine jobs (Routine) and our labor market outcome (LMO) variables which correspond to the employment rate and the participation rate. Formally, we estimate for each outcome

$$LMO_{a,t} = \alpha_1 Routine_{a,t} + \alpha_2 (Routine \times MW)_{a,t} + \alpha_3 MW_{a,t} + \beta X_{a,t} + \gamma_a + \delta_t + u_{a,t}$$
(1)

where  $\gamma_a$ ,  $\delta_t$ ,  $u_{a,t}$  correspond respectively to an area fixed-effect, a time fixed-effect and the error term which captures all other factors not correlated with our controls which may also explain our Routine variable and the labor market outcome variables (LMO), with  $E(u_{a,t}) = 0$ . In 1,  $X_{a,t}$  is a vector of control variables described earlier.  $MW_{a,t}$  corresponds to the minimum wage in area a at time t.

We then turn to the IV estimates. In order to estimate the causal impact of the job market polarization process on labor market outcomes at the local labor market level, we use an instrumental variable strategy. The correlation we observe may be due to an omitted variable correlated with both labor market outcomes and the occupational composition of the workforce. We control for the most obvious factors such as the skill supply, demographic factors and area and time fixed-effects to account for unobserved heterogeneity, but some omitted variables may still bias our estimates. For instance, polarization could be related to a global increase in skill-supply, which will affect the occupational composition of the workforce, but which do not correspond to a shock affecting labor demand as we have in mind. Second, bad labor market conditions and economic outcomes may affect the decision to destroy routine jobs, and thus accelerate the diffusion of technologies. In our IV strategy, we thus try to isolate a technology shock that will impact labor demand through its impact on the destruction of routine jobs. The disappearance of routine jobs is mainly explained by the diffusion of information technologies (see Goos et al. (2014) or Autor et al. (2013)). In the same spirit of Karabarbounis and Neiman (2013), we use the investment price of ICT capital which decreased sharply over the period we study, and which explains the massive diffusion of ICT capital in the economy. In order to identify how each areas have been exposed to such a price shock, we use the initial industrial specialization of each areas and the computer use intensity of each sector at the national level from KLEMS. The instrument's construction follows the same logic of Autor et al.

(2013) for trade shock, making use of a nationwide variation in trade at the sector level (ICT prices in our case) with the initial specialization of the area. More formally, our instrument writes:

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

Where s, a and t respectively correspond to sector, area and year.  $P_{s,t}^{ICT}$  corresponds to the price of ICT capital for sector s at year t for the US economy.  $K_{s,2000}^{ICT}$  and  $L_{s,2000}$  correspond respectively to the the ICT capital stock and employment in sector s in the year 2000.  $L_{s,a,2000}$  and  $L_{a,2000}$  correspond respectively to employment in sector s and area a and to employment in area a. In this equation,  $(L_{s,a,2000}/L_{a,2000})$  is the industrial specialization in the year 2000 and  $(K_{s,2000}^{ICT}/L_{s,2000})$  corresponds to the ICT capital stock per workers in sector s in the US in year 2000. Here, the idea is that the exposure of an area to price shock in ICT should depend on its intensity of computer use which is defined as each sector share in total employment times the ICT capital stock per workers in the year 2000 in this sector. We use the year 2000 as a reference year as data are available for all areas. In other words, our instrument is area specific, given that the intensity of ICT use  $(\frac{L_{s,a,2000}}{L_{a,2000}} \times \frac{K_{s,2000}^{IC}}{L_{s,2000}})$  is area specific. Our instrument varies over time, due to our ICT price variable, which is industry-year specific.

Following Woolridge (2000) recommendation for estimating a model with interaction terms in which one regressor is endogenous (Routine), the first stage equations we estimate are

$$Routine_{a,t} = \beta_1 techshock_{a,t} + \beta_2 (techshock \times MW)_{a,t} + \beta_3 MW_{a,t} + \beta X_{a,t} + \gamma_a + \delta_t + u_{a,t}^{(3)}$$
$$(Routine \times MW)_{a,t} = \beta_1 techshock_{at} + \beta_2 (techshock \times MW)_{a,t} + \beta_3 MW_{a,t} + \beta X_{a,t} + \gamma_a + \delta_t + u_{a,t}$$

where the  $techshock_{at} \times MW_{at}$  is used as an instrument for  $Routine_{at} \times MW_{at}$ . We use the fitted value of 3 in the second stage

$$LMO_{a,t} = \alpha_1 \widehat{Routine_{a,t}} + \alpha_2 (\widehat{Routine \times MW})_{a,t} + \alpha_3 MW_{a,t} + \beta X_{a,t} + \gamma_a + \delta_t + u_{a,t}$$

We finally estimate the impact of the variation in the proportion of routine on the proportion of lowpaid manual jobs in an area. 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 distribution in order to provide enough jobs to low-skill workers that lost their routine jobs and who cannot reallocate in abstract occupations due to skill mismatch. As a result, in the presence of a high minimum wage, we should observe a lower increase in the proportion of low-paid occupations following a decrease in the proportion of routine occupations. We use the same OLS and IV specifications except we use the proportion of low-paid jobs as our outcome variable. Finally, we estimate 1 using two dummy variables for high (in the top-third of the minimum wage distribution) and low (in the bottom-third of the minimum wage distribution) minimum wage in order to see if the conditional effect is linear in the minimum wage.

## 4 Results

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

## 4.1 Labor market outcomes, OLS results

The estimated coefficients of equation (1) are presented in Table 1 when considering the employment rate as the labor market outcome and in Table 2 when considering the participation rate. 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. Then, we gradually add control variables defined at the local labor market level: proportion of male, skill-levels proportion and proportion of young and old individuals. Area fixed-effects are present in all regressions, and time fixed-effects are not included in column 1 and 3 (as indicated in Table 1 and 2). Standard-errors are clustered at the area level. For each regression, we compute the threshold value of the minimum wage such that the marginal effect of routine equals zero ( $\alpha_1 + \alpha_2 \times MW = 0$ ).

Focusing first on Table 1, we can see that coefficients are significant in all specifications. The threshold values for the minimum wage are decreasing as we are adding control variables. In the most complete specification in column 7, the threshold value is equal to 0.389, meaning that when the national minimum wage level, calculated as a fraction of the average wages of full-time workers, exceeds 0.389, the reduction of the proportion of middling occupations has a negative effect on employment according to our estimation (i.e. the marginal impact of routine  $\alpha_1 + \alpha_2 \times MW$  is positive).

If we look at the impact on the participation rate, results are almost identical. All coefficients are significant, and the threshold value is decreasing as we are adding controls, even if it's slightly higher than for the previous estimations for the employment rate. That is, when the minimum wage become suf-

Table 1 – OLS Regressions

	Employment Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Percentage middling	-0.654***	-0.139**	-1.851***	-1.700***	-1.694***	-0.945***	-0.588***	
	(0.0568)	(0.0548)	(0.236)	(0.209)	(0.206)	(0.191)	(0.162)	
Middling $\mathbf{X}$ Minimum Wage			$2.906^{***}$	$3.877^{***}$	$3.847^{***}$	$2.395^{***}$	$1.511^{***}$	
			(0.502)	(0.520)	(0.510)	(0.474)	(0.375)	
Minimum Wage			$-1.170^{***}$	$-1.349^{***}$	$-1.322^{***}$	-0.713***	-0.467***	
			(0.200)	(0.206)	(0.198)	(0.192)	(0.160)	
Percentage male					0.286	$0.398^{**}$	$0.445^{**}$	
					(0.252)	(0.173)	(0.182)	
Percentage high-skill						$0.673^{***}$	$0.456^{***}$	
						(0.0810)	(0.0758)	
Percentage low-skill						-0.0350	$-0.134^{***}$	
						(0.0518)	(0.0507)	
Percentage old							-1.184***	
							(0.214)	
Percentage young							-0.739***	
							(0.0933)	
Threshold value	-	-	0.637	0.438	0.440	0.395	0.389	
Area FE	yes	yes	yes	yes	yes	yes	yes	
Time FE	no	yes	no	yes	yes	yes	yes	
Ν	1223	1223	1223	1223	1223	1197	1197	
Countries	8	8	8	8	8	8	8	
Nb of areas	86	86	86	86	86	86	86	
within - $R^2$	0.349	0.576	0.400	0.681	0.682	0.749	0.792	

Robust standard errors clustered by areas are in parentheses. Sample stops in 2007.

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.

Table 2 – OLS Regressions

			5					
	Participation Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Percentage middling	-0.499***	-0.103***	-1.170***	-1.002***	-0.990***	-0.602***	-0.413***	
	(0.0371)	(0.0385)	(0.152)	(0.155)	(0.151)	(0.150)	(0.137)	
Middling $\mathbf{X}$ Minimum Wage			$1.663^{***}$	$2.225^{***}$	$2.169^{***}$	1.428***	$0.969^{***}$	
			(0.331)	(0.369)	(0.356)	(0.352)	(0.310)	
Minimum Wage			-0.769***	-0.876***	-0.824***	-0.496***	-0.391***	
C C			(0.133)	(0.149)	(0.142)	(0.141)	(0.128)	
Percentage male					0.534***	$0.589^{***}$	0.549***	
C					(0.168)	(0.124)	(0.122)	
Percentage high-skill						0.321***	0.228***	
0 0						(0.0617)	(0.0539)	
Percentage low-skill						-0.0554	-0.0894*	
-						(0.0499)	(0.0500)	
Percentage old							-1.087***	
							(0.160)	
Percentage young							-0.331***	
							(0.0649)	
Threshold value	-	-	0.703	0.450	0.456	0.422	0.426	
Area FE	yes	yes	yes	yes	yes	yes	yes	
Time FE	no	yes	no	yes	yes	yes	yes	
Ν	1223	1223	1223	1223	1223	1197	1197	
Countries	8	8	8	8	8	8	8	
Nb of areas	86	86	86	86	86	86	86	
within - $R^2$	0.382	0.607	0.419	0.660	0.669	0.704	0.743	

Robust standard errors clustered by areas are in parentheses. Sample stops in 2007.

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.



Figure 3 – The marginal effect of the proportion of routine occupations on labor market outcomes, conditional on the value of the minimum wage. The figure is based on regression estimates from column 7 of Tables 1 and 2. Dashed lines represent 90% confidence intervals.

ficiently high, the decrease of the proportion of routine decreases the participation rate (i.e the marginal effect of routine  $\alpha_1 + \alpha_2 \times MW$  is positive).

Figure 3 provides a visualization of the conditional marginal effects estimated in column 7 of Tables 1 and 2, i.e. on employment rate and participation rate. The plotted line shows the effect of a marginal increase of the proportion of middling occupations on the labor market outcomes  $(\alpha_1 + \alpha_2 \times MW)$ . The plot is super-imposed over a histogram of the distribution of minimum wage levels, in order to provide a sense of the empirical relevance of the range of minimum wage levels for which the effect of the reduction of the proportion of middling occupations is significant. We can see on the left panel of Figure 3 that the marginal effect of a decrease in the proportion of routine jobs 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 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 the minimum wage is high, which we interpret as the poor ability of such economies to create a sufficient amount of low-paying occupations for workers which do not reallocate in the abstract high-paying occupations. We can see on the right panel of Figure 3 that the marginal effect of a decrease in the proportion of routine jobs on the participation rate is negative and significant  $(\alpha_1 + \alpha_2 \times MW > 0)$  for high level of the minimum wage (above 0.49) and positive and significant  $(\alpha_1 + \alpha_2 \times MW < 0)$  for low values (below 0.36). This is consistent with our findings on the employment rate. When the minimum wage is high the decrease in

employment rate translates into a decrease in the participation rate. When the minimum wage is low, the economy is able to create a high quantity of low-paying jobs in the service sector. It is very likely that this finding reflects the fact that the participation rate of women increased, in order to compensate the low employment and wage prospect of workers previously employed in a routine occupation as shown by Verdugo and Allègre (2017). This could lead to an overall increase in participation rate when the minimum wage is low given the fact that the employment opportunities of male are unaffected by the decrease in the proportion of routine jobs. We can see from Figure 3 that most countries/areas are characterized by very high or very low levels of the minimum wage, such that the polarization process has a significant impact on the employment and participation rates. Only a very few observations are characterized by an intermediate level of the minimum wage, such that the effect of polarization is non-significant. Over the period 1992-2010, the proportion of routine jobs decreases by approximately ten percentage points, this shock had an heterogeneous impact. Over the period, according to our estimates (Table 1 and Table 2), participation rate decreases by 0.74 percentage point for France, which is characterized by a high-level minimum wage over the period (0.50). In the other hand, over the same period in the United-Kingdom, a low-level minimum wage country (0.36), it has triggered an increase of 0.62 percentage point of the participation rate. Concerning the employment rate, polarization lead to a decrease of 1.71 percentage points in France, and an increase of 0.41 percentage point in England, if the proportion of routine jobs diminishes by ten percentage points. Those effects are economically sizeable.

#### 4.2 Labor market outcomes, IV results

To tackle the endogeneity issue mentioned above, we have re-estimated equation 1 using an instrumental variable strategy. Here, both outcomes are displayed in the same table. As we have clustered standard-errors at the area level, we provide the cluster-robust Kleibergen-Paap Wald rk F-statistic version to determine if our instrument is strong. All estimations contain area and time fixed-effects.<sup>2</sup> When looking at column 4 and 8, which display the most complete specification for the participation rate and the employment rate, we can see that all coefficients are statistically significant. Robust f-statistics are satisfyingly high to draw conclusions from these specifications (around 10). Threshold values are slightly higher than in OLS specifications and the magnitude of coefficients higher, but our results are qualitatively unchanged. They confirm our previous estimations, the minimum wage level plays a role in

<sup>2.</sup> First-stage results are available in appendix.

Table 3 – IV Regressions	
--------------------------	--

		Participa	ation Rate		Employment Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Percentage middling	-0.250	-1.451**	-0.821	-1.001**	-0.575	-2.333***	-1.580*	-1.845**
	(0.281)	(0.595)	(0.603)	(0.505)	(0.406)	(0.836)	(0.863)	(0.733)
Middling $\mathbf{X}$ Minimum Wage		$3.415^{***}$	$2.127^{**}$	$2.498^{***}$		$5.282^{***}$	$3.787^{***}$	$3.961^{***}$
		(1.021)	(0.984)	(0.778)		(1.398)	(1.411)	(1.141)
Minimum Wage		$-1.257^{***}$	-0.718*	-0.935***		$-1.868^{***}$	$-1.248^{**}$	$-1.418^{***}$
		(0.428)	(0.414)	(0.327)		(0.588)	(0.602)	(0.487)
Percentage male			$0.523^{***}$	$0.415^{**}$			$0.472^{**}$	$0.445^{**}$
			(0.171)	(0.177)			(0.208)	(0.209)
Percentage low-skill			-0.0261	-0.0315			-0.00403	-0.0319
			(0.0642)	(0.0611)			(0.0645)	(0.0620)
Percentage high-skill			$0.374^{***}$	$0.288^{***}$			$0.507^{***}$	$0.329^{***}$
			(0.0965)	(0.0882)			(0.120)	(0.113)
Percentage old				$-1.132^{***}$				$-1.091^{***}$
				(0.209)				(0.266)
Percentage young				-0.256***				$-0.499^{***}$
				(0.0824)				(0.104)
Threshold value	-	0.425	0.386	0.401	-	0.442	0.417	0.466
Area FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
N	909	909	909	909	909	909	909	909
Countries	8	8	8	8	8	8	8	8
Nb of areas	86	86	86	86	86	86	86	86
F-Statistic	33.742	13.597	10.209	9.367	33.742	13.597	10.209	9.367
within - $R^2$	0.506	0.552	0.630	0.669	0.435	0.540	0.648	0.658

Robust standard errors clustered by area are in parentheses. Sample stops in 2007. \*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.

the shape taken by the polarization phenomenon.<sup>3</sup> Using the coefficients in column 4 and 8, we can compute the partial effect of the reduction of the proportion of routine jobs, conditionally on the value of the minimum wage. If we consider the reduction of the proportion of routine occupations over the period 1992-2010, we find that, according to our estimates, in a high-level minimum wage country like France, the participation rate decreases by 2.54 percentage points, while the same shock increased the participation rate by 0.97 percentage point in the United-Kingdom, a low-level minimum wage country. Concerning the employment rate, polarization lead to a decrease of 1.48 percentage points in France, and an increase of 0.409 percentage point in England, if the proportion of routine jobs diminishes by ten percentage points.

