Job polarization, technological change and routinization: evidence for Portugal

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Abstract

This paper studies labor market polarization in Portugal, a country with slow capital accumulation and a low share of highly educated workers. We use firm census data for 1986-2007 and uncover polarization in employment and wages in the second half of this period. This mostly appears to be due to technological change. Our results show a sharp increase of both employment and wage premium for abstract tasks relative to routine tasks. In contrast to the existing literature, we separate between routine manual tasks and routine cognitive tasks. We uncover a sharp decline in routine manual employment but the decline in routine cognitive employment is modest and coupled with an increased wage premium that does not appear to be due to worker selection. This latter result is mainly explained by the large expansion of the service sector which employs many workers in routine cognitive-intensive jobs and the likely slower computer capital adