

Sebastian, Raquel; Harrison, Scott

Working Paper

Beyond technological explanations of employment polarisation in Spain

GLO Discussion Paper, No. 154

Provided in Cooperation with:

Global Labor Organization (GLO)

Suggested Citation: Sebastian, Raquel; Harrison, Scott (2017) : Beyond technological explanations of employment polarisation in Spain, GLO Discussion Paper, No. 154, Global Labor Organization (GLO), Maastricht

This Version is available at:

<https://hdl.handle.net/10419/172190>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Beyond technological explanations of employment polarisation in Spain

Raquel Sebastian¹ and Scott Harrison

ABSTRACT

This paper presents new evidence on the evolution of job polarisation over time and across skill groups in Spain between 1994 and 2008. Spain has experienced job polarisation over the whole period, with growth at the upper part of the wage distribution always exceeding that in the lower part. Results show that the decline in the middle-occupations is accounted by non-graduates and pushing their reallocation at the bottom part of the occupational skill distribution. The growth at the top occupations is explained by compositional changes, as a result of the increase in the number of graduates. Therefore, this study has demonstrated that education plays an important factor. Researchers need to go beyond technological explanations for job polarisation, not just in Spain, but possibly globally.

KEYWORDS: Job Polarisation, Spain, occupational mobility, Technological Change

JEL classification: J21, J23, J24, O33

¹ Corresponding author: University of Salamanca. C/ Despacho 113, Facultad de derecho, Campus Miguel de Unamuno (37007) Salamanca, Spain. Email: Raquel.sebastian@usal.es

Beyond technological explanations of employment polarisation in Spain

1. Introduction

Technological advances are a leading explanation of how the nature of work is changing in the 21st century. In particular, Routine Biased Technical Change (RBTC) has been shown to explain the decline in measures of employment share and relative wages. However, the RBTC concept falls short in explaining two recent empirical findings. The first observation is the downturn in growth of highly skilled occupations (Beaudry, Green and Sand, 2016), which concluded the supply of graduates grew faster than the demand of high-skilled jobs. The second observation is that wage polarisation has not been detected in Germany (Kampelmann and Rycx, 2011), UK (Akcomak et al., 2013) and Spain (Sebastian, 2017a) and more recently, Autor (2015) proved the disappearance of wage polarisation in the US since the year 2000. Importantly, researchers interpret changes in routine employment as technology driven, while using routine task indexes as proxies for technology (Goos et al., 2010, 2014). This suggest that while technology may be a significant factor to current labour market dynamics, a more thorough investigation is required to understand the complex relationships between technology, labour, and other variables which could have an influencing effect.

In this study, the focus is placed on developing a more complete understanding of the Spanish labour market. Anghel et al. (2014) and Sebastian (2017a) have already documented job polarisation in Spain. Using graphical measures, they ranked the jobs using the 1995 ESS (1995 Earnings Structure Survey, 1995 ESS) to explain job polarisation, understanding that technology is the main

determinant. With this study, new evidence on the evolution of employment in Spain is presented. In particular, graduates and migrants represent two groups of labour market participants whose relative size have changed the most in recent times. To understand in more detail job polarisation in Spain, we provide suggestive evidence on the role of labour supply changes in shaping the structure of employment for the period 1994-2008.

For the analysis two central research questions are investigated. First, what are the major factors that contribute to changes within and between skill groups to job polarisation? Second, what is the extent can compositional changes explain the decline in routine employment? In answering these questions, this study has five key objectives: 1) To analyse job polarisation in Spain using index number approaches; 2) To use updated labour market survey information from the 2002 ESS, which includes additional measures not included in the 1995 ESS; 3) To explore job polarisation using educational rankings based on education itself, rather than inferred from wages; 4) To analyse polarisation in a more detailed manner than previous studies, providing insights into how different skills and demographic groups have been affected. Importantly, there is a need to understand the role played by changes in the composition of the workforce, and understand the challenges that different skills groups are facing in an increasing polarized labour market; 5) To use sensitivity analysis to investigate alternative measures of routines to understand how compositional changes can account for the decline in routine employment.

The study is broken up into seven sections, with this introduction forming the first section. The second section reviews the current literature on job polarisation and labour market share, relevant to the Spanish labour market. The third section provides a thorough overview of the data set and methods used for analysis. The fourth section

presents the evolution of employment measuring with wages and education, and the index used for analysis combining these elements. The fifth section provides a shift-share analysis of the labour market. The sixth section provides a more detailed analysis and discussion about the role of occupations. The seventh and final section concludes the study by providing a summary of results and an indication of future possible research.

2. Literature review

In many developed countries, employment growth concentrates among employees categorised with low or highly developed skill sets, while the employment outcomes of workers in the middle of the wage distribution deteriorates. This U-shaped pattern is defined as *job polarisation* (Goos and Manning, 2007). This phenomenon was explored in the US (Autor et al., 2006), the UK (Goos and Manning, 2007; Sarkar, 2017), Germany (Kampelmann and Rycx, 2011), Sweden (Adermon and Gustavsson, 2016), Portugal (Fonseca et al., 2016) and Spain (Sebastian, 2017a).

Autor et al. (2003, hereafter ALM) explains the phenomenon of job polarisation, focusing on the impact of computerization on the different categories of workplace tasks. ALM provide the “routinisation” hypothesis which is consistent with a “task-biased” version of technological change. In the ALM model, work is conceptualized into a series of tasks, characterized as routine and non-routine, depending on their substitutability or complementarity with computer technology. Routine tasks are well defined and follow explicit rules, which makes them particularly susceptible to substitution by computer technology. In contrast, computers complement non-routine cognitive tasks that involve high complexity and problem solving, as they rely heavily on information as an input, resulting in

productivity gains of employees performing these tasks. Non-routine manual tasks, which require environmental and interpersonal adaptability, are not directly influenced by computerization. Declining demand for routine tasks leads to employment polarisation because these tasks are in the center of the wage distribution.

In a later study, Autor and Dorn (2013) extend the ALM model and present a general equilibrium model for routine replacement. The authors explain the growth of low-skilled service occupations through the interaction of two forces: on the one hand technological progress replacing low-skilled labour in routine occupations, while on the other hand, consumer preferences favouring variety over specialization such that goods cannot substitute services. Using the US Census and Current Population Survey (CPS), they find robust support for technology driven employment polarisation. Beyond technology, Autor and Dorn (2013) consider alternative hypotheses of job polarisation, i.e., the increasing relative supply share of graduates and of low skilled immigrants, the aging of the population, and the growing offshorability of job tasks. Many of these explanatory factors receive empirical support but none of them appears to play a leading role.

In Spain, the first evidence on job polarisation is provided by Anghel et al. (2014). The study uses data from the Spanish Labour Force Survey (ES-LFS) for the period 1997-2012. A counterfactual exercise tests the routinisation hypothesis against changes in the composition of the labour force, i.e. the increasing employment of women, of graduates, and the changing age structure in the labour market. The authors conclude that the routinisation hypothesis provides the most plausible explanation for the polarized shape of the employment distribution. In the same line, Sebastian (2017a) investigates the role of routinisation for Spain. Differently from

Anghel et al. (2014), this paper does not rely on task measures for the US to quantify the task intensities associated to each occupation. No assumption on the same task composition of occupations and the same impact of technology in the two countries is therefore needed. She provides clear evidence of job polarisation in her sample, confirming that between 1994 and 2008 employment share in Spain increased at the two extreme of the job wage distribution

More recently, Sebastian (2017b) applied the analysis of Autor and Dorn (2013) to Spain. The analysis combines the Spanish Labour Force Survey for the years 1994 and 2008, and the O*Net data set. 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.

3. Methods

In this section we describe the main data sources to investigate the job creation in high, middle, and low-wage jobs. The methodology requires two types of information: data on evolution of jobs and data on the wage of such jobs. One of the main drawbacks at the Spanish level, is that there is not a single survey which measures data on jobs, and at the same time, information on wages. Due to its limitations, we combine data from two different data sources: employment figures come from the Spanish Labour Force Survey (ES-LFS), and wages information come from the Earnings Structure Survey.

3.1 Employment: Spanish Labour Force Survey

Our main data source is the Spanish Labour Force Survey (ES-LFS) administered by the National Institute of Statistics. The ES- LFS is a continuous household survey of the employment circumstances of the Spanish population. It contains hundreds of variables which cover many features of the Spanish labour market and related topics.

Our analysis focuses on the period 1994-2008. Two reasons motivate the choice of this timeframe. First, it is a period of marked and prolonged job expansion. It has been shown that during recessions, the destruction of jobs concentrates in the middle income earners, bringing polarisation into the structure of employment (Jaimovich and Siu, 2012). Therefore, understanding whether the evolution of employment structure follow a scenario of progressive upgrading, or instead follow a process of polarisation during a period of job expansion may provide important new lessons on this topic. Second, for the chosen period, there are not changes regarding the classification neither at occupational level (CNO-94) nor at the activity level (CNAE-93). Moreover, the occupational (CNO-94) and the industrial (CNAE-93) are fully harmonized with ISCO-88 and NACE.Rev.1, respectively².

For the purpose of this analysis, the ES-LFS is far from ideal. The main problem is the lack of income data necessary to rank selected job cells on earnings-based quality. To overcome this problem, we merge it with the Earnings Structure Survey.

3.2 Wages: Earnings Structure Survey

The Earnings Structure Survey (in Spanish, *Encuesta de Estructura Salarial*, EES) is administered by the official statistical office. The survey aims at collecting

² Appendixes A2 and A3 provide an overview of the 27 two-digit ISCO1988 occupations and 59 NACE Rev.1 two-digit main groups industries available in the EPA

harmonised data on gross earnings, weekly working hours and annual days of leave at establishment level. Although the unit of analysis of the ESES is the employee, the information is gathered through enterprises.

For the period under study, the survey has been carried out three times (1995, 2002 and 2006). For the 1995 ESS not all the employed population is covered: the survey is only representative of employees working in companies of at least 10 employees in the sectors C to O (excluding L) of the NACE classification of economic activities.³ For the 2002 ESS and the 2006 ESS, the coverage of the survey is extended to include some non- market services (educational, health, and social services sectors). Throughout our paper, we use the 2002 wave rather than the 1995 or the 2006 as our results remain invariant and is preferable because first 1995 EES does not include employees working in companies of at least 10 workers, self-employed workers, and public employees. Second, between 2002 ESS and 2006 EES, we rather prefer the 2002 ESS as it is closer to the initial period.

3.3 Methods of Analysis

Our enquiry builds on a methodology first proposed by Joseph Stiglitz for the study of occupational change in the US, later refined by Wright and Dwyer (2003). Due to its simplicity, it is subsequently applied subsequently applied to the UK (Goos and Manning, 2007; Sarkar, 2017), German (Kampelmann and Rycx, 2011), Sweden (Adermon and Gustavsson, 2015) and European data (Goos et al. 2009, 2014; Fernández-Macías, 2012). Three steps are usually followed (look at Appendix A for an in depth explanation).

³ The economic activities excluded are: A - Agriculture, forestry and fishing; B - Mining and quarrying; L - Real estate activities; P – Education; Q - Human health and social work activities; R - Arts, entertainment and recreation; S - Other services activities; T - Activities of households as employers; undifferentiated goods and services producing activities of households for own use.

In the first step, we define a job as a particular occupation in a particular industry. Therefore, jobs are classified into a matrix whereas the columns are economic sectors and the rows are occupations. Examples of these jobs would be managers in the agricultural sector or clerks in the construction industry. Throughout our investigation, we use two-digit International Standard Occupational Classification (ISCO-88) code and one-digit industry codes from the Classification of Economic Activities in the European Community (NACE REV.1) as a measure of jobs. Individuals aged 18 to 66 are placed in cells, and weighted by the total population of each cell. Because many cells are empty, two filters are applied to the data. We first drop observations for which information on the job variable is missing. Second, we also drop Melilla and Ceuta region due to no accurate information, reducing the total number of jobs from 245 to 226 jobs.

In the next step, we compute jobs' real hourly wage by taking the ratio of the gross annual salary to the total number of hours actually worked. The salary figure includes extraordinary payments. We then rank jobs according to their mean wage in the first year.⁴

In the last step, we represent graphically the evolution of jobs in terms of their wages where there are three possibilities of representation: 1) the actual point of jobs where which plots the percent change in employment share against the (log) mean wage; 2) display smoothing regressions rather than the actual data point. In the last representation, jobs are grouped into quintiles. That is, jobs are grouped into the lowest-paid 20 percent, up to the top 20 percent based on their mean wage and cell size in 1994; 3) Calculate changes in the number of jobs in each of the 1994 quintiles.

⁴ The shape of the graph does not change if median average are used for determining job quality.

4. Results and Discussion

4.1 Descriptive Analysis

4.1.1 Evolution of employment ranked by wage

In this section we investigate the phenomenon of employment polarisation as a preliminary step for the subsequent analysis. We compute, on the basis of the number of workers, employment shares for each job and their changes over time. We then rank occupations according to their 2002 EES mean hourly wage. Since the EES provides gross monthly hours labour income, this variable is transformed into hourly wages (first transforming income per hour into weekly income, then dividing it by the actual weekly hours).

The most common way of analyzing the development of jobs is through graphical illustration. To detect it, we perform three different types of illustration. In the first graphical method (Figure 1), we compute employment shares by each job and their changes over time. To avoid that small jobs, drive our results, we weight each job by its total employment. We rank jobs according to their initial wage. And then, we plot the percentage point change in employment share against the log mean hourly wage. In Figure 1, we can detect a U-shaped curve, in which the higher and lower part of the wage distribution has increased while shrinking the middle-wage part.

The second representation method is by defining job wage percentile. In this particular case we display smoothing regressions rather than the actual data point. Therefore, we plot changes in employment share against the percentile of the initial earnings distribution. One more time, we clearly detect a perfect U-shaped curve. The main advantage of this method is that the biggest increases and loses are observable. For Spain, the biggest losers were between the 40th and the 60th percentile of the initial mean wage distribution.

The last plot is shown in Figure 3. In this occasion, we follow the methodology first done by Wright and Dwyer (2003) and then applied in Europa by Fernández-Macías (2012). In Figure 3, we plot the relative employment share by job wage quintile. Quintiles are created by ranking jobs by their initial mean wage and aggregating them into five quintiles. Each group contains the 20% of employment in the initial year. The resulting graph (Figure 3) demonstrates an even clearer pattern of job polarisation. In this case, top- and low-income jobs grow up and there is a decline in middling job.

Figure 1

Employment shares growth in Spain (1994-2008), jobs ranked by 2002 mean wage

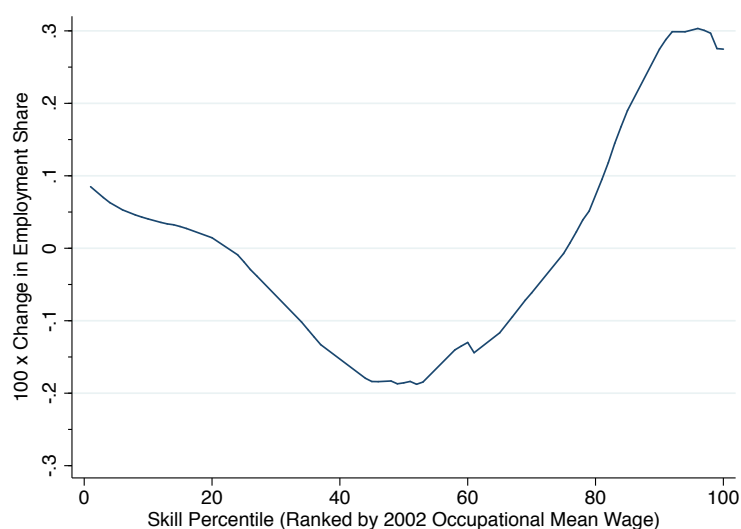


Notes: Scatter plot and quadratic prediction curve. The dimension of each circle corresponds to the number of observations within each ISCO-88 two-digit occupation and NACE REV.1 one-digit occupation in 1994; the grey area shows 95% confidence interval. Employment shares are measured in terms of workers.

Sources: Spanish Labour Force Survey (1994, 2008), Earnings Structure Survey (2002).

Figure 2

Smoothed changes in employment in Spain (1994-2008), jobs are ranked by 2002 wage percentile

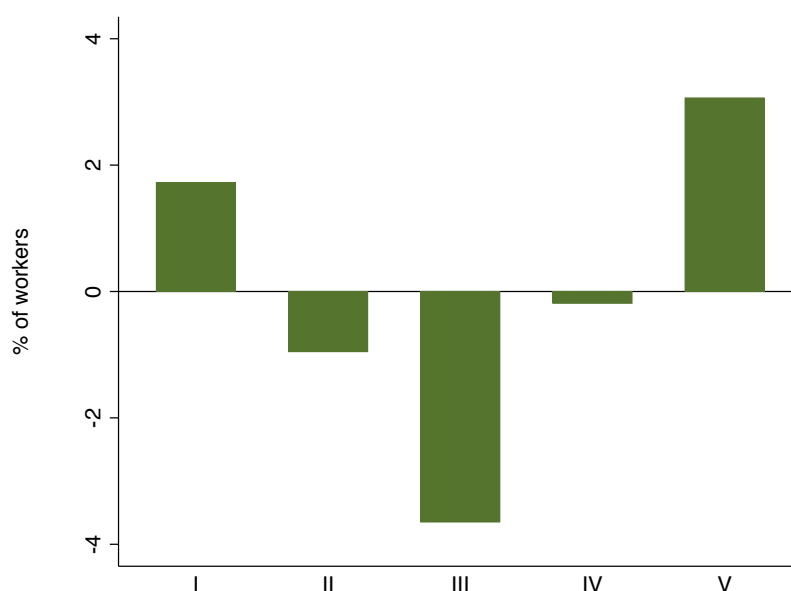


Notes: The figure plots log changes in employment share by 2002 job skill percentile rank using a locally weighted smoothing regression (bandwidth 0.75 with 100 observations), where skill percentiles are measured as the employment-weighted percentile rank of a job's mean log wage in the 2002 Wage Structure Survey.

Sources: Spanish Labour Force Survey (1994, 2008), Earnings Structure Survey (2002).

Figure 3

Relative net employment change between 1994 and 2008 ranked by 2002 wage mean



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on median wages in 2002. It shows the relative net employment change quintiles (in percentage points).

Sources: Spanish Labour Force Survey (1994, 2008), Earnings Structure Survey (2002).

4.1.2 An index to measure Job Polarisation

Most previous studies have relied on graphical measures to measure job polarisation. To the best of our knowledge, there are just two studies which explore econometric analysis, Goos and Manning (2007) and Dauth and Blien (2016). In this section we formally test the phenomenon of job polarisation as a subsequent step for the analysis. In 2016, Dauth and Blien refine Goos and Manning (2007) equation, using also a quadratic form, they measure the change in a wage percentile's relative employment share on its rank. The proposed model is the next one:

$$100 * \Delta E_j = \beta_0 + \beta_1 \text{rank}_{j,t-1} + \beta_2 \text{rank}_{j,t-1}^2 \quad (3)$$

where ΔE_j is the change in the employment share of job j between t and $t-1$, $\text{rank}_{j,t-1}$ is the rank wage of job j in $t-1$, and $\text{rank}_{j,t-1}^2$ is the square of the initial mean wage. As in the previous case, polarisation in employment implies that the linear term is negative and the quadratic term is positive, giving them a U-shaped in employment growth.

Table 1 shows the estimation results for the overall sample. The coefficients are with the expected sign supporting the hypothesis that there has been employment polarisation in Spain. This is especially remarkable for the long period. In conclusion, there is evidence for job polarisation in Spain for the period from 1994 to 2008. The contraction in the employment share has ceased to decline in the lower percentiles and in the upper percentiles of the wage distribution. A contrary development has taken place in the middle of the distribution. Those occupations have experienced a huge decrease in the employment share.

Table 1. Regressions for Job Polarisation Analysis

	Change in employment share	
	1994-2000	1994-2008
	(1)	(2)
Rank wage 1994	-0.43 (0.19)	-0.80* (0.32)
Sq. rank wage 1994	0.01*** (0.001)	0.01*** (0.001)
Constant	6.72 (1.13)	12.43 (9.88)
N	219	226
Adj. R-square	0.07	0.07
F	6.91	8.60

Notes: Each job is weighed by the initial number of observations. Robust standard errors in parentheses, significance levels ***p < 0.01, **p < 0.05, *p < 0.10

Sources: Spanish Labour Force Survey (1994, 2008), Earnings Structure Survey (2002)

We draw on the work of Dauth and Biel (2016) to quantify the magnitude of job polarisation. In our analysis we entirely follow its equation and empirical specifications.

A natural way to test job polarisation is by measuring how well the curvature fits the data represented by the parameter of the squared term in the regression equation (3). A close alternative to the coefficient of the quadratic term is its t-value. Building on this idea, they provided the so-called Polarisation Index (henceforth, PI):

$$t_{rank^2} = \hat{\beta}_{rank^2} / \frac{\hat{\sigma}}{[SST_{rank^2} (1-p(rank; rank^2)^2)]^{1/2}} = \frac{\hat{\beta}_{rank^2}}{\hat{\sigma}} c = PI \quad (4)$$

here $\hat{\beta}_{\text{rank}^2}$ denotes the estimated coefficient of the quadratic term, SST_{rank^2} is the total sum of squares, $p(\text{rank}; \text{rank}^2)$ its correlation coefficient with the level term, and $\hat{\sigma}$ the standard error of the regression. Since the variables rank and rank² do not vary between the countries or regions under analysis, the denominator of the last fraction is a constant c. Hence, the t-value depends only on the curvature of the regression curve $\hat{\beta}_{\text{rank}^2}$ and its fit to the data ($\hat{\sigma}$).

The advantage of this measure is that it allows for a statistical test of polarisation: if the rank wage structure, represented by 226 jobs, is polarized then the t-value of the quadratic term should be larger than the critical value of a t-distribution with 150 degrees of freedom, for example 1.65 for the five percent level of significance (one sided test). In the case of Spain, the t-value is 3.32, which is well beyond any conventional critical value.

4.1.3 The role of occupations

The role of occupations plays an important part in understanding changes in the labour market. Table 2 shows the contribution of each of the ISCO-88 major occupational groups to changes in employment shares in the three segments of the occupational wage distribution. We draw on the work of Fernández-Macías (2012) to classify these occupations into three major groups which we label as bottom, middle and top-paying occupations. Our groups are three even groups: 33% of the employment population in each group.⁵

⁵ Goos et al.'s (2010, 2014) groups include 6,10, and 8 occupations respectively. Fernández-Macías (2012) criticises the methodology strategy by Goos et al. (2010,2014) claiming that a division in even groups would not lead to conclude that there was a pervasive polarisation in Europe. As we can see from table 1 our finding are robust to Fernández-Macías classification.

Table 2. Contribution of major occupational groups to employment changes in different segments of the occupational wage distribution

	Bottom		Middle		Top		All	
ISCO 88	1994 share	2008-1994 (pp change)	1994 share	2008-1994 (pp change)	1994 share	2008-1994 (pp change)	1994 share	2008-1994 (pp change)
1 Legislators	-	-	-	-	2.16	0.68	2.16	0.68
2 Professionals	-	-	0.52	0.15	11.80	1.82	12.32	1.97
3 Technicians	-	-	4.39	3.93	3.22	1.84	7.62	5.77
4 Clerks	2.45	0.88	7.59	-2.02	2.07	-1.02	12.10	-2.16
5 Service workers	6.33	1.63	9.54	0.15	-	-	15.86	1.78
6 Skilled agricultural	0.04	-0.02	0.05	-0.02	-	-	0.10	-0.04
7 Craft and trades workers	0.71	-0.38	22.86	-3.83	0.18	-0.08	23.75	-4.29
8 Machine and assemblers	0.29	-0.10	13.04	-2.14	0.15	-0.05	13.48	-2.29
9 Elementary occupations	9.92	-0.29	2.56	-1.00	0.13	-0.13	12.61	-1.42
Total	19.74	1.72	60.55	-4.78	19.71	3.06	100.00	0.00

Notes: Occupations are ranked in ascending order by their ISCO-88 code. Cells highlight in grey are the lowest values in the columns, cells highlight in bold are the highest values in columns.

Sources: Spanish Labour Force Survey.

From Table 2 the estimates show that overall, middle income earners loose ground in the labour market, with a loss of -4.78pp of employment share. This employment share is redistributed to either end of the spectrum, 3.06pp goes to the top income earners, and 1.72 goes to bottom income earners. Looking at specific sectors, craft and trades workers lost shares in the labour market across all income categories. At the bottom, service is the main driver of growth, contributing 1.63pp out of the 1.72pp of growth observed for lower income earners. The decline in middle occupations is driven by a strong reduction in craft and trades workers (-3.83pp) and machine and assemblers (-2.14). A significant but smaller contribution comes from clerks (-2.02pp). The expansion at the top is driven by technicians (1.84pp) and

professionals (1.82pp). In part, these declines may be confounded by the global economic downturn of 2008, however, this will be factored into further analysis. As we seen from Table 2, the polarisation trend is not unique to the manufacturing industry: occupational categories losing the most are machine operators, assemblers and craft related in the manufacturing sector while office clerks in the non-manufacturing sector.

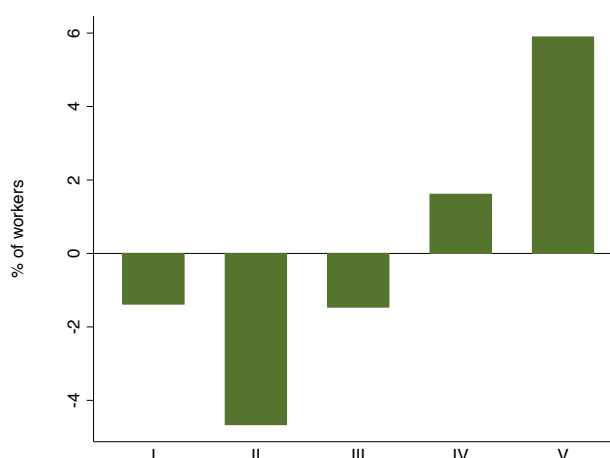
4.1.4 Raking employment by education

In Figure 4, jobs are ranked by mean education of labour market participants, instead of being ranked by wage. In this case we use the 1994 education mean because is the first year of the analysis which forms the base year for analysis. When occupations are ranked by their 1994 education mean we again find the distinctive U-shaped pattern typical of job polarisation.

Figure 5, we split the time period of analysis into two equal periods. This is a way of accounting for the different economic climates that were observed during these periods. Overall, the two graphs are similar in pattern.

Figure 4

Changes in employment share between 1994 and 2008 ranked by 1994 mean education

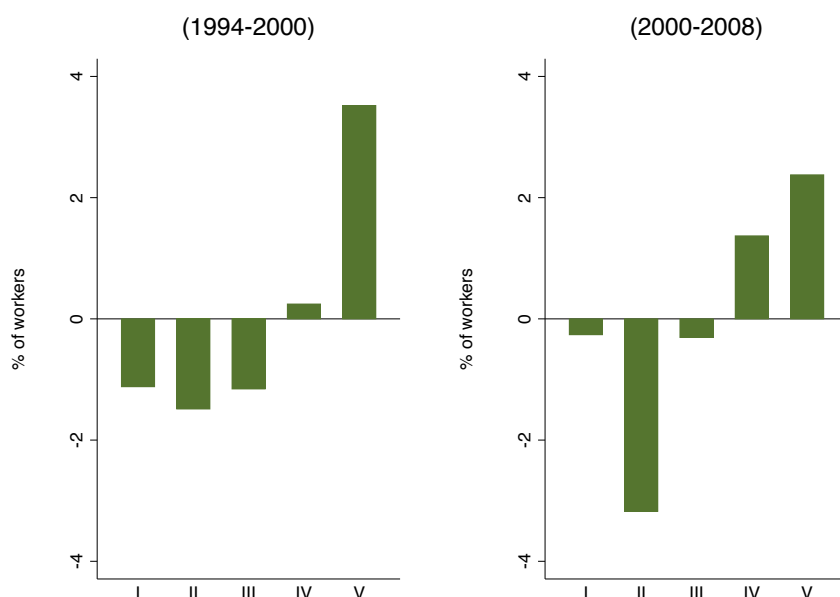


Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on media wages in 2002. It shows the relative net employment change quintiles (in percentage points).