	OLS				IV			
Percentage middling	-0.284***	-0.273***	-0.742***	-0.837***	-0.327***	-0.571***	-1.514***	-1.415***
0 0	(0.0280)	(0.0503)	(0.118)	(0.111)	(0.0416)	(0.216)	(0.474)	(0.458)
Middling $\mathbf{X}$ Minimum Wage	· · · ·	. ,	0.593**	0.833***	· /	. ,	2.168***	2.504***
			(0.279)	(0.268)			(0.722)	(0.661)
Minimum Wage			$-0.251^{**}$	-0.330***			-0.877***	$-0.976^{***}$
			(0.119)	(0.113)			(0.319)	(0.294)
Percentage male			$0.343^{***}$	$0.296^{**}$			$0.321^{**}$	0.190
			(0.117)	(0.118)			(0.160)	(0.162)
Percentage high-skill			$-0.413^{***}$	$-0.344^{***}$			$-0.394^{***}$	$-0.274^{***}$
			(0.0543)	(0.0625)			(0.0904)	(0.0970)
Percentage low-skill			$0.0838^{**}$	$0.120^{**}$			$0.163^{***}$	$0.195^{***}$
			(0.0387)	(0.0459)			(0.0424)	(0.0450)
Percentage old				0.0669				-0.219
				(0.133)				(0.172)
Percentage young				$0.228^{***}$				$0.315^{***}$
				(0.0667)				(0.0815)
Area FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	no	yes	yes	yes	no	yes	yes	yes
$\mathbb{R}^2$	0.210	0.300	0.438	0.452	0.289	0.312	0.415	0.421
F-Statistics					30.933	9.44	7.918	10.131
Observations	1223	1223	1197	1197	909	909	909	909
Nb. clust.	86	86	86	86	86	86	86	86

Table 4 – OLS Regressions - Share of low-paying occupations

Robust standard errors clustered by area are in parentheses. Sample stops in 2007.

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.

## 4.3 Alternative specifications

In order to check if the previous results are really linked to the fact that the minimum wage prevents the creation of low-paid jobs and thus reducing the employment rate when the number of middling occupations decreases, we slightly modify the equation 1: instead of focusing on one of our labor market outcome variable, we will now estimate the effect of the reduction of the proportion of middling occupations on

<sup>3.</sup> Those results are not significant in the 2010 sample. This is explained by the fact that we use investment at the industry level, and our definition is not fully consistent over time, due to the change of classification. This creates a very important discontinuity in our instrument which cannot be consistently used over the period as a result.

the proportion of low-paying occupations. As the right-hand side is the same as before, we can also use the same IV method than our previous estimates. Results are displayed in Table 4. OLS regressions are displayed from column 1 to 4, and IV regressions are displayed from column 5 to 8. The mechanism we have previously highlighted seems to be confirmed by OLS results. All coefficients are highly significant, and seem to yield the same result; when the proportion of middling occupations decreases, the proportion of manual occupations increases, but this increase is conditional on the level of the minimum wage, the higher the minimum wage is, the lower the resulting increase in the proportion of manual occupations. When looking at IV results, the effect seems to be stronger than in the OLS case, but both sets of estimates confirm the mechanism we have in mind.

	Employment Rate			Participation Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	
Percentage middling	-0.0236	0.0641	0.0323	-0.00125	0.0293	0.0163	
	(0.0701)	(0.0576)	(0.0450)	(0.0451)	(0.0418)	(0.0368)	
Middling <b>X</b> High Minimum Wage	$0.0874^{*}$	0.0783	$0.0804^{*}$	0.0581	0.0305	0.0489	
	(0.0494)	(0.0531)	(0.0422)	(0.0373)	(0.0328)	(0.0299)	
Middling $\mathbf{X}$ Low Minimum Wage	$-0.365^{***}$	$-0.184^{***}$	$-0.0927^{*}$	-0.260***	$-0.171^{***}$	-0.139***	
	(0.0725)	(0.0592)	(0.0508)	(0.0450)	(0.0385)	(0.0355)	
High Minimum Wage	-0.0433**	-0.0382	$-0.0371^{**}$	-0.0303*	-0.0178	-0.0249*	
	(0.0214)	(0.0233)	(0.0186)	(0.0157)	(0.0136)	(0.0126)	
Low Minimum Wage	$0.148^{***}$	$0.0716^{***}$	0.0338	$0.107^{***}$	$0.0693^{***}$	$0.0568^{***}$	
	(0.0300)	(0.0248)	(0.0214)	(0.0192)	(0.0167)	(0.0156)	
Percentage male		0.222	$0.341^{*}$		$0.514^{***}$	$0.505^{***}$	
		(0.194)	(0.183)		(0.125)	(0.122)	
Percentage high-skill		$0.837^{***}$	$0.516^{***}$		$0.363^{***}$	0.227***	
		(0.108)	(0.0868)		(0.0663)	(0.0531)	
Percentage low-skill		0.0901	-0.0819		-0.00969	-0.0733	
		(0.0678)	(0.0586)		(0.0526)	(0.0498)	
Percentage old		. ,	-1.423***		. ,	-1.143***	
			(0.178)			(0.144)	
Percentage young			-0.841***			-0.320***	
			(0.109)			(0.0731)	
Area FE	yes	yes	yes	yes	yes	yes	
Time FE	yes	yes	yes	yes	yes	yes	
Ν	1197	119 7	1197	1197	1197	1197	
Countries	8	8	8	8	8	8	
Nb of areas	86	86	86	86	86	86	
within - $B^2$	0.634	0.718	0.784	0.662	0.703	0.750	

