Job Polarisation and the Spanish Local Labour Market

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Abstract

This paper provides first empirical evidence on the effect of technological exposure on local labour markets in Spain. The analysis combines the Spanish Labour Force Survey for the years 1994 and 2008, and the O*Net. The identification strategy exploits spatial variation in the exposure to technological progress which arises due to initial regional specialization in routine task-intensive activities. Results confirm that technology partially explains the decline of middle-paid workers, and its subsequent relocation at the bottom part of the employment distribution. However —and different to the US— technology does not explain the increase found at the top of the employment distribution.

JEL Classification: J21, J23, J24.

Keywords: Job polarisation, structural change, local labour market, technology.

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1 Introduction

A consensus has emerged among labour economists that there is an increase in both "good" and "bad" jobs relative to "middling jobs", a fact first introduced by Wright and Dwyer (2003) and later corroborated by Goos and Manning (2007). One of the key findings is the U-shaped relationship between growth in employment share and occupation's percentile in the wage distribution. Goos and Manning (2007) have termed this phenomenon as *job polarisation* basing their discussion on UK data. This fact is later corroborated in other developed countries such as the US (Autor and Dorn, 2013; Autor et al., 2006) and Germany (Dustmann et al., 2009; Kampelmann and Rycx, 2011; Spitz-Oener, 2006). However, results are mixed for Spain (Anghel et al., 2014; Oesch and Rodríguez Menés, 2011; Sebastian, 2017).

The economic literature highlights the role of technology as one of the main determinants of job polarisation (Autor, Levy and, Murnane, 2003; thereafter ALM). Goos and Manning (2007) explain job polarisation through the routine biased technical change hypothesis (RBTC, thereafter): driven by persistently cheaper computerisation, technology replaces human labour in routine tasks, ceteris paribus. Since non-routine tasks are located at the low and high end of the occupational distribution and routine tasks in the middle, the RBTC predicts two effects: 1) there is an employment decline in the middle of the occupational distribution, and 2) there is an employment growth at the bottom and top of the occupational distribution. Hence, the polarisation effect of recent technical change is explained by the RBTC.

The RBTC model fits well with the evidence provided so far (Autor and Dorn, 2013; Goos et al., 2014; Michaels et al., 2014). However, this prominent theory is not able to explain three new empirical facts in the US during the 2000s. First, a decrease of the employment share in high-skilled occupations (Autor, 2015; Beaudry et al., 2016) where the supply of graduates grew faster than the demand of high-skilled jobs. Second, low-skilled jobs are growing more than middle- and high-skilled jobs. Job growth is therefore concentrated at the bottom of the employment distribution (Beaudry et al., 2016). Finally, Beaudry et al. (2016) show little evidence of wage porlarisation in the US. It has also not been found in other countries, such as Canada (Green and Sand, 2015), the UK (Salvatori, 2015) and Spain (Sebastian, 2017).[1] In light of the available evidence,

[1]Wage polarisation is defined as follows: if we rank all occupations according to their mean wage at

it is clear that the relationship between technology and labour is more complex than the one assumed by the RBTC literature.

Alongside technological changes, change in the labour force supply constitutes another determinant of job polarisation advanced in the literature. Oesch and Rodríguez Menés (2011) highlight its importance as the driving force affecting occupational change to some extent. Their study graphically shows two new ideas: first, the increase at the bottom is partially explained by migrants. Second, the increase at the top reflects a rapid educational upgrading. This paper casts some doubts on the role of technology as the main driver behind occupational changes and suggests that supply-side changes are likely to be important in order to understand the phenomenon.

On the policy side, the phenomenon of job polarisation raises two significant issues in terms of job quality and occupational mobility. Firstly, the shrinking of middle jobs has consequences in the possibilities of moving up of low-skilled workers. Secondly, middle-paid workers are more likely to be reallocated in bottom-paid jobs. Therefore, for policy makers and governments it is important to understand the main determinants of job polarisation; this information will help them design economic policies that best promote sustainable growth.

Focusing on the case of Spain, this work contributes to the existing literature on polarisation in Spain by analysing novel evidence at the level of local labour markets inspired by the analysis of Autor and Dorn (2013). To the best of our knowledge we are the first ones exploring this issue outside the US. Therefore, using the Spanish Labour Force Survey and O*Net, we exploit geographical variation across Spanish provinces in their specialisation in the routine-intensive employment share, to identify the effect between technology and employment changes.

The study also contributes to the wider literature on job polarisation since we take into account other determinants beyond technology. In this case, and as pointed out by Muñoz de Bustillo and Antón (2012) and by Sebastian and Harrison (2017), two main factors have changed the Spanish labour market: the increase of migrants and increase in graduates. For migrants, in 1994 they represented only 0.62 per cent of total employment, whereas fourteen years later, the proportion has climbed up to almost 13 per cent. The

date t-1, then wage polarisation between t-1 and t means that the mean wage of occupations situated in the middle of the ranking has decreased relative to occupations at the top and bottom of the wage ranking in t-1.

increase of graduates has shifted from 21 per cent to 33 per cent of total employment from 1994 to 2008 respectively. Therefore we aim to disentangle the effect of technology and the role of supply changes in shaping the structure of employment in Spain between 1994 and 2008.

Our empirical findings are not completely in accord with the predictions of Author's and Dorn model (2013). In line with them, we show that Spanish provinces with initially higher degree of routine task exhibit larger declines in middle-paid occupations and its subsequent displacement to bottom-paid occupations. However, no technological effect is found at the high-paid occupations where the graduate share and the high-skilled migrants share are the main drivers in explaining the growth at the top of the employment distribution.

Evidence on the long-run effects of demographic factors is then presented. At the bottom of the occupational distribution, a higher local graduate share has a negative effect on employment growth. At the top part of the occupational distribution, high-skilled migrant concentrations are positively associated with the growth of employment. Regarding the concentration of graduates, it has a different effect depending on the decade: during the 1990s is negative and, during the 2000s, is positive. This is due to the possible catch-up in the first decade: provinces with initial lower human capital increase more than provinces with high initial human capital.

In the last part, because of potential endogeneity, we construct an instrumental variable based on the industrial information across Spanish provinces in the year 1977, almost two decades before the boom of computerisation in the workplace. Although the instruments are not strong, the findings obtained do not significantly differ from those of the baseline analysis.

Overall, this paper provides new evidence on the main drivers behind job polarisation. On the one hand, technology explains the decrease in middle-skilled workers and its subsequent reallocation at the lower part of the employment distribution. On the other hand, technology does not play any role in explaining the growth at the top of the employment distribution. Graduate and high-skilled migrants supply changes are the main determinants behind the increase at the upper part of the employment distribution.

The paper is organised as follow: Section 2 presents an overview of the relevant literature relating to job polarisation and local labour markets. In Section 3, we describe the data, the definition of local labour markets, the routine task intensity index, and the routine intensity measure. Section 4 presents initial evidence on job polarisation by occupation, demographic groups and by Spanish provinces. Section 5 discusses the empirical specification and the identification strategy. Section 6 reports results from the empirical analysis. In Section 7 we perform a sensitivity analysis and several robustness checks. Section 8 summarizes the main findings of the work.

2 Literature review

In the ALM model (2003), firms substitute routine tasks for technology, a process driven by the falling price in computers while complement abstract tasks. Manual tasks are not directly affected by technology.

Autor and Dorn (2013) build on the RBTC model and present a general equilibrium model for routine replacement. In their economy there are two sectors which produce "goods" and "services" using computer capital and three labour task inputs: abstract, routine, and manual. The good production function uses abstract and routine labour while the service production function uses only manual labour. They assume that computer capital is a relative complement for abstract tasks and a relative substitute for routine tasks. In their model, there are two types of workers: high-skilled and low-skilled workers. High-skilled workers have a comparative advantage in abstract tasks, while low-skilled workers have a comparative advantage in routine and manual tasks. The main driver of the model is the exogenous falling price in computers. The basic implications in equilibrium are: 1) technological progress replaces low-skilled workers in routine occupations, and 2) since middle-workers have a comparative advantage in manual occupations; a greater reallocation at the bottom of the occupational distribution is expected.

The RBTC model has been empirically proven in the UK (Akcomak et al., 2013; Goos and Manning, 2007), Germany (Kampelmann and Rycx, 2011), Portugal (Fonseca et al., 2016), and Spain (Sebastian, 2017). These studies conclude that the RBTC hypothesis provides a convincing explanation for the role that technology plays in shaping the structure of labour market.

A more recent paper by Sebastian and Harrison (2017) complements the previous studies in two ways: first, job polarisation is studied through a shift-share analysis presenting changes within and between skills groups. Second, they study to which extent compositional changes could explain changes in the employment distribution. Results suggest that the growth at the top of the employment distribution is explained by the increase in the number of graduates.

As far as our understanding goes, no Spanish study has tried to test alternative hypotheses of job polarisation, i.e., the increasing supply share of graduates and migrants, the gaining of the population, or the growing offshorability of job tasks. This paper aims at understanding the effect of technology on employment and at the same time provides evidence on the role of labour supply. To the best of our knowledge, this is the first paper proving a complete view on the determinants affecting the employment distribution using the Spanish local labour markets.

3 Data source and measurements

This section is concerned with a description of the data sets as well as the construction of the Routine Task Index. The main data set is the Spanish Labour Force Survey (*Encuesta de Población Activa* EPA, in Spanish) for the years 1994 to 2008, providing a representative sample of the Spanish workforce. We exclude the 2008-2014 years because of substantial changes in the ISCO code (from ISCO-88 to ISCO-08). In addition, we boost the sample size by pooling together 1994, 2000 and 2008 waves. The EPA is a continuous household survey of the employment circumstances of the Spanish population. It is conducted by the Statistical National Institute (*Instituto Nacional de Estadística*, INE). The EPA has been running on a quarterly basis from 1964 to 1968, it then became biannually from 1969 to 1974, and finally quarterly again from 1975 onwards. Each quarter covers 65,000 individuals, making up about 0.2 per cent of the Spanish population. In order to avoid problems with seasonality, we only retain the second quarter of each relevant year. Sampling weights adjusted for responses are used through the analysis.

We restrict the analysis to employees in paid work (i.e., employees and self-employed), aged between 16 and 64 in Spain. Occupations in the EPA are classified using the Spanish Classification Code (CNO-94). We recode occupations according to the International Standard Classification of Occupations (ISCO-88). Occupations are defined at the two-digit level. We exclude from our analysis workers associated with armed forces (ISCO

01), legislators and senior officials (ISCO 11), and agricultural occupations (ISCO 61 and ISCO 92). Employment in these occupations represents a small share of the total working population.[2]

The EPA does not include information on wages. To overcome this problem, we integrate our main source with the Structure of Earnings Survey (in Spanish *Encuesta de Estructura Salarial*, ESS). The ESS provides information on employee's wages and occupations. The survey has been carried out three times during the period of analysis (1995, 2002, and 2006). Throughout our paper, we use the 1995 survey results, rather than the 2002 or the 2006, as our results remain invariant and is the closest to our starting period of analysis, 1994.[3][4] Average hourly wages are computed by first converting annual data into weekly income and then dividing by the weekly working hours (including overtime).

Our study needs time-consistent definitions of local labour areas. The area study, by Autor and Dorn (2013), interprets local labour markets as US commuting zones. The EPA does not include commuting zones; as such we choose 50 provinces as our econometric unit of analysis. Ceuta and Melilla are excluded from the analysis.

In order to properly measure the impact of technology on local labour markets, the assumption of low or null mobility of workers between provinces as a result of the effect of technological change must hold. If there were internal migration of workers, this would disperse the effect of technology exposure across the Spanish economy and undermine the effect. In Spain, the results are clear. Using Labor 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 (2011) find a very week correlation between Spanish-born mobility and immigrant inflows at the level of local areas between 2001 and 2006. We can argue that the assumption that labour markets are regional in scope is a reasonable one.

[2]Results remain invariant with the exclusion of those occupations. There results are available upon request.

[3]There results are available upon request.

[4]The high value of the Spearman correlation coefficients (0.92 between ESS1995 and ESS2002, 0.96 between ESS1995 and ESS2006, and 0.98 between ESS2002 and ESS2006) suggest that the wage rank is remarkably stable over time.

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

In order to investigate the effect that technological exposure has on local labour markets, we need information on routine task activities within provinces. Following Autor and Dorn (2013), we measure routine task activities with the Routine Task Intensity (RTI) index at the occupational level from an additional source, O*Net.[5] This index combines the routine, abstract, and manual task content of occupations, to create a summary measure, measuring the importance of routine tasks by removing measures of abstract and manual tasks. The index is calculated as follows:

$$RTI_k = \ln T^R_{k,1994} - \ln T^A_{k,1994} - \ln T^M_{k,1994} = \ln \frac{T^R_{k,1994}}{T^A_{k,1994} T^M_{k,1994}} \tag{1}$$

where $\ln T^R_{k,1994}$, $\ln T^A_{k,1994}$, and $\ln T^M_{k,1994}$ are the routine, abstract, and manual task abilities for each occupation k in the sample base year, 1994.

To contextualise the RTI, we derive our RTI at the occupational level from O*Net. This source is provided by the US Department of Labor. In O*Net, analysts at the Department of Labor assign scores to each task according to standardised guidelines, to describe their importance within each occupation.[6] Therefore, O*Net is a primary source of occupational information, providing data on key attributes and characteristics of occupations. O*Net data is collected for 812 occupations based on the Standard Occupation Classification (SOC2000). We convert SOC2000 codes into International Standard Classification of Occupations (ISCO-88) using a crosswalk made available by the Cambridge Social Interaction and Stratification Scale (CAMSIS) project.[7]

We follow the literature as close as possible by selecting components from O*Net which resemble those selected by Autor and Dorn (2013). We retain responses on "Harm-hand steadiness" and "Manual dexterity" for the manual aspect, on "GED math", and "Administration and management" for the abstract tasks, and on "Finger dexterity" and "Customer and personal services" for the routine dimension. After mapped into our ISCO-88 classification, we then normalized the RTI to have zero mean and unit standard

[5] We use the framework by Autor and Dorn (2013) because they create the RTI. Other frameworks are Fernández-Macías and Hurley (2016), Fernández-Macías and Bisello (2017), and Matthes et al. (2014).

[6] We use version 11.0 of the survey, available at: http://www.onet.org

[7] Available at: http://www.cardiff.ac.uk/socsi/CAMSIS/occunits/us00toisco88v2.sps

deviation.

Table 1 presents the abstract, routine, manual, and RTI by Spanish region. It should be noted that Spain contains 52 provinces that are organised in 17 regions. For simplicity reasons we present the information at the regional level and not at the province level. The percentage of routine task intensity varies from 1.36 to -1.97, Galicia being the highest in routine task intensity and Madrid being the lowest. The difference between both is obvious: Madrid region has by far the largest city in Spain, it is a flourishing region with corporate headquarters, IT companies, multinationals, whereas Galicia is structurally weak. Another important difference is that while Madrid region has the most important city in Spain with 3.5 million of citizens (Madrid city), the biggest city in Galicia is Vigo with just 250 thousand citizens.

Table 1: Task measures and RTI index by region

Region	Abstract index	Routine index	Manual index	RTI
	(1)	(2)	(3)	(4)
Galicia	0.38	0.44	0.33	1.36
Extremadura	0.38	0.43	0.33	1.23
Andalusia	0.39	0.44	0.33	1.09
Principality of Asturias	0.38	0.42	0.32	0.75
Cantabria	0.39	0.43	0.32	0.55
Castile and Leon	0.38	0.42	0.32	0.53
Aragon	0.38	0.42	0.32	0.43
Castile-La Mancha	0.38	0.42	0.32	0.36
Region of Murcia	0.38	0.42	0.32	0.33
Balearic Islands	0.39	0.42	0.32	0.23
Canary Islands	0.39	0.42	0.32	0.08
Valencian Community	0.39	0.41	0.31	-0.40
Catalonia	0.39	0.40	0.31	-0.77
Basque Country	0.40	0.41	0.31	-0.89
La Rioja	0.38	0.39	0.30	-1.19
Navarre	0.39	0.39	0.29	-1.72
Madrid	0.40	0.39	0.29	-1.97

Notes: Regions are ordered in descending order by the RTI.
Sources: Author's analysis from the EPA (1994) and O*Net.

To measure the RTI we rely on O*Net (Look at Appendix A for construction of the indices). Therefore we measure the task content of occupations from a US survey. In Section 7, we further corroborate this results exploiting the task content of occupations from a European survey data, the European Working Condition Survey (EWCS). Differently from O*Net, the EWCS is a workers' survey data and it is administered by the European

Foundation for the Improvement of Living and Working Conditions (Eurofound) and has become an established source of information about working conditions and the quality of work and employment. With six waves (one every five years) having been implemented since 1990, it enables monitoring of long-term trends in working conditions in Europe. At each wave, information on employment status, working time arrangements, work organisation, learning and training, and work-life balance among others is collected. In this research we focus on the second wave (1995). More information on the items selected is found in Section 7.

In order to measure the Routine Employment Share (RSH) within province we follow Autor and Dorn (2013), and we take take two more steps. First, using the RTI we classify as routine-intensity occupations those in the highest employment-weighted third share of RTI in 1994. Table 2 reports the 24 two-digit occupations, ranked in descending order by the RTI values. It also presents the employment distribution in 1994 and the cumulative distribution. Lastly, occupations that are considered routine-intensive occupations are indicated: "Other craft and related trades workers" (ISCO 74), "Machinery operators and assemblers" (ISCO 82), "Precision, handicraft, printing, and trades workers" (ISCO 73), "Metal, machinery, and related trades workers" (ISCO 72), and "Extraction and building trade workers" (ISCO 71).

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

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

where L_{pkt} is employment in occupation k in province p at time t, $1[.]$ is a indicator function taking value of one if it is routine intensity. In other words, it is the routine employment share divided by employment share. The mean of RSH is 0.23 in 1994, and the interquartile (Iqr, henceforth) is 7 percentage points (RSH^{p25}=0.163 and RSH^{p75}=0.303). Accordingly, Table 3 shows the 1994 RSH by region ranked from low to high values where a higher RSH indicates a higher initial routine concentration.

Table 2: Task measures and RTI index by occupation

Occupation	ISCO-88	RTI	1994	Cumulative	Top 33 per cent
		(1)	(2)	(3)	(4)
Other craft and related trades workers	74	1.63	4.40	4.40	X
Machine operators and assemblers	82	1.34	4.67	9.07	X
Precision, handicraft, printing and related trades worker	73	1.02	1.17	10.24	X
Metal, machinery and related trades workers	72	0.89	7.26	17.49	X
Extraction and building trades workers	71	0.89	8.89	26.38	X
Drivers and mobile-plant operators	83	0.83	6.69	33.07	
Stationary-plant and related operators	81	0.82	1.25	34.32	
Labourers in mining construction, and manufacturing	93	0.76	5.48	39.80	
Sales and services elementary occupations	91	0.36	9.34	49.14	
Physical and engineering science associate professionals	31	0.26	1.73	50.87	
Models, salespersons and demonstrators	52	0.21	6.19	57.06	
Personal and protective services workers	51	0.14	10.02	67.08	
Life science and health associate professionals	32	-0.02	0.60	67.69	
Life science and health professionals	22	-0.18	2.62	70.30	
Office clerks	41	-0.38	8.03	78.33	
Customer services clerks	42	-0.68	4.94	83.27	
Physical, mathematical and engineering science profession	21	-0.95	1.80	85.06	
Other associate professionals	34	-1.12	5.27	90.34	
Other professionals	24	-1.19	0.48	90.81	
Corporate managers	12	-1.24	2.07	92.88	
Business associate professionals	33	-1.33	0.15	93.03	
Teaching professionals	23	-2.05	6.97	100.00	

Notes: Regions are ordered in descending order by the RTI.
Sources: Author's analysis from the EPA (1994) and O*Net.