Sources: Spanish Labour Force Survey (1994, 2008), Wage Structure Survey (2002).

Figure 5

Changes in employment share by decade ranked by 1994 mean education



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on media wages in 2002. It shows the relative net employment change quintiles (in percentage points).

Sources: Spanish Labour Force Survey (1994, 2008), Wage Structure Survey (2002).

To provide more detail, Table 3 presents the distribution of major occupational groups across the mean educational level in 1994 and the mean wage in 2002. Like the previous work of Spitz-Oener (2006), job polarisation need not be identified using wages alone. It can be reflected in the educational levels of the employees itself, given that education and wages have strong empirical relationships.

Table 3. Distribution of major occupational groups across the wage and educational distribution

ISCO 88	Bottom		Middle		Top		All	
	Wage	Education	Wage	Education	Wage	Education	Wage	Education
1 Legislators	-	-	-	-	26,30	12,26	26,30	12,26
2 Professionals	-	-	9,87	15,72	15,46	15,90	15,23	15,89
3 Technicians	-	-	10,54	11,42	14,24	11,79	12,11	11,57
4 Clerks	5,58	11,24	7,75	10,65	14,62	11,86	8,48	10,98
5 Service workers	5,65	8,42	6,88	9,18	-	-	6,39	8,88
6 Skilled agricultural	5,56	8,38	7,01	5,55	-	-	6,36	6,83
7 Craft and trades workers	5,20	7,48	7,35	7,90	13,65	8,91	7,33	7,90
8 Machine and assemblers	4,89	7,82	7,840	7,80	12,53	9,91	7,82	7,82
9 Elementary occupations	5,06	7,13	6,64	7,03	-	6,54	5,46	7,10

Notes: Occupations are ranked in ascending order by their ISCO-88 code. Wage distribution is based on their median wage of 2-digit occupation and 1-digit industry in 2002. Education distribution is based on 1994 mean education.

Sources: Spanish Labour Force Survey and Wage Structure Survey (2002).

The results illustrate the differences between education levels and wages for the nine ISCO categories. Overall, an important distinction to note is the diagonal arrangement of the table, where no workers in the top 3 income earning professions were classified in the bottom earning section. Vice versa, service workers, skilled agricultural workers and elementary occupations do not appear in the top wage earners. However, some elementary occupations in terms of education levels do fall into the top bracket. Focusing on the bottom income earners, an important distinction across categories is that the mean income level varies little between the occupations. However, when looking at education levels, the variation is significantly higher. In particular, clerks have on average another four years of educational level, but only earn just above 0.5 units more salary. For middle income earners, the same six occupations that appeared in the bottom income earners, again have similar mean

salaries in the middle income bracket. Professionals and technicians which had no data in the bottom income bracket, earn a lot more than other occupations. When focused on education however, professional spend more time being educated, but actually earn on average less than technicians. This has important implications for middle income earners as there may be significant opportunity cost for choosing to be a professional when the better alternative may have been less time in education and earning more training to be a technician. Finally, for the top income earners, all represented occupations but legislators have a similar average wage. What does stand out is that legislators spend less time in education than professional, but wages are much greater on average. This descriptive analysis is further explored in the following section with a more thorough econometric estimation used for shift-share analysis.

4.2 Hypotheses for Job Polarisation: a shift-share analysis

4.2.1 Changes in labour supply: aggregate results

This section presents the results of a shift-share analysis which decomposes changes in employment share of each occupational tercile. Mathematically, this relationship can be expressed as follows:

$$\Delta S_{ot} = \sum_g \Delta S_{gt} w_{og} + \sum_g \Delta w_{jogt} S_{gt} \quad (1)$$

where ΔS_{ot} is the change in employment share of tercile o between the initial and the last year of the analysis. ΔS_{gt} is the change in employment share of demographic group g and Δw_{jogt} is the change in the share of group g employed in occupation tercile o . Finally, w_{og} is the average share of group g employed in tercile o between

the initial and the final year of the analysis, and S_{gt} is the average employment share of demographic group g over the same period.

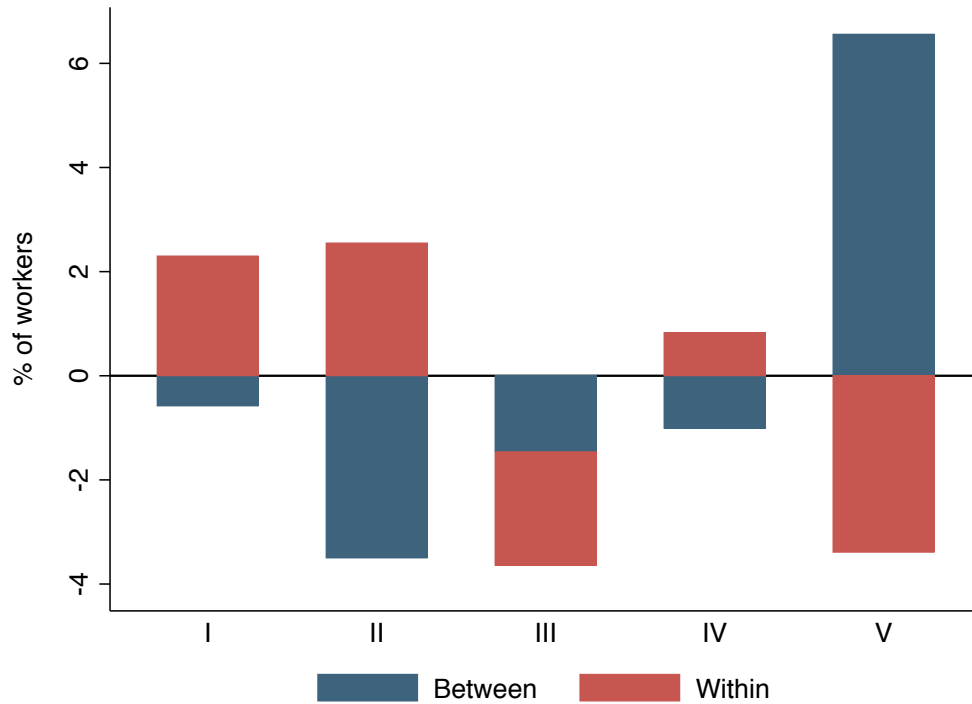
The first term on the RSH of equation (1) is the between component, i.e. the change in employment share accounted for by changes in the share of different skills groups, holding constant the distribution of each skill group across the occupational quintiles. The second term is the within-group component, i.e. the change in occupational share due to changes in the distribution of the skill groups across occupations, holding constant the relative size of the skills groups.

Goos and Manning (2007) and Goos et al. (2014) used this methodology to conclude that compositional changes do not explain job polarisation in the UK, and in Europe respectively. For this analysis, Figure 6 reports the results of the shift-share results, using 36 skill groups, defined by education, age, migration, and gender. These groups are categorically organized, such that the same 3 educational groups (low, medium and highly educated) are used from section 4.4; age is divided into three categories, less than 30 years old, between 30 and 50 years old and above 50; migrant status indicates a binary outcome, either migrant or national; gender indicates a binary classification of either male or female.

From figure 6, one idea is clear. On the one hand, changes in demographic share characteristics explain the reallocation of employment shares towards top occupations. On the other hand, changes in the allocation of skill groups across occupations have fueled the relative growth of the bottom.

Figure 6

Shift-share decomposition of changes in employment shares of 2002 occupational quintiles



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on media wages in 2002. It shows the relative net employment change quintiles (in percentage points). Between occupations refer to change in employment share due to changes in demographic composition. Within occupations refer to changes in employment share due to changes in occupational shares within demographic group. We work with 36 groups: 3 by education, 3 by age, 2 by gender, and 2 by migration.

Sources: Spanish Labour Force Survey (1994, 2008), Earnings Structure Survey (2002).

Table 4. Shift-share decomposition of changes in job shares by different set of groups

	Education (3 groups)			36 groups		80 groups	
	Total	Between	Within	Between	Within	Between	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1994-2008							
Bottom	1.72	-2.66	4.38	-0.58	2.30	-0.61	2.33
Middle	-4.78	-3.84	-0.94	-5.98	1.2	-6.09	1.31
Top	3.06	6.50	-3.44	6.56	-3.50	6.78	-3.72
1994-2000							
Bottom	0.93	-0.17	1.11	-0.41	1.34	-0.71	1.64
Middle	-3.06	-0.03	-3.04	-0.07	-2.99	-0.14	-2.92
Top	2.13	0.20	1.93	0.24	1.89	0.41	1.72
2000-2008							
Bottom	0.79	-2.40	3.19	-0.17	0.96	0.1	0.69
Middle	-1.72	-1.47	-0.25	-5.91	4.19	-5.95	4.23
Top	0.93	3.87	-2.93	6.32	-5.39	6.37	-5.44

Notes: Education groups (higher, medium, and low). 36 groups: 3 education groups, 3 age groups, 2 gender status, 2 migration status. 80 groups: 4 education groups, 5 age groups, 2 gender status, 2 migration status.