Table 5 – OLS Regressions - Minimum Wage Dummies

Robust standard errors clustered by area are in parentheses. Sample stops in 2007.

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.

We finally estimate an alternative OLS specification using some high and low minimum wage dummies interacted with our routine variable rather than using an interaction with the level of the minimum wage, as in our previous specification. The conditional impact of the proportion of routine is not necessarily linear in the minimum wage. We have slightly modified equation 1, in order to estimate the impact of the proportion of routine for low and high minimum wage observations. A country has a high-minimum wage level in year t if it belongs to the top-third of the distribution of minimum wage in year t. Similarly, we define low-minimum wage observations in year t if it belongs to the bottom-third of the minimum wage distribution. Results for this specification are reported in Table 5. Area and time fixed-effects are included in all specifications. We can see two things from this table. Looking at column 3, we can see that the marginal impact of the proportion of routine is positive and significant for high minimum wage countries (0.0323 + 0.0804) but negative for low minimum wage countries (0.0323 - 0.0927). This confirms our previous findings of a negative impact of the decrease in the proportion of routine jobs on employment when the minimum wage is high, and a positive impact when the minimum wage is low. Looking at column 6, we can see that for the participation rate, results are slightly different in magnitude relative to our previous estimates. When the minimum wage is high, the the proportion of routine jobs has only a weak positive impact on the participation rate. Coefficients (routine and its interaction) considered separately are not significant but are jointly significant. The positive impact (0.0163 + 0.0489) is however much smaller than the negative impact displayed for low minimum wage (0.0163 - 0.139) which is highly significant. The polarization seems to have a stronger positive impact on the participation rate in low minimum wage countries, than the negative impact on high-level minimum countries (in absolute value). This is highly consistent with the finding of Verdugo and Allègre (2017) who show that the decrease in the proportion of middling occupations which has natively affected job market opportunities for male has lead to an increase labor market participation of women in the household. We show this is likely to translate into a sizeable increase in the overall participation rate in low minimum wage economies.

## 5 Conclusion

Over the past years, a growing literature has focused on the causes of the labor market polarization, but little attention has been paid to the possible impact on the labor market outcomes of this phenomenon. Our hypothesis was that the minimum wage level changed the shape taken by polarization, by preventing the creation of low-paid jobs at the bottom of the skill distribution, impacting as a consequence the participation and employment rates. Using the European Union Labor Force Survey, we have estimated the impact of the reduction of the proportion of routine jobs on labor market outcomes, such as the participation and employment rates. Our estimations seem to indicate that the minimum wage level plays a crucial role in the shape taken by the polarization: economies characterized by high minimum wage saw their employment decrease as the proportion of routine jobs decreases, while it is the opposite in low minimum wage countries. In addition, we have showed that those results are consistent with the mechanism we have in mind, that a high minimum wage can prevent the creation of low-paid jobs. Our estimations indicate that the proportion of manual jobs doesn't increase as a response of the reduction of routine jobs, when the minimum wage is high enough.