Table 3: RSH by region

Region	RSH
Canary Islands	0.14
Andalusia	0.19
Galicia	0.19
Extremadura	0.20
Principality of Asturias	0.20
Balearic Islands	0.21
Cantabria	0.22
Castile and León	0.24
Region of Murcia	0.24
Aragon	0.25
Catalonia	0.26
Castile-La Mancha	0.26
Basque Country	0.27
Valencian Community	0.27
Madrid	0.28
La Rioja	0.32
Navarre	0.33

Notes: Regions are ordered in ascending order by the RSH.
Sources: Author's analysis from the EPA (1994) and O*Net.

4 Initial evidence of job polarisation

4.1 By occupational groups

We start our analysis by documenting the evolution of employment changes between 1994 and 2008. First, we compute employment shares for each job and their changes over time.[8] Second, we rank jobs according to their 1995 mean hourly wage.[9] Finally, we aggregate them into five equally sized groups containing almost the same percentage of employment in the initial year.[10] In Figure 1, we show the changes in employment share from 1994 to 2008 by job wage quintile. The figure shows a clear U-shaped curve of job polarisation: there is an increasing employment share at the bottom and top of the wage distribution (low and high-skilled jobs) and a decline in the employment share at the middle of the wage distribution (middle-skilled jobs). Figure 1 reveals a similar pattern as found by Anghel et al. (2014) and Sebastian (2017) for Spain, which is different from

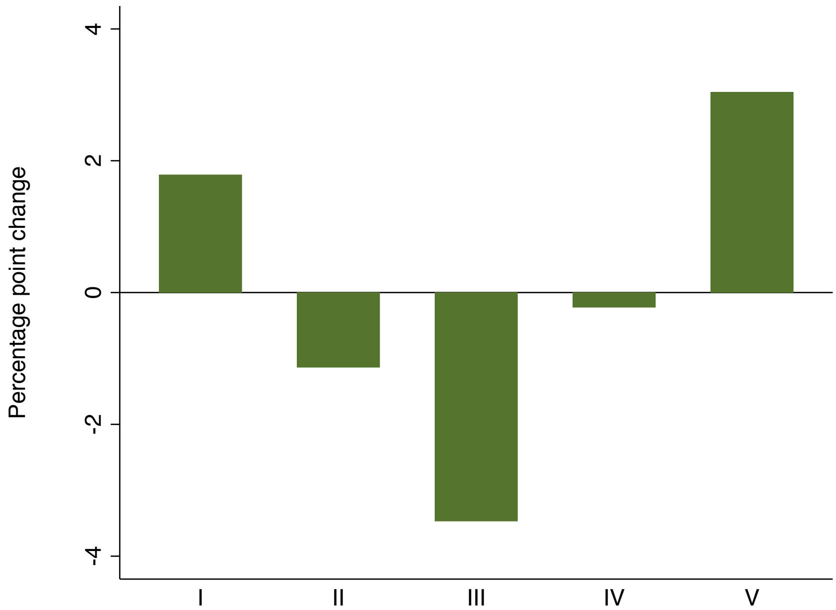
[8] In this occasion jobs are defined as the combination between two-digit occupation (ISCO-88) and one-digit industry (CNAE-93).

[9] Results remain invariant if we use the median.

[10] Jobs are defined as inseparable units therefore it is not possible to create groups that contain exactly the same percentage of employment.

the results reported by Oesch and Rodríguez Menés (2011).

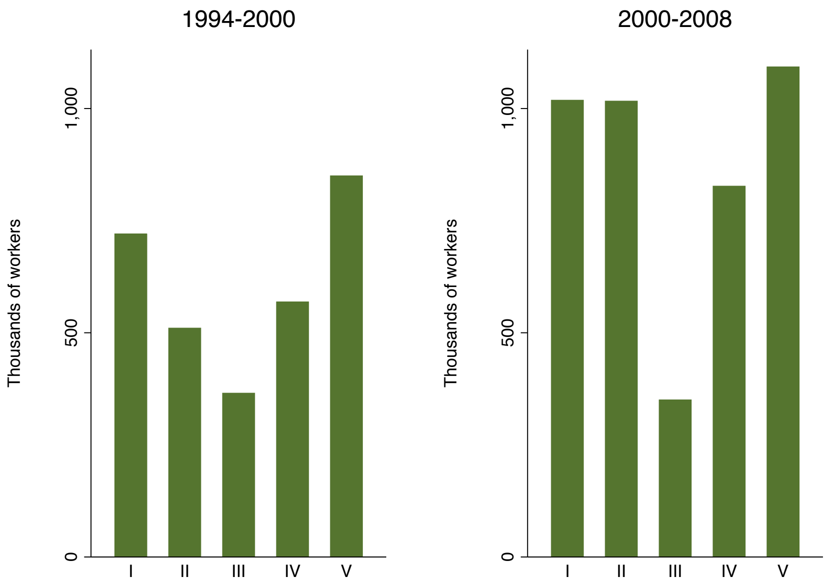
Figure 1: Evolution of employment changes between 1994 and 2010 by wage quintile



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on medan wages in 1995.
Sources: Author's analysis from the EPA (1994, 2008) and ESS (1995).

In Figure 2, we plot the percentage point change in employment share in each decade (1994-2000 and 2000-2008), ranked by hourly mean wage. Both scenarios are characterised by polarisation in employment growth. However, in the first decade there is a decline in the middle employment share of middle-skilled jobs (second, third and fourth quintiles), whereas in the second decade, just the third quintile decreased in the middle of the distribution. This pattern in the second decade is explained by the role of the construction during the first two years of the crisis (2007 and 2008).

Figure 2: Evolution of employment changes by time periods



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and ESS (1995).

To provide a more in depth analysis of these effects, we further analyse at the ISCO-88 two-digit level. Table 4 presents the major occupational groups ranked by their initial hourly mean wage (column 1), the level of employment during the period 1994 and 2008 (column 2 to 4), and the percentage point change in their employment between 1994 and 2008 (column 5). Drawing on Goos et al. (2014) we classify occupations into three groups which we label bottom, middle, and top-paid occupations. We again observe the job polarisation phenomenon among occupations: middling occupations are the ones with the higher decline (-8.56pp) compared to the bottom and top-paid occupations (-1.78pp and +10.35pp, respectively). Among the bottom-paid occupations, two out of six have a growing employment share. This group is driven by a mix effect: on the one hand service workers experience a significant positive employment growth (+3.49pp), while on the other hand, handicraft and printing workers exhibit a negative employment growth (-2.65pp). Within the middle-paid occupations, clerks (-3.33pp), metal, machinery and related workers (-2.66pp), and assemblers (+1.60pp) are those that experience the most significant employment losses. Concerning the group of top-paid occupations, those gaining more employment share between 1994 and 2008 are legal, social and related associate professionals (+4.32pp), and teaching professionals (+1.83pp).

To focus on the relevance RTI has in understanding job polarisation, Table 5 reports the average values of task occupations as well as the RTI in 1994. The middle-paid occupations have the highest positive values of RTI, therefore consistent with job polarisation. Occupations at the bottom are positive, occupations at the middle are either positive or negative, while occupations at the top score higher on the abstract measure and show negative values in RTI.

From Table 5 we classify these occupations into three major groups: routine, manual, and abstract occupations. First, the occupations with the highest RTI are defined as *routine-intensive occupations* (RI), as explained in Section 3 (occupational categories in bold). Second, we define the occupations in the top as *non routine abstract* (NRA). Finally, the remaining occupations in the bottom and middle category are defined as *non routine manual* (NRM).

One important question is whether the polarisation trend occurs in the manufacturing industry. For this purpose, we disentangle Table 4 by two sectors: manufacturing and non-manufacturing. Table 6 shows that job polarisation happens in both sectors: middle-paid occupations exhibit the highest declining shares with respect to the bottom and the top. One important difference is the manufacturing sector in the bottom is declining by 3.31 points, whereas the non-manufacturing sector is increasing by 0.21. Specifically, the manufacturing sector occupational categories losing the most are “Metal, machinery, and related trades worker” (ISCO 72), and “Handicraft and printing workers” (ISCO 74); in the non-manufacturing sector, it is “General and keyboard clerks” (ISCO 41). This result aligns with previous results from Autor et al. (2015), where they find job polarisation across economic sectors.

Table 4: Occupation, mean wage and RTI

Occupation	Code	Wage	1994	2000	2008	2008-1994	RTI
		(1)	(2)	(3)	(4)	(5)	(6)
Bottom occupations							
Labourers in mining, construction, manufacturing and transport	93	7.22	5.48	5.95	3.66	-1.82	0.76
Sales and services elementary occupations	91	8.04	9.34	8.46	10.06	0.71	0.36
Other craft and related trades workers	**74***	8.17	4.40	3.05	1.75	-2.65	1.63
Personal and protective services workers	51	8.45	10.02	10.45	13.51	3.49	0.14
Models, salespersons and demonstrators	52	9.50	6.19	5.77	5.88	-0.31	0.21
Extraction and building trades workers	**71***	9.65	8.89	9.57	7.68	-1.20	0.89
Middle occupations							
Drivers and mobile-plant operators	83	10.11	6.69	5.99	5.61	-1.07	0.83
Machine operators and assemblers	**82***	10.28	4.67	5.15	3.07	-1.60	1.34
Precision, handicraft, printing, and trades workers	**73***	10.33	1.17	0.79	0.40	-0.77	1.02
Customer services clerks	42	10.97	4.94	4.83	5.50	0.57	-0.68
Metal, machinery and related trades workers	**72***	12.78	7.26	5.91	4.59	-2.66	0.89
Office clerks	41	13.20	8.03	6.36	4.70	-3.33	-0.38
Teaching associate professionals	33	14.08	0.15	0.17	0.33	0.18	-1.33
Life science and health associate professionals	32	14.35	0.60	0.68	1.05	0.45	-0.02
Stationary plant and machine operators	81	15.34	1.25	0.97	0.92	-0.33	0.82
Top occupations							
Physical and engineering science associate professionals	31	18.44	1.73	2.16	3.11	1.38	0.26
Other associate professionals	34	18.95	5.27	8.04	9.59	4.32	-1.12
Other professionals	24	21.68	0.48	0.70	0.93	0.46	-1.19
Life science and health professionals	22	22.34	2.62	2.81	3.14	0.52	-0.18
Physical, mathematical and engineering science profession	21	24.31	1.80	2.28	3.14	1.34	-0.95
Teaching professionals	23	25.91	6.97	7.58	8.80	1.83	-2.05
Corporate managers	12	33.11	2.07	2.33	2.58	0.51	-1.24

Notes: Occupations are ranked by ascending order by the mean hourly wage in 1995. Occupations in bold and with asteristic are those defined as routine-intensity.

Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Table 5: Task measures and RTI index by occupation

Occupation	Code	Group		Abstract index	Routine index	Manual index	RTI
			(1)	(2)	(3)	(4)	
Bottom occupations							
Labourers in mining, construction,and manufacturing	93	NRM	0.34	0.48	0.38	0.76	
Sales and services elementary occupations	91	NRM	0.30	0.38	0.30	0.36	
Other craft and related trades workers	**74***	RI	0.24	0.60	0.45	1.63	
Personal and protective services workers	51	NRM	0.33	0.33	0.32	0.14	
Models, salespersons and demonstrators	52	NRM	0.34	0.40	0.29	0.21	
Extraction and building trades workers	**71***	RI	0.35	0.50	0.42	0.89	
Middle occupations							
Drivers and mobile-plant operators	83	NRM	0.30	0.45	0.37	0.83	
Machine operators and assemblers	**82***	RI	0.29	0.58	0.44	1.34	
Precision, handicraft, printing and related trades worker	**73***	RI	0.35	0.52	0.45	1.02	
Customer services clerks	42	NRM	0.40	0.28	0.23	-0.68	
Metal, machinery and related trades workers	**72***	RI	0.40	0.53	0.45	0.89	
Office clerks	41	NRM	0.40	0.35	0.24	-0.38	
Teaching associate professionals	33	NRM	0.32	0.41	0.07	-1.33	
Life science and health associate professionals	32	NRM	0.45	0.33	0.38	-0.02	
Stationary plant and machine operators	81	NRM	0.38	0.53	0.41	0.82	
Top occupations							
Physical and engineering science associate professionals	31	NRA	0.45	0.41	0.39	0.26	
Other associate professionals	34	NRA	0.47	0.29	0.18	-1.12	
Other professionals	24	NRA	0.47	0.32	0.15	-1.19	
Life science and health professionals	22	NRA	0.57	0.36	0.38	-0.18	
Physical, mathematical and engineering science profession	21	NRA	0.62	0.39	0.20	-0.95	
Teaching professionals	23	NRA	0.52	0.30	0.09	-2.05	
Corporate managers	12	NRA	0.59	0.30	0.20	-1.24	

Notes: Occupations are ranked by ascending order by the mean hourly wage in 1995. Occupations in bold and with asteristic are those defined as routine-intensity.
Sources: Author's analysis from the EPA (1994) and O*Net.

Table 6: Task measures and RTI index by type of industry

		Manufacturing				Non manufacturing			
Occupation	Code	1994	2000	2008	2008-1994	1994	2000	2008	2008-1994
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bottom occupations									
Labourers in mining construction, and manufacturing	93	8.89	8.99	5.93	-2.96	4.47	5.14	4.29	-0.18
Sales and services elementary occupations	91	1.49	0.94	0.87	-0.62	11.67	10.46	11.30	-0.37
Other craft and related trades workers	74	16.22	14.28	14.23	-1.99	1.01	0.73	0.42	-0.59
Personal and protective services workers	51	0.55	0.24	0.38	-0.17	12.83	13.17	14.19	1.36
Models, salespersons and demonstrators	52	1.02	0.93	1.05	0.03	7.73	7.06	6.86	-0.87
Extraction and building trades workers	71	4.46	5.07	6.85	2.39	10.20	10.76	11.06	0.86
Middle occupations									
Drivers and mobile-plant operators	83	3.57	3.43	4.44	0.87	7.61	6.68	6.02	-1.59
Machine operators and assemblers	82	18.73	22.69	18.68	-0.05	0.50	0.49	0.51	0.01
Precision, handicraft, printing and related trades worker	73	4.27	3.27	2.40	-1.87	0.25	0.13	0.09	-0.15
Customer services clerks	42	1.59	1.70	1.75	0.16	5.93	5.66	5.93	0.01
Metal, machinery, and related trades workers	72	15.83	11.79	10.26	-5.57	4.60	3.68	3.07	-1.53
Office clerks	41	6.60	5.13	4.90	-1.70	8.45	6.69	4.72	-3.73
Teaching associate professionals	33	0.19	0.22	0.33	0.14	0.19	0.22	0.33	0.14
Life science and health associate professionals	32	0.20	0.38	0.52	0.32	0.72	0.76	0.98	0.26
Stationary-plant and related operators	81	4.22	4.07	5.62	1.41	0.37	0.15	0.18	-0.19
Top occupations									
Physical and engineering science associate professionals	31	2.43	3.34	3.87	1.45	1.52	1.84	2.51	0.99
Other associate professionals	34	4.16	6.57	8.71	4.55	5.60	8.43	9.52	3.91
Other professionals	24	0.06	0.11	0.14	0.08	0.60	0.85	0.88	0.29
Life science and health professionals	22	0.28	0.29	0.42	0.14	3.31	3.48	3.25	-0.06
Physical, mathematical and engineering science profession	21	2.01	2.11	3.46	1.45	1.73	2.32	2.70	0.97
Teaching professionals	23	0.40	1.21	1.40	1.00	8.91	9.28	8.87	-0.04
Corporate managers	12	3.02	3.47	4.11	1.09	1.79	2.02	2.31	0.52

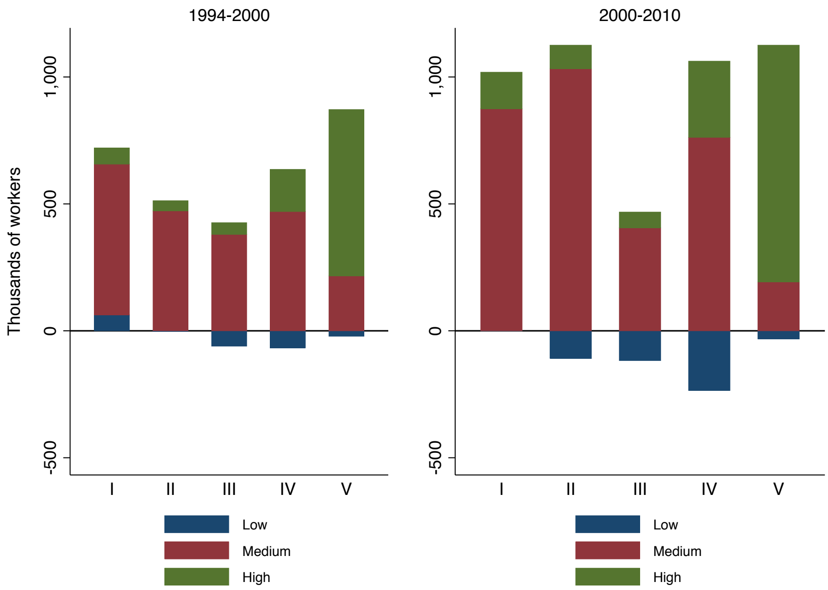
Notes: Occupations are ranked by ascending order by the mean hourly wage in 1995. Occupations in bold and with asteristic are those defined as routine-intensity.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

4.2 By demographic groups

We proceed with our analysis by examining changes in demographic groups, measured by educational qualification, migration status, and type of industry. Figure 3 plots changes in total employment in each decade from 1994 to 2008 by occupation wage quintiles. Graduates are represented by individuals with a university degree. Non-graduates are divided in two: low (primary and secondary education) and medium (upper secondary and post-secondary, non-tertiary education).[11]

Figure 3 shows that the low educated workers are losing employment in the middle of the wage distribution. Moreover, medium- and highly educated workers are gaining employment along the whole distribution, but medium educated workers have gained at the bottom whereas high educated at the top of the wage distribution. We further use number of years of education instead of using the categorical variable consisting in the highest level of educational attainment reached by workers. Results are robust to this alternative specification.

Figure 3: Evolution of employment changes by educational qualification and decade

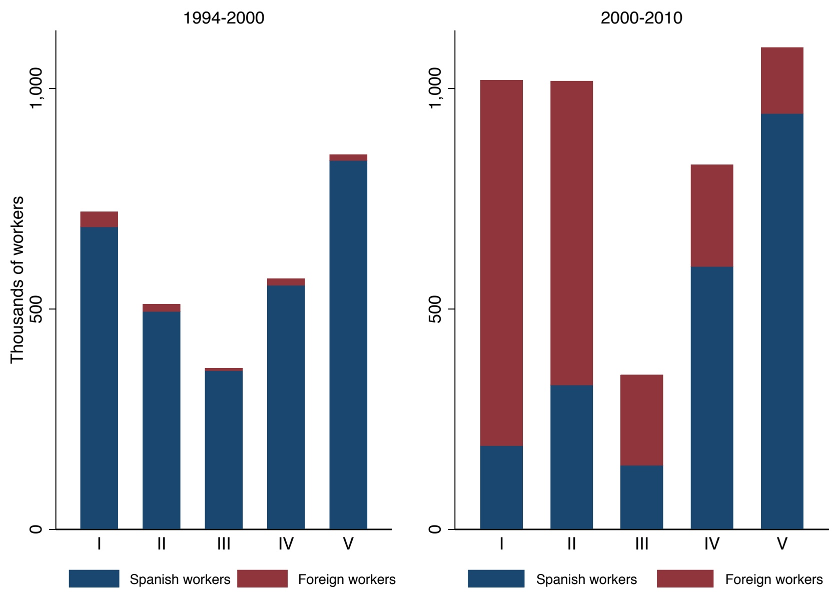


Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 3 shows absolute net employment change in job quintiles (in thousands of workers) by educational classification.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and ESS(1995).

[11]The usual ISCED division into low, medium and high is adopted where low is equivalent to ISCED 0-2 (i.e., primary and lower secondary education), medium is given by ISCED 3-4 (i.e., upper secondary and post-secondary non-tertiary education) and high is ISCED 5-7 (i.e., tertiary education).

To understand how migration status relates to job polarisation, in Figure 4 the employment distribution is broken into Spanish workers and foreigners. One observation is that the employment distribution of native employees is polarized in both periods but in larger magnitude in the first period. When we look at migrants, we observe an increase of foreign workers in bottom-paid occupations. Two thirds of the growth of jobs of the first quintile are taken by the immigrant workforce. These figures explain 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. Often these jobs were taken by workers with higher qualifications, giving way to a specific problem of over-education.

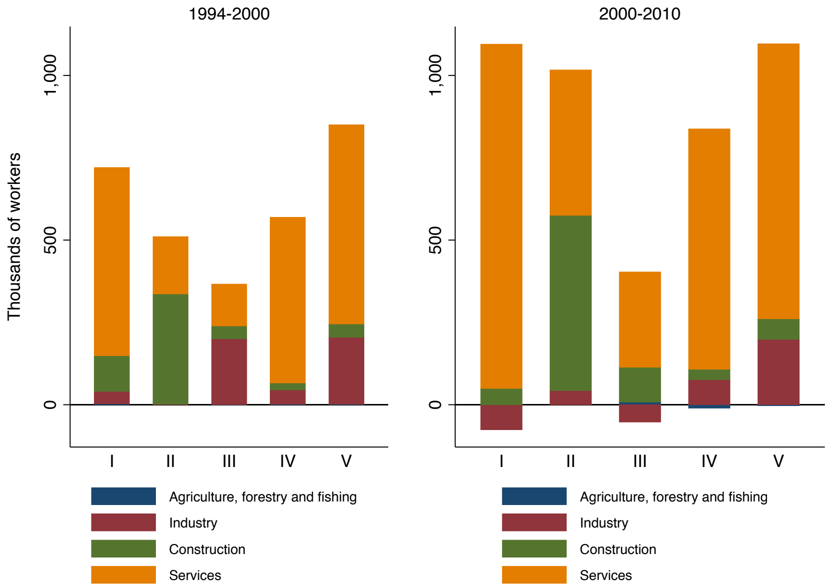
Figure 4: Evolution of employment changes by migration status and decade



Notes:Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 4 shows absolute net employment change in job quintiles (in thousands of workers) by Spanish workers (blue) and foreign workers (red). *Sources*: Author's analysis from the EPA(1994, 2000, 2008) and ESS(1995).

Analysing by industry, Figure 5 shows changes in thousands of workers by type of industry. In order to do so, we use a classification of sector of activity comprising a manageable number of categories: agriculture, industry, construction, and services. Figure 5 reproduces the absolute changes in employment by quintile and sector of activity. Focusing on the main patterns, the following factors can be highlighted: first, services contribute in all quintiles, with a larger presence at the two extremes of the distribution. Moreover, the contribution of services outweights that of agriculture, industry, and construction. Second, the growth of construction is located, most of it, in the second quintile. Third, in the second decade, the destruction of employment is explained by the industry.

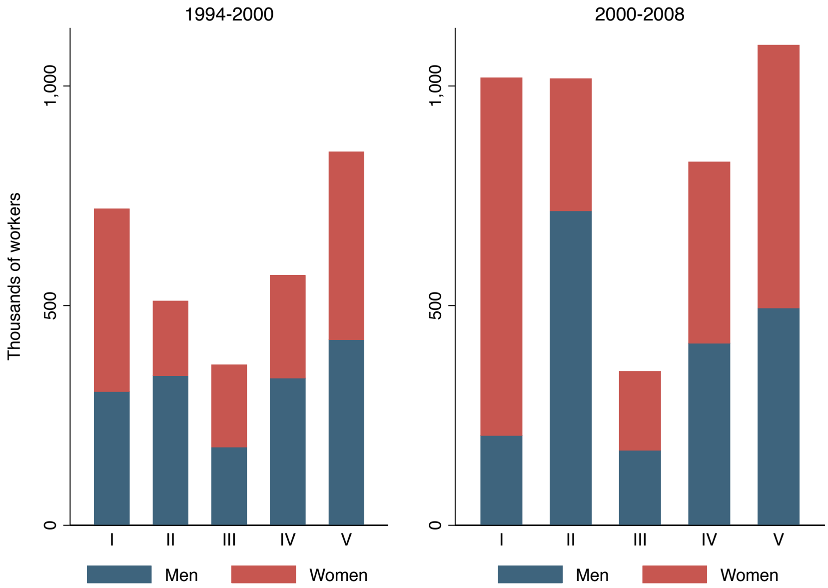
Figure 5: Evolution of employment changes by type of industry and decade



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 5.5 shows absolute net employment change in job quintiles (in thousands of workers) by type of industry.
Sources: Author's analysis from the EPA (1994, 2008) and ESS (1995).

To complete the initial analysis, in Figure 6 we replicate the analysis by gender. Our findings are in line with previous figures. There are several highlights found in the chart: first, overall the gender perspective does not change the conclusion presented in relation to the nature of employment distribution. Both men and women have an employment distribution that fits with the polarisation phenomenon: losing employment in the middle of the wage distribution while gaining at the extremes. Second, within this general shared pattern, the employment change of women during both decades is more intensively polarizing. Third, the lack of growth of female employment in the second quintile. This "anomaly" is explained by the role of construction in this segment of the job distribution, a male dominated industry.

Figure 6: Evolution of employment changes by gender and decade



Notes:Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 5.4 shows absolute net employment change in job quintiles (in thousands of workers) by gender.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and ESS(1995).

4.3 By labour market area

Table 7 presents descriptive statistics of the sample for a number of measures. This includes the routine employment share in local labour markets (RSH), the relative graduate share (GradSH), the migrant population share (MigSh), and the manufacturing population share (ManfSH) in 1994, 2000 and 2008.

As one can expect, the employment share in routine-intensity occupations decreases by 4 percentage points in two decades (from 1994 to 2008). Similarly, the relative share of manufacturing looses 2 percentage points in the period under study. On the contrary, the relative share of graduates and relative share of migrants increases over time. In the case of relative share of graduates grows in 6 percentage points in each decade, almost doubling between 1994 and 2008. The relative share of migrants increases during both decades and has accelerated during the second decade (+0.1pp), being almost explained by the increased in high-skilled migrants.

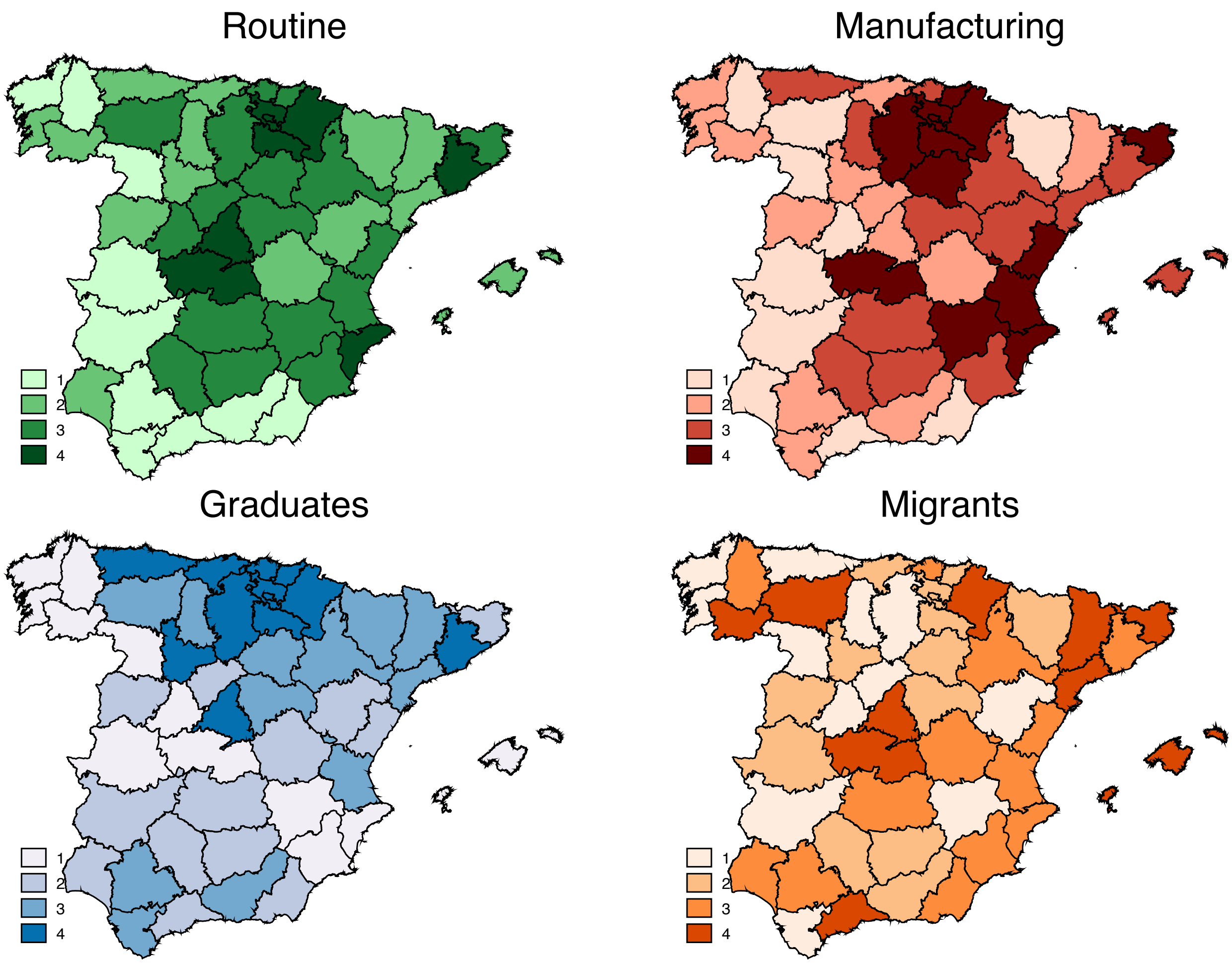
Table 7: Summary statistics

	1994			2000			2008		
	Mean	Std. Dev	Iqr	Mean	Std. Dev	Iqr	Mean	Std. Dev	Iqr
RSH	0.233	0.050	0.070	0.213	0.047	0.061	0.190	0.030	0.033
GradSH	0.193	0.052	0.060	0.255	0.056	0.064	0.316	0.068	0.086
MigSH	0.004	0.004	0.004	0.009	0.010	0.010	0.109	0.070	0.113
HigMigSH	0.001	0.001	0.002	0.003	0.003	0.002	0.022	0.018	0.023
LowMigSH	0.003	0.003	0.002	0.006	0.007	0.007	0.087	0.055	0.094
ManufSh	0.143	0.058	0.082	0.131	0.055	0.076	0.119	0.038	0.051

Sources: Author's analysis from the EPA(1994, 2000, 2008).

