Gender job polarisation

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Abstract

Job polarisation refers to the increase of employment in top and bottom-paid occupations at the expense of middle-paid jobs. Despite that the impact of technology on employment may be quite different for men and women, given the potential segregation of some jobs, the literature has equally treated male and female workers. To explore this possibility, this paper studies gender-specific changes in occupations. Surprisingly, employment polarisation is found for women, but not for men. The Routine Bias Technological Change (RBTC) hypothesis is able to explain the decrease of employment in the middle part of the wage distribution, being this effect higher for male than for female workers. However, the RBTC does not account for the changes observed at the tails of the distribution for women. Structural change based on structural transformation or marketization does. When better opportunities for women exist in the market, education becomes more attractive which increases the number of females willing to study. This enhances the participation of women in the labour market and, consequently, reduces their work at home. In addition, consumption spillovers that make women in top-paid occupations to consume more services exist.

JEL Classification: E20, E21, J16.

Keywords: Job polarization, Structural Change, Routine Biased Technical Change, Gender, Home Production

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1 Introduction

Job polarisation is a well-documented phenomenon found in the US and Europe since the 1980s.[2] After ranking employment in occupations by skill requirements, it is generally observed that the bottom and the top of the wage distribution increase more strongly than the medium ranked occupations. This U-shaped pattern of employment changes is known as "*job polarization*", following the terminology proposed by Goos and Manning (2007). The leading explanation behind this phenomenon is the Routine Biased Technical Change (RTBC) hypothesis introduced by Autor et al. (2003, ALM henceforth), which reformulated the previous Skill Biased Technological Change (SBTC) hypothesis. Due to a fall in computer prices, the information and computer technologies (ICT) have two effects on the labour market: first, they substitute human labour in routine tasks (predominantly located in the middle of the wage distribution). Second, technology complements abstract tasks (placed at the upper tail of the wage distribution). Manual tasks, used in occupations at the lower tail of the wage distribution, are instead not affected by the technological change. However, middle workers have a comparative advantage in manual occupations rather than in abstract occupations. As a result, a greater relocation of workers at the bottom of the wage distribution is expected (Autor and Dorn, 2013).

Over the same period, the structure of employment has changed dramatically. On the supply side, one of the most notable changes is the rise in female participation. In the US, the woman employment rate has more than double going from 35 percent in 1945 to 77 percent at the end of the 20th century. At the European level, it grew from 46.3 percent in 1990 to 50.93 percent in 2015. During the same period, Spain started in a lower level (33.84 percent) and ended in an upper level than the European Union (52.32 percent).[3] To explain these trends, recent papers have highlighted the role of human capital investment, technological progress in the household, medical progress, and declining fertility.[4] Also, a recent line of research have emphasized the secular expansion of the service economy and its role in raising the relative demand for female

[2] See for example Autor (2019), Autor and Dorn (2013), and Autor et al. (2006) for the US; Montresor (2019) and Goos and Manning (2007) for the UK; Fonseca et al. (2018) for Portugal; Sebastian (2018) and Anghel et al. (2014) for Spain; Spitz-Oener (2006) for Germany; Goos et al. (2014) for the set of European countries.

[3] See Appendix for the evolution of the female rate participation in the US, European Union, and Spain from 1990 to 2015.

[4] See Goldin (2006) for a comprehensive overview of historical trends and their causes. See, among others, Goldin and Katz (2002) and Albanesi and Olivetti (2016) for the role of medical progress; Greenwood et al. (2005) for the role of technological progress in the household; Galor and Weil (1996) for the role of declining fertility.

work (Ngai and Petrongolo, 2017). The proposal consists in two simultaneous mechanisms. First, service occupations (located at the bottom of the wage distribution) are related to a more intensive use of communication and interpersonal skills, being those occupations not easy to be automated. For service occupations, women have a comparative advantage because the production of services is more 'brain' (not 'brawn') intensive (Goldin, 2006; Galor and Weil, 1996) and, therefore, a bigger increase in female occupation is expected. The second mechanism is related to women's work in the household. If the expansion of the service sector makes it cheaper to outsource these activities, a greater reallocation of women's work from the household to the market is expected. Consequently, structural transformation explains the fall in male market work at the central part of the wage distribution, while marketization boosts female market work at the bottom and the upper part of the employment distribution.

Given these two strands of the literature, one fundamental question is to know whether job polarisation is due to technology change or to structural change (structural transformation or marketization). To answer this question properly, the gender issue, largely ignored by the literature, must be confronted. The literature has typically assumed that male and female workers are equally affected by the RBTC process, but this may not be the case. For example, if there is occupational segregation by gender, technology may have a different impact on men and women. This possibility will allow to contrast the role of technology (RBTC) and structural change (supply and demand) in explaining job polarization. Which model explains better the empirical findings?

To answer this question, we disentangle the causal effect of technological exposure on gender building on the spatial approach of Autor and Dorn (2013) for Spain (2000-2015). The empirical strategy exploits geographical variation across Spanish provinces in their specialisation in the routine-intensive employment share to identify the effects of technology and structural changes. For the latter, apart from the rise in female participation (demand side), I find that two main factors have changed in the Spanish labour market (supply side): the number of migrants and graduates. For migrants, they represented only 1.14 percent of total employment in 2000, whereas fifteen years later, the proportion climbed up to almost 13 percent. The increase of graduates has shifted from 24 percent to 37 percent of total employment between 2000 and 2015.

Employment data is derived from the Spanish Labour Force Survey (ES-LFS), information on tasks from O*Net, and local labour markets are proxied by the Spanish provinces. To this end, my framework addresses two problems: the first one concerns the potential endogeneity. Therefore, I construct an instrumental variable based on the activity sector (industrial information) across Spanish provinces in the year 1977, almost two decades before the boom of computerisation in the workplace. The instrument is strong, and the findings obtained do not significantly differ from those of the baseline analysis. The second relates to the use of provinces as measures of local labour markets which is validated by the unresponsive mobility of the working-age population to technological exposure observed across these areas.

For middle-paid occupations, the empirical findings are in line with the predictions of Author's and Dorn model (2013). In Spain, provinces with initially higher degree of routine task exhibit larger declines in middle-paid occupations but there is not a subsequent displacement to bottom-paid occupations. Moreover, this effect is larger for male workers than female workers. Hence, middle occupations are decreasing due to technology, although this has not caused a downward shift of middle workers.

For bottom-paid occupations, however, estimates show that a greater relative supply of college-educated individuals favours female manual occupations among noncollege workers, and a greater concentration of immigrants. Moreover, female bottom occupations grow faster in provinces with larger female participation rate. These results are better explained by the process of structural transformation proposed in Ngai and Petrongolo (2017): sectors that typically favour female occupations (services) increase their share in the economy with respect to those of male occupations.

Regarding top-paid occupations, no effect of technology-skill complementarity is found. In contrast, the initial share of human capital and immigration concentration are positively associated with employment growth in abstract occupations. The relative demand for graduates has increased which has helped to accommodate the faster change in relative supply, being this change especially important for women.

Overall, I find that employment polarization happens only for women. While female employment shares increase at the bottom and upper parts of the wage distribution, male employment shares only increase at the upper part. In addition, the RBTC is able to explain the decrease in the middle part of the wage distribution, being this effect higher for male workers than female workers. However, the RBTC does not account for the facts found at the tails of the distribution, while the structural change (structural transformation or marketization) hypothesis does. The positive sign of education for women at the bottom, middle, and upper part of the employment distribution suggest that when there are better opportunities for women in the market, education becomes more attractive which increases the number of females willing to study. This enhances the participation of women in the labour market and, consequently, reduces their work at home. This fact is reinforced by the positive sign of consumption spillovers (proxied by changes in average annual hours worked by graduates). It seems that high-skilled female workers substitute market for home production.

The paper is organised as follow: In Section 2, I describe the data, the definition of local labour markets, the routine task intensity index, and the routine intensity measure. Section 3 presents initial evidence on job polarisation by occupation, demographic groups, and by provinces. Section 4 discusses the empirical specification and the identification strategy. Section 5 reports the main results from the empirical analysis. In Section 6, I perform a sensitivity analysis and finally, in Section 7, I summarize the main findings.

2 Data sources and measurement

This section describes the data sets and develops the construction of the Routine Task Index (RTI) and the Routine Employment Share (RSH).

2.1 Data sources

The main data set is the Spanish Labour Force Survey (*Encuesta de Población Activa* − EPA− in Spanish) for the years 2000 and 2015, which provides a representative sample of the Spanish workforce. The sample size is augmented by pooling together 2000-2001, 2007-2008 and 2014-2015 waves. The EPA is a continuous household survey of the employment conditions of the Spanish population. Conducted by the Statistical National Institute (Instituto Nacional de Estadística, INE), it has been run on a quarterly basis since 1975. Each quarter covers 65,000 individuals, about 0.2 per cent of the Spanish population. To avoid seasonality problems, I retain the second quarter of each relevant year. Sampling weights adjusted for responses are used through the analysis.

