Explaining Job Polarisation in Spain from a Task Perspective[1]

Raquel Sebastián-Lago[2]

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1 Introduction

For long, the consensus has been that most of the recent technological changes have been skill biased, that is complementing high-skill workers and substituting low-skill employees (see, e.g., Katz and Autor, 1999). However, skill biased technological change on its own cannot explain a prominent and relatively recent phenomenon: the decline in the share of middle wage occupations relative to high and low-wage occupations. This phenomenon has been defined as "job polarization" (Goos and Manning, 2007).

While the main drivers behind job polarization are still subject to some debate, the main candidate is the so-called routinization hypothesis (Autor et al., 2003) (hereafter called ALM). The basic idea of this model is that recent technologies, such as computers, replace workers performing routine tasks, a process driven by the declining price of computer capital. This labour-capital substitution reduces the relative demand of labour in middle-wage occupations due to the increasing ability of machines to perform routine tasks, which characterise these occupations. The innovative aspect of this model is that it predicts that computerization has a non-linear effect on labour demand.

The notion that middle-skill jobs have been disproportionately destroyed and that the job distribution has hollowed out in the middle has been identified as a key aspect of contemporaneous rising labour market inequality (Acemoglu and Autor, 2010; Goos et al., 2009, 2014). Therefore, understanding how the employment structure evolves is crucial for governments and policy makers. Firstly, they need to understand whether the occupational change can transform societies into one with a large middle-class or one where the middle-class is more divided. Furthermore, they also need an

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[2] Marie Curie PhD candidate at University of Salamanca, e-mail: raquel.sebastian@usal.es.

accurate understanding on occupational employment in order to anticipate future skills needs and job opportunities.

Despite the importance of this topic, the results of research assessing the existence and degree job polarization in Spain are mixed and little has been done to understand the different results reported by researchers. On the one hand, Anghel et al. (2014) conclude that the employment structure has been polarising between 1997 and 2012. On the other hand, Oesch and Menés (2011) show a pattern of progressive upgrading for the same period. Moreover, two recent studies based on the European Labour Force Survey, and thus, covering Spain, diverge in their results: Goos et al. (2009, 2014) conclude that on average the employment structure in Spain has been polarising between 1993 and 2006. Using the same period of analysis, Fernández-Macías' (2012) work conversely shows an upgrading process (high-wage occupations expanding at the expenses of low-wage jobs) and does not provide evidence of a pervasive polarization.[3]

Focusing on the Spanish case, this paper contributes to the existing literature on the evolution of the employment and wage structure in four complementary ways. First, we shed some light to the literature on employment polarisation in Spain, providing clear evidence of job polarisation in our sample, confirming that between 1994 and 2008 employment share in Spain increased at the two extreme of the job wage distribution, while it decreased in the middle. We also contribute to widen the literature as long as we are the first ones assessing whether employment remuneration is in line with employment trends. In the U.S., Autor and Dorn (2013) find a clear correspondence between employment and wages. However, the polarisation of wages does not seem to be common in Spain, as there is no evidence that pay followed the same pattern as occupations. This contrasts with standard labour markets models predicting that a positive demand shock increases both employment and earnings.

Second, after classifying the occupations in manual (versus non-manual) and routine (versus non-routine) according to the ALM model and examine the association between employment changes and the tasks content of occupations, we analyse in detail the tasks content of those occupations over time. Differently from the majority of the empirical studies that have analysed the content of tasks using O*NET, we rely on the British Skill Survey (BBS) for two reasons. Among other

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[3] It must be noted that the methodology is not exactly the same. For a more detailed explanation see Sebastián-Lago (2015).

good characteristics, the BBS allows for time dynamics to measure routine tasks and it was conducted exclusively for research.[4] Using this survey, we first show that occupations that carried out routine tasks in 1994 have lost relative employment shares until 2008. Furthermore, we carry out a shift-share analysis to explore if the changes in the task-content of occupations are due to changes in the intensive margin (within occupations) or extensive margin (between occupations).

Third, we also enrich the literature exploring the relationship between computer use and routine tasks inputs, which we define on the basis of the frequency of repetitive activities that workers perform on the job. Following Green (2009, 2012), we create a pseudo-panel to analyse the relationship between computerisation and routine and we find that technology is significantly negatively related with routine.

Our last contribution consists in investigating the displacement of middle-workers integrating our main source with an additional dataset, the Survey of Living Conditions (SLC). Taking advantage of the new database, we exploit restrospective questions on past jobs. We find that middle-skilled workers became increasingly more mobile over time and predominantly shift towards low-skilled occupations, consistent with the ALM predictions.

The paper is organised as follows. Section 2 clarifies the main concepts and provides a review of the literature. Section 3 describes the data. In Section 4, we present evidence on labour market polarization, on both employment and pay structure. Section 5 examines the contribution of each job to changes in the employment share [still thinking on whether this section will be in or out]. Section 6 investigates the association between employment changes and the task content of occupations. Section 7 focuses on the evolution of tasks. Section 8 looks at the impact of computer adoption on routine tasks. In Section 9, we analyse the occupational mobility of middle-pay workers. Section 10 summarizes the main conclusions of the paper.

2 Literature review

Job polarisation appears under different names in the literature. The broadest definition refers to the relative job growth in the lower and upper tail of the wage

[4] The widely used ONET task database from the U.S. has information for only one point in time, and thus, is not suitable to analyse changes over time. The BBS has three comparable waves (1997, 2001, and 2006) that allows us to analyse changes in the task-content of occupations.

distribution relative to the middle-wage ones. This well-known phenomenon has been found in the U.S. (Wright and Dwyer, 2003; Autor et al. 2006; Autor and Dorn, 2013), the U.K. (Goos and Manning, 2007; Akcomak et al., 2013; Salvatori, 2015), Germany (Spitz-Oener, 2006; Dustmann et al., 2009; Kampelmann and Rycx, 2011), Sweden (Adermon and Gustavsson, 2015), and Portugal (Fonseca et al., 2015). With respect to Europe, the results are more controversial. On the one hand, Goos et al. (2009, 2014) show that on average the employment structure in Europe has been polarizing from 1993 to 2006. On the other hand, Fernández-Macías (2012) find heterogeneous results in Western European countries and conclude that there is not a clear and universal pattern of a pervasive polarization.[5] As for Spain, conclusions also diverge between polarization (Anghel et al., 2015) and occupational upgrading (Oesch and Menés, 2010)

While in the U.S wage polarization has occurred hand with hand with job polarization (Autor et al., 2006), the polarization of wages does not seem to be common to other countries. Goos and Manning (2007) failed to find wage polarisation for the U.K despite the strong evidence of job polarisation. Antoncyzk et al. (2010) and Kapelmman and Ryck (2011) show little evidence of wage polarisation in Germany. More generally, Massari et al. (2013) conclude that there is no wage polarization in Europe as a whole. With regards to Spain, there is not a single study which explores this phenomenon.

Different theories have tried to explain the main drivers behind the phenomenon. While there are some explanations based on supply mechanisms (skill composition), almost all the theoretical explanations are based on three different demand mechanisms. The first mechanism is the propensity to offshore activities, which is not the same in all occupations. According to Blinder (2009), certain jobs are potentially more vulnerable to offshoring than others. They show that production jobs are easier to reallocate in low-income countries than service jobs. In the second place, Autor and Dorn (2013) explain that income inequality increases income in the top earners and increasing as a consequence the demand for low-paid job services. It is well known that these two factors affect specific occupations. However, the economic literature

[5] Fernández-Macías (2012) classifies jobs in five equally size groups (showing the 20% of population in each quintile). Instead, Goos et al. (2009, 2014) classify the ranked jobs in three categories (good, middling, and bad jobs), which have uneven sizes in terms of number of occupations (8-9-4) and in terms of employment shares in the first year of the period studied (29,-49, and -22%, respectively).

suggests that these two factors play a minor role in explaining the demand shift towards skilled workers in advanced countries (see e.g. Autor and Katz, 1999; Feenstra, 2010; Acemoglu and Autor, 2011; Michaels et al., 2014).

On the contrary, the most prominent theory accounting for job polarisation is the well-known routinisation hypothesis (formulated by Autor et al. 2003). In their seminal paper, ALM propose a classification of tasks along two different dimensions: *routine* (as opposed to *non-routine*) and *manual* (as opposed to *non-manual,* or also called *cognitive*) tasks. Routine tasks are defined as those that "*require methodical repetition of an unwavering procedure*" (ALM, 2003: 1283). The cognitive dimension generally refers to tasks that require gathering and processing of information and problem solving (analytic), as well as those that need creativity, flexibility and communication in order to be performed (interactive).

In this model, they argue that the way in which occupations are affected by new technologies depends to a large extent on the tasks they perform ("task biased technological change"), rather than on their educational level. [6] In the ALM, technological progress takes the form of exogenous drop in the price of computers which lead to a reduction of routine tasks (manual and non-manual tasks).

In sum, routine manual tasks are carried out by assembler and machine operators, while routine non-manual tasks are performed by clerks and administrative workers. Given the strong substitution with computers (or ICT technologies), these tasks can be replicated by machines. Therefore, the model predicts employment decline in middle-skilled workers. Conversely, non-routine non-manual tasks are characterised mainly within managerial, professional and creative occupations and are usually performed by high-skilled workers. These types of tasks are not only difficult to be replaced by machines, but they are also complementary to computer technologies. Finally, non-routine manual tasks are typical of low skilled services occupations such as truck drivers, plumbers or anitors. These tasks exhibit neither strong substitution nor complementarity with computers [7] Yet, the employment increase in low-skilled services could be the consequence of a displacement effect of workers *à la* Baumol

[6] Goos and Manning (2007) and Goos et al. (2009) also refer to this process as "routinisation". This term might lead to confusion since it also evokes the phenomenon of standardization or de-complexification of work.

[7] On the one hand, non-routine manual tasks are difficult to automate as they require direct physical proximity. On the other hand, they do not need problem solving or managerial skills to be carried out, so there is limited room for complementarity.

(1967), away from technologically progressive industries, where labour input is substituted by machine to perform routine tasks.

3 Data

We use two different datasets covering the period 1994-2008. Data on the evolution of jobs and socio-demographic characteristics come from the Spanish Labour Force Survey. Data on the evolution of wages come from the Structure of Earnings Survey. Below, we describe both data sources in detail.

3.1. Spanish Labour Force Survey

The primary data source used is the Spanish Labour Force Survey (EPA, in Spanish) administered by the National Institute of Statistics. The EPA was carried out quarterly from 1964 to 1968, then biannually from 1969 to 1974, and finally quarterly again from 1975 onwards. The EPA is used to estimate employment and unemployment within the ILO framework and is the basic source by which researchers can construct data series on occupations.

Although the data is compiled quarterly and available from all years since 1964, our analysis focuses on the period 1994-2008 where we select the second quarter of each relevant year in order to avoid seasonality problems. The total sample size is 57,231, 66,636, and 69,809 individuals for 1994, 2000, and 2008, respectively. The EPA contains data on employment status, weekly hours worked, two-digit occupational level (CNO-94) and one-digit industry level (CNAE-93), education, region, nationality, sex, age, and the population in each cell among others. The dataset is weighted to reflect employment in absolute numbers.

The EPA 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 Structure of Earnings Survey. We explore the evolution of jobs after having applied to the data all the necessary restrictions to obtain a comparable sample. In other words, we retain only those jobs which appear in both surveys, dropping a total of 58 jobs.

3.2. Structure of Earnings Survey (SES)

The Structure of Earnings Survey (in Spanish, *Encuesta de Estructura Salarial*, EES) is administered by the official statistical office. This survey consists of a random sample of workers from private-sector firms of at least 10 employees in the manufacturing, construction, and service sectors.

The sampling takes place in two stages. In the first stage, firms are randomly selected from the Social Security General Register of Payments records, which are stratified by region and firm size. In the second stage, a sample of workers is randomly sampled from each of the selected firms. The survey collects detailed information on workers' wages; personal characteristics such as gender, age, educational attainment, and nationality; and job characteristics, including sector, occupation, contract and job type, firm size and ownership, and region.

For the period under study, the survey has been carried out three times (1995, 2002 and 2006). In 2002, the coverage of the survey is extended to include some non-market services (educational, health, and social services sectors) that are not included in the 1995 wave. Throughout our paper, to measure job polarization, we use the 1995 wave rather than the 2002 or the 2006 as my results remain invariant and is preferable because 1995 is closer to the base year of the period of analysis.

4 The evolution of employment and pay rules in Spain

4.1 The evolution of employment

The starting point of our analysis is to investigate the pattern of employment change in the Spanish Labour as a preliminary step for the subsequent analysis. Unless otherwise noted, throughout this paper we model employment by occupation (ISCO-88 two-digit level) and by industry (NACE Rev.1 at one-digit level). All earnings data used in this article refer to hourly wages deflated to the year 1995 using the Consumer Price Index (CPI). Employment share is computed from EPA data, while the employment ranking is based on the mean wage from the 1995 EES data.[8]

The most common way of analysing the development of jobs is through graphical illustration. To detect it, 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 mean wage.[9] And then, we plot the percentage point change in employment share against the log mean hourly wage. If the structure of employment has polarised, one should clearly see

[8] We merge the EPA with the EES, and two filters are applied to the final data. First, we drop workers associated with the primary sector, public administration and defense (These correspond to the industries (NACE) A, B, C, L and Q, and the occupations (ISCO) 11, 61 and 92.). Second, we retain only those jobs which appear in both surveys and with at least 5 observations. After applying both filters, we reduce the total number of jobs from 218 to 160 jobs. See Appendix for details on the measures discussed in this section.
[9] The shape of the graph does not change if median average earnings are used for determining job quality.

employment in low and high-paying jobs increased while it decreased in the middle of the distribution.

Figure 1 corresponds to the evolution of Spanish employment between 1994 and 2008. Following Goos et al. (2014), employment shares are measured by two-digit occupations (ISCO-88) and by one-digit sectors of activity (NACE Rev.1). Earnings are measured by the logarithm of hourly mean in each job in 1995. The employment changes in Spain shows a clear pattern of job polarization, in which the higher and lower part of the earnings distribution has increased while shrinking the middle-earnings part. We can clearly detect a U-shaped curve in the evolution of employment shares when jobs are ranked according to the mean wage.

Figure 1
Employment shares growth in Spain (1994-2008) by mean hourly wage

Notes: Author's analysis. 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. Colours represent the quintile of each job (green, first quintile; yellow, second quintile, grey, third quintile; red, fourth quintile;, and violet, fifth quintile)
Sources: Spanish Labour Force Survey (1994, 2008), Wage Structure Survey (1995)

Using the parametric graph, we test in a more rigorously job polarization. In order to do so, we estimate the following model of the quadratic form as proposed by Goos and Manning (2007):

$$\Delta \log E_j = \beta_0 + \beta_1 \log(w_{j,t-1}) + \beta_2 \log(w_{j,t-1})^{2} \qquad (1)$$

where $\Delta \log E_j$ is the change in the log employment share of job j between *t-1* and *t*, $\log(w_{j,t-1})$ is the logarithm of the median wage of job j in *t-1*, and $log(w_{j,t-1})^{2}$ is the square of the initial median wage. A U-shaped relationship between the employment growth and the wages implies that the linear term is negative and the quadratic term is positive.

Table 1, panel (1) and (2), presents the results of the OLS regression using weekly hours worked as a measure for employment shares rather than expressing them in terms of bodies. Moreover, we estimate the equation in two time periods: 1994-2000 (short period), and 1994-2008 (long period). I estimate Equation (1) by weighting each job by its initial employment share in 1994 to avoid that results are biased by compositional changes in small jobs. All regression coefficients have the expected sign and are significant at the 1% level. For the longest period (1994-2008), the coefficients increase in absolute value, as well as the adjusted R-squared. The results indicate that Spain has been characterized by a marked polarisation in employment growth from 1994 to 2008. The phenomenon of job polarisation is also robust to the use of the median instead of the mean.

Table 1. Regressions for Job Polarisation Analysis

	Log change in employment share		Change in employment share	
	1994-2000 (1)	1994-2008 (2)	1994-2000 (3)	1994-2008 (4)
(log) mean hourly wage 1994	-8.17*** (2.12)	-8.88*** (2.31)	-2.03 (0.87)	-4.61 (1.96)
Sq. (log) mean hourly wage 1994	1.56*** (0.40)	1.73*** (0.43)	0.42* (0.16)	0.98* (0.37)
Constant	9.23*** (2.12)	10.76*** (3.01)	2.69 (1.12)	6.07 (3.01)
N	109	126	156	163
Adj. R-square	0.10	0.12	0.06	0.07
F	7.81	8.84	6.49	7.92

Notes: Each job is weighed by the initial number of observations. Robust standard errors between parentheses, significance levels ***p < 0.01, **p < 0.05, *p < 0.10.
Sources: Author's analysis from Spanish Labour Force Survey (1994, 2008), Wage Structure Survey (1995).

Goos and Manning (2007) calculate the change in logarithms, measuring therefore a smooth trend. As one might be worried about it, thinking that the logarithm could drive the result, we compute the relative change between 1994 and 2008. We estimate the next quadratic form:

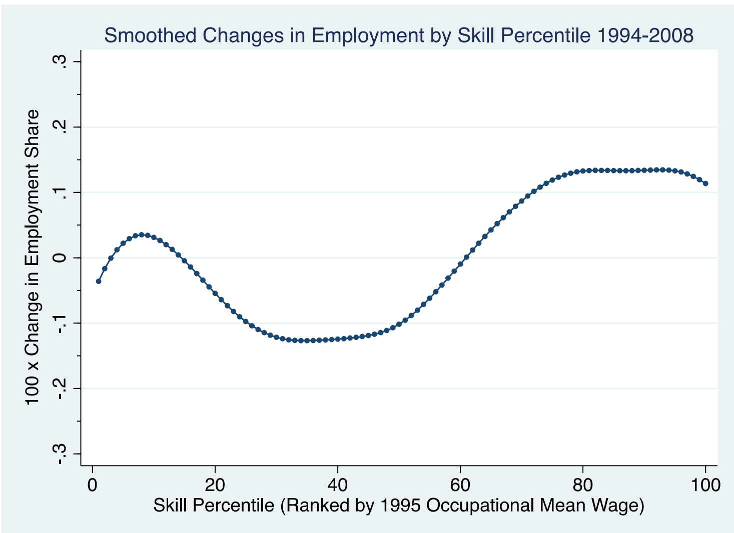
$$\Delta \mathrm{E_j} = \beta_0 + \beta_1 \log(\mathrm{w_{j,t-1}}) + \beta_2 \log(\mathrm{w_{j,t-1}})^2 \qquad (2)$$

where ΔE_j is the change in the employment share of job j between t and t-1, $\log(w_{j,t-1})$ is the logarithm of the median wage of job j in t-1, and $log(w_{j,t-1})^2$ is the square of the initial median wage.

In Table 1, panel (3) and (4), coefficients have the expected sign and are larger in magnitude when moving to the longest period, as it happens with the adjusted R-squared. However, and as expected, results are not as significant as in the previous scenario.

We also analyse job polarization by defining job wage percentile [10] In this particular case we display smoothing regressions rather than the actual data point (the previous case). 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 losses are observable. For Spain, the biggest losses are between the 20th and the 40th percentile of the initial mean wage distribution. Overall, the shape of employment changes in the EPA data updates other studies with Spanish data and suggests that job polarisation is a robust phenomenon in Spain.

Figure 2
Smoothed changes in Employment by wage percentile (1994,2008)



Notes: Author's analysis. The figure plots log changes in employment share by 1995 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 1995 Wage Structure Survey.
Sources: Spanish Labour Force Survey (1994, 2008), Wage Structure Survey (1995).

[10] This methodology has been applied by Autor and Dorn (2013).

We implement three robustness tests for the results presented above. First, we test whether results are sensitive to the choice of the reference year as one might be concerned whether results are sensitive to the choice of the year. We select the 2000 EES and 2006 EES. Second, we rank jobs by median rather than mean earnings. And third, we evaluate the impact of an alternative definition of job. In this case, we defined a job by two-digit ISCO (following Anghel et al. 2014) and by two-digit ISCO and two-digit NACE (as Macías-Fernández, 2012). In all three cases, graphs result invariant and we can always detect a U-shaped curve in the evolution of employment shares. Therefore, we can conclude that employment changes in Spain clearly reflect a polarisation pattern with considerable increases for high and low-wage jobs, while decreases for middle-wage jobs.

4.2 The evolution of wages

In this section, and after studying the evolution of employment, we investigate the evolution of remuneration of jobs. We examine whether changes in the labour market's quantity side find their natural counterpart in changes in price side. If the trend in the evolution of pay rules matches the trend in the evolution of employment, we would expect a similar pattern to emerge for the case of jobs pay rules. Therefore, a natural way to predict changes in wages is using the same quadratic model with which we detect a U-shaped evolution of employment shares (Kampelmann and Rycx, 2011). To test for wage polarization, we estimate the following model:

$$\Delta \log(w_j) = \beta_0 + \beta_1 \log(w_{j,t-1}) + \beta_2 \log(w_{j,t-1})^{2} \qquad (3)$$

where $\Delta \log(w_j)$ is the change in the log mean wage of job *j* between *t-1* and *t*, $\log(w_{j,t-1})$ is the logarithm of the median wage of job *j* in *t-1*, and $log(w_{j,t-1})^{2}$ is the square of the initial median wage.

Table 2 shows the results of OLS regression using the initial number of observations in each job and is weighted by the number of individuals within a job in 1994. Coefficients have the expected sign but are not significant. Results obtained show that there is no evidence of wage polarisation for the period 1994-2008.

Table 2. OLS regression for wage polarization analysis

	Change in (log) mean wage, 1995-2006
(log) mean hourly wage 1995	-0.70*
	(0.25)
Sq. (log) mean hourly wage 1995	0.13
	(0.05)
Constant	0.74
	(0.28)
N	160
Adj. R-square	0.07
F	7.06

Notes: Each job is weighed by the initial number of observations. Robust standard errors between parentheses, significance levels ***p < 0.01, **p < 0.05, *p < 0.10.
Sources: Author's analysis from Earnings Structure Survey, 1995 and 2006

To test directly for whether changes in employment share match changes in pay rules, we have computed the corresponding correlation coefficient. Contrary to the existing evidence in the U.S. or in Germany, our results suggest that the link between changes in employment share and changes in the mean earnings is extremely weak and negative in Spain (Table 3).

Table 3.Correlation between change in employment share and mean wage

	Change in employment share	Change in (log) mean wage
Change in employment share	1.0	
Change in (log) mean wage	0.09	1.0

Notes: correlations are computed at the 2-digit occupational level and 1-digit sector.
Sources: Spanish Labour Force Survey and Earnings Structure Survey

5 Finding for the pattern of job changes, 1994-2008

We continue our analysis by examining the contribution of each job to changes in the employment share in three segments of the job occupational wage distribution. To do so, we proceed by aggregating the 160 jobs so far considered at the ISCO-88 two-digit level and we classify these occupations into three major groups which we label as bottom (1st, 2nd and 3rd deciles), middling (4th, 5th, 6th and 7th deciles) and top-high occupations (8th, 9th and 10th).[11] Table 4 presents the 22 two-digit occupations, the

[11] We decide to divide the three groups using the wage distribution, and not using the occupational code as Goos et al. (2009, 2014). Their groups include the eight highest-paying occupations, the nine middiling occupations and

employment shares, and the percentage point change in their employment share of the bottom wage distribution (which is reported in column 1 and 2), the middle (column 3 and 4), the top (column 5 and 6), and all (column 7 and 8). The bottom makes clear the magnitude of the shift in employment from middle to the top: of the 3.52pp of employment gained at the top of the wage distribution, 2.61pp have been lost in middling occupations and only 0.91pp in the bottom. In other words, job expansion is clearly biased to high-paid occupations.

The bottom part is characterised by a small declined in occupation where there are two opposite forces driving the result. On the one hand, there is a sharp reduction in "handicraft and printing workers" and in "labourers in mining, construction, manufacturing and transport", which account for a reduction of 4 points in the employment share. On the other hand, service occupation made a large contribution to the expansion of the low-paid employment. Table 4 shows that the decline in craft occupations has been features of all two decades while the growth of service occupations is concentrated in the 2000s. It also shows that "labourers in mining, constructions, manufacturing and transport" only lose employment in the 2000s. Almost the entire (modest) decline in growth on bottom occupations is characterized by a heavy increase in service occupations and huge decline in craft occupations.

The decline in the middling occupations is driven by the heavy reduction in "assemblers" occupations, which account for half of the reduction. "Metal and machinery workers", "handicraft and printing workers", "drivers and plant operators" and clerks" count for the other half. Particularly interest, is this case, as Table 5 reveals that "assemblers" grow significantly during the 90s and only start to lose employment share in the 2000 and made a large contribution than the other occupations to the decline in the middling occupations during the whole period. On the other hand, "building and related trade workers" have instead increased shares and their growth was equally concentrated in both periods.

Finally, managers and associate professionals are the main drivers of growth at the top, as they almost double their share over the 15 years. Within this group the largest expansion is found in "Legal, social and related associate professionals". "Science and engineering professionals" and "business and administration

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the four lowest-paying occupations. Fernández-Macías (2012) criticises the methodology strategy developed by Goos et al. (2009), claiming that a division in even groups would not lead to conclude that there was a pervasive polarization in Europe. Our results for Spain are robust to both definitions.

professionals" also made a large contribution to the expansion of top-paid employment. "General and keyboard clerks" and "Metal, machinery and trade workers" have instead lost share. Table 5 shows that the growth of "legal and social and related professionals" was more concentrated in the first decade. It also displays the growth of managers and professionals and the decline of clerks and metal workers was a pattern of the whole period.

Summarizing, strongly growing occupation can be divided in two groups: the first comprises highly qualified occupations like managers and professionals (three out of five fastest growing occupations) while The second includes jobs related to construction.[12] More in detail the second fastest growing occupation is building and related trades workers. In the declining occupations, we also can distinguish two groups. A first group comprises the victims of de-industrialization and includes production workers such us mechanics, maintenance filters and assemblers[13] The second group is characterised by clerical support workers. Both groups are not particularly low-paid, spreading across the middle deciles. Two main ideas are inside these two tables: job expansion is clearly biased to high-paid occupations and second, employment declined most in the middle.

[12] This corresponds to ISCO 34, 21 and 22.
13 This correponds to ISCO 72,73, 74 and 82.

Table 4. Contribution of two-digit ISCO-88 categories to employment changes in different segments of the occupational wage distribution, 1994-2008

		Bottom		Middle		Top		All	
Occupation	ISCO 88	1994 share (1)	1994-2008-1994 (pp change) (2)	1994 share (3)	1994-2008 (pp change) (4)	1994 Share (5)	1994-2008 (pp change) (6)	1994 share (7)	1994-2008 (pp change) (8)
Corporate manager	12	-	-	-	-	2.44	0.76	2.44	0.76
Science and engineering professionals	21	-	-	-	-	2.12	1.33	2.12	1.33
Health professionals	22	-	-	-	-	0.49	0.13	0.49	0.15
Teaching professionals	23	-	-	-	-	1.61	1.00	1.61	1.00
Business and administration professionals	24	-	-	-	-	0.21	0.06	0.21	0.06
Science and engineering associate professionals	31	-	-	-	-	1.95	1.14	1.96	1.15
Health associate professionals	32	-	-	0.18	0.09	0.08	0.10	0.28	0.20
Business associate professionals	33	-	-	-	-	0.01	0.01	0.01	0.01
Legal, social and related associate professionals	34	-	-	-	-	5.32	4.47	5.32	4.47
General and keyboard clerks	41	-	-	3.15	-0.62	5.28	-2.35	8.44	-2.97
Customer service clerks	42	1.68	0.81	1.19	0.21	1.61	-0.32	4.49	0.70
Personal service workers	51	6.29	1.64	0.01	-0.01	0.40	-0.01	6.71	1.63
Sales workers	52	0.09	0.02	8.22	-0.21	-	-	8.31	-0.20
Building and related trades workers	71	-	-	11.29	2.28	0.25	-0.09	11.54	2.19
Metal, Machinery and related trades workers	72	-	-	3.41	-0.68	6.21	-2.37	9.62	-3.06
Handicraft and printing workers	73	-	-	1.59	-0.94	-	-	1.59	-0.96
Electrical and electronic trades workers	74	5.94	-3.19	0.03	-0.01	-	-	5.97	-3.20
Stationary plant and machine operators	81	-	-	0.07	-0.05	1.57	-0.14	1.65	-0.20
Assemblers	82	0.18	0.08	6.04	-1.66	0.02	-0.01	6.25	-1.59
Drivers and mobile plant operators	83	1.22	-0.17	6.93	-0.70	0.03	-0.02	8.19	-0.90
Cleaners and helpers	91	4.49	1.19	0.72	-0.36	0.24	-0.17	5.47	0.66
Labourers in mining, constructions, manufacturing and transport	93	6.82	-1.29	0.42	0.09			7.24	-1.28
	Total	26.74	-0.91	43.33	-2.61	29,.2	3.52	100	0

Table 5. Contribution of ISCO-88 two-digit level to employment changes in different segments of the occupational wage distribution by decade

		Bottom		Middle		Top		All	
Occupation	ISCO 88	1994-2000	2000-2008	1994-2000	2008-2000	1994-2000	2000-2008	1994-2000	2000-2008
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Corporate manager	12	-	-	-	-	0.35	0.41	0.35	0.41
Science and engineering professionals	21	-	-	-	-	0.61	0.72	0.61	0.72
Health professionals	22	-	-	-	-	-0.01	0.14	-0.01	0.15
Teaching professionals	23	-	-	-	-	0.47	0.53	0.47	0.52
Business and administration professionals	24	-	-	-	-	0.06	-	0.06	0
Science and engineering associate professionals	31	-	-	-	-	0.5	0.64	0.49	0.65
Health associate professionals	32	-	-	-0.02	0.11	0.06	0.04	0.03	0.16
Business associate professionals	33	-	-	-	-	0.01	-	0.01	0
Legal. social and related associate professionals	34	-	-	-	-	2.89	1.58	2.89	1.57
General and keyboard clerks	41	-	-	-0.6	-0.02	-0.93	-1.42	-1.53	-1.44
Customer service clerks	42	0.16	0.65	0.03	0.18	-0.23	-0.09	-0.03	0.73
Personal service workers	51	0.52	1.12	-	-0.01	-0.1	0.09	0.42	1.21
Sales workers	52	-0.02	0.04	-0.47	0.26	-	-	-0.5	0.3
Building and related trades workers	71	-	-	1	1.28	-0.02	-0.07	0.98	1.19
Metal. Machinery and related trades workers	72	-	-	-0.48	-0.2	-1.37	-1.00	-1.86	-1.2
Handicraft and printing workers	73	-	-	-0.52	-0.42	-	-	-0.52	-0.44
Electrical and electronic trades workers	74	-1.86	-1.33	-	-0.01	-	-	-1.86	-1.33
Stationary plant and machine operators	81	-	-	-0.05	-	-0.28	0.14	-0.33	0.13
Assemblers	82	0.08	-	0.57	-2.23	-	-0.01	0.65	-2.24
Drivers and mobile plant operators	83	-0.16	-0.01	-0.54	-0.16	-	-0.02	-0.71	-0.19
Cleaners and helpers	91	0.08	1.11	-0.16	-0.20	-0.09	-0.08	-0.18	0.84
Labourers in mining. constructions. manufacturing and transport	93	0.61	-1.9	-	0.09	-	-	0.59	-1.83
	Total	-0.59	-0.32	-1.24	-1.35				

6 Task-based analysis of employment changes

To interpret previous findings on job polarization in Spain, we follow a task-based approach exploiting information on the activities carried out by workers on workplaces. Each worker performs a bundle of tasks but they do it with different intensities. Therefore each job is not defined by one single tasks but it can be classified as with a predominant task. To proceed with our analysis, we need to gather further information concerning the nature of tasks performed by workers. Data on the tasks workers perform on their jobs comes from the British Skill Survey.

6.1. British Skill Survey (BSS)

The data that we use to measure tasks come from the three UK Skills Surveys of 1997, 2001, and 2006. The three repeated cross-sections cover altogether 14,717 workers, respectively 2,467 in 1997, 4,470 in 2001, and 7,780 in 2006. The main aim of these surveys is to collect information on the generic tasks that are being done in jobs, where the same task can be done to a greater or a lesser degrees, or at different levels, across the whole spectrum of jobs.

There are two different features between the U.S. O*NET and the British Skill Survey. Firstly, while the original purpose of the U.S. O*NET was an administrative evaluation by Employment Services offices of the fit between workers and occupations, the U.K. Skill Surveys were conducted exclusively for research. [14] Secondly, differently from the U.S. O*NET, where analyst at the Department of Labour assign scores to each task according to standardised guidelines, the U.K. Skill Survey derive individual tasks measures. This means that the U.K. Skill Survey presents a higher level of subjectivity, giving the advantage of a more precise idea of the tasks performed within each occupation.[15]

Applying the U.K. Skill Survey to our data poses some challenges. Mainly, the BSS codify 296 occupations using U.K. SOC codes which we had to convert into ISCO codes, as we only have the occupations in ISCO. We aggregate the 296 occupations into 67 ISCO codes (3-digit level), and then into 27 ISCO codes (2 digit level).[16] Regarding the sector, the BSS codify 57 sectors using the U.K. SIC codes that are the same as the NACE Rev.1.

[14] The study was directed by Francis Green, Alan Felstead, Duncan Gallie and Ying Zhou.

[15] Autor and Handel (2009), who use a similar type of survey as the U.K. Skills Survey, prove that their data have a greater explanatory power for wages tan those derived from the O*NET.

[16] U.K SOC census 1900 and U.K SOC census 2000 codes in the British Skill Survey are matched by the Camsis Project to the International Standard Classification of Occupations (ISCO-88).

6.2. Occupational task measures definitions

In order to establish the task content of each job's measures, we use the same framework as Autor, Levy and Murnane (2007). Their classification is based on a two-dimensional typology: manual, as opposed to non-manual (being later divided into analytical and interactive subsets), and routine, as opposed to non-routine.

We measure manual, analytic and interactive tasks using 35 questions on job content. At each wave, each respondent is asked how much a particular activity is important at his/her job on a 5-point scale ranging from 5 ("not at all/does not apply") to 5 ("essential"). These variables in Likert scale are converted into increasing cardinal scale from 0 ("not at all/does not apply") to 1 ("essential"). Examples of analytical tasks are making speeches and presentations, thinking ahead, problem solving, analysing complex problems in depth and doing calculations using advanced statistical procedures. Among the interpersonal characteristics we include dealing with people, listening carefully to colleagues or selling a product or a service. Finally, working for long periods on physical activities or carrying, pushing and pulling heavy objects are considered as manual tasks. Further details about the derivation of all the other variables used in the empirical analysis can be found in the Appendix A.

We define routine tasks as in the ALM model being those that follow clear rules and procedures that can be "specified in computer code and execute by machines" (p.1283). To follow the ALM model we take into account tasks that can be easily replicated by machined and readily subject to automation. Individuals in the UK Skill Survey were asked how often their jobs involve carrying out short and repetitive tasks. To this item they could respond on a 5-point scale ranging from "never" to "always" (intermediate answer were "rarely", "sometimes" and "often").[17]

In table 6 we present the correlation among the tasks and the education variable at the 2-digit occupational level. The manual dimension is negatively correlated with the analytical and interpersonal measures and positive correlated with the routine measure. The education measure is positive corralled with the two non-manual dimensions, while is negative with the manual dimension. The routine measure is negatively correlated with the analytical and inter personal measures and with the level of educational attainment and positively with the manual measure. Results are

[17] Arguing that the a priori identification of routine activities is difficult, Green (2012) considers as such only repetitive manual activities.

similar as the ones provided by Green (2012), where he explores at the individual level the correlation between job skill indexes with the education variable.[18]

Table 6. Correlation among the task measures and the education variable

	Analytical	Interpersonal	Manual	Routine	Education
Analytical	1				
Interpersonal	0.603	1			
Manual	-0.4854	-0.438	1		
Routine	-0.796	-0.476		1	
Education	0.792	0.509	-0.783	-0.738	1

Notes: Correlations are computed at 2-digit occupation.
Sources: Spanish Labour Force Survey and UK Skill Surveys.

6.3 Employment changes and tasks intensities

In this section, we explore the routinization hypothesis by looking at changes in employment share and the task content of each occupation's measure. We aggregate the 160 jobs at the ISCO-88 two-digit level to offer a clear interpretation of the occupations that mainly contributed to the polarisation of the employment structure. Table 6 presents the 22 two-digit occupations ranked in ascending order by the mean hourly wage in 1995, reported in column 1, the mean level of education in 1995 (column 2), and their percentage point change in their employment share during the period 1994-2008. In contrast to Table 4 and Table 5, we draw on the work of Goos and Manning (2009, 2009) to classify occupations in three major groups that we label as low, middling and high-pay. Our groups include 6, 9, and 7 occupations. In Table 7 we report the average values of the task measures for each occupation. Looking at Table 6 and 7 we can have a clear picture of the task content of the occupation which determined employment polarisation in Spain between 1994 and 2008.[19]

6.3.1. Non-manual and manual dimensions

Among the group of low-pay occupations, we find that half of the occupations have a growing employment share. Those occupations are "Cleaners and helpers" (ISCO 91), "Personal service workers" (ISCO 51) and "Building and related trades workers" (ISCO 71). Table 6 also shows that half of the occupations lose employment share. Those one are "Labourers in mining, construction, manufacturing and transport" (ISCO 93), "Electrical workers" (ISCO 74), and "Sales workers" (ISCO 52). Our

[18] The main differences between our analysis and Green (2012) have to do with the fact that he uses the required education of the job and not worker's actual highest education.
[19] The BSS does not pose information on the ISCO code 33, "business associate professional". We drop this occupation.

findings confirm the hypothesis that the increase in the lower tail of the distribution is driven by a job expansion in the service sector. The task component of these jobs is mixed: on the one hand, service occupations score higher in the interpersonal dimension. On the other hand, elementary occupations score higher in the manual dimension. This result is in line with the fact that low-paid occupations rely both on physical proximity and interpersonal communication and, therefore, they are not directly affected by the technological progress.

Concerning the middling-pay occupation, three occupations lose more employment share between 1994 and 2008. Those are “Clerks” (ISCO 41), “Metal machinery and related trades workers” (ISCO 72), and “Assemblers” (ISCO 82), scoring respectively in the manual measure 0.75, 0.81, and 0.76.

Finally, within the group of the highest paying occupations, “Legal, social, and related associate professional” (ISCO 34) and “Science and engineering associate professionals” (ISCO 24) are those that experienced the most significant employment growth. All the seven highest occupations score higher on the non-manual dimension, than on the manual one. This is consistent with the ALM model as these occupations demand tasks such as flexibility, creativity, problem solving and complex communication. Therefore, the likelihood of technology to substitute for workers in carrying out these tasks is very limited.

6.3.2. Routine dimension

After presenting the manual and non-manual dimension, we take into account an additional dimension regarding the repetitiveness of activities. In the ALM model, they split the routine dimension into two components: routine cognitive (for instance documenting and processing information) and routine manual (for example repetitive assembly). In our case, the single question on repetitiveness in the U.K. Skill Survey does not allow this decomposition. For the sake of completeness, we measure the correlation between the U.K Skill Survey routine measure and O*NET routine-manual and routine-cognitive. In Table 8, we show that our measure of Skill Survey

Table 6. Occupations, mean wage and education

Occupation	ISCO-88	Mean wage in 1995	Mean level of education in 1995	Total change in employment share 1994-2008
		(1)	(2)	(3)
Labourers in mining construction, and manufacturing	93	7.21	1.22	-0.92
Cleaners and helpers	91	8.03	1.18	0.23
Handicraft and printing workers	74	8.17	1.18	-2.36
Personal service workers	51	8.44	1.51	1.89
Sales workers	52	9.50	1.47	-0.28
Building and related trades workers	71	9.65	1.23	1.48
Drivers and mobile plant operators	83	10.10	1.20	-0.92
Assemblers	82	10.27	1.29	-1.18
Handicraft and printing workers	73	10.33	1.48	-0.69
Customer service clerks	42	10.96	2.26	0.31
Metal, machinery, and related trades workers	72	12.77	1.49	-2.35
General and keyboard clerks	41	13.19	2.33	-3.28
Business associate professionals	33	14.08	2.31	0.12
Health associate professionals	32	14.34	2.94	0.30
Stationary plant and machine operators	81	15.33	1.45	-0.17
Science and engineering associate professionals	31	18.44	2.66	1.01
Legal, social and related associate professionals	34	18.94	2.39	4.10
Business and administration professionals	24	21.68	3.88	0.28
Health professionals	22	22.33	3.91	0.17
Science and engineering professionals	21	24.30	3.92	1.02
Teaching professionals	23	25.90	3.89	0.68
Corporate managers	12	33.10	2.64	0.53

Notes: occupations are ranked in ascending order by the mean hourly wage in 1995; column 2 reports the mean of the educational attainment in 1994, based on for-vales variable (elementary, basic, medium, high), column 3 shows the percentage point in employment share over the period 1994-2008.
Sources: Spanish Labour Force Survey and British Skill Survey

Table 7. Tasks measures by occupations

Occupation	isco88	Interpersonal (1)	Analytical (2)	Manual (3)	Routine (4)
Labourers in mining construction, and manufacturing	93	0.68	0.70	0.87	0.58
Cleaners and helpers	91	0.63	0.60	0.67	0.60
Handicraft and printing workers	74	0.49	0.55	0.79	0.78
Personal service workers	51	0.75	0.68	0.68	0.62
Sales workers	52	0.84	0.60	0.47	0.61
Building and related trades workers	71	0.71	0.70	0.80	0.53
Drivers and mobile plant operators	83	0.60	0.53	0.60	0.57
Assemblers	82	0.62	0.68	0.70	0.62
Handicraft and printing workers	73	0.59	0.68	0.66	0.64
Customer service clerks	42	0.73	0.62	0.35	0.74
Metal, machinery, and related trades workers	72	0.63	0.70	0.81	0.57
General and keyboard clerks	41	0.59	0.64	0.75	0.62
Health associate professionals	32	0.74	0.73	0.52	0.42
Stationary plant and machine operators	81	0.45	0.61	0.76	0.52
Science and engineering associate professionals	31	0.63	0.67	0.47	0.52
Legal, social and related associate professionals	34	0.72	0.72	0.30	0.46
Business and administration professionals	24	0.71	0.76	0.26	0.34
Health professionals	22	0.77	0.77	0.58	0.49
Science and engineering professionals	21	0.68	0.76	0.34	0.39
Teaching professionals	23	0.73	0.79	0.37	0.39
Corporate managers	12	0.78	0.76	0.32	0.43

Notes: Occupations are ranked in ascending order by the mean hourly wage in 1995. Column 1 to 4 reported normalised tasks measures in 1997, ranging [0,1]
Sources: Spanish Labour Force Survey and British Skill Survey

routine correlates positive with both the O*NET routine-cognitive (0.52) and O*NET routine-manual (0.37).[20] Our results are similar as the ones found by Autor and Handel (20009, p. 20) using the data from the Princeton Data Improvement Initiative Survey (PDII). The question on repetitiveness used in their case is almost identical as the one in the U.K. Skill Survey, finding instead that their measure of routines correlates positively with the O*NET routine manual scale (0.36) and negatively with the O*NET routine cognitive scale (-0.22). They conclude that it placed far greater weight on the manual rather than the cognitive dimension of repetitiveness.

Table 8. Correlation between U.K Skill Survey and O*NET

	Skill Survey routine	O*NET routine-cognitive	O*NET routine-manual
Skill Survey routine	1		
O*NET routine-cognitive	0.37	1	
O*NET routine-manual	0.52	0.39	1

Notes: Correlations are computed at 2-digit occupation level.
Sources: Author's analysis from UK Skill Survey and O*NET data.

We now analyse the routine dimension among the occupations previous considered. As expected the group of the lowest paying occupations (ISCO 24, 21, 23) are characterized by non-routine activities. It is also noted that high-paying activities are the ones that required the less routine activities. By contrast, middling occupations are characterised by high routine activities. "Clerks" (ISCO 42) have the highest measure in routine (0.74), followed by "Handicraft and printing workers" (ISCO 73) and "Assemblers" (ISCO 82) with 0.64 and 0.62 respectively. These results is in line with ALM hypothesis which clearly predicts that the impact of computerisation caused a substantial substitution with routine tasks typical of middling-paying occupations and strong complementarity with non-routine tasks performed by high-paying occupations.

Concerning the group of lowest paying occupation, results are more controversial, being those occupations mostly of a routine nature. Our explanation on this result is that the repetitiveness dimension could have been interpreted by respondents as mundane and tedious rather than mechanistic and readily to

[20] U.S. Census 2000 codes in the O*NET are matched to the International Standard Classification of Occupations (ISCO-88) using the codes publicly offered by David Autor-

automation. In this regard, also Autor and Handel (2009), who use a similar question on repetitiveness, find that service occupations score really high in the routine dimension. These findings should be therefore interpreted carefully and not considered in construct to the ALM theoretical model.

Table 9. OLS regression of changes in employment share and the initial level of routine intensity

	Dependent variable Change in employment share 1994-2008
Routine intensity 1997	-1.90***
	(0.62)
N	97
Adj. R-square	0.10
F	9.19

Notes: the regression includes a constant. Robust standard errors between brackets. The dependent variable is measured using 2-digit ISCO and 1-digit NACE
Sources: Spanish Labour Force Survey and U.K Skill Survey

Table 9 presents the OLS regression of changes in employment share and the initial level of routine intensity for each job. In this case, we measure 97 jobs using the matrix combination at two-digit ISCO and one-digit NACE. As expected, there is a negative relationship between the two variables and the coefficient is statistically significant.

7. Tasks importance over time

In this section we investigate the evolution of tasks measures across time. The composition of tasks constitutes a vital piece of information to test the routinization hypothesis. We plot, on the basis of the occupations at 1-digit, the mean task points in 1994 and in 2008. Figure 3 shows two different features: firstly, a sharp reduction in the importance of manual and routine tasks consistent with a gradual shift from manufacturing to services; secondly, analytical tasks and interpersonal task increase their relevant throughout the period for any given job. Overall the results are in line with the routinization hypothesis: routine tasks decrease over time, while analytical and interpersonal become more important.

Figure 3

Importance of tasks over time

Sources: Author's analysis from the Spanish Labour Force Survey and U.K Skill Survey

In the light of the above finding, we now analyze whether changes in the task structure of the labour market rely on the changes within occupations (i.e. the intensive margin) or between occupations (i.e. the extensive margin). The BBS allows us to decompose the changes of the importance if the four tasks groups into changes in the intensive and extensive margin. In Table 10, we present the results of the shift-share analysis, which decompose the change in importance of tasks of each occupation as follows:

$$\Delta T_k = \sum_j \Delta E_j \ \gamma_{jk} + \sum_j \Delta\gamma_{jk} E_j \qquad (4)$$

where ΔT_k is the change in importance of task k between 1994 and 2008; ΔE_j is the change in employment share in national employment of occupation j and γ_{jk} represents the importance of task k in occupation j. Finally, $\Delta\gamma_{jk}$ is the change in the share of task k in occupations and E_j is the average share of occupation j .The first term on the right-hand-side equation is the extensive margin, i.e. the task importance is held constant (and represents the average task importance across the two years) and time variation relies on changes across occupations. The second term is the intensive margin where occupational employment is held constant while the importance of tasks within occupations is allowed over time.

Table 10 compares the importance of the four tasks groups in 1994 and 2008 and the change between 1994 and 2008. We find that routine and manual become less important in the Spanish economy while the importance of interpersonal and analytical. In addition, the last two rows in Table 10 present the decomposition of these changes in to changes in the intensive margin and the extensive margin. The decreasing importance of the routine tasks occurs at the extensive and intensive margins whereas manual tasks decrease its importance due to changes within jobs. Interpersonal and analytical tasks win in employment due to increasing tasks importance between jobs. The impact of the extensive margin is larger for interpersonal and analytical while the decreasing importance of manual tasks seems to rely mainly on the extensive margin.

Table 10. Tasks shifts, intensive and extensive margin

	Interpersonal	Analytical	Manual	Routine
Importance 1994	27.54	26.56	23.16	22.72
Importance 2008	28.38	27.27	22.01	22.32
Change	0.85	0.73	-1.15	-0.42
Extensive Margin	0.63	0.63	-1.05	-0.20
Intensive Margin	0.22	0.10	-0,.9	-0.22

Sources: Spanish Labour Force Survey and U.K Skill Survey

8. Technological change and routine tasks

We now take a closer look at the effect of computerisation on routine-task inputs similar to Green (2012). To do so, we analyse the relationship between computerisation and routine tasks inputs at the occupational level creating a pseudo-panel. Unlike previous studies using the same data, we decide to evaluate the routine index by itself and not combined with the manual one as in Green (2012).

We collapse the variables of interest at the 3-digit ISCO-88 occupational level, specifying the following model:

$$\bar{T}_{jt} = \beta \bar{C}_{jt} + \sum_{t=1}^{T-1} \theta_t + \delta_j + \bar{\varepsilon}_{jt} \qquad (5)$$

where $\bar{T}_{jt}$ is the routine task measure at the occupational level at time t, $\bar{C}_{jt}$ is the variable capturing computer intensity in occupation j at time t, θ_t is a set of year effects and δ_j is a set of occupation effects. Time fixed effects control for omitted variables which are constant across occupations but evolve over time; occupation fixed effects are included to control for omitted variables that vary across occupations but not over time.

Table 11 reports the estimates using fixed effects with occupation cell size as weights. We find that technology is significantly negatively relates with routine task inputs. Although one important limitation is that we cannot disentangle the effect of computerisation on the routine cognitive and manual components (typical of clerical and production work, respectively), it is reasonable to think that both aspects are embedded in the basic measure.

Table 11. Impact of computer on adoption on task measures

	Dependent variable			
	Routine	Interpersonal	Analytical	Manual
Computer use	-0.52*	-0.170***	0.23***	0.193***
	(0.076)	(0.063)	(0.05)	(0.06)
N	96	96	96	96
R-square	0.78	0.94	0.92	0.94
F (Years dummy)	2.83	1.50	6.81	6.83

Notes: Fixed-effects estimates at the 2-digit ISCO and 1-digit NACE and weighted by the cell size
Sources: Spanish Labour Force Survey and U.K Skill Survey

For the sake of completeness, we estimate equation (5) also for analytical and interpersonal tasks. This is done to investigate whether non-manual tasks, which mainly refer to those individuals working in professional, managerial and creative non-routine occupations, are complements with computer use. Our findings are in line with the positive effect of computer technology on the use of greater generic skills found in Green (2009 and 2012).

9. Occupational mobility of middle-paid workers

Similarly to Cortes (2016), we further test the routinization hypothesis by looking at the displacement of middle-py workers. We examine whether changes in the labour maket's quantities find their natural counterpart in changes occupational mobility. Increasing demand for low-pay and high-pay occupations could be compensated by labour supply shifts of middle-pay workers performing routine activities. Therefore, we would expect that workers that are in the middle of the distribution, those performing routine activities, become more mobile over time.

To obtain information on past jobs, we integrate our main source with the European Community Household Panel (ECHP). The ECHP is a longitudinal database compiled annually from1994 to 2001 and each wave provides information on job characteristics and working conditions, including details on activity and employment status, job characteristics and education, earnings and education. We restrict the sample to individuals that are in both years of the analysis, restricting the sample to 4,308 between 1994 and 1997, and 2,924 for the period 1997-2000.

Table 12 presents the occupational change by educational group. Here, we compute the percentages of workers who changes occupation among those with the same educational attainment computed from a three-level education variable ranging from 1 (low-education) to 3 (high-education). We divided the period in two: 1994-1997, whose resultsa are reported in column 1, and 1997-2000, in column 2. In column 3 we can observe mobility over time. As expected, we observe that middle-skilled workers became increasingly more mobile over time (5.53), against low-skilled (4.67) and high-skilled workers (2.44).

Table 12. Occupational change by educational group

	Occupational change		
Education	1994-1997 (1)	1997-2000 (2)	Mobility (3)
Low	7.11	11.78	4.67
Medium	9.15	14.68	5.53
High	6.38	8.82	2.44
N	4,308	2,924	

Notes: the table shows the percentage of workers that change occupation among those with the same educational attainment
Source: Spanish Labour Force Survey and Living Conditions Survey

Building on the ALM model, we decide to study whether middle-paid workers moved either towards low or high-paid occupations. ALM model predicts that marginal routine workers are induced to reallocate their labour supply to non-routine intense occupations. Therefore, we expect over time an increasing probability of middle-paid workers to move towards low-income occupations. We analyse only downward and upward mobility and not flows into unemployment or inactivity as in Schmidpeter and Winter-Ebmer (2016).

We build on the analysis of transition probability matrix. In a transition probability matrix each cell corresponds to the probability of being in one state and move to another given by:

$$p_{ij} = \Pr(X_t = j | X_t = i) \qquad (6)$$

The probability from equation 6 can be computed as expressed in equation (7)

$$p_{ij} = N_{ij} / \sum_{j=1}^{n} N_{ij} \qquad (7)$$

where N_{ij} is the total number of workers changing from state i to state j (the cell counts) and $\sum_{j=1}^{n} N_{ij}$ is the total number of workers in a group (the row counts).

To obtain a larger period, we merge our data with the Survey of Living Conditions (SLC). Using the SLC, we investigate occupational mobility from 2004 to 2008 after applying all the necessary restrictions to obtain a comparable sample. Each cell in Table 13 corresponds to the transition probability from one state to another in three different periods: from 1994 to 1997, from 1997 to 2000 and from 2005 to 2008. Three important facts are pointed out from this table. First, the probability that workers in middling-pay occupations did not change is the lowest one in two periods (0.74 against 0.75 and 0.83 in the first period, and 0.83 against 0.84 and 0.93 in the last period). As expected, these workers have the highest level of mobility. Our finding is in line with the fact that middle-paid jobs rely on routine tasks, therefore are directly affected by technological progress (Autor et al., 2003).

Table 13: Transition probability matrix

		Occupation in 1997			
		Low	Middling	High	Total
Occupation in 1994	Low	0.75	0.15	0.10	1
	Middling	0.09	0.74	0.17	1
	High	0.06	0.11	0.83	1

.

		Occupation in 2000			
		Low	Middling	High	Total
Occupation in 1997	Low	0.73	0.18	0.09	1
	Middling	0.09	0.79	0.12	1
	High	0.09	0.17	0.74	1

		Occupation in 2008			
		Low	Middling	High	Total
Occupation in 2005	Low	0.84	0.11	0.07	1
	Middling	0.10	0.83	0.07	1
	High	0.03	0.06	0.91	1

Notes: Each cell corresponds to the transition probability form one state to another.
Occupations are grouped into low, middling and high-pay.
Sources: Authors' analysis from ECHP and SLC.

Second, middle-pay workers did predominantly move to low-pay occupations. In other words, the probability of moving towards high-paying occupations decreased over time. These results are compatible with the ALM routinisation hypothesis that clearly predicts a displacement of workers towards low-pay occupations.

Finally, the probability of being in the same occupation over time increased in low and high occupations (respectively from 0.75 to 0.83, and from 0.83 to 0.91). Surprisingly, it also increased in middle occupations (from 0.74 to 0.83). Our interpretation

7 Conclusions

In this paper we contribute to the debate on labour market polarisation in Spain using U.K. task data to measure the job content of occupations. We confirm that employment in Spain experienced a polarisation trend at the occupational level between 1994 and 2008 but there is no evidence of a similar course in wages. Our sample suggests that jobs in high and low-paying occupations increased, while employment shares decreased in the middle of the distribution.

We interpret the evolution of occupational employment from a task-based perspective exploring ALM model's prediction. We find that high-paying occupations which increased the most can safely classified as non-routine non-manual, while middling-paying occupations which have lost significant employment shares are predominantly routine (both manual and non-manual). The tasks content of low-paying occupations is more mixed, with elementary occupations being predominantly manual and service occupations scoring higher in the interpersonal dimension, and the routine dimension appears more difficult to evaluate. Still, we find that changes in employment shares are negatively related to the initial level of routine intensity.

Similar to Green (2012), we formally test the association between routine task inputs and technology in workplaces. From a comparison with O*NET, we show that the routine measure in the U.K. Skill Surveys well captures bith the manual and the cognitive routine dimension. The negative impact of computerisation that we find is therefore likely to be associated with manual and cognitive routine jobs, although we are not able to disentangle the effect.

Finally, we exploit retrospective questions on past jobs to evaluate the extent to which the displacement of middle-paid workers, caused by an adverse impact of technological advances, contributed to the employment growth at the lower tail of the distribution. We find that workers in middling-paying occupations become more mobile over time. However, they did not predominantly move towards low-paying occupations.

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Appendix: Description of variables

A.1. List of tasks

Analytical

Paying close attention to detail

Teaching people (individuals or groups)

Making speeches/ presentations

Working with a team of people

Specialist knowledge or understanding

Knowledge of how organisation works

Spotting problems or faults

Working out cause of problems/faults

Thinking of solutions to problems

Analysing complex problems in depth

Checking things to ensure no errors

Noticing when there is a mistake

Planning own activities

Planning the activities of others

Organising own time

Thinking ahead

Reading written information (e.g. forms, notices and signs)

Reading short documents (e.g. reports, letters or memos)

Reading long documents (e.g. manuals, articles or books)

Writing materials (e.g. forms, notices and signs)

Writing short documents (e.g. reports, letters or memos)

Writing long documents with correct spelling and grammar

Adding, subtracting, multiplying and dividing numbers

Calculations using decimals, percentages or fractions

Calculations using advanced statistical procedures

Interpersonal

Dealing with people

Persuading or influencing others

Selling a product or service

Counselling, advising or caring for customers or clients
Listening carefully to colleagues
Knowledge of particular products or services

Manual
Physical strength (e.g. to carry, push or pull heavy objects)
Physical stamina (e.g. to work on physical activities)
Skill or accuracy in using hands/fingers (e.g. to assemble)
Knowledge of use or operation of tools/equipment machinery

A.2. Variables construction

Wages. Our wage variable (*hwage*) is the gross hourly pay. This derived variable is available in the two wage data sources: The Wage Structure Survey (WSS) and the Survey of Living Conditions (SLC). For all the cases hwage was computed as gross usual weekly pay divided by usual hours and minutes worked per week, including usual overtime. Wages are measured in euro. We trim our data such that hourly wages lower than 1 and higher than 100 are excluded.

Occupations. We classify occupations according to the International Standard Classification of Occupations (ISCO-88) (see ILO, 1990). Occupations were originally classified according to the National Classification of Occupations (CNO-94). Codes are manually matched on the basis of the guidelines distributed by the Occupational Information Unit of the Office for National Statistics, correcting both for employment status and the size of the organisation/establishment (number of people working) when available. This harmonisation allows researchers to compare occupations over time to make our results strictly comparable to other papers. ISCO-88 defines four levels of aggregation, consisting of 10 major groups (one-digit), 28 sub-Major groups (two-digits), 116 minor groups (three-digits) and 390 unit groups (four-digits).

Industry. I classify industry according to the Statistical Classification of Economic Activities in the European Commission (NACE, Rev. 1.1). Industry codes were originally classifies according to the National Classification of Economic Activities (CNAE-93). Codes are manually matched on the basis of the guidelines distributed by EUROSTAT. This harmonisation allows researchers to compare occupations over time to make our results strictly comparable to other papers. NACE Rev. 1.1 defines five levels of aggregation, consisting of 17 one-letter sections, 31 two-letter sub-sections, 60 two-digit main groups, 222 three-digit groups, and 513 four-digit sub-groups. NACE Rev 1 was in turn based on the International Standard Industrial Classification of All Economic Activities (ISIC) Rev 3, published by the United Nations.

Education. Our education variable distinguishes four groups of workers: elementary, basic, medium, and high educated (skilled). In the Spanish Labour Force Survey I exploit the variable *(estud)* which indicates the highest qualification held by the interviewee. Both educational and vocational qualification levels are available in the list provided to respondents. The usual ISCED division into low, medium and high is then 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). The derived categorical variable for education takes value of 1 for low educated, 2 for medium and 3 for high.

A.3 List of ISCO-88

1 Managers

- 11 Chief executives, senior officials and legislators
- 12 Administrative and commercial managers
- 13 Production and specialized services managers

2 Professionals

- 21 Science and engineering professionals
- 22 Health professionals
- 23 Teaching professionals
- 24 Business and administration professionals

3 Technicians and associate professionals

- 31 Science and engineering associate professionals
- 32 Health associate professionals
- 33 Business and administration associate professionals

34 Legal, social, cultural and related associate professionals

4 Clerical support workers

41 General and keyboard clerks

42 Customer services clerks

5 Service and sales workers

51 Personal service workers

52 Sales workers

6 Skilled agricultural, forestry and fishery workers

61 Market-oriented skilled agricultural workers

7 Craft and related trades workers

71 Building and related trades workers, excluding electricians

72 Metal, machinery and related trades workers

73 Handicraft and printing workers

74 Electrical and electronic trades workers

8 Plant and machine operators, and assemblers

81 Stationary plant and machine operators

82 Assemblers

83 Drivers and mobile plant operators

9 Elementary occupations

91 Cleaners and helpers

92 Agricultural, forestry and fishery labourers

93 Labourers in mining, construction, manufacturing and transport

0 Armed forces occupations

01 Commissioned armed forces officers

A.3 List of NACE REV.1

A Agriculture, hunting and foresty

01 Agriculture, hunting and related service activities

02 Forestry, logging and related service activities

B Fishing

05 Fishing, fish farming and related service activities

C Minning and quarrying

10 Mining of coal and lignite; extraction of peat

11 Extraction of crude petroleum and natural gas; service activities incidental to oil and gas extraction, excluding surveying

13 Mining of metal ores

14 Other mining and quarrying

D Manufacturing

15 Manufacture of food products and beverages

16 Manufacture of tobacco products

17 Manufacture of textiles

18 Manufacture of wearing apparel; dressing and dyeing of fur

19 Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear

20 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materialsin

21 Manufacture of pulp, paper and paper products

22 Publishing, printing and reproduction of recorded media

23 Manufacture of coke, refined petroleum products and nuclear fuel

24 Manufacture of chemicals and chemical products

25 Manufacture of rubber and plastic products

26 Manufacture of other non-metallic mineral products

27 Manufacture of basic metals

28 Manufacture of fabricated metal products, except machinery and equipment

29 Manufacture of machinery and equipment n.e.c.

30 Manufacture of office machinery and computers

31 Manufacture of electrical machinery and apparatus n.e.c.

32 Manufacture of radio, television and communication equipment and apparatus

33 Manufacture of medical, precision and optical instruments, watches and clocks

34 Manufacture of motor vehicles, trailers and semi-trailers

35 Manufacture of other transport equipment

36 Manufacture of furniture; manufacturing n.e.c.

37 Recycling

E Electricity, gas and water supply

40 Electricity, gas, steam and hot water supply

41 Collection, purification and distribution of water

F Construction

45 Construction

G Wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household

50 Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel

51 Wholesale trade and commission trade, except of motor vehicles and motorcycles

52 Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods

H Hotels and restaurants

55 Hotels and restaurants

I Transport, storage and communitcation

60 Land transport; transport via pipelines

61 Water transport

62 Air transport

63 Supporting and auxiliary transport activities; activities of travel agencies

64 Post and telecommunications

J Financial intermediation

65 Financial intermediation, except insurance and pension funding

66 Insurance and pension funding, except compulsory social security

67 Activities auxiliary to financial intermediation

K Real estate, renting and business activities

70 Real estate activities

71 Renting of machinery and equipment without operator and of personal and household goods

72 Computer and related activities

74 Other business activities

L Public administration and defence; compulsory social security

75 Public administration and defence; compulsory social security

M Education

80 Education

N Health and social work

85 Health and social work

O Other community, social and personal service activities

90 Sewage and refuse disposal, sanitation and similar activities

91 Activities of membership organizations n.e.c.

92 Recreational, cultural and sporting activities

93 Other service activities

P Activities of households

95 Activities of households as employers of domestic staff

Q Extraterritorial organizations and bodies

99 Extra-territorial organizations and bodies