Sources: Spanish Labour Force Survey (1994, 2008).

Table 4 compares the shift-share analysis based on the 36 groups presented in Figure 6, with those obtained using either more or fewer cells. From Table 4, the importance of education in explaining polarisation can be seen; whether including more groups (36 groups) or even more again (80 groups), our between and within results are stable. This result indicates stability in the models, an indication of the importance of the educational variable. Occupations in the top increase by 3.06pp due

to a double effect: compositional effect accounts for 6.5pp, while the shift of employment towards other occupations account for the other half (3.5pp). For the bottom income earners, this effect is reversed, where growth from within accounted for an increase by 4.38pp, being offset by a decrease between 2.66pp. This indicates that when decomposing the estimates of occupation share, new insights show that high income earners are growing for a different reason than bottom income earners.

Focusing on the two different time periods, it is clear that between 1994-2000, this time period accounted for the majority of shift to other occupations. The second period (2000-2008) accounts mostly for the compositional effect, reflecting the increase in the educational attainment of the workforce. For occupations in the middle income bracket, they decreased by 4.77p, similar to the results obtained in section 4.3, and this is mostly accounted by the compositional changes (-3.83). This estimated effect demonstrates that polarisation itself, while observed for the whole time period of analysis, polarisation has different reasons for occurring at different points of time. To make a more thorough investigation of these findings, the next section introduces two demographic groups that change the most (education and migrants).

4.2.2 Changes in labour supply: graduates and migrants

Accounting for education has already been shown important when discussing job polarisation. To provide more detail to the analysis, Table 5 presents the breakdown by graduates versus non-graduates.

Table 5. Shift share decomposition of changes in occupational shares (pp) by education

	Total (36 groups)			Graduates			Non-graduates		
	Total	Between	Within	Total	Between	Within	Total	Between	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1994-2008									
Bottom	1.72	-0.58	2.30	1.05	0.37	0.68	0.67	-1.96	2.63
Middle	-4.78	-5.98	1.2	2.94	1.72	1.22	-7.72	-5.32	-2.4
Top	3.06	6.56	-3.50	3.93	5.83	-1.90	-0.87	-0.64	-0.23
1994-2000									
Bottom	0.93	-0.41	1.34	0.40	0.14	0.26	0.53	-0.95	1.48
Middle	-3.06	-0.07	-2.99	1.33	0.79	0.54	-4.39	-2.67	-1.72
Top	2.13	0.24	1.89	2.22	3.01	-0.79	-0.09	-0.33	0.24
2000-2008									
Bottom	0.79	-0.17	0.96	0.65	0.22	0.43	0.14	-1.02	1.16
Middle	-1.72	-5.91	4.19	1.61	0.91	0.70	-3.33	-2.63	-0.70
Top	0.93	6.32	-5.39	1.71	2.84	-1.13	-0.78	-0.32	-0.46

Notes: 36 groups: 3 education groups, 3 age groups, 2 gender status, 2 migration status.

Sources: Spanish Labour Force Survey.

The decline in middle income occupations is explained by non-graduates. They contributed 7.72pp to the change in employment share of middling occupations. 2/3 of this (5.31pp) is explained by the declined in their relative number (between column), while the rest is due to other factors. The compositional change has been the driving force in the decline of non-graduate employment, as indicated in the between non-graduate column in Table 5. Non-graduates have also seen major shift in the distribution of their employment from middling to bottom occupations. This shift has contributed to the loss of 2.4pp in middling occupations which have been reallocated in bottom occupations (2.63pp).

Graduates have contributed to the growth of all three segments of the occupational distribution. And as we can see from column 4 the higher growth is at the top. From column 5 and column 6 we can see that this growth is explained by the large expansion in graduate numbers (column 6). The shift in graduate employment away from top occupations is very small (column 5) if we compare it with the expansion in graduate numbers (column 6). For example, between 1994-2008 the increase in number of graduates account for 5.84pp, while the reallocation to lower occupations only subtracted 1.90pp. The within-group change among graduates has been negative in each decade at the top, and higher in the second decade. The shift of graduate employment towards the bottom is more pronounced in the 2000s than in the 1990s.

At the bottom of the distribution we see the following: graduates account for the growth in bottom occupation between 1994-2008 and a higher proportion of them is found in bottom occupations between 1994-2008 (1.04pp represent graduates while 0-67pp represent non-graduates). Graduates have more-than –offset this decline through both changes: between and within. Looking at decades, the contribution of graduates to the growth of bottom occupations only exceed non-graduates in the 2000s (0.64 against 0.14).

Table 6 presents the breakdown by migration status. The first that we notice when looking at Table 6, is that overall, the role of migrants have increased over time. The increase in the number of migrants between 1994 and 2008 contributed to the growth of bottom and middle occupations (you can see this in column 5) but more the middle than the bottom. This leads to the result that migrants' largest contribution in absolute terms occurred at the middle, where they account for 6.94pp. For example, between 1994 and 2008 the increase in the share of migrants accounted for a 5.97pp

growth in middle occupation, while their reallocation towards other occupations accounts for 0.97pp. However, it is in the bottom part that they made the largest contribution relative to natives. For top income earners, it is important to note that while overall there was growth in the migrant dimension, this was offset by a loss within the top bracket itself, indicating more top earning migrants leaving the labour market. Looking at the temporal component, the lower panels reveal that migrants accounted for most of the growth in bottom occupation in the second decade. This is an important finding for policy, as it may help inform our understanding of what to expect for more recent migration patterns that are outside the scope of this study.

Table 6. Shift share decomposition of changes in occupational shares (pp) by migrant status

	Total (36 groups)			Migrant			Native		
	Total	Between	Within	Total	Between	Within	Total	Between	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1994-2008									
Bottom	1.72	-0.58	2.30	5,11	4,71	0,40	-3,39	-2,49	-0,90
Middle	-4.78	-5.97	1.2	6,95	5,98	0,97	-11,73	-7,58	-4,15
Top	3.06	6.56	-3.39	0,91	2,28	-1,37	2,15	-2,90	5,05
1994-2000									
Bottom	0.93	-0.41	1.34	0.21	0.18	0.03	0.72	-0.11	0.83
Middle	-3.06	-0.07	-2.99	0.25	0.22	0.03	-3.31	-0.31	-3.00
Top	2.13	0.24	1.89	0.07	0.13	-0.06	2.06	-0.11	2.17
2000-2008									
Bottom	0.79	-0.17	0.96	4,9	4,53	0,37	-4,11	-2,38	-1,73
Middle	-1.72	-5.91	4.19	6,7	5,76	0,94	-8,42	-7,28	-1,14
Top	0.93	6.32	-5.39	0,84	2,15	-1,31	0,09	-2,79	2,88

Notes: 36 groups: 3 education groups, 3 age groups, 2 gender status, 2 migration status.

Sources: Spanish Labour Force Survey.

To summarise, the improvements in educational attainment have sustained the shift from middling to top occupations, while the reallocation of workers across occupations within skills groups has led to substantial shift from middle to the bottom. The decline in middling occupations is account for non-graduates who have decreased their number and become more concentrated at the bottom. Migrants account for the increase in bottom and middle part of the distribution. Moreover, the largest contribution of migrants relative to native is at the bottom part.

4.3 Change in labour demand: technology (routinisation process)

4.3.1 Routine occupations versus non-routine occupations

In this section the role of routine occupations in accounting for changes in employment shares across the occupational distribution is investigated. Three different classifications are used based on three different approaches from previous studies. The first approach is based on Autor and Acemoglu (2011). This approach is the simplest one. They use occupations as proxies for job tasks. They classify occupations based on the type of task that is perceived as typical of that occupations. Following their classification, we classify as routine tasks the following groups: clerks (ISCO 4), craft and related trade workers (ISCO 7), and stationary plant and machine operators and assemblers (ISCO 8),

The second approach is based on Autor and Dorn (2013). In their approach they classify tasks into three dimensions (abstract, routine, and manual). In the second step, they provide a summary index increasing in the routine task importance and decreasing in manual and abstract task importance. The RTI is calculated with O*Net data and then mapped to the European ISCO-88 classification in Goos et al. (2014) (henceforth, GSM in Table 6).

The third approach is based on Sebastian (2017a). Sebastian (2017a) uses job task information collected directly in the European Working Condition Survey (EWCS), therefore it contains Spanish data. Sebastian (2017a) constructs and RTI index in the same fashion as Autor and Dorn (2013). As explained in Biagi and Sebastian (2017) no definition is superior to the other one. Differences among the three definitions can be for multiple reasons: 1) information is collected for other country (like is the case with the two first definitions, they use O*Net), 2) differences in the range of tasks covered in the original data source, 3) the classification per se between routine and non-routine.

Table 7. Distribution of routine employment across 1-digit ISCO-88 based on three different classifications.