The analysis is restricted to employees in paid work (i.e., employees and self-employed) aged between 16 and 65. Occupations are classified using the Spanish Classification Code (CNO-94 and CNO-2011), and are accorded to the International Standard Classification of

Occupations (ISCO-88) at the two-digit level. I use the official Eurostat crosswalk to create concordance across the two codes. Occupations that represent a small share of the total working population are excluded from the analysis. These are "armed forces" (ISCO-88 01), "legislators and senior officials" (ISCO-88 11), "teaching professionals" and "teaching associate professionals" (ISCO-88 23 and ISCO-88 33), and "agricultural occupations" (ISCO-88 61 and ISCO-88 92). Employment is measured by the thousands of workers employed (given by the EPA survey weights).[5]

The EPA does not include information on wages. To overcome this problem, the Structure of Earnings Survey (in Spanish, *Encuesta de Estructura Salarial*, ESS) is integrated to the main source. The ESS provides information on employee's wages and occupations. Throughout the analysis, I use the 2002 survey results. Average hourly wages are computed in two steps: first, annual wages are transformed into weekly wages, and then, I divide them by the weekly working hours (including overtime).

The study needs time-consistent definitions of local labour areas. Autor and Dorn (2013) interpret as local labour markets the US commuting zones. The closest local labour market area available in the EPA is the Spanish province. Consequently, the spatial units of analysis will be 50 provinces. Ceuta and Melilla are excluded from the analysis for being unrepresentative.

The measurement of the impact of technology on local labour markets will be correct if the mobility of workers between provinces caused by technological change is low or null. Otherwise, internal migration of workers would disperse the effect of technology exposure across the Spanish economy which could undermine the effect. For Spain, the literature is clear. Using Labour Force Survey data, Bentolila and Dolado (1990) show little evidence of any significant trend in regional mobility during the period 1960 to 1990. More recently, Gonzalez and Ortega (2010) find a very week correlation between Spanish-born mobility and immigrant inflows at the province level between 2001 and 2006. Hence, the assumption that labour markets are provincial in scope is reasonable.

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[5]Employment can also be measured by the thousands of weekly hours worked (EPA survey weights multiplied by usual weekly hours), although the results are invariant.

2.1.1 The Routine Task Intensity (RTI) and the Routine Employment Share (RSH)

An important input into the analysis is to measure the effect that technological exposure has on local labour markets. I need information on routine task activities within provinces, being constructed with the Routine Task Intensity (RTI) index proposed by Autor and Dorn (2013). This index combines the abstract, routine, and manual task content of occupations. It measures the importance of routine tasks by removing measures of abstract and manual tasks. The index is calculated as follows:

$$RTI_k = \ln T^R_{k,t-1} - \ln T^A_{k,t-1} - \ln T^M_{k,t-1} = \ln \frac{T^R_{k,t-1}}{T^A_{k,t-1}\, T^M_{k,t-1}} \qquad (1)$$

where $T^R_{k,t-1}$, $T^A_{k,t-1}$, and $T^M_{k,t-1}$ are the routine, abstract, and manual task abilities for each occupation k in the sample base year.

In this paper, the RTI index is derived from O*Net database. This source is provided by the US Department of Labor where analysts assign scores to each task according to standardised guidelines. I therefore work under the assumption that the US task composition is the same as in Spain.[6]

Applying O*Net data to Spain requires two steps. First, O*Net is coded using ONET-SOC, i.e., I mapped O*Net task items to the corresponding occupations in SOC (Standard Occupation Classification) using a crosswalk made available by the O*Net project. From this exercise, I get 812 occupations based on SOC2000. Second, I convert SOC2000 codes into International Standard Classification of Occupations (ISCO-88) using the official ILO crosswalk. In other words, I aggregate the 812 (SOC occupations) into 67 ISCO-88 codes (three-digit level).

To construct the job content measures, I use the task measures proposed in the literature (a detailed list of descriptors by task is in Appendix B). After mapped into ISCO-88 classification, the RTI is normalized to have zero mean and unit standard deviation across occupations. Table 1 presents a summary of the main components. The table computes the average task value across all occupations and then for each occupational group indicates if the value is larger than the average (+) or smaller (-). Matching the task measures of occupations (Table 1) with the

[6] Although the assumption seems strong, Sebastian and Ulceluse (2019) show that US occupation-based (O*Net) and European skills survey-based (PIAAC and EWCS) lead to similar outcomes in Germany. Moreover, Biagi and Sebastian (2020) compare tasks' content using four databases (O*Net, PDII, EWCS, and PIAAC) and show similar results for 15 European countries. They argue that it is methodologically valid to use US data to construct occupational measures in European countries.

statistics on changes in employment shares (Table 3, in the next section), a clear picture of the task content of the occupations is observed. Service and elementary occupation are the low-paying occupations with a high index of manual tasks. Middle-paying occupations with the highest RTI index are productive and administrative occupations. And professional and managerial, high-paying occupations, have a high index of abstract tasks. Therefore, it helps to further classify occupations as manual, routine and abstract. First, occupations at the bottom of the wage distribution are defined as manual occupations. Second, middle-paid occupations are classified as routine. Finally, abstract occupation are occupations at the top.

Table 1. Task measures by major groups in 2000

Occupation	Code	RTI Index	Abstract Index	Routine Index	Manual Index
Legislators, senior officials and managers	1	-	+	-	-
Professionals	2	-	+	-	-
Technicians and associate professionals	3	-	+	-	-
Clerks	4	+	-	+	-
Service workers	5	-	-	-	+
Craft and related trades workers	7	+	-	+	+
Plant and machine operators and assemblers	8	+	-	+	+
Elementary occupations	9	+	-	+	+

Sources: Author's analysis from the EPA (2000) and O*Net.

To measure the Routine Employment Share (RSH) by province, two more steps are necessary. First, using the RTI, I classify as routine-intensity occupations those in the highest employment-weighted third share of RTI in 2000. Table 1 reports the 21 two-digit occupations, ranked in descending order by the RTI values (column 1). It also presents the employment distribution in 2000 (column 2) and the cumulative distribution (column 3). Lastly, the occupations that are considered routine-intensive occupations are highlighted (column 4): "office clerks" (ISCO 41), "precision, handicraft, printing and related trades workers" (ISCO 73), "customer service clerks" (ISCO 42), "customer service clerks" (ISCO 74), "machine operators and assemblers"(ISCO 82), and "metal, machinery, and related trades workers" (ISCO 72).

Table 2. RTI classification using the 2000 employment distribution

Occupation	Code	RTI (1)	Level (2)	Cumulative (3)	Top 33% (4)
Machine operators and assemblers	82	1.79	5.16	5.16	X
Other craft and related trades workers	74	1.41	3.06	8.22	X
Office clerks	41	1.33	9.23	17.45	X
Customer service clerks	42	1.28	1.98	19.43	X
Metal, machinery and related trades workers	72	1.05	5.92	25.35	X
Precision, handicraft, printing and trades workers	73	0.87	0.79	26.14	X
Sales and services elementary occupations	91	0.79	8.48	34.62	
Models, salespersons and demonstrators	52	0.03	5.78	40.4	
Personal and protective service workers	51	-0.01	10.47	50.87	
Labourers in mining, const., manu.,. and transport	93	-0.02	5.96	56.83	
Other associate professionals	34	-0.06	8.05	64.88	
PMES professionals	31	-0.18	2.16	67.04	
Life science and health associate professionals	32	-0.50	0.68	67.72	
Stationary plant and related operators	81	-0.51	0.98	68.7	
Drivers and mobile plant operators	83	-0.55	6.01	74.71	
Extraction and building trade workers	71	-0.63	9.58	84.29	
PMES professionals	21	-0.94	2.28	86.57	
Other professionals	24	-1.08	3.18	89.75	
General Managers	13	-1.16	5.11	94.86	
Life science and health professionals	22	-1.42	2.81	97.67	
Corporate managers	12	-1.51	2.33	100	

Notes: The table contains the full list of two-digit ISCO-88 occupations in the sample, ranked from high to low values of the RTI index. The levels and cumulative employment shares of each occupation are shown for the year 2000.
Sources: Author's analysis from the EPA (2000) and O*Net.

Second, I compute for each province j, a routine employment share (RSH), calculated as:

$$RSH_{pt} = \left(\sum_{k=1}^{k} L_{pkt} * 1\ [RTI_k > RTI^{66}]\right)\left(\sum_{k=1}^{k} L_{pkt}\right)^{(-1)} \qquad (2)$$

where L_{pkt} is employment in occupation k and province p at time t, and 1[.] is an indicator function taking value of one if it is routine intensity. Equation (2) represents the routine employment share divided by employment share.