Our results suggest that the cost of the minimum wage could be magnified in an environment in which routine jobs are destroyed. Those jobs provided good wage opportunities for low-skilled workers, and employment opportunities for this category of workers has been deteriorated as a result. In this environment, in which many low-skilled workers cannot reallocate in abstract well-paid occupations, the ability of an economy to create manual low-paid jobs is necessary to maintain the employment rate constant, which may not be possible in high minimum wage economies. Given the higher cost of a nationwide minimum wage, alternative policy intervention could be attractive in order to prevent such a pervasive impact on local labor markets affected by a shock. For instance, employment subsidies could be a credible alternative, since it does not modify the relative labor cost between low-skilled and high-skilled workers. Another alternative for those countries could 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, in order to make labor market institutions more flexible to heterogeneous technological shocks.

## Références

- Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies : Implications for employment and earnings. Hanbook of Labor Economics.
- Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., Price, B., 2014. Return of the solow paradox? IT, productivity, and employment in US manufacturing. American Economic Review 104 (5), 394–399.
- Acemoglu, D., Restrepo, P., 2017a. Low-skill and high-skill automation. Journal of Human Capital.
- Acemoglu, D., Restrepo, P., 2017b. The race between machine and man : Implications of technology for growth, factor shares and employment. American Economic Review.
- 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.

- Autor, D., Dorn, D., 2009. This job is "getting old" : Measuring changes in job opportunities using occupational age structure. American Economic Review 99 (2), 45–51.
- Autor, D. H., Dorn, D., Hanson, G. H., 2013. The china syndrome : Local labor market effects of import competition in the united states. American Economic Review 103 (6), 2121–2168.
- Autor, D. H., Katz, L. F., Kearney, M. S., 2006. The polarization of the u.s. labor market. American Economic Review 96 (2), 189–194.
- Autor, D. H., Levy, F., Murnane, R. J., 2003. The skill content of recent technological change : An empirical exploration. The Quarterly Journal of Economics 118 (4), 1279–1333.
- 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., 2017. Where have the middle-wage workers gone? a study of polarization using panel data. Journal of Labor Economics 34 (1), 63–105.
- Goos, M., Manning, A., 2007. Lousy and lovely jobs : The rising polarization of work in britain. Review of Economics and Statistics 89 (1), 118–133.
- Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization : Routine-biased technological change and offshoring. American Economic Review 104 (8), 2509–2526.
- Jaimovich, N., Siu, H., 2012. The trend is the cycle : Job polarization and jobless recoveries.
- Karabarbounis, L., Neiman, B., 2013. The global decline of the labor share. Quaterly Journal of Economics.
- Lordan, G., Neumark, D., 2017. People versus machines : The impact of minimum wages on automatable jobs. Tech. rep.
- Menes, J. R., Oesch, D., 2010. Upgrading or polarization? occupational change in britain, germany, spain and switzerland, 1990-2008. SSRN Electronic Journal.

- 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.
- Salvatori, A., 2015. The anatomy of job polarisation in the uk.
- Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands : Looking outside the wage structure. Journal of Labor Economics 24 (2), 235–270.
- Verdugo, G., Allègre, G., 2017. Labour force participation and job polarization : Evidence from europe during the great recession. OFCE Working Paper.
- Woolridge, J. M., 2000. Econometric analysis of cross section and panel data.

## A For online publication

In this online appendix, we provide some further results, more details on the methodology, and many robustness tests. Table A1 and Table A2 present the results of the estimation of equation 1, on a sample that stops in 2010. Table A3 displays the first-stage regression of our IV estimates in Table 3.

### 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 Additional Results

	Employment Rate								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
Percentage middling	-0.602***	-0.150**	-1.507***	-1.327***	-1.313***	-0.628***	-0.363**		
	(0.0472)	(0.0574)	(0.197)	(0.179)	(0.178)	(0.155)	(0.145)		
Middling ${\bf X}$ Minimum Wage			2.218***	2.969***	2.925***	1.661***	1.006***		
			(0.428)	(0.435)	(0.431)	(0.360)	(0.335)		
Minimum Wage			-0.929***	-0.998***	-0.970***	-0.402**	-0.229		
			(0.184)	(0.177)	(0.174)	(0.154)	(0.148)		
Percentage male					0.234	0.331*	0.355**		
					(0.230)	(0.173)	(0.177)		
Percentage high-skill						0.592***	0.496***		
						(0.0813)	(0.0860)		
Percentage low skill						-0.0912	-0.101*		
						(0.0560)	(0.0609)		
Percentage old							-0.909***		
							(0.184)		
Percentage young							-0.396***		
							(0.0631)		
Threshold value	-	-	0.679	0.447	0.449	0.378	0.361		
Area FE	yes	yes	yes	yes	yes	yes	yes		
Time FE	no	yes	no	yes	yes	yes	yes		
Ν	1481	1481	1481	1481	1481	1455	1455		
Countries	8	8	8	8	8	8	8		
Nb of areas	86	86	86	86	86	86	86		
within - $R^2$	0.367	0.595	0.402	0.673	0.674	0.736	0.760		