	1994 share	AA (2011)	GMS (2014)			Sebastian (2017)		
ISCO-88			30%	40%	No weight	30%	40%	No weight
					weight			
1 Legislators	2.16							
2 Professionals	12.32							
3 Technicians	7.62				0.63			0.79
4 Clerks	12.10	12.10	12.10	12.10	12.10			12.10
5 Service workers	15.86							
6 Skilled agricultural	0.10							
7 Craft and trades workers	23.75	23.75	14.15	14.15	18.89	23.75	23.75	9.30
8 Machine and assemblers	13.48	13.48	5.20	6.55	13.48	5.20	13.48	13.48
9 Elementary occupations	12.61			5.96	5.96		5.96	
Total	1000	49.33	31.45	38.76	51.06	28.95	43.19	35.67

Notes: Results from a shift-share analysis based on 36 groups. Details on the routine definitions are provided in the Appendix.

Sources: European Labour Force Survey, O*Net, European Working Condition Survey (1995).

In Table 7, the distributions of routine employment for the three different definitions are shown. For the last two cases where we measure the RTI index, we

consider employment weighted measures (i.e. we classify routine as those occupations in the highest employment-weighted third share of the RTI in 1994) and un-weighted measures (i.e. occupations with an RTI larger than average).

From Table 7 we observe that craft and related trades workers (ISCO 6) and stationary-plant and machine operators and assemblers (ISCO 7) are consistent in all the three definitions. However, there are notable differences: clerks are classified as routine by Acemoglu and Autor (2011) and GMS (2014), but not under Sebastian (2017). Elementary occupations are classified as routine in GMS (2014) and Sebastian (2017a) but not under Acemoglu and Autor (2011). The implications of this are discussed in the following section, which focuses on the results of the shift-share analysis.

4.3.2 Results of the shift-share analysis

Building off the previous section, Table 8 shows the results of the shift-share analysis for routine and non-routine occupations following the three different definitions presented in the previous section. We use the Acemoglu and Autor (2011), and the two definitions using the top employment-weighted 30% occupations based on Goos et al. (2014) and Sebastian (2017a).

Table 8. Shift-share decomposition of changes in occupational shares (pp) by three different routine definitions.

		Routine occupations		No routine occupations	
	Total	Between	Within	Between	Within
Autor and Acemoglu (2011)					
Bottom	1.72	-0.72	1.12	2.70	-1.38
Middle	-4.78	-7,68	-0,31	2,97	0,24
Top	3.06	-0.35	-0.81	3.08	1.14
GMS (2014)					
Bottom	1.72	-1.32	1.81	2.22	-0.99
Middle	-4.78	-7,63	-1,27	4,77	-0,65
Top	3.06	-0.58	-0.54	2.54	1.64
Sebastian (2017a)					
Bottom	1.72	-0,14	-0,25	1,52	0,59
Middle	-4.78	-5,48	0,29	2,51	-2,12
Top	3.06	-0,03	-0,05	1,61	1,53

Notes: Results from a shift-share analysis base don 36 groups. Details on the routine definitions are provided in the Appendix.

Sources: European Labour Force Survey, O*Net, European Working Condition Survey (1995).

The results presented in table 8 show that overall, routine occupations have experienced a decline, while non routine occupations have grown. This supports the technological hypothesis as a factor of job-polarisation, where routine tasks are the easiest to replace with technological solutions. For all three cases, most of the decline in routine occupations is accounted by compositional changes (between occupations). Routine occupations account for most of the decline in middling occupations and their contribution here is mostly from between-group changes. Finally, two out of three definitions (Acemoglu and Autor and Goos et al. (2014)) show routine workers are shifting to the bottom.

Overall, if it is true that there are some differences between routine classifications, one can draw some rather robust conclusions. First, routine occupations have declined relative to non-routine occupations. Second, routine occupations account for most of the decline in middling occupations. Third, the overall decline in routine occupations is mostly accounted for by between groups. Fourth, the contribution to the increase in bottom occupations is driven by within-group changes.

5. Conclusions

The objective of this study was to answer two research questions. The first was, what are the major factors that contribute to changes within and between skill groups to job polarisation? The results show that technology is a significant factor, especially when looking at the replacement of labour on routine tasks. However, increasing education levels of middle income earners is helping them transition into the higher income bracket, while labour in the lower income bracket is being replaced by migrant labour. This is an important conclusion as it shows that job polarisation itself is composed of many confounding factors.

The second research question was to what extent can compositional changes explain the decline in routine employment? Again, compositional changes in routine employment have both educational and migrant factors which contributed to the changes in the Spanish labour market. As shown in section 6, this was especially prevalent in the second time period, covering 2000 to 2008.

The key findings of the study can be contrasted against previous studies. The first key finding is a difference between the US and Spanish labour markets and their experience with job polarisation. In the United States, job polarisation only occurred

in the 1990s and employment growth has progressively favoured bottom occupations since the 1980s and culminating in the 2000s. In the 2000s low-paid occupations gained share relative to other (Autor, 2014, Beaudry et al., 2016). By contrast to US, Spain has polarised during the 1990s and 2000s. And moreover, differently from the US, growth in high-skill occupations have exceeded that in low skill ones. Mishel et al. (2013) have disputed the exact timing of polarisation in the US using alternative ranks, however, in this study show that our analysis remain invariant

The second key finding was the importance of other factors rather than technology. The difference between US and Spain suggest that other factors than technological change might be at play. This point has been already in related papers on Canada (Green and Sand, 2015) and Germany (Antonczyk et al. 2010). The results of the shift-share analysis show that the increase in the educational attainment is likely to contributed to the feature of job polarisation in Spain. Moreover, the importance of migrants has increased over time, having a crucial role in explaining the increase at the bottom of the occupational distribution. The shift-share analysis also shows that the decline in middling occupation in Spain is accounted by non-graduates. This is the result of both the decrease in their relative number and of their reallocation to different occupations. Unlike the US (Autor and Dorn, 2013; and Autor, 2014) graduates have played no role in explaining the declining in middle occupations, but they play an important role in explaining the increase at the top of the employment distribution.

Significant implications of this study show that migration patterns and education levels need to be accounted for. In context of more recent global people movements, subsequent research will be required to see how migration patterns beyond 2008, particularly between 2014 and 2016, have affected labour markets and

how it contributed to job polarisation. Furthermore, this study has demonstrated that education plays an important factor. From a theoretical perspective, it would not be unreasonable to link education and technological change, which opens the avenue for confounding variables in explaining job polarisation. Further research is needed using more detailed data sets to fully understand the determinants of job polarisation. What is clear for now, is that researchers need to go beyond technological explanations for job polarisation.

References:

- Acemoglu D, Autor D (2011) Skills, tasks and technologies: Implications for employment and earnings. In *The Handbook of Labour Economics*, volume 4, chapter 12, pages 1043-1171. Elsevier.
- Adermon A, Gustavsson M (2015) Job polarisation and task-biased technological change: Evidence from Sweden, 1975-2005. *The Scandinavian Journal of Economics*, 117(3):878-917.
- Akcomak S, Kok S, Rojas-Romagosa H (2013) The effects of technology and offshoring on changes in employment and task-content of occupations. Technical report, CPB Netherlands Bureau for Economic Policy Analysis. Discussion Paper No. 233.
- Anghel B, De la Rica S, Lacuesta A (2014) The impact of the Great Recession on employment polarisation in Spain. *SERIEs*, 5(2-3):143-171.
- Antonczyk D, DeLeire T, Fitzenberger B (2010) Polarisation and rising wage inequality: Comparing the US and Germany. Technical report, IZA Discussion Paper No. 4842.
- Autor D (2015) Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives*, 29(3):3-30.
- Autor D (2014) Skills, Education, and the Rise of Earnings Inequality among the “other 99 percent”. *Science*, 344 (6186), 843-851.
- Autor D, Dorn D (2013) The growth of low-skill service jobs and the polarisation of the US labour market. *American Economic Review*, 103(5):1553-1597.
- Autor D, Katz LF, Kearney MS (2006) The polarisation of the US labour market. Technical report, National Bureau of Economic Research. Discussion paper No. 11986.
- Autor D, Levy F, Murnane RJ (2003) The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279-1333.
- Beaudry P, Green DA, Sand BM (2016) The great reversal in the demand for skill and cognitive tasks. *Journal of Labour Economics*, 34(S1):S199-S247.
- Biagi F, Sebastian R (2017) A review on routine biased technical change. Technical report, JRC Technical Report (forthcoming).
- Dauth W, Blien U (2016) Job polarisation on local labour markets. IAB working paper. Discussion paper No. 201418.

Fernández-Macías E (2012) Job polarisation in Europe? Changes in the employment structure and job quality, 1995-2007. *Work and Occupations*, 39(2):157-182.

Fonseca T, Lima F, Pereira S (ed) (2016) Job polarisation, technological change and routinisation: Evidence for Portugal. Annual Meeting of the Portuguese Economic Journal.

Gimpelson V, Kapeliushnikov R (2016) Polarisation or upgrading? Evolution of employment in transitional Russia. *Russian Journal of Economics*, 2(2), 192-218.

Goos M, Manning A (2007) Lousy and lovely jobs: The rising polarisation of work in Britain. *The Review of Economics and Statistics*, 89(1):118-133.

Goos M, Manning A, Salomons A (2009) Job polarisation in Europe. *American Economic Review Paper and Proceedings*, 99(2):58-63.

Goos M, Manning A, Salomons A (2010) Explaining job polarisation in Europe: The roles of technology, globalization and institutions. Technical report, Discussion paper No. 1026, CEP.

Goos M, Manning A, Salomons A (2014) Explaining job polarisation: Routinebiased technological change and offshoring. *American Economic Review*, 104(8):2509-2526.

Green DA, Sand BM (2015) Has the Canadian labour market polarized? *Canadian Journal of Economics/Revue canadienne d'_economie*, 48(2):612-646.

Jaimovich N, Siu HE (2012) The trend is the cycle: Job polarisation and jobless recoveries. Technical report, National Bureau of Economic Research. Discussion Paper No. 18334

Kampelmann S, Rycx F (2011) Task-biased changes of employment and remuneration: The case of occupations. Technical report, IZA Discussion Paper No. 5470.

Oesch D, Rodríguez Menés J (2011) Upgrading or polarisation? Occupational change in Britain, Germany, Spain and Switzerland, 1990-2008. *Socio-Economic Review*, 9(3):503-531.

Sarkar S (2017) Employment polarisation and over-education in Germany, Spain, Sweden and UK. *Empirica*, 1-29.

Sebastian R (2017a) Explaining job polarisation in Spain from a task perspective. Technical report, AIAS working paper. Discussion Paper No.176.

Sebastian R (2017b) Job polarisation and the Spanish labour market. Technical report, AIAS working paper. Discussion Paper No.176.

Spitz-Oener A (2006) Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labour Economics*, 24(2):235-270.

Wright EO, Dwyer RE (2003) The patterns of job expansions in the USA: a comparison of the 1960s and 1990s. *Socio-Economic Review*, 1(3):289-325.

Acknowledgements

We acknowledge the financial support of the Eduworks Marie Curie Initial Training Network Project (PITN-GA- 2013-608311) of the European Commission's 7th Framework Program.

Appendices

Appendix A: A brief summary of the methodological approach

The main objective is to investigate net job creation/destruction in high-, middle-, and low-wage jobs. The first one using this methodology while working in the Clinton administration was Joseph Stiglitz. He studied the job expansion over fairly short span of time, 1994-1996. His objective was to see what proportion of the job expansion in this period comprised 'good' jobs and what proportion 'bad' jobs. Wright and Dwyer (2000, 2003) refined Stiglitz's methodology to explain changes in the employment structure. Due to its simplicity and elegance, it was subsequently applied to the UK (Goos and Manning, 2007), Germany (Spitz-Oener, 2006; Dustmann et al. 2009; and Kampelmann and Rycx, 2011), Sweden (Adermon and Gustavsson, 2015), Russia (Gimpelson and Kapeliushnikov, 2016), Spain (Anghel et al. 2014, Sebastian, 2017) and European Data (Sarkar, 2017; Goos et al. 2009, 2015; Fernández-Macías, 2012; Oesch and Menés, 2011).

This technique is based on two broad principles. First, they carried out the analysis at "job" level rather than individual level, with jobs being defined or as

specific occupations within specific industries or using just occupations. Second, those jobs are then defined by some indicator of job quality: normally but not always, wages. Consequently, these studies depend on the availability of large-scale individual dataset, which contain detail information on “jobs” (information on occupations and economic sectors) and measures of the wages. Therefore, this new method for studying structural change in the labour market allows researchers to achieve their final goal: evaluate the quality of jobs created/destroyed during a period of time. To achieve this goal, six steps are usually followed.

A.1. Definition of the job

First, for each study researchers give a definition of their understanding of what a job means. As explained before, the main idea is that behind this definition, researchers capture the full complexity of the structure of employment. In most of the occasions, “jobs” are classified into a matrix whereas the columns are economic sectors and the rows are occupations. Examples of these “jobs” would be managers in the agricultural sector or clerks in the construction industry (see Figure 1). Sometimes, “jobs” are categorized using just the occupation information (Anghel et al., 2014; and Kampelmann and Rycx, 2011). In all the cases, occupations are defined by the International Standard Classification of Occupations (ISCO) at three-digit level or two-digit level, and sectors are defined by the International Classification of Economic Activities (NACE) at the two-digit level. Moreover, variables holding demographic and employment information of the people within each job are also included.

Besides the different definitions of “jobs”, it is important to point out that a “good definition of job” reduces concerns about omitted industries or occupations and

allows researchers to build the whole structure of employment. In other words, when researchers use a “poor definition of job” they are not taking into account the boundaries of the division of labour and the jobs are not detailed enough to involve reasonably homogenous employment situations.

Figure 1: The job Matrix

Occupation\Sector	Agriculture	Fishing	Mining	...
Managers	Job 1	Job 2	Job 3	...
Professionals	Job 4	Job 5	Job 6	...
...

Source: Author's table

A.2. Determine the job quality

The second step is to determine whether a given job is good or bad, desirable or undesirable, advantageous or disadvantageous. The main problem is that different attributes affect the definition of job quality: earnings, promotion, job security, autonomy, flexibility... Therefore, there is no consensus on how to define “good” and “bad” jobs and alternative criteria are used by different authors.

In the literature there are three different proxies to measure job quality. The first one is based on initial earnings (Goos and Manning, 2007, Goos et al., 2009). This is the most common criterion as researchers argue that it is the most reliable and the most consequential measure indicator. In this case, they calculate the job's median earnings at the beginning of the time period under study. Further proxies using

earnings are current earnings (Acemoglu, 2011) or the average median earnings over the period under study (Oesch and Menés, 2010; Goos et al., 2014). The second proxy to measure quality is education. In this case, researchers define job quality in terms of initial skill levels and operationalize skills through average years of schooling (Autor et al., 2006) or by proxying skills through wage premia (Spitz-Oener, 2006). The last measure is based on the aggregation of different variables measuring non-pecuniary conditions of work and employment (Macías-Fernández, 2010).

Finally, job quality plays an important role, but it is a secondary one. The intention of this literature is to study the implications of the transformation in the jobs structure on the quality of existing jobs, rather than study job quality itself.

A.3. Rank the jobs by their quality

In the third step, researchers aggregate the information from step one and step two, linking quantitative information (on employment number by job) and quantitative information (on quality levels by job). Therefore, jobs are ranked by their quality. In other words, jobs are ordered from the lowest-paid (or lowest-education) to the highest-paid (or higher-education).

A.4. Measure the change in employment

The fourth step consists in measuring the change in employment between $t-1$ and t . Two different measures have been used: the first one is the absolute change in thousand of workers between the first and last year studied. This gives net job creation/destruction of each job. The second measure is the relative change measuring the percentage point change in employment shares under the period studied.

A.5. Represent the evolution over a period of time

In the fifth step, researchers represent graphically the change for the period under study. There are two types of graphs: aggrupation (or also called “coarse-grained”) and dispersion.

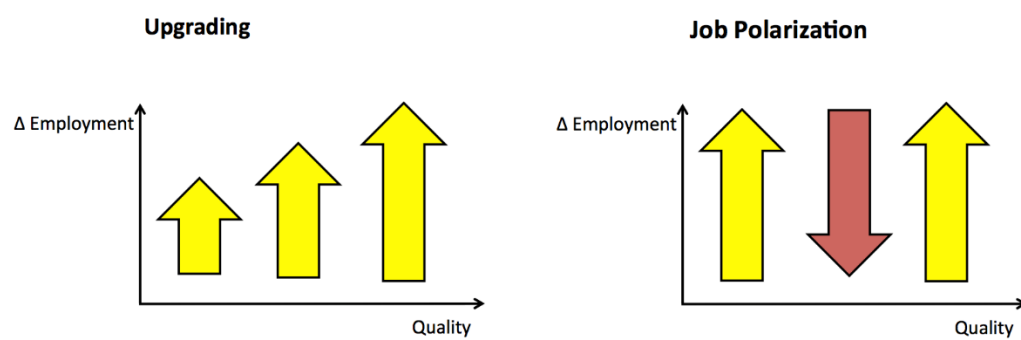
In the case of aggrupation or coarse-grained, researchers can group in terciles, quintiles or deciles (from more aggregation groups to less ones). Moreover, they can aggregate in equal-size groups (Wright and Dwyer, 2000; Oesch and Menés, 2010; and Fernández-Macías, 2012) or unequal-size groups (Goos et al., 2009, 2014). Moreover, when researchers aggregate in equal-size groups there are two possibilities: or hold in the first year the same mount of population (Wright and Dwyer, 2000; Oesch and Menés, 2010) or hold in the middle year of the period under study the same amount of population (Fernández-Macías, 2012). More in detail, what researchers do when they cluster in equal quintile sets is that they group into the lowest paid 20 percent (quintile 1), the second lowest paid 20 percent, up to the top 20 percent based on the quality measure (as we said before, normally is based on their median wage at date $t-1$). Then, to study net job creation in different parts of the wage distribution between $t-1$ and t , they compute changes in number of jobs in each of the $t-1$ quintiles. In other words, the number of individuals in $t-1$ that have jobs that are in the lowest quintile are compare to the number of individuals in the same job in t . This gives net job creation of the lowest paying jobs. However, in the second case, they have unequal-size groups, holding in the first year different amount of population in each group. For example, Goos et al. (2009) classified the ranked jobs in three categories (good, middling and bad jobs) which have very uneven sizes in terms of employment shares in the first year of the period studied (29%-49%-22%).

In the case of dispersion, scholars do not group the observations, plotting therefore each job (Goos et al., 2009, 2010; Kampelmann and Rycx, 2011). They normally rank percentage point changes in job employment shares between $t-1$ and t according to the respective earnings in $t-1$ (earnings are measured by logarithms of hourly median earnings in each job). Another way of illustrating the evolution of job trends is to chart changes in employment shares against the percentiles of the initial earnings distribution as proposed by Dustmann et al. (2009).

A.6. The pattern of employment growth is identified

In the last step and looking at the graph, scholars are able to explain whether the structure of employment is following a process of progressive upgrading or whether is polarizing. The first scenario (progressive upgrading) suggests the job expansion at the top of the distribution, therefore, expects a linear relationship between growth in employment share and earnings. The second scenario (job polarisation) predicts an increase in “good” and “bad” jobs relative to “middling” jobs. In other words, if we rank all jobs according to their median wage at date $t-1$, then employment polarisation between $t-1$ and t means that the employment share (median wage) of jobs situated in the middle of the ranking has decreased relative to jobs at the top and bottom of the wage ranking in $t-1$ (For a clear picture, look at Figure 2). Therefore, the alternative scenario expects a U-shaped relationship between growth in employment share and their position in the earnings distribution. Other studies also define job polarisation in terms of changes in the wage distribution, for instance as a rise in the ratio between the 80th percentile and the median, combined with a decrease in the ratio of the median and the 20th percentile (Antonczyk et al., 2010).

Figure 2: Examples of Upgrading and Job Polarisation



Source: Author's graph

Appendix B: shift-share analysis by age and gender

Table 8 presents the shift-share analysis decomposition by gender. Table 9 presents the shift-share analysis decomposition by age.

Table 8. Shift share decomposition of changes in occupational shares (pp) by gender

	Total (36 groups)			Female			Male		
	Total	Between	Within	Total	Between	Within	Total	Between	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1994-2008									
Bottom	1.72	-0.58	2.30	3.68	2.33	1.37	-1.96	-1.35	-0.62
Middle	-4.78	-5.97	1.2	1.62	4.02	-2.40	-6.40	-5.33	-1.07
Top	3.06	6.56	-3.39	3.02	1.98	1.04	0.04	-1.64	1.69
1994-2000									
Bottom	0.93	-0.41	1.34	1.33	1.01	0.32	-0.39	-0.65	0.25
Middle	-3.06	-0.07	-2.99	0.76	1.91	-1.15	-3.82	-2.44	-1.38
Top	2.13	0.24	1.89	1.74	0.90	0.83	0.39	-0.74	1.13
2000-2008									
Bottom	0.79	-0.17	0.96	2.35	1.32	1.05	-1.57	-0.7	-0.87
Middle	-1.72	-5.91	4.19	0.86	2.11	-1.25	-2.58	-2.89	0.31
Top	0.93	6.32	-5.39	1.28	1.08	0.21	-0.35	-0.9	0.56

Notes: 36 groups: 3 education groups, 3 age groups, 2 gender status, and 2 migration status.

Sources: Spanish Labour Force Survey.

Table 9. Shift share decomposition of changes in occupational shares (pp) by age

	Total (36 groups)			Age (3 groups)		Age (4 groups)	
	Total	Between	Within	Between	Within	Between	Within
	(1)	(2)	(3)	(5)	(6)	(8)	(9)
1994-2008							
Bottom	1.72	-0.58	2.30	-0.47	2.19	-0.49	2.21
Middle	-4.78	-5.97	1.2	0.06	-4.84	0.05	-4.83
Top	3.06	6.56	-3.39	0.41	2.65	0.45	2.61
1994-2000							
Bottom	0.93	-0.41	1.34	-0.01	0.97	0.01	0.92
Middle	-3.06	-0.07	-2.99	0.03	-3.10	0.03	-3.09
Top	2.13	0.24	1.89	-0.02	2.15	-0.03	2.16
2000-2008							
Bottom	0.79	-0.17	0.96	-0.46	1.22	-0.5	1.29
Middle	-1.72	-5.91	4.19	0.03	-1.74	0.02	-1.74
Top	0.93	6.32	-5.39	0.43	0.5	0.48	0.45

Notes: 36 groups: 3 education groups, 3 age groups, 2 gender status, and 2 migration status.

Age (3 groups): <20, 20-50, >50

Age (4 groups): <20, 20-35, 35-50, >50

Sources: Spanish Labour Force Survey.

Appendix C: Measuring routine occupations

Autor (2015) suggest to use “off the shell” measures of routine task intensities of different occupations. In this paper we use three different definitions.

The first one comes from Autor and Acemoglu (2011). In their paper they based their task intensities using the occupational codes rather than measures at the task level. Using US Census and CPS occupations they define occupations as follow:

- 1) Non- routine cognitive: managerial, professionals, and technical occupations.
- 2) Routine cognitive: sales, clerical, and administrative support occupations.
- 3) Routine manual: production and operative occupations.
- 4) Non routine manual: service occupations.

These occupational codes at one-digit level are easy to match at the ISCO-88 one digit level.

Our second classification is based on the Routine Task Index provided in Table 1 by Goos et al. (2014). As they explain in their paper they collapse the original five tasks provided by Autor, Levy and Murnane (2007) in three. They use the DOT data source to define each task. The Manual task measure corresponds to the DOT variable for “eye-hand-foot- coordination”; the Routine task measure is an average of “set limits, tolerances and standards” and “finger dexterity”; the Abstract task measure is the average of “direction control and planning” and “GED Math” –which measures mathematical and formal reasoning requirements. Moreover, because the DOT data source use US SOC codes, they convert these codes into ISCO-88 codes. They report their RTI index for 21 occupations. Finally, we define RTI using

employment-weighted measures (as in Autor and Dorn, 2013) or any occupation with an RTI higher than the unweighted average (look at Table 8 for clarification).

Table 8: RTI classification using the 1994 employment distribution by GMS (2014)

Occupation	Code	RTI	Top	Top
			33%	40%
Office clerks	41	2.24	X	X
Precision, handicraft, printing and related trades workers	73	1.59	X	X
Customer service clerks	42	1.41	X	X
Other craft and related trades workers	74	1.24	X	X
Machine operators and assemblers	82	0.49	X	X
Metal, machinery and relates trades workers	72	0.46	X	X
Labourers in mining, construction, manufacturing and transport	93	0.45		X
Stationary plant and related operators	81	0.32		X
Models, salespersons and demonstrators	52	0.05		
Sales and services elementary occupations	91	0.03		
Extraction and building trade workers	71	-0.19		
Life science and health associate professionals	32	-0.33		
Physical, mathematical, and engineering science associate professionals	31	-0.4		
Other associate professionals	34	-0.44		
Personal and protective service workers	51	-0.6		
Other professionals	24	-0.73		
Corporate managers	12	-0.75		
Physical, mathematical and engineering science professioanls	21	-0.82		
Life science and health professionals	22	-1		
Drivers and mobile plant operators	83	-1.5		
General managers	13	-1.52		

Source: Table 1 by Goos et al. (2014)

Our third classification follows Sebastian (2017a). Differently from Goos et al. (2014) that they use US data, Sebastian (2017a) provide the RTI using Spanish data (taken from the European Working Condition Survey). For the abstract tasks, she retains responses on “learning new things”, “solving unforeseen problems”, and “assessing yourself the quality of your job”.⁶ For the manual tasks, she selects 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).⁷ For routine tasks, she opts for routine activities they performed within their job: “does your main job involve (1) dealing with people, (2) repetitive tasks, (3) dealing with customers. Finally, she defines RTI using employment-weighted measures (as in Autor and Dorn, 2013):

- 1) She computes the occupation-level average score for each individual task in 1995.
- 2) She divides the tasks into three groups: routine, abstract, and manual (as in Table 12). For each occupation, she computes a score for each of these three groups of tasks.
- 3) Then for each occupation she compute a routine task intensity index as:
 $\ln(\text{routine}) - \ln(\text{service}) - \ln(\text{cognitive})$.
- 4) This is then standardised across occupations.
- 5) She then identifies the “routine occupations” based on the level of their RTI index, using both employment-weighted and unweighted measures, as explained.

⁶ These three items are closed questions (1=yes, 2=no).

⁷ Questions provide answer in intensity frequencies (1=all of the time, 2=almost all of the time, 3=around $\frac{3}{4}$ of the time, 4=around half of the time, 5=around $\frac{1}{4}$ of the time, 6=almost never, 7=never).

Table 2. Task measures and RTI index by occupation

	ISCO 88	RTI	1994	Cumulative	Top 33%
Handicraft and printing workers	74	1.63	4.40	4.40	X
Assemblers	82	1.34	4.67	9.07	X
Precision, handicraft, printing, and trades workers	73	1.02	1.17	10.24	X
Metal, machinery, and related trades workers	72	0.89	7.26	17.49	X
Building and related 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 machine operators	81	0.82	1.25	34.32	
Labourers in mining construction, manufacturing	93	0.76	5.48	39.80	
Cleaners and helpers	91	0.36	9.34	49.14	
Science and engineering associate professionals	31	0.26	1.73	50.87	
Sales workers	52	0.21	6.19	57.06	
Personal service workers	51	0.14	10.02	67.08	
Health associate professionals	32	-0.02	0.60	67.69	
Health professionals	22	-0.18	2.62	70.30	
General and keyboard clerks	41	-0.38	8.03	78.33	
Customer service clerks	42	-0.68	4.94	83.27	
Science and engineering professionals	21	-0.95	1.80	85.06	
Legal, social and related associate professionals	34	-1.12	5.27	90.34	
Business and administration 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	

Source: Table 2 by Sebastian (2017)