3 Initial evidence

3. 1 Occupational groups

The analysis starts by documenting the change between 2000 and 2015 in employment share for all workers (Figure 1) and by gender (Figure 2).[7] Occupations are grouped into employment-weighted quintiles of the 2002 wage distribution. In line with previous results (Anghel et al., 2014; and Sebastian, 2018), Figure 1 shows a clear U-shaped curve of job polarization: there is an increasing employment share at the bottom and top of the wage

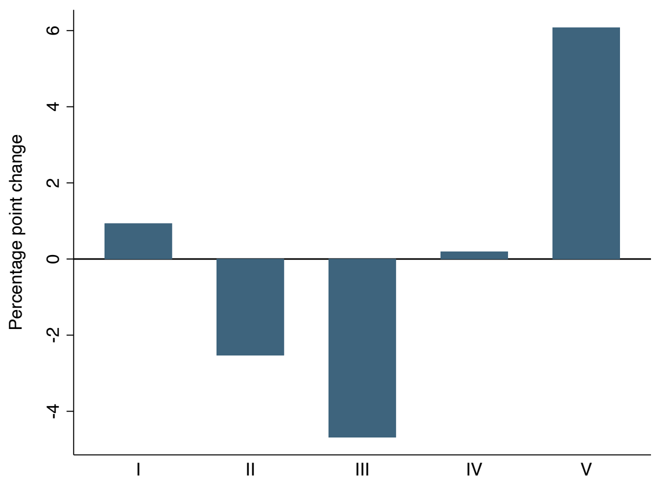
[7] The three steps behind the Figures: first, I compute the employment share for each occupation and their changes over time. Then, occupations are ranked according to their 2002 mean hourly wage. Finally, occupations are aggregated into five equally sized groups showing the change over time.

distribution (low- and high-skilled jobs), and a decline in the employment share at the middle of the wage distribution (middle-skilled jobs). Moreover, the graph is skewed to the right: the increase at the fifth quintile is much higher than at the bottom. More specifically, middle income earners (from the second to the fourth quintile) loose ground in the labour market, with a loss of -7.00 per centile points (pcp, henceforth) of employment share. This employment share is redistributed to either end of the spectrum: 6.07pcp goes to top income earners, and 0.93pcp goes to bottom income earners.

One surprising fact appears in Figure 2: job polarisation is driven by women. Female employment shares largely increase at the bottom and upper parts of the wage distribution, generating the previous U-shaped curve (4.73pcp and 5.35pcp, respectively). On the contrary, male employment shares decrease over the first four quintiles (showing a higher decline in the second and third quintile), and just increase at the top (-10.74pcp and 1.69pcp, respectively).

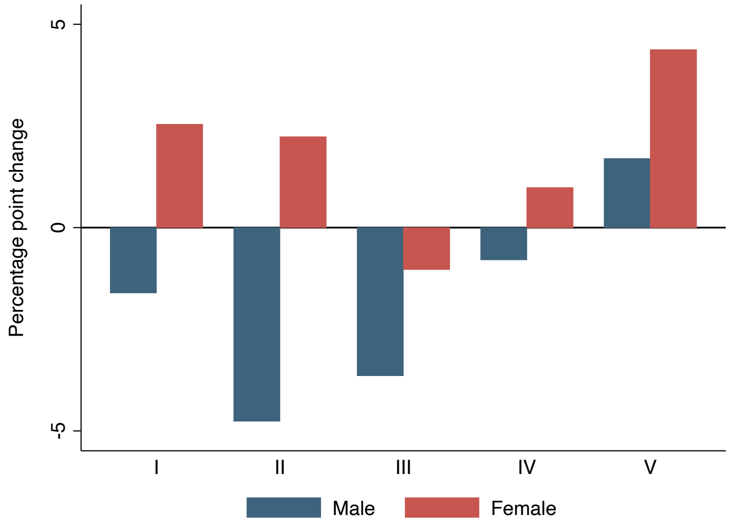
While Figure 1 is a well-known established fact, less-known is what happens when the distribution is divided by gender. Surprisingly, the U-shaped appears when gender is aggregated. The question that must be solved then is if technology plays any role in explaining these empirical facts. In particular, does the RBTC hypothesis explain the rise in relative employment shares for female workers? Before solving this puzzle, I present some more evidence of this issue.

Figure 1: Evolution of employment changes between 2000 and 2015



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 2002.
Sources: Author's analysis from the EPA (2000, 2015) and ESS (2002).

Figure 2: Evolution of employment changes between 2000 and 2015 by gender



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 2002.
Sources: Author's analysis from the EPA (2000, 2015) and ESS (2002).

Table 3 presents the major occupational groups ranked by their initial hourly mean wage (column 1), the level (columns 2 to 5) and percentage point change in their employment for male and female workers (columns 6 and 7) during the period 2000-2015. Matching the task content of occupations (Table 1) with the statistics on changes in employment shares (Table 3), a clear picture of the task content of the occupations is observed. Service and elementary occupations being the low-paid occupations possess a high index in manual tasks. Middle-paid occupations, productive and administrative occupations, present the highest RTI index. Professional and managerial which are high-paid occupations have a high index in abstract tasks. Following these findings, occupations can be classified as manual, routine and abstract. Occupations at the bottom of the wage distribution are defined as manual occupations (93, 91, 74, 51, and 52). Middle-paid occupations are classified as routine (71, 42, 83, 82, 73, 41, 72, 32, and 81). Finally, abstract occupation are the occupations at the top (34, 31, 13, 22, 24, 21, 12).

Table 3. Levels and changes in employment share for male and female workers, 2000-2015

Occupation	Code	Log wage (1)	Level 2000 Male (2)	2000 Female (3)	2015 Male (4)	2015 Female (5)	Delta Male (6)	Female (7)
Bottom occupations – Manual occupations							*-1.16*	*5.96*
Labourers in mining, const., manufacturing and transport	93	1.58	4.84	2.09	1.12	0.80	-2.75	-0.32
Sales and services elementary occupations	91	1.69	2.33	1.62	6.15	7.47	-0.70	1.32
Other craft and related trades workers*	74	1.76	2.03	1.18	1.03	0.63	-0.85	-0.39
Personal and protective service workers	51	1.82	4.88	6.61	5.59	8.60	1.73	3.01
Models, salespersons and demonstrators	52	1.85	1.96	3.37	3.82	6.16	1.41	2.34
Middle occupations – Routine occupations							*-10.10*	*-1.10*
Extraction and building trade workers	71	1.89	9.40	4.25	0.19	0.07	-5.14	-0.12
Customer service clerks*	42	1.92	0.63	1.25	1.36	3.43	0.62	2.08
Drivers and mobile plant operators	83	2.00	5.90	5.01	0.10	0.20	-0.89	0.10
Machine operators and assemblers*	82	2.01	3.48	0.49	1.68	0.16	-2.99	-1.52
Precision, handicraft, printing and trades workers*	73	2.07	0.63	0.39	0.16	0.11	-0.24	-0.05
Office clerks*	41	2.14	3.78	2.43	5.45	3.25	-1.36	-2.19
Metal, machinery and related trades workers*	72	2.16	5.81	5.20	0.10	0.09	-0.62	-0.02
Life science and health associate professionals	32	2.17	0.29	0.22	0.39	0.40	-0.07	0.00
Stationary plant and related operators	81	2.29	0.91	1.50	0.06	0.68	0.59	0.62
Top occupations – Abstract occupations							*2.07*	*4.33*
Other associate professionals	34	2.52	4.49	4.80	3.56	3.38	0.31	-0.18
PMES professionals	31	2.57	1.73	1.87	0.43	0.41	0.14	-0.02
General Managers	13	2.64	1.96	1.86	3.16	4.17	-0.10	1.02
Life science and health professionals	22	2.77	1.17	1.18	1.64	2.60	0.01	0.96
Other professionals	24	2.80	1.74	3.12	1.44	2.88	1.38	1.44
PMES associate professionals	21	2.86	1.94	2.17	0.34	0.82	0.23	0.48
Corporate managers	12	3.29	1.97	2.08	0.36	0.99	0.11	0.63

Notes: Occupations are ordered by the mean hourly wage in 2000. Occupations with an asterisk are those defined as routine-intensity.
Sources: Author's analysis from the EPA (2000 and 2015) and O*Net.

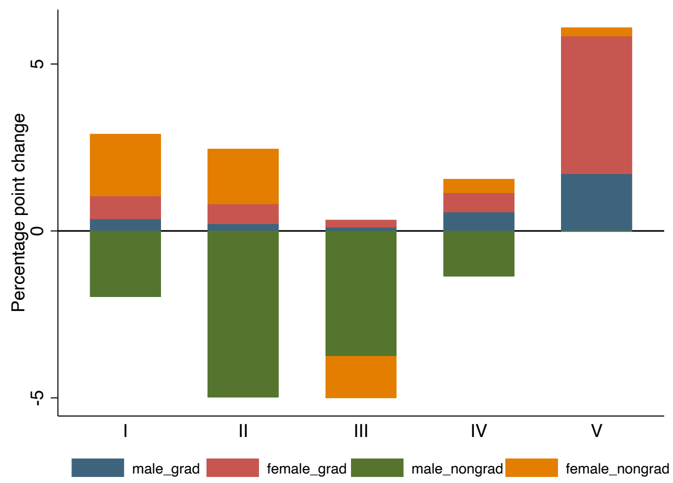
In line with Figure 2, the changes in employment shares are different for male and female workers. While for female workers there is an increase in employments at the bottom and the top parts of the wage distribution (5.96pcp and 4.33pcp, respectively), for male workers the increase is just at the top part (2.07pcp). Concerning the group of bottom-paid occupations, elementary occupations (91, and 93) has a mix effect: while male workers are experiencing a negative employment growth (-3.45pcp), female workers show a positive increase (+1.00pcp). Moreover, service workers present a significant positive employment growth, being much higher for female workers (+5.35pcp and +3.14pcp). Within the middle-paid occupations, those losing more employment share between 2000 and 2015 depend on the sex we look at: "extraction and building trade workers" for male workers (-5.14pcp), and "office clerks" for female workers (-2.19pcp). Finally, among top-paid occupations, those gaining more employment share are "other professionals" (+1.38pcp and +1.44pcp for male and female, respectively), and "life science and health professionals" just for female workers (+0.96pcp).