In the light of the above findings, Figure 7 shows the graphical distribution of routine, manufacturing, graduates, and migrants across Spanish province in 1994. Several important insights are revealed; first, higher levels in 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 higher levels of graduates shares are Madrid and Barcelona, provinces that are typically specialised towards professionals, scientific and technical activities. Moreover, graduates share is more concentrated in the north with high presence in Asturias, Cantabria, Basque Country, Navarra and La Rioja. Third, migrants working share are instead more spread geographically, with high concentration in the Mediterranean area.

Figure 7: Graphical distribution of routine, manufacturing, graduates and migrants employment share in 1994



Notes: We include the same number of provinces inside each group. As we have 50 provinces, our 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 (1994, 2008).

5 Model specification

Until now, the descriptive statistics in Table 1 to Table 7, and Figure 1 through Figure 7 showed preliminary evidence of the displacement of labour on routine tasks, leading to a polarized employment distribution.

To test more rigorously the effect that technology has on labour and exploiting our regional database, we follow the Routine Biased Technical Change (RBTC) hypothesis. RBTC predicts that recent technological change is biased towards replacing labour in routine tasks (tasks that require methodological repetition, therefore being easier to automate). This progressive substitution of technology leads to two different effects depending on workers' relative comparative advantage: first, technology fosters workers who have a relative advantage in abstract tasks, expecting therefore a growth in high-skill occupations. Second, since technology substitutes routine workers with a comparative advantage in low-skill tasks (rather than in high-skilled tasks), we expect a greater reallocation of workers in jobs with routine tasks in non-manual occupations.

In the local labour market, we expect that provinces that initially have higher routine employment share, experience two different effects: first, a higher relative employment decline in routine occupations; second, a higher relative employment increase in manual (low-skilled workers) and abstract (high-skilled workers).

To test this hypothesis, we build on Autor and Dorn (2013) to analyse variation across the Spanish local market. We use the following model:

$$\Delta \mathrm{Y}_{pct} = \alpha_t + \beta_1 \mathrm{RSH}_{pt-1} + \beta_4 \mathrm{X}'_{pt-1} + \gamma_c + \delta_t + \epsilon_{pct} \tag{3}$$

where $\Delta \mathrm{Y}_{pct}$ is the change in local employment shares in (1) routine, (2) manual, and (3) abstract occupations, in province p located in region c, between the initial year and the final year considered (1994-2008). The RSH_{pt-1} is the variable capturing the initial local employment share of routine occupations in province p (see Section 3.1 for further details on how is derived). In order to control for potential shifts in local supply and demand, a vector of covariates is included (X'_{jt-1}). This includes information on the local initial relative shares of graduates and migrants, and the local initial share of manufacturing employment. To be more precise, the latter variable tries to capture the international import competition. To control for region-specific time trends, we include a dummy for regions in Spain (NUTS-2). The stacked regression also includes a dummy for time periods to account for changes over time.

6 Results and discussion

6.1 Changes in routine employment occupations

The first test is to identify whether historically routine intensive provinces have larger declines in routine occupations. We estimate equation (3) by ordinary least squares (OLS).

Table 5.8 displays the estimates of the OLS regression model in routine occupations (panel a), graduates (panel b), and non-graduates (panel c). Table 5.8 also shows the estimates for time periods and for the stacked specification.

Table 8 (panel a) confirms that provinces with higher levels of routine employment shares, experience a higher decline in routine occupations. Single decades estimates are positive but only significant in the second decade, suggesting that the magnitude of this effect increases over time. The OLS estimates in panel (a) column (1) point out a decrease of 1.06 percentage points for provinces starting at the 75^{th} percentile more than those at the 25^{th} percentile of the routine employment distribution. The sign of this coefficient is the same as the findings in the US but the coefficient is lower. Autor and Dorn (2013) show that US commuting zones with a routine employment share at the 75^{th} percentile in 1990, decreased 1.8 percentage points more than a US commuting zone at the 25^{th} percentile during the first decade.

We continue our analysis by dividing the population between graduate workers (panel b) and non-graduate workers (panel c). Two main remarks can be made: first, for graduate workers, the RSH estimates are not significant and negative, describing job polarisation as a non-graduate phenomenon. Second, for non-graduate workers, the RSH estimates are significant, positive, and the effect increases over time.

Table 8: Changes in routine occupations

	1994—2000	2000—2008	1994—2008
	(1)	(2)	(3)
Panel A: All			
RSH_{pt-1}	-0.106	-0.439*	-0.537*
	(0.171)	(0.222)	(0.289)
R^2	0.016	0.119	0.188
Panel B: Graduates			
RSH_{pt-1}	-0.347	-0.738	-0.456
	(1.293)	(0.454)	(1.177)
R^2	0.305	0.155	0.115
Panel C: Non-graduates			
RSH_{pt-1}	-0.269*	-0.411**	-0.676**
	(0.136)	(0.194)	(0.280)
R^2	0.099	0.131	0.138
N	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

The next stage of the analysis investigates the role of potential shifts in demand and supply in non-graduate workers. In Table 9 column 1-3, the econometric specification comprises the routine employment share, the relative local graduate share, and the relative local migrant share. In columns 4-6, we include the initial share of manufacturing.

Looking at column 1-3, our results indicate that the initial level of routine is significant, and the magnitude is the same as the previous case. The inclusion of the initial graduate share and the initial migrant concentrations do not affect our results. The initial human capital has a negative effect on employment changes in non-graduate workers, being higher in the second decade. Therefore, higher levels of human capital experience a higher decline in the middle of the employment distribution for non-graduate workers. Differently from graduates, the initial relative share of migrants appears not significant in the first period and the stacked period. However, it is significant in the second decade. This predicts that provinces with initially higher migrant share experience a higher rise in routine occupations.

For columns 4-6, the initial share of manufacturing employment is included. It should be noted that the correlation between the main regressor of interest (RSH) and the initial share of manufacturing is high (0.48). When all the controls are added, the initial routine share is significant and increases its magnitude. The control variables are not significant in the first decade and the specification with stacked periods. However, during the 2000s, the initial migrant concentration has a positive effect and the initial share of manufacturing has a negative effect on employment changes in non-graduate workers.

Considering the effect of technology in routine occupations, provinces with initially higher specialization in routine-intensive occupations experience larger declines in non-graduate routine-intensive occupations.

Table 9: Changes in routine occupations

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
RSH_{pt-1}	-0.301**	-0.314*	-0.616***	-0.196*	-0.841**	-1.225***
	(0.131)	(1.165)	(0.045)	(0.099)	(0.391)	(2.02)
$GradSh_{pt-1}$	-0.134**	-0.176*	-0.306**	-0.034	0.053	0.026
	(0.060)	(.103)	(.142)	(0.083)	(.075)	(0.129)
$MigSh_{pt-1}$	0.063	0.244**	0.248	-0.189	0.189*	0.165
	(0.677)	(0.116)	(0.157)	(0.571)	(0.098)	(0.126)
$ManufSh_{pt-1}$				-0.370	-0.852***	-1.030
				(0.333)	(0.290)	(0.747)
R^2	0.185	0.233	0.237	0.297	0.555	0.529
N	50	50	100	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

6.2 Changes in manual employment occupations

In analysing changes in manual jobs, we expect that low-skilled workers reallocate from routine to manual tasks at the bottom of the employment distribution. This follows Autor and Dorn (2013) framework. The assumption behind the previous idea is that low-skilled workers comparative advantage is higher in low-skilled than in high-skilled tasks.

The results contained in Table 10 confirm this hypothesis. It displays the estimates of the regression model for all the workers (panel a), graduates (panel b), and non-graduates (panel c). OLS results point out a significant and positive effect of technological exposure on non-graduates in every decade as well as stacked periods. Therefore, provinces with initially higher routine tasks have a larger increase in non-graduate, manual occupations.

Table 10: Changes in manual occupations

	1994—2000	2000—2008	1994—2008
	(1)	(2)	(3)
Panel A: All			
RSH_{pt-1}	0.243	0.296	0.554
	(0.237)	(0.193)	(0.433)
R^2	0.084	0.143	0.128
Panel B: Graduates			
RSH_{pt-1}	1.227	0.726	2.075
	(0.742)	(0.843)	(1.558)
R^2	0.221	0.162	0.165
Panel C: Non-graduates			
RSH_{pt-1}	0.146*	0.255*	0.409**
	(0.079)	(0.133)	(0.180)
R^2	0.134	0.156	0.167
N	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Table 11 shows the results of the analysis on the reallocation of non-graduate workers in manual occupations. Again, we include the initial relative labour supply shares of graduates and low-skilled migrants (column 1-3) and the initial local share of manufacturing (column 3-6).

With respect to the initial labour supply share (column 1-3), the RSH coefficients are significant and positive. Therefore, the main results still hold when the control variables are plugged-in. Looking at the initial share of graduates, the results are significant, meaning that provinces with higher graduate share in the first year are negatively associated with employment changes in non-graduate manual occupations during the whole period. Therefore, the higher the graduate shares, the larger the decline in non-graduate manual occupations. However, no effect is found using the initial relative share of migrants.

In the last columns (4-6), the initial share of manufacturing employment is conditioned. Three observations can be done. First, the point estimate on the RSH variable remains significant. Second, the initial share of human capital is negatively associated with employment changes in manual occupations. Third, the initial share of migrants and the initial share of manufacturing do not have any effect.