## Table A1 – OLS Regressions

Robust standard errors clustered by area are in parentheses. Sample stops in 2010.

\*\*\* / \*\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.

Table A2 – OLS Regressions

	Participation Rate								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
Percentage middling	-0.556***	-0.114**	-1.414***	-1.147***	-1.118***	-0.745***	-0.519***		
	(0.0375)	(0.0442)	(0.139)	(0.140)	(0.135)	(0.127)	(0.118)		
Middling ${\bf X}$ Minimum Wage			2.111***	2.588***	2.496***	1.824***	$1.265^{***}$		
			(0.302)	(0.339)	(0.325)	(0.297)	(0.269)		
Minimum Wage			-0.917***	-0.992***	-0.932***	-0.603***	-0.471***		
			(0.126)	(0.139)	(0.131)	(0.122)	(0.114)		
Percentage male					0.495***	0.524***	0.506***		
					(0.158)	(0.126)	(0.122)		
Percentage high-skill						0.262***	0.179***		
						(0.0543)	(0.0471)		
Percentage low-skill						-0.110**	-0.112***		
						(0.0446)	(0.0424)		
Percentage old							-1.082***		
							(0.137)		
Percentage young							-0.329***		
							(0.0531)		
Threshold value	-	-	0.670	0.443	0.448	0.408	0.410		
Area FE	yes	yes	yes	yes	yes	yes	yes		
Time FE	no	yes	no	yes	yes	yes	yes		
Ν	1481	1481	1481	1481	1481	1455	1455		
Countries	8	8	8	8	8	8	8		
Nb of areas	86	86	86	86	86	86	86		
within - $R^2$	0.469	0.650	0.517	0.721	0.727	0.755	0.795		

Robust standard errors clustered by area are in parentheses. Sample stops in 2010.

\*\*\* / \*<br/>\* / \* represent significance at the 0.01 / 0.05 / 0.10 levels, respectively.

## A.3 Instrumental Variables - First-Stage

Table A3 – IV Regressions - First Stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	MiddlingOcc	MiddlingOcc	middlXMinWage	MiddlingOcc	middlXMinWage	MiddlingOcc	middlXMinWage
IV_PIT	$0.00871^{***}$	$0.00369^{*}$	-0.00124	0.00148	-0.00212**	0.00162	-0.00211**
	(0.00150)	(0.00213)	(0.000873)	(0.00228)	(0.00101)	(0.00224)	(0.000985)
IV_PITXminwage		$0.00840^{***}$	$0.00872^{***}$	0.0120***	$0.0103^{***}$	$0.0113^{***}$	0.0100***
		(0.00302)	(0.00125)	(0.00316)	(0.00138)	(0.00323)	(0.00144)
MinWage		-0.143***	0.299***	-0.190***	0.277***	-0.182***	0.277***
		(0.0485)	(0.0244)	(0.0543)	(0.0269)	(0.0518)	(0.0249)
Male prop				0.356***	0.150***	0.369***	0.151***
				(0.135)	(0.0582)	(0.132)	(0.0574)
LS prop				0.132**	0.0675***	0.123**	0.0636***
				(0.0513)	(0.0225)	(0.0542)	(0.0238)
HS prop				-0.191***	-0.0587*	-0.197***	-0.0645**
				(0.0654)	(0.0321)	(0.0610)	(0.0285)
Old proportion				· · · ·	· /	0.0980	-0.00636
* *						(0.180)	(0.103)
Young proportion						-0.0254	-0.0221
						(0.0949)	(0.0474)
Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbb{R}^2$							
Observations	909	909	909	909	909	909	909
Nb. clust.	86	86	86	86	86	86	86