3. 2 Demographic groups

The analysis continues by examining demographic changes: education and migration. Figure 3 shows the relative changes in employment between 2000 and 2015 by gender and education, where education refers to graduate workers.[8] On the one hand, male non-graduate workers are losing employment at the bottom and middle part of employment distribution. On the other hand, female workers are gaining employment along the whole distribution. In detail, non-graduate and gradate female workers have gained at the bottom and at the top of the wage distribution, respectively. I further use the number of years of education instead of the categorical variable consisting in the highest level of educational attainment reached by workers. Results are robust to this alternative specification.

To understand how migration status relates to the evolution of employment changes, in Figure 4 the employment distribution is broken by gender and nationality. Migrants are defined as foreign-born individuals. Looking at migrants, we observe an increase of foreign female workers in bottom-paid occupations and top-paid occupations. Different from expectation, the growth of jobs in the first quintiles are taken by the national workforce. This figure explains how, in a very short period of time, there was a radical change in the labour landscape in certain jobs such as hotels, catering or household services.

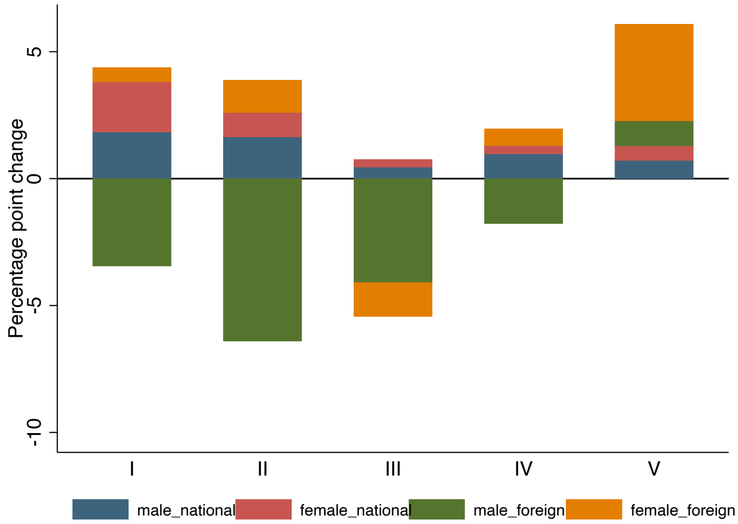
Figure 3: Evolution of employment changes between 2000 and 2015 by gender and education



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 2002.
Sources: Author's analysis from the EPA (2000, 2015) and ESS (2002).

[8] ISCED classification is used: ISCED 0-2 (i.e., primary and lower secondary education), ISCED 3-4 (i.e., upper secondary and post-secondary non-tertiary education), and ISCED 5-7 (i.e., tertiary education).

Figure 4: Evolution of employment changes between 2000 and 2015 by gender and nationality



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 2002.
Sources: Author's analysis from the EPA (2000, 2015) and ESS (2002).

3. 3 Local labour markets

Table 4 presents some descriptive statistics of the sample for the routine employment share (RSH), the relative graduate share (GradSH), and the relative migrant share (ImmSh) in local labour markets for the years 2000, 2007, and 2015. GradSh and ImmSh are calculated as ratios to non-graduate population.

As expected, the employment share in routine-intensive occupations decreases by 3pcp between 2000 and 2015. On the contrary, the relative share of graduates and immigrants, and the employment share of partial jobs increase over time. In the case of the relative share of graduates the growth was of 12pcp. Likewise, MigSh registers a huge acceleration before the crisis (+13pcp) but decreases a bit after it (+2pcp).

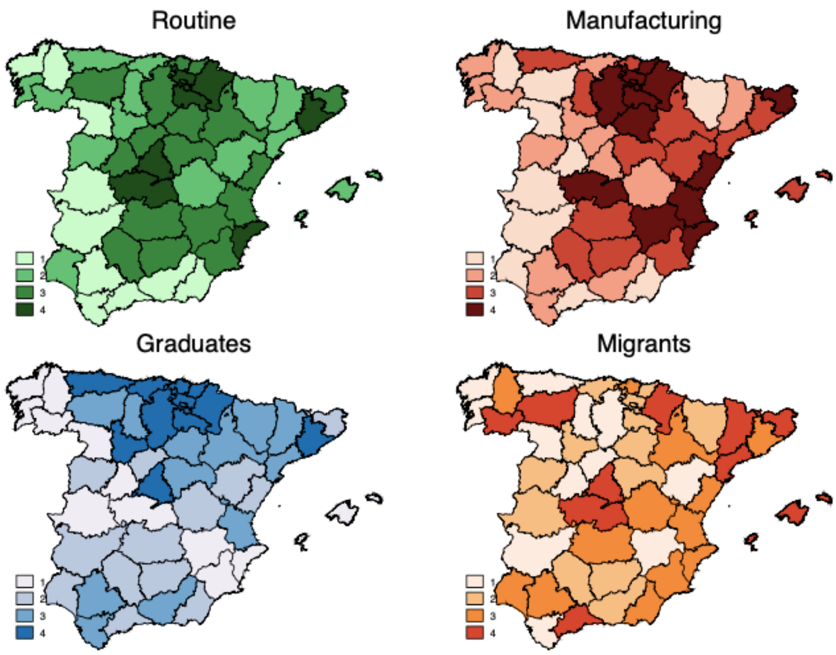
Table 4. Summary statistics of relevant variables, 2000-2015

	2000			2007			2015		
	Mean	S.D	Iqr	Mean	S.D	Iqr	Mean	S.D	Iqr
RSH	0.206	0.055	0.074	0.184	0.032	0.040	0.173	0.027	0.032
GradSH	0.245	0.061	0.086	0.294	0.077	0.085	0.372	0.092	0.120
ImmSH	0.011	0.011	0.013	0.147	0.090	0.112	0.126	0.078	0.106
PtimeSH	0.085	0.026	0.038	0.124	0.016	0.025	0.166	0.026	0.028

Notes: This table shows the mean, standard deviation and interquartile range values of relevant variables in the analysis. RSH is the province employment share in routine-intensive; GradSH is the province relative share of graduates as a ratio with respect to the non-graduate population; ImmSH is the province employment share of immigrants as a ratio with respect to the non-graduate population; and PtimeSH is the province employment share in partial time jobs.

To illuminate the above findings, Figure 5 plots the graphical distribution of routine, graduates, immigrants, and worker in the manufacturing sector across Spanish provinces in 2000. Some remarks are in order. First, the highest levels of routine and manufacturing are concentrated in the same provinces, i.e. Navarra, La Rioja, and Basque country. Two exceptions to this rule are Madrid and Barcelona where they are more intense in routine employment than manufacturing specialization. Second, the two provinces with the highest levels of graduate shares are Madrid and Barcelona, provinces that are typically specialised on professionals, scientific and technical activities. Moreover, graduate shares are more concentrated in the north of Spain with high presence in Asturias, Cantabria, Basque Country, Navarra and La Rioja. Migrants working shares are geographically more spread, with higher concentration in the Mediterranean area.

Figure 5: Relevant variables by local labour markets in 2000



Notes: Each label contains the same number of provinces. As there are 50 provinces, groups are uneven: the first group includes 12 provinces, the second group 13 provinces, the third group 13 provinces, and the fourth group 12 provinces.
Sources: Author's analysis from the EPA (2000).

4 Estimation strategy

The AD model predicts that technology replaces labour in routine tasks. This progressive substitution by technology leads to two effects depending on workers' relative comparative advantage: first, an increase in high-skilled occupations who have a comparative advantage in abstract tasks. Second, because technology substitutes routine workers, a greater reallocation of routine workers in manual occupations as its comparative advantage is in low-skilled tasks rather than high-skilled tasks.

Focusing on local labour markets, it is expected that provinces which initially have higher routine employment shares experience two effects: a higher relative employment decline in routine occupations and a larger relative employment increase in non-routine manual (low-skilled workers) and non-routine abstract (high-skilled workers) occupations. I test the routinization hypothesis estimating the following equation model:

$$\Delta Y_{jt} = \alpha + \beta_1 RSH_{jt-1} + X'_{jt-1}\beta_4 + \gamma_s + \epsilon_{jt}, \tag{3}$$

where ΔY_{jt} is the change in local employment shares in routine, non-routine manual, and non-routine abstract occupations between the initial year and the final year of the period 2000-2015. The RSH_{jt-1} is the local employment share of routine occupations in the initial year. Additionally, the vector X'_{jt-1} includes a set of covariates controlling for potential shifts in local supply and demand rather than technology. It includes the initial ratio between graduates and non-graduates workers, and between migrants and non-graduates workers.

4.1 Instrumental variable: endogenous allocation of occupations

The measurement of the effect of technology on local labour markets requires that the variation of the routine occupation share (RSH) is exogenous and not driven by time-varying local unobservable variables. To understand this problem, consider the following version of the previous equation:

$$\Delta Y_{jt} = \alpha + \beta_1 RSH^*_{jt-1} + \beta_2 \gamma_{jt-1} + \epsilon_{jt}, \tag{4}$$

where assuming that $RSH_{jt-1} = RSH^*_{jt-1} + \gamma_{jt-1}$, RSH^*_{jt-1} represents the long-run quasi-fixed component of the industrial structure and γ_{jt-1} stands for time-varying attributes that affect at the same time changes in employment shares (ΔY_{jt}) and locals' routine occupation shares (RSH). As a result, OLS estimates of equation (3) are biased under one of these two cases:

1. If $\beta_2 > \beta_1$ and Var (γ_1)>0 in equation (4), OLS estimates of β_1 in equation (3) will be upward biased.

2. If $\beta_2 < \beta_1$ and Var (γ_1)>0 in equation (4), OLS estimates of β_1 in equation (3) will be downward biased.

To address this endogeneity problem, I construct an instrumental variable for the routine employment share levels in line with Autor and Dorn (2013) using data from the EPA in 1977. It exploits the historical local industry information to remove the long-run quasi-fixed component of the routine occupation share. The instrument is constructed as follows:

$$RSH_j^{IV} = \sum_i E_{i,j,1977} \ * \ R_{i,-j,1977} \quad (5)$$

where $E_{i,j,1977}$ is the employment share in industry i and province j, and $R_{i,-j,1977}$ is the routine occupation employment share in industry i in all the Spanish provinces except the one that includes the province j.

The estimates of the first stage regression are shown in Table 5. The correlation between the industrial and employment mix in 1977 and local changes in routine occupation in 2000 is positive and significant. It seems, therefore, that it is a good instrument for RSH: past industrial information is correlated with the long-run component, but uncorrelated with current economic shocks.

Table 5. Changes in routine occupations, first stage: 2000-2015

	All workers (1)	Male workers (2)	Female workers (3)
OLS			
RSH_j^{IV}	0.683***	0.656***	0.741***
	(0.172)	(0.167)	(0.179)
R^2	0.566	0.551	0.601
N	200	100	100

Notes: All models include an intercept, a region dummies (NUTS-1), and a time period dummy. Standard errors clustered at the regional level. Observations are weighted by the initial share of national population.
Sources: Author's analysis from the EPA (1977, 2000, 2007, 2015) and O*Net.
***Significant at 1 percent level, **Significant at 5 percent level, *Significant at 10 percent level.

5 Results

5.1 Changes in routine employment

I first test whether historically routine intensive provinces have registered larger declines in middling occupations. To do so, equation (3) is estimated by ordinary least squares (OLS) and two stage least squares (2SLS), clustering errors at the regional level. Table 6 presents the changes in routine occupations for the total number of workers (columns 1-4), male workers (columns 5-8), and female workers (columns 9-12). The baseline model is shown with the routine share measure (RSH: columns 1, 5, and 9). I further add two variables to control for the potential shifts in demand and supply: the relative share of graduates (GradSh: columns 2, 6, and 10) and the relative share of immigrants (ImmSh: columns 3, 7, and 11). The whole set of explanatory variables are in the remaining columns (4, 8, 12).

Regarding the baseline model, it is expected a negative effect of technological exposure on routine occupations for both genders. Columns 1, 5, and 9 show that provinces with the highest initial levels of routine employment shares experience a larger decline in routine occupations. For both techniques (OLS and 2SLS) the coefficients are negative and significant, being their magnitude higher for male workers (column 5). The Kleibergen-Paap F-statistics is well above 10 (15.83 for males and 16.09 for females) so the instrument works well for both women and men.[9] Remember that the Iqr for RSH in 2000 is 0.07. The 2SLS estimates in column (1) suggests that a province with a routine employment share at the 75th percentile in 2000 decreased 2pcp more than a province at the 25th percentile during the first decade. This coefficient is in line with the findings of Autor and Dorn (2013) for the US. They show that US commuting zones with a routine employment share at the 80th percentile in 1980 decreased 1.8pcp more than US commuting zones at the 20th percentile. These findings are robust to the inclusion of controls because the initial level of routine keeps is negative and significant for both OLS and 2SLS estimations.

When analysing the initial level of human capital, GradSH is significant but the sign depends on the sex of the workers: for males the effect is negative, while it is positive for females. This result is consistent with the general educational catch-up between male and female workers that happened in Spain during the 2000s. Provinces that at the beginning of the period had low levels of female human capital registered the highest increase in the share of graduates. The coefficient of GradSH indicates that, given an initial Iqr of 0.05, the Iqr differential for initially more human capital-intensive areas is of about -1.4pcp for male workers, and 0.31pcp for female workers. Moreover, higher initial concentration of immigrants (Imm SH) is not significant.

[9] The instrumental variable strategy that I have followed is correct as long as the historical local differences in industrial specialization have significantly persisted over time. The results of the first-stage regressions (see Table 5) show that the industrial structure in 1977 is a good predictor of recent routine employment.

Overall, provinces with initially higher specialization in routine-intensive occupations experience larger declines in middle occupations, being this effect robust, and higher for male than female occupations. The empirical strategy works well as the predictive strength is similar for gender.

5.2 Changes in manual employment

The next step investigates changes at the bottom of the employment distribution, analysing the reallocation of workers from routine to manual occupations. The assumption behind is that low-skilled workers have a comparative advantage in manual tasks (located at the bottom of the wage distribution) rather than in abstract tasks (located at the upper part of the wage distribution) so a greater reallocation of middling workers at the bottom of the wage distribution is expected.

Table 7 measures the changes in manual occupations.[10] Results show that the effect of the RSH variable depends on the gender under consideration: negative for male workers, and positive for females. Moreover, when I look at the more restricted regression, the RSH coefficient is not significant for women, depicting the increase at the bottom of the employment distribution as a non-technological phenomenon. This result is robust to the inclusion of controls. The Iqr differential effect for RSH on local manual employment is about -2.5pcp for male workers, and +0.8pcp for female workers.

Provinces with initially higher routine task specialization had larger declines in manual occupation for male workers, but the opposite is not true for female workers. This result highlights that occupational segregation by gender is important and confirms the distinct impact that technology has on men and women. In fact, the rise in the relative demand for female workers in manual occupations is not explained by technology, which is consistent with the result in Cerina et al. (2016).

Turning now to the initial level of graduates (columns 2, 6 and 10), the same results are similar to the ones for routine occupations (Table 6): significant and positive for female workers, and negative and significant for male workers. In other words, the initial level of graduate workers implies a greater increase in female manual occupations among non-college workers. This result is in line with Ngai and Petrongolo (2017) and Rendall (2017), where they explain that

[10] Results remain the same when the sample is restricted to low-skilled workers.

female workers have a comparative advantage in service occupations. According to them, at the bottom of the employment distribution there is a shift from more physical ("brawn") to more intellectual ("brain") skills requirements.

With respect to the initial relative share of immigrants (columns 3, 7, and 11), it is only significant and positive for women, i.e., female manual employment is growing faster in provinces with higher levels of immigrants. Given an Iqr of 0.013, the Iqr differential effect for ImmSh on local female manual employment is about 2pcp. Therefore, greater supply of immigrants predicts rising manual occupations only for female workers.

Finally, the whole set of explanatory variables is included (columns 4, 8, and 12). Again, results are different when looking at gender. On one hand, the decline in male manual occupations is explained by the initial local level of routine share (RSH is negative). On the other hand, the increase in female manual occupations is due to the initial local level of graduates and immigrants (GradSH and ImmSh are positive and significant).

Alternative hypotheses

Table 8 test the previous results by exploring alternative hypothesis that have been proposed in the literature: the role of offshoring, local demand conditions, and demographic groups in the labour force. For simplicity, I present only the restricted model (2SLS).

Offshorability is measured as in Firpo et al. (2011) and the technique applied to measure the RSH is replicated: first, I classify as offshorability-intensity occupations those at the highest employment-weighted third of my measure in 2000. Then, I compute for each province the offshorability employment share (see Appendix for further details about its derivation and check the robustness section to see the measure constructed following Blinder and Kruger, 2013).

Column 1 (panel a for male and panel b for female) tests if provinces with initial higher levels of offshorability have different levels of growth in manual occupations. Offshorability is negative for male workers and positive for female workers, suggesting different effects depending on the sex of the worker. However, these effects are not significant which is consistent with Goos et al. (2014) and Montresor (2019) who have shown that the RTI index has a major explanatory role.

Columns 2 and 3 show two measures of local demand conditions: the initial level of unemployment rate and the manufacturing employment share. It is expected that provinces with higher unemployment rate and larger manufacturing sector experience less growth at the bottom of the employment distribution. Both measures (U_rate and ManuSH) are found to be small and non-significant.

Columns 5 and 6 consider two potential changes in demand: the initial level of female employment rate and the elderly population share. It has been proved that a higher female rate participation raises the demand for services such as restaurants and housekeeping (Manning, 2004: and Mazzaroli and Ragusa, 2013). Since these occupations are placed at the bottom of the employment distribution, it is expected an increase in manual occupations. Similarly, senior citizens may need home help assistance, assistance or nursing homes. So, a higher initial level of senior citizens raises the demand for these services which are located at the bottom. Results are surprising: while the elderly share does not show any relevant contribution, the female rate is positive and significant for women. Therefore, female manual occupations grow faster in provinces with a larger female participation rate. My finding here is in line with the recent work by Ngai and Petrongolo (2017) where it is found that the rise in service occupations raises woman's relative wages and market hours.