Table 11: Changes in manual occupations: Non graduates

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
RSH_{pt-1}	0.102*	0.212**	0.208**	0.283**	0.131**	0.179**
	(0.118)	(0.095)	(0.099)	(0.109)	(0.057)	(0.068)
$GradSh_{pt-1}$	-0.211**	-0.167***	-0.372***	-0.153	-0.232***	-0.378***
	(0.094)	(0.044)	(0.113)	(0.105)	(0.052)	(0.132)
$MigSh_{pt-1}$	-1.227	0.128	-1.159	-1.319	0.235	-1.150
	-1.104	(0.592)	-1.501	-1.092	(0.582)	-1.533
$ManufSh_{p,t-1}$				-0.207	0.229*	0.0206
				(0.141)	(0.120)	(0.114)
R^2	0.456	0.388	0.567	0.488	0.449	0.567

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Overall, the econometric analysis provides evidence for the displacement of middle-workers from routine occupations to manual occupations. Our results clearly suggest that provinces with initial higher level of routine task specialisation predict higher changes in manual occupations at the bottom of the distribution. Moreover, the initial number of graduate shares is significant and negatively associated to changes with non-graduates employment changes at the bottom of the occupational distribution. This finding differs from the result obtained by Autor and Dorn (2013) for the US.

6.3 Change in abstract employment occupations

So far we have showed the decline of employment share for non-graduate routine job workers and its next reallocation at the low part of the employment distribution. To finish the puzzle, we need to study employment changes in abstract occupations at the upper part of the occupational distribution. As explained in Section 5, due to a complementarity effect between high-skilled workers and technology, the model predicts an increased level of employment share for graduate abstract task workers.

In Table 12, we investigate the effect that technology has at the top of the employment distribution. Table 12 presents changes in abstract occupations for the total number of workers (panel a), graduate workers (panel b), and non-graduate workers (panel c). One expectation can be formulated from the model: a positive effect of technological exposure on employment in abstract occupations. However, the initial relative share of routine labour is not statistically significant in any of our three scenarios. Therefore, we can conclude that technological change has not caused an upward shift of the marginal high-skilled workers.

Table 12: Changes in abstract occupations

	1994—2000	2000—2008	1994—2008
	(1)	(2)	(3)
Panel A: All			
RSH_{pt-1}	0.165	0.129	0.165
	(0.106)	(0.088)	(0.106)
R^2	0.037	0.193	0.194
Panel B: Graduates			
RSH_{pt-1}	0.001	2.897	3.226*
	(0.625)	(1.828)	(1.897)
R^2	0.062	0.155	0.158
Panel C: Non-graduates			
RSH_{pt-1}	0.405	0.709	1.102
	(0.345)	(0.556)	(0.782)
R^2	0.099	0.221	0.227
N	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Because of the absence of technological effect, the focus of the analysis shifts to the role of labour supply and demand shifter in increasing of graduate employment in top occupations. The results of the analysis are presented in Table 13.

Table 13 includes the initial local routine employment, the initial share of graduate concentrations, and the initial share of high-skilled migrants. The initial relative share of graduates is significant and negatively associated with high-educated workers changes in the first decade, while it is significant and positively associated with this variable during the second decade. The explanation behind this is a general education catch-up across areas during the first decade. Provinces with a larger proportion of worker with university degrees experiences the smallest increases in education, while in the 2000s, initial local graduate share has a positive effect on changes in graduate abstract occupations. For migrant share, the initial local high-skilled migration is significant and has a positive effect on changes in graduate abstract occupations. Provinces with higher high-skilled migration share have a larger increase in abstract occupations. Our intuition is that this variable is capturing the expanding process of the European Union.

In column 4-6, the full set of explanatory variables is included, incorporating the initial share of manufacturing employment. The introduction of initial share of manufacturing employment does not alter our results.

Table 13: Changes in abstract occupations: Graduates

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
RSH_{pt-1}	0.114	0.127	0.240	0.668	0.074	0.663
	(0.315)	(0.179)	(0.393)	(0.720)	(0.380)	-1.022
$GradSh_{pt-1}$	-0.317**	0.205**	-0.112	-0.193**	0.233**	0.0315
	(0.124)	(0.101)	(0.214)	(0.093)	(0.112)	(0.302)
$MigSh_{pt-1}$	0.407**	0.609***	1.017***	0.401**	0.637***	1.010***
	(0.172)	(0.176)	(0.318)	(0.190)	(0.173)	(0.341)
$ManufSh_{pt-1}$				-0.558	-0.107	-0.645
				(0.590)	(0.231)	(0.798)
R^2	0.226	0.367	0.489	0.293	0.427	0.519

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and O*Net.

To summarise, technology exposure (the initial routine share) does not play any role in explaining changes in graduate abstract occupations. An important observation different from Autor and Dorn (2013) is that the initial share of graduates and migrants are positively related to changes in graduate abstract occupations.

7 Extensions and robustness checks

7.1 Potential endogeneity

The measurement of the causal effect of technology on local labour markets could require one identification assumption which is discussed in the literature. The assumption of OLS estimates is that the variation of routine occupation shares (RSH) is exogenous and is not driven by time-varying local specific unobservable. In what follows, we discuss this problem.

In order to understand the previous problem, a simplified version of equation (3) is used to replace the main regressor of interest:

$$\mathrm{RSH}_{pt-1} = RSH_p^* + \upsilon_{pt-1} \tag{4}$$

Replacing now (4) in (3), the latter equation can be rewritten as:

$$\Delta \mathrm{Y}_{pct} = \alpha_t' + \beta_1' \mathrm{RSH}_p^* + \beta_2' \upsilon_{pt-1} + \epsilon_{pt}' \tag{5}$$

where RSH_p^* represents the long-run quasi-fixed component of industrial structure which in our model determines provinces' routine occupation shares. Additionally, υ_{pt-1} stands for unobservables. In other words, time-varying attributes that affect at the same time changes in employment share ($\Delta \mathrm{Y}_{pt}$) and local routine occupation shares (RSH). If that is the case, we will obtain biased OLS estimates in equation (3). There are two possibilities:

(1) If $\beta_2' > \beta_1'$ and Var $(\upsilon_1) > 0$ in equation (5), OLS estimates of β_1 in equation (3) will be upward biased.

(2) If $\beta_2' < \beta_1'$ and Var $(\upsilon_1) > 0$ in equation (5), OLS estimates of β_1 in equation (3) will be downward biased.

To address this endogeneity problem, we construct an instrumental variable for the routine employment share levels based on the Autor and Dorn's (2013) instrument. It consists of exploiting historical local industry information to remove the long-run quasi-fixed component of the routine occupation share. The instrument is constructed as follows:

$$\text{RSH}_p^{IV} = \sum \text{E}_{i,p,1977} * \text{R}_{i,-p,1977} \tag{6}$$

where $\text{E}_{i,p,1977}$ is the employment share in industry i in province p, and $\text{R}_{i,-p,1977}$ is the routine occupation employment share in industry i in all the Spanish provinces except p.

This measure is an appropriate instrumental variable for RSH: we expect that past industrial information is correlated with the long-run component and uncorrelated with current economic shocks. Therefore, we can obtain an exogenous measure for the routine employment share.

In Table 14, we estimate equation (6) by two-stage least squares (2SLS) regression model. Panel (a) displays the changes in routine occupations, panel (b) shows the changes in manual occupations, and panel (c) indicates the changes in abstract occupations. Table 14 reports as well the the Kleibergen-Papp F-statistics from each of the first-stage regression.[12]

As can be seen from Table 14, the initial routine employment share coefficient for the routine, manual, and abstract do not differ from the main analysis. However, the Kleibergen-Papp F-statistics is below the Staiger and Stock's (1997) rule of thumb threshold of 10. Although the instrument is not strong, the results are in line with those of the baseline analysis.

[12] Look at Appendix B for the first stage.

Table 14: Changes in occupations

	1994—2008
Panel A: Routine occupations	
RSH_{pt-1}	-0.406**
	(0.192)
Panel B: Manual Occuparions	
RSH_{pt-1}	-0.505*
	(0.286)
Panel C: Abstract occupations	
RSH_{pt-1}	-0.094
	(0.104)
First stage	
F-K test	6.990
N	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1977, 1994, 2000, 2008) and O*Net.

7.2 Contemporaneous labour supply changes

To explore the effect of the technology, the model must control for contemporaneous labour supply changes. The analysis addresses this by including the relative growth of graduates and migrants. Table 15 reports the estimates from OLS for the routine (panel a), manual (panel b) and abstract (panel c) specifications. It contains information on single decades and stacked periods.

Looking now to non-graduates 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.

Panel b displays changes in manual occupations. The initial relative share of routine is positive related with changes in manual occupations. It suggests that the growth at the bottom part of employment distribution is explaining by technological exposure, confirming previous results. However, OLS results show a more substantial relevance of labour of labour supply changes. Initial local graduates' concentrations are significantly related to manual occupations and this association grows over time.

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

Table 15: Conditional on local labour supply

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-graduates routine occupations						
RSH_{pt-1}	-0.269*	-0.411**	-0.676**	-0.269*	-0.415**	-0.689**
	(0.137)	(0.194)	(0.281)	(0.137)	(0.195)	(0.278)
$GradSh_{pt-1}$				-0.067	-0.243*	-0.301***
				(0.0577)	(0.131)	(0.112)
$MigSh_{pt-1}$				0.0137	0.00750	0.0213
				(0.0110)	(0.0198)	(0.0189)
Panel B. Non-graduate manual occupations						
RSH_{pt-1}	0.146	0.255*	0.409	0.138	0.256***	0.398**
	(0.238)	(0.135)	(0.341)	(0.154)	(0.078)	(0.161)
$GradSh_{pt-1}$			-0.365**	-0.312***	-0.675***	
				(0.136)	(0.037)	(0.153)
$MigSh_{pt-1}$			-0.019	-0.005	-0.025	
				(0.013)	(0.010)	(0.015)
Panel C. Graduate abstract occupations						
RSH_{pt-1}	0.405	0.709	1.102	0.378	0.671*	1.108*
	(0.345)	(0.556)	(0.782)	(0.354)	(0.375)	(0.635)
$GradSh_{pt-1}$			0.0184	0.727**	0.719	
				(0.217)	(0.313)	(0.493)
$MigSh_{pt-1}$				0.052*	0.002	0.057
				(0.026)	(0.049)	(0.064)
N	50	50	100	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

7.3 Alternative database: EWCS

Until now, and following previous research, the study relied on O*Net to measure the RTI index. To test whether the results are robust to the use of this database (designed for the US), the same analysis is performed using the European Working Condition Survey (EWCS) dataset. One advantage is that assumptions on task composition between the US and Spain can be relaxed, the EWCS collect information on the latter country. However, there is no perfect correspondence between the two datasets, we selected those items that are similar in both databases (see Appendix C for more detailed).

Table 16 reports OLS and 2SLS estimates using the EWCS. Following Autor and Dorn (2013) as close as possible, a measure of task intensity at the occupational level was constructed. For the abstract tasks, responses on "learning new things", "solving unforeseen problems", and "assessing yourself the quality of your job" are retained. For the manual tasks, we selected questions on "physical strength" (e.g., carrying or moving heavy loads), "skill or accuracy in using fingers/hands" (e.g., repetitive hand or finger movements), and "physical stamina" (e.g., painful positions at work). For routine tasks, we opt for routine activities they performed within their job: "does your main job involve (1) dealing with people, (2) repetitive tasks, (3) dealing with customers". The items for manual and routine tasks are on a 7-point scale ranging from 1 ("all of the time") to 7 ("never"). These variables in Likert scale are then normalized to range from 0 to 1. After collapsing each index at the ISCO-88 two-digit level, weighting each observation for the Spanish sampling weight, we merge the EWCS index to the EU LFS. The results obtained employing this database are very similar to the ones reported above, both in terms of statistical significance and size of the coefficients.

Table 16: Finding using EWCS

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-graduates routine occupations						
RSH_{pt-1}	-0.0676	-0.264*	-0.316*	-0.176	-0.240*	-0.416**
	(0.108)	(0.155)	(0.181)	(0.136)	(0.134)	(0.204)
$GradSh_{pt-1}$				-0.164**	-0.216*	-0.373**
				(0.0704)	(0.109)	(0.155)
$MigSh_{pt-1}$				0.043	0.273**	0.312
				(0.083)	(0.127)	(0.187)
Panel B. Non-graduate manual occupations						
RSH_{pt-1}	0.344	0.341***	0.691*	0.065	0.232**	0.304*
	(0.238)	(0.135)	(0.341)	(0.154)	(0.078)	(0.161)
$GradSh_{pt-1}$				-0.204**	-0.130**	-0.328***
				(0.097)	(0.052)	(0.120)
$MigSh_{pt-1}$				-0.019	-0.005	-0.025
				(0.013)	(0.010)	(0.015)
Panel C. Graduate abstract occupations						
OLS						
RSH_{pt-1}	0.144	1.016*	1.156	0.0414	0.212	0.171
	(0.374)	(0.579)	(0.882)	(0.296)	(0.188)	(0.341)
$GradSh_{pt-1}$				-0.324***	0.177	-0.148
				(0.117)	(0.115)	(0.215)
$MigSh_{pt-1}$				0.450**	0.596***	1.047***
				(0.183)	(0.179)	(0.329)
N	50	50	100	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and EWCS (2000, 2005, 2010, 2015).

7.4 Alternative definition of RSH

The overall analysis indicates that in Spanish provinces with higher routine specialization experience declines in routine occupations and larger increases in manual occupations. Nevertheless, the routine task specialisation is not able to explain the increases in high-skilled occupations. The initial graduate share and the initial high-skilled migrants are the main drivers of the employment growth at the top of the employment distribution.

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, we re-construct the technology exposure measure using the top 40 per cent. Table 17 reports the estimates obtained by the new definition. In line with the baseline results, the estimates on the alternative routine share measures are similar in magnitude to the baseline, although they are less precisely estimated. We confirm the results presented above.

Table 17: Robustness check: top employment-weighted 40 per cent

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-graduates routine occupations						
OLS						
RSH_{pt-1}	-0.206	-0.431**	-0.639*	-0.298*	-0.400*	-0.713*
	(0.172)	(0.199)	(0.330)	(0.174)	(0.209)	(0.348)
$GradSh_{pt-1}$				-0.258**	-0.336*	-0.591
				(0.123)	(0.171)	(0.261)*
$MigSh_{pt-1}$				-0.018	0.268*	0.240
				(0.080)	(0.136)	(0.162)
Panel B. Non-graduate manual occupations						
OLS						
RSH_{pt-1}	0.193	0.291**	0.229**	0.022	0.235*	0.142
	(0.254)	(0.122)	(0.107)	(0.116)	(0.119)	(0.158)
$GradSh_{pt-1}$				-0.386**	-0.248***	-0.624***
				(0.143)	(0.085)	(0.185)
$MigSh_{pt-1}$				-0.146	0.044	-0.109
				(0.151)	(0.081)	(0.208)
Panel C. Graduate abstract occupations						
OLS						
RSH_{pt-1}	0.405	0.709	1.102	0.125	0.271	0.395
	(0.345)	(0.556)	(0.782)	(0.362)	(0.189)	(0.464)
$GradSh_{pt-1}$				-0.512**	0.399*	-0.113
				(0.229)	(0.203)	(0.403)
$MigSh_{pt-1}$				0.509**	0.719**	1.228**
				(0.245)	(0.273)	(0.481)

Notes: All models include an intercept and region dummies. The stacked regression includes 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. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and O*Net.

8 Conclusion

During the last two decades, the employment structure of many developed economies has undergone substantial changes. On the supply side, many economies experience the simultaneous effects of an ageing and more feminine labour force, as well as increasing supplies of higher-education and foreign workers. On the demand side, economists have paid attention to employment effects of technological change and trade. This paper contributes to this literature by examining the relationship between technological progress and employment polarisation in Spain exploiting the spatial variation of technological exposure at the local labour market.

We find that provinces with initial higher level of routine task adopted technology faster and witnessed a larger reallocation of routine employment at the bottom of the employment distribution. However, technology does not have any effect at the top of the employment distribution, countering Autor and Dorn's (2013) predictions. Our econometric analysis highlights the importance of supply side factors in order to understand the main drivers behind the growth at the upper part of the employment distribution. Concretely, initial high-skilled migrants concentrations and initial local graduates' concentrations show larger increases at the top part of the employment distribution.

In the last section we further cope with the potential endogeneity of the share of routine work within territories, we assess the robustness of OLS analysis employing the historical pattern of specialisation in each province as an instrumental variable. Results are in line with the OLS.

One important observation can be made from the study. While employment in Spain experienced a polarising trend at the occupational level between 1994 and 2008, technology is far from being represented as the only explanation for this phenomenon. As we can see from our analysis, there is a strong importance of demographic factors on employment changes. The dramatic changes in graduate labour supply affect the downward shift of middle-skilled workers as well as the increase in graduate abstract occupations. While the economic literature highlights the role of technology as the main driver behind job polarisation, this paper highlights that understanding the main drivers behind job polarisation is more difficult than expected. Much remains to be understood specially when making predictions on the future of jobs.

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Appendix

A The construction of the indices

The procedure we have followed for constructing the indices can be summarized in a number of steps:

1. Identification of variables: we first selected the variables that could match the elements in our model.

2. Normalization of variables to a 0-1 scale: in the original sources, the individual variables use different scales which are not directly comparable. Therefore, they had to be normalized before they could be aggregated. We opted for a normative rescaling to 0-1, with 0 representing the lowest possible intensity of performance of the task in question, and 1 the highest possible intensity.

3. Correlation analysis: once the variables related to an individual element in our model were normalized, we proceeded to analyse the correlations between them. In principle, different variables measuring the same underlying concept should be highly correlated, although there are situations in which they may legitimately not be (for instance, when two variables measure two compensating aspects of the same underlying factor). Beside standard pairwise correlations, we computed Cronbach's Alpha to test the overall correlation of all the items used for computing a particular index, and a Principal Components Factor Analysis to evaluate the consistency of the variables and identify variables that did not fit our concept well.

4. Once we selected the variables to be combined into a single index, we proceeded to combine them, by simply averaging.[13] Unless we had a particular reason to do otherwise, all the variables used for a particular index received the same weight.

5. Finally, we proceeded to compute their average scores for all the occupation combinations at the two-digit level and one-digit level. When the data source included the information at the individual worker level, we computed also the standard deviation and number of workers in the sample, for later analysis.

[13]The results remained invariant if we use the first component of the principal component analysis

6. Data from the European Union-Labour Force Survey (EU-LFS) on the level of employment in each job was added to the dataset holding the task indices. These employment figures were later used for weighting the indices.

B First stage

In order to calculate the first stage, the following equation model is used:

$$\text{RSH}_{pt-1} = \alpha_t + \beta_1 \text{RSH}^*_p + \gamma_c + \delta_t + \epsilon_{pct} \tag{7}$$

The results of the first stage are displayed in Table 18.

Table 18: First stage regression

	Dependent variable RSH_{pt-1}
	1994—2008
RSH^*_p	16.944*
	(9.690)
F-K test	6.990

Notes: The model includes an intercept, region dummies, and a time period dummy. Standard errors clustered at the province level are showed in parentheses. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1977, 1994, 2000, 2008) and O*Net.

C Task items

Table 19: Task items among O*Net, EWCS, and PIAAC

Skill sub-type	O*Net	EWCS
Abstract tasks	1) GED match	1) Learning new things
	2) Administration and management	2) Solving unforeseen problems
Routine tasks	1) Finger dexterity	1) Physical stenght
	2)Customer and personal services	2) Repetitive hand or finger movements
		3) Painful positions at work
Manual tasks	1)Harm-hand steadiness	Does your main job involve:
	2) Manual dexterity	a) dealing with people
		b) repetitive tasks
		c) dealing with customers

Notes: Items selected in O*Net and EWCS.
Sources: O*Net and EWCS.