Finally, columns 7 and 8 analyse if there is a substitution or income effect from high-skilled workers in augmenting bottom occupations. The former effect captures changes in the labour supply of high-skilled workers that substitutes home services for market hours. It is calculated as the change in mean annual hours worked by graduates in each province. The latter effect measures changes in the wage structure, being proxied by the change in the 90th percentile of the log weekly wage distribution.[11] Results support the substitution effect just for female workers while there is no evidence of income effects. This finding is particularly relevant: the increase in working hours by females at the top of the employment distribution raise female occupations at the bottom.

In sum, while technology plays an important role in explaining the decrease in male occupations at the bottom of the employment distributions, it has no effect for women. This result is controversial as points out divergencies with the mainstream literature, i.e. the routine

[11] To compute the change in the 90th percentile of the log wage distribution, I add to the EES2002 database 2014. Therefore, I compute the change between 2002 and 2014.

task content as a main driver of changes at the bottom. On the contrary, my findings show two main facts: the raise at the bottom of the wage distribution happens only for female workers; the increase in female manual occupations is partially explained by the initial female rate participation and the increase in the number of hours worked by women at the top of the employment distribution.

5.3 Changes in abstract employment

To complete the picture, I investigate employment changes in abstract occupations at the upper part of the employment distribution. As said, due to a complementarity effect between high-skilled workers and technology, the model predicts an increase of employment share for abstract task workers. Therefore, I investigate whether technology has a positive effect on employment changes at the top of the distribution.

Table 9 focuses on changes in abstract occupations.[12] Results are different from what is expected: the initial level of technology has a complementary effect on employment growth for female abstract occupations (RSH is significant and positive in both models) but has no effect for male abstract occupations (RSH is not significant). Therefore, while capital-skill complementary theory is corroborated for female occupations, technological change has not caused an upward shift of high-skilled workers. Nevertheless, the RSH coefficient is not significant when controls are introduced (columns 10-12).

The coefficients of GradSH and ImmSh are significant and positive for female and male workers. Therefore, abstract employment grows more in areas with higher initial human capital and greater stock of immigrants. The Iqr differential for GradSH is about 3pcp for male workers and 13pcp for female workers so the initial female human capital has a higher effect on abstract occupations. Moreover, the Iqr association with initially higher concentration of immigrants is 1.42pcp and 1.61pcp for men and women, respectively. The first result is consistent with the rapid educational upgrading of women in Spanish. The second result is related to the European policy framework: since the end of the 1990s, the European Union has promoted a unified European labour market and the Spanish governments have been in favour of high-skilled immigration.

[12] I do not restrict the sample to graduate occupations as Montresor (2019) since the results remain the same.

Table 6. Changes in routine occupations with controls: 2000-2015

	All workers				Male workers				Female workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OLS												
RSH_{pt-1}	-0.287***	-0.290**	-0.272**	-0.285**	-0.416*	-0.410*	-0.475**	-0.467**	-0.181**	-0.180***	-0.187***	-0.183***
	(0.091)	(0.099)	(0.108)	(0.106)	(0.248)	(0.225)	(0.208)	(0.204)	(0.059)	(0.058)	(0.054)	(0.055)
$GradSH_{pt-1}$		-0.190***		-0.182		-0.299***		-0.281***		0.061**		0.052*
		(0.041)		(0.039)		(0.071)		(0.058)		(0.028)		(0.026)
$ImmSH_{pt-1}$			-0.460	-0.157			-0.808	-0.344			0.262	0.172
			(0.528)	(0.273)			(0.827)	(0.401)			(0.183)	(0.128)
R^2	0.135	0.220	0.151	0.222	0.261	0.563	0.390	0.411	0.263	0.277	0.271	0.281
2SLS												
RSH_{pt-1}	-0.298***	-0.304***	-0.294***	-0.301***	-0.534***	-0.510***	-0.521***	-0.517***	-0.155**	-0.151**	-0.155**	-0.156**
	(0.095)	(0.104)	(0.091)	(0.103)	(0.202)	(0.174)	(0.201)	(0.195)	(0.075)	(0.067)	(0.074)	(0.068)
$GradSH_{pt-1}$		-0.190***		-0.180***		-0.299***		-0.277***		0.062**		0.047**
		(0.039)		(0.037)		(0.067)		(0.054)		(0.027)		(0.023)
$ImmSH_{pt-1}$			-0.450	-0.153			-0.782	-0.349			0.251	0.140
			(0.517)	(0.276)			(0.807)	(0.408)			(0.182)	(0.126)
P-K F-test	15.75	15.64	15.97	16.29	15.83	15.21	15.60	16.09	16.09	16.01	17.17	17.12
N	200	200	200	200	100	100	100	100	100	100	100	100

Notes: All models include an intercept and region dummies (NUTS-1) and a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population.
Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.
***Significant at 1 percent level, **Significant at 5 percent level, *Significant at 10 percent level.

Table 7. Changes in manual occupations with controls: 2000-2015

	All workers				Male workers				Female workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OLS												
RSH_{pt-1}	-0.091	-0.092	-0.125**	-0.122**	-0.364**	-0.365**	-0.360**	-0.365**	0.123**	0.119**	0.055	0.064
	(0.075)	(0.069)	(0.052)	(0.052)	(0.145)	(0.151)	(0.155)	(0.157)	(0.048)	(0.046)	(0.053)	(0.060)
$GradSH_{pt-1}$		0.097		0.064*		-0.105*		-0.105***		0.263**		0.195***
		(0.064)		(0.030)		(0.025)		(0.028)		(0.123)		(0.054)
$ImmSH_{pt-1}$			0.805***	0.715***			-0.108	0.015			1.64**	1.340***
			(0.240)	(0.134)			(0.316)	(0.228)			(0.653)	(0.318)
R^2	0.007	0.022	0.040	0.046	0.305	0.332	0.306	0.332	0.198	0.309	0.339	0.395
2SLS												
RSH_{pt-1}	-0.124*	-0.123**	-0.137*	-0.134**	-0.383***	-0.383***	-0.381***	-0.392***	0.064	0.067	0.043	0.057
	(0.074)	(0.059)	(0.067)	(0.053)	(0.133)	(0.148)	(0.136)	(0.146)	(0.119)	(0.114)	(0.082)	(0.064)
$GradSH_{pt-1}$		0.097		0.064**		-0.105***		-0.110***		0.263**		0.190***
		(0.062)		(0.029)		(0.024)		(0.029)		(0.118)		(0.047)
$ImmSH_{pt-1}$			0.811***	0.716***			-0.097	0.057			1.650***	1.288***
			(0.235)	(0.130)			(0.304)	(0.223)			(0.634)	(0.287)
P-K F-test	16.39	16.18	16.35	16.62	17.88	17.67	17.52	17.84	14.90	14.57	14.93	15.17
N	200	200	200	200	100	100	100	100	100	100	100	100

Notes: All models include an intercept and region dummies (NUTS-1) and a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population.

Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.

***Significant at 1 percent level, **Significant at 5 percent level, *Significant at 10 percent level.

Table 8. Alternative hypotheses, changes in manual occupations with controls: 2000-2015

	Panel a: male workers						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2SLS							
RSH_{pt-1}	-0.386***	-0.407***	-0.377***	-0.323***	-0.359***	-0.381***	-0.392***
	(0.131)	(0.142)	(0.132)	(0.123)	(0.136)	(0.121)	(0.124)
$Offsh_{pt}$	0.050						
	(0.134)						
U_rate_{pt-1}		-0.051					
		(0.055)					
$ManuSH_{pt-1}$			0.650				
			(0.818)				
$Female_{pt-1}$				-0.196			
				(0.120)			
Old_{pt-1}					-1.766		
					(1.168)		
$\Delta GradSH_{pt}$						0.009	
						(0.029)	
$\Delta Wage(p90)_{pt}$							0.024
							(0.193)
P-K F-test	22.54	16.90	20.87	21.78	20.42	21.16	21.29s
	Panel b: female workers						
RSH_{pt-1}	0.075	0.043	0.047	0.062	0.028	0.091	0.093
	(0.105)	(0.142)	(0.132)	(0.149)	(0.145)	(0.071)	(0.077)
$Offsh_{pt}$	-0.147						
	(0.384)						
U_rate_{pt-1}		-0.041					
		(0.075)					
$ManuSH_{pt-1}$			-0.798				
			(0.525)				
$Female_{pt-1}$				0.432**			
				(0.184)			
Old_{pt-1}					0.394		
					(0.421)		
$\Delta GradSH_{pt}$						0.196*	
						(0.112)	
$\Delta Wage(p90)_{pt}$							0.299
							(0.123)
P-K F-test	21.598	13.48	17.38	18.60	17.32	17.57	17.62

Notes: All models include an intercept and region dummies (NUTS-1) and a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population.

Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.

***Significant at 1 percent level, **Significant at 5 percent level, *Significant at 10 percent level.

Table 9. Changes in abstract occupations with controls: 2000-2015

	All workers				Male workers				Female workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OLS												
RSH_{pt-1}	0.120***	0.006	0.112	0.076	-0.093	-0.094	-0.085	-0.090	0.394***	0.413***	0.267**	0.330***
	(0.029)	(0.101)	(0.077)	(0.067)	(0.065)	(0.065)	(0.061)	(0.065)	(0.079)	(0.091)	(0.120)	(0.123)
$GradSH_{pt-1}$		0.334***		0.210***		0.144*		0.0412		0.554***		0.406***
		(0.103)		(0.051)		(0.078)		(0.039)		(0.147)		(0.079)
$ImmSH_{pt-1}$			2.043***	1.429***			1.269***	1.140***			2.909**	1.786***
			(0.595)	(0.263)			(0.373)	(0.327)			(1.091)	(0.486)
R^2	0.027	0.210	0.230	0.284	0.335	0.347	0.456	0.461	0.162	0.589	0.515	0.692
2SLS												
RSH_{pt-1}	0.178***	0.129	0.156	0.135*	-0.105	-0.101	-0.098	-0.100**	0.331**	0.261	0.226	0.256
	(0.051)	(0.090)	(0.104)	(0.072)	(0.073)	(0.071)	(0.068)	(0.069)	(0.013)	(0.236)	(0.144)	(0.174)
$GradSH_{pt-1}$		0.332***		0.206***		0.142*		0.037		0.552***		0.400***
		(0.101)		(0.050)		(0.074)		(0.040)		(0.142)		(0.075)
$ImmSH_{pt-1}$			2.066***	1.465***			1.292***	1.179***			1.465***	1.219***
			(0.573)	(0.251)			(0.368)	(0.348)			(0.523)	(0.313)
P-K F-test	14.08	13.99	15.28	16.47	15.34	13.70	14.65	15.81	36.37	13.80	15.36	16.54
N	200	200	200	200	100	100	100	100	100	100	100	100

Notes: All models include an intercept and region dummies (NUTS-1) and a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population.

Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.

***Significant at 1 percent level, **Significant at 5 percent level, *Significant at 10 percent level.

6 Robustness checks

As said in Section 3, this exercise is valid as long as the internal mobility of workers among provinces due to technology is weak. So far, I have presented two papers that corroborates that the regional mobility in Spain is low (Bentolila and Dolado, 1990; and Gonzalez and Ortega, 2010). In here, I extend the analysis restricting the analysis to mobility caused by technology. Remember that, if there were mobility as consequences to technological shocks, this would disperse the effect and undermine the results. To do so, the dependent variable in Table 10, shows the change in the log of the working-age population (column 1-2), male working-age population (column 3-4), and female working-age population (column 5-6). Looking at OLS and 2SLS, the results remain robust to this new specification. I therefore can conclude that the empirical strategy is valid.

Table 10. Effects on the working-age population 2000-2015

	All workers		**Male workers**		**Female workers**	
	(1)	(2)	(3)	(4)	(5)	(6)
OLS						
RSH_{pt-1}	-0.027	0.158	0.039	0.115	-0.222	-0.304
	(0.297)	(0.215)	(0.269)	(0.185)	(0.376)	(0.306)
$GradSH_{pt-1}$		0.007		-0.133		0.236*
		(0.122)		(0.126)		(0.136)
$ImmSH_{pt-1}$		3.194***		3.608***		2.113***
		(0.733)		(0.747)		(0.774)
R^2	0.752	0.755				
2SLS						
RSH_{pt-1}	0.141	0.095	0.119	0.114	-0.040	-0.055
	(0.404)	(0.360)	(0.357)	(0.319)	(0.533)	(0.457)
$GradSH_{pt-1}$		0.016		-0.123		0.244*
		(0.111)		(0.114)		(0.126
$ImmSH_{pt-1}$		3.038***		3.460***		1.972***
		(0.686)		(0.679)		(0.752)
P-K F-test	16.27	16.66	16.48	16.73	15.43	15.59
N	200	200	100	100	100	100

Notes: the dependent variable is changes in the log of the working-population. All models include an intercept, a region dummies (NUTS-1), and a time period dummy. Standard errors clustered at the regional level. Observations are weighted by the initial share of national population.
Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.

Table 11 explores the sensitivity of the analysis by controlling for contemporaneous changes in the labour supply. The analysis addresses this issue by including the relative growth of graduates and immigrants. Table 15 reports the estimates from OLS and 2SLS for male workers (column 1-4) and female workers (column 5-8) for changes in the routine occupations (panel a), manual (panel b) and abstract (panel c).

Looking now at changes in routine occupations (panel a), results are in line with the main analysis: the decline at the middle part of the employment distribution is explained by technology exposure. However, and contrary to previous results, technological exposure is higher for female workers (2SLS, column 8).

Panel b displays changes in manual occupations confirming previous results. For male workers the initial relative share of routine is negative related with changes in manual occupation. For female workers the RSH coefficient is not significant in the 2SLS analysis where the endogeneity has been controlled by the instrument. In this case, OLS and 2SLS results show a more substantial relevance of labour supply changes: initial local immigration concentrations are significantly related to female manual occupations.

Panel c reports changes in abstract employment. Different from what we found previously, OLS results suggest a significant positive effect of technology exposure on female workers. As in the main analysis, findings indicate that the initial graduates and high-skilled migrant share are positively correlated with changes in abstract occupations, and therefore, explain top employment growth.

Finally, one limitation is that the study relies on Autor and Dorn's measure to define the local routine share employment (RSH). However, the 30 per cent top of routine-intensive occupations of the RTI index may not be that restrictive. To test this, I re-construct the technology exposure measure using the top 40 per cent. Table 12 reports the estimates obtained by the new definition. In line with the baseline results, the estimates are similar in magnitude to the baseline, although they are less precisely estimated. It does not alter the interpretation of the main results.

7 Conclusion

[To be added]

Table 11. Conditioning on local labour supply 2000-2015

	Male workers				Female workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Routine employment changes							
OLS								
RSH_{pt-1}	-0.372**	-0.312*	-0.355**	-0.306*	-0.181**	-0.196***	-0.183***	-0.196***
	(0.128)	(0.170)	(0.131)	(0.167)	(0.059)	(0.047)	(0.058)	(0.047)
$\Delta GradSH_{pt-1}$		-0.221*		-0.195**		0.085***		0.080***
		(0.121)		(0.090)		(0.022)		(0.016)
$\Delta ImmSH_{pt-1}$			-0.182	-0.151*			0.040	0.024
			(0.109)	(0.071)			(0.038)	(0.025)
R^2	0.335	0.455	0.422	0.512	0.263	0.287	0.269	0.289
2SLS								
RSH_{pt-1}	-0.201***	-0.146*	-0.176***	-0.131*	-0.155**	-0.181***	-0.163**	-0.184***
	(0.086)	(0.079)	(0.066)	(0.071)	(0.075)	(0.053)	(0.073)	(0.052)
$\Delta GradSH_{pt-1}$		-0.223*		-0.200**		0.084***		0.079***
		(0.120)		0.087		(0.023)		(0.017)
$\Delta ImmSH_{pt-1}$			-0.182*	-0.151**			0.039	0.024
			(0.106)	(0.069)			(0.036)	(0.024)
P-K F-test	15.34	13.61	14.12	12.81	17.09	16.38	15.98	15.35
	Panel B: Manual employment changes							
OLS								
RSH_{pt-1}	-0.182**	-0.171*	-0.178**	-0.170*	0.123**	0.064	0.100*	0.057
	(0.072)	(0.083)	(0.075)	(0.084)	(0.048)	(0.050)	(0.052)	(0.054)
$\Delta GradSH_{pt-1}$		-0.068		-0.060		0.191		0.147
		(0.044)		(0.041)		(0.147)		(0.087)
$\Delta ImmSH_{pt-1}$			-0.053	-0.042			0.274**	0.250***
			(0.043)	(0.038)			(0.110)	(0.073)
R^2	0.305	0.315	0.312	0.320	0.198			
2SLS								
RSH_{pt-1}	-0.191***	-0.174**	-0.182***	-0.169**	0.064	0.046	0.018	0.101
	(0.066)	(0.033)	(0.069)	(0.083)	(0.119)	(0.184)	(0.089)	(0.143)
$\Delta GradSH_{pt-1}$		-0.068*		-0.060		0.206		0.168*
		(0.040)		(0.038)		(0.148)		(0.088)
$\Delta ImmSH_{pt-1}$			-0.052	-0.042			0.278***	0.252***
			(0.040)	(0.036)			(0.109)	(0.072)
P-K F-test	17.88	15.71	16.20	14.65	14.90	12.81	13.66	12.04
	Panel C: Abstract employment changes							
OLS								
RSH_{pt-1}	-0.082*	-0.093**	-0.087*	-0.094**	0.394***	0.282**	0.318**	0.247*
	(0.049)	(0.041)	(0.049)	(0.041)	(0.079)	(0.119)	(0.117)	(0.134)
$\Delta GradSH_{pt-1}$		0.220***		0.204***		0.479**		0.373**
		(0.071)		(0.057)		(0.224)		(0.137)
$\Delta ImmSH_{pt-1}$			0.114	0.050			0.475**	0.370**
			(0.096)	(0.043)			(0.213)	(0.128)
R^2	0.261	0.432	0.307	0.440	0.162	0.440	0.439	0.596
2SLS								
RSH_{pt-1}	-0.106***	-0.124***	-0.110***	-0.125***	0.331**	0.027	0.138	0.021
	(0.040)	(0.023)	(0.040)	(0.0244)	(0.013)	(0.403)	(0.175)	(0.278)
$\Delta GradSH_{pt-1}$		0.234***		0.216***		0.508**		0.396***
		(0.058)		(0.044)		(0.221)		(0.136)
$\Delta ImmSH_{pt-1}$			0.122	0.057			0.487**	0.381***
			0.093	(0.041)			(0.209)	(0.128)
P-K F-test	13.83	12.06	13.49	12.4	36.37	12.39	14.12	13.20

Notes: the dependent variable is changes in the log of the working-population. All models include an intercept, a region dummies (NUTS-1), and a time period dummy. Standard errors clustered at the regional level. Observations are weighted by the initial share of national population.

Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.

Table 12. Routine intensity 40% of employment share

	Male workers				Female workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Routine employment changes				
OLS								
RSH_{pt-1}	-0.389**	-0.371**	-0.338*	-0.363*	-0.152*	-0.155*	-0.180**	-0.176**
	(0.139)	(0.152)	(0.182)	(0.177)	(0.081)	(0.076)	(0.069)	(0.071)
$GradSH_{pt-1}$		-0.286***		-0.281***		0.067*		0.051*
		(0.061)		(0.060)		(0.033)		(0.028)
$ImmSH_{pt-1}$			-0.580	-0.095			0.391*	0.300*
			(0.909)	(0.479)			(0.199)	(0.162)
R^2	0.343	0.551	0.369	0.552	0.240	0.257	0.257	0.266
2SLS								
RSH_{pt-1}	-0.411***	-0.416**	-0.405***	-0.413**	-0.165*	-0.160**	-0.165*	-0.167**
	(0.157)	(0.178)	(0.156)	(0.182)	(0.089)	(0.079)	(0.087)	(0.081)
$GradSH_{pt-1}$		-0.285***		-0.278***		0.067**	0.375*	0.045*
		(0.057)		(0.056)		(0.032)	(0.207)	(0.024)
$ImmSH_{pt-1}$			-0.500	-0.060				0.268
			(0.901)	(0.512)				(0.169)
P-K F-test	24.64	23.35	29.63	30.88	26.12	24.43	29.21	29.30
				Panel B: Manual employment changes				
OLS								
RSH_{pt-1}	-0.169**	-0.167*	-0.178*	-.0183*	0.199**	0.178**	0.036	0.052
	(0.075)	(0.083)	(0.092)	(0.092)	(0.093)	(0.052)	(0.072)	(0.072)
$GradSH_{pt-1}$		-0.098***		-0.110***		0.257**		0.195***
		(0.032)		(0.032)		(0.115)		(0.054)
$ImmSH_{pt-1}$			0.162	0.301			1.628**	1.309***
			(0.441)	(0.345)			(0.690)	(0.351)
R^2	0.283	0.307	0.285	0.313	0.214	0.320	0.337	0.393
2SLS								
RSH_{pt-1}	-0.199***	-0.199**	-0.201**	-0.072**	0.065	0.069	0.044	0.059
	(0.081)	(0.088)	(0.084)	(0.091)	(0.122)	(0.118)	(0.086)	(0.070
$GradSH_{pt-1}$		-0.097***		-0.115***		0.261**		0.191***
		(0.033)		(0.033)		(0.116)		(0.047)
$ImmSH_{pt-1}$			0.219	0.390			1.617**	1.244***
			(0.426)	(0.341)			(0.676)	(0.321)
P-K F-test	26.32	25.15	32.40	34.10	24.42	22.80	29.00	30.15
				Panel C: Abstract employment changes				
OLS								
RSH_{pt-1}	-0.079	-0.084	-0.119*	-0.117*	0.525***	0.460***	0.248	0.314*
	(0.073)	(0.064)	(0.061)	(0.059)	(0.162)	(0.107)	(0.147)	(0.154)
$GradSH_{pt-1}$		0.165*		0.045		0.530***		0.403***
		(0.090)		(0.042)		(0.136)		(0.081
$ImmSH_{pt-1}$			1.551***	1.407***			2.770**	1.614***
			(0.497)	(0.436)			(1.150)	(0.551)
R^2		0.255	0.407	0.413	0.215	0.604	0.506	0.680
2SLS								
RSH_{pt-1}	-0.112*	-0.106***	-0.109**	-0.107**	0.198	0.267	0.232	0.262
	(0.049)	(0.041)	(0.048)	(0.047)	(0.287)	(0.255)	(0.160)	(0.199)
$GradSH_{pt-1}$		0.173*		0.039		0.538***		0.399***
		(0.089)		(0.042)		(0.140)		(0.077)
$ImmSH_{pt-1}$			1.628***	1.504***			2.788**	1.672***
			(0.505)	(0.469)			(1.122)	(0.589)
P-K F-test	16.38	19.85	26.48	28.71	22.20	20.51	30.08	32.57

Notes: the dependent variable is changes in the log of the working-population. All models include an intercept, a region dummies (NUTS-1), and a time period dummy. Standard errors clustered at the regional level. Observations are weighted by the initial share of national population.

Sources: Author's analysis from the EPA (2000, 2007, 2015) and O*Net.

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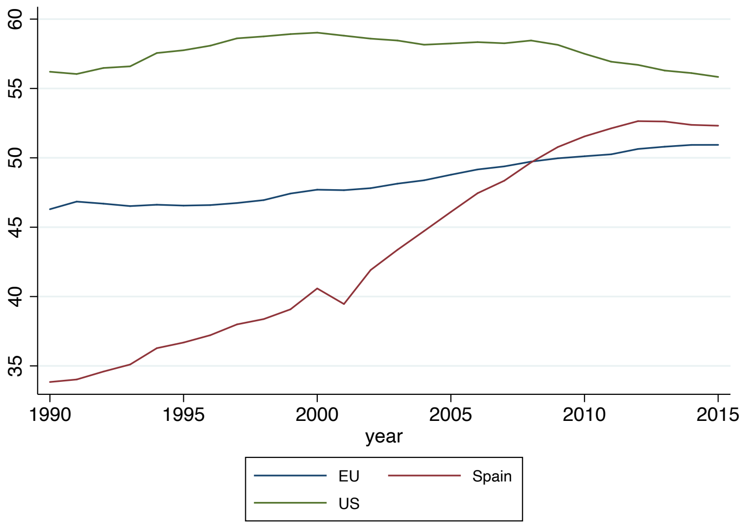
Appendix A: figures

Figure 6: Evolution of the female participation rate in the US, EU, and Spain



Sources: Our world in data

Appendix B: measures

B.1 Routineness

Table 13. Detailed list of descriptors by task

Abstract items	
4.A.2.a.4	Analyzing Data or Information
4.A.2.b.2	Thinking Creatively
4.A.4.a.1	Interpreting the Meaning of Information for Others
4.A.4.b.5	Coaching and Developing Others
4.A.4.b.4	Guiding, Directing, and Motivating Subordinates
4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships
Routine items	
4.C.3.b.4	Importance of Being Exact or Accurate
4.C.3.b.7	Importance of Repeating Same Tasks
4.C.3.b.8	Structured versus Unstructured Work (reverse)
4.C.3.d.3	Pace Determined by Speed of Equipment
4.C.2.d.1.i	Spend Time Making Repetitive Motions
4.A.3.a.3	Controlling Machines and Processes
Manual items	
1.A.1.f.1	Spatial Orientation
1.A.2.a.2	Manual Dexterity
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment
4.C.2.d.1.g	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls

Notes: O*Net tasks measures based on Acemoglu and Autor (2011).

Table 14. Initial level of abstract, routine, and manual tasks by occupation

Occupations	Code	Abstract	Routine	Manual
Bottom occupations				
Labourers in mining, const., manu., and transport	93	-0.57	0.97	1.58
Sales and services elementary occupations	91	-0.48	1.10	0.49
Other craft and related trades workers*	74	-1.24	1.27	0.55
Personal and protective service workers	51	-0.19	-0.24	-0.05
Middle occupations				
Extraction and building trade workers	71	-0.12	0.31	1.32
Models, salespersons and demonstrators	52	-0.38	-0.55	-0.23
Customer service clerks*	42	-0.59	0.21	-1.00
Drivers and mobile plant operators	83	-0.26	0.40	1.43
Machine operators and assemblers*	82	-1.15	1.94	0.62
Precision, handicraft, printing and trades workers*	73	-1.60	0.07	0.42
Office clerks*	41	-0.59	0.21	-1.00
Metal. machinery and related trades workers*	72	-0.90	1.68	1.14
Life science and health associate professionals	32	0.70	-0.43	-0.43
Stationary plant and related operators	81	-0.82	-0.09	-1.14
Top occupations				
Other associate professionals	34	0.27	-0.96	-1.17
PMES professionals	31	0.17	0.04	0.12
General Managers	13	1.51	-0.90	-0.79
Life science and health professionals	22	1.46	-1.01	-0.49
Other professionals	24	1.39	-1.67	-1.57
PMES associate professionals	21	1.27	-1.11	-1.06
Corporate managers	12	1.82	-1.37	-1.08

Notes: Occupations are ordered by the mean hourly wage in 2000. Occupations with an asterisk are those defined as routine-intensity.
Sources: Author's analysis from the EPA (2000) and O*Net.

B.2 Offshorability

To operationalize offshorability, I use a simple average of the two variables *Face-to-Face Contact* and *On-Site Job* that Firpo, Fortin, and Lemieux (2011) derive from the US Department of Labor's Occupational Information Network database (O*NET). This measure captures the degree to which an occupation requires either direct interpersonal interaction or proximity to a specific work location. The commuting zone level offshorability index is equal to the average offshorability score of employment in each commuting zone and year, and is further normalized to have a mean of zero and a cross commuting zone standard deviation of one in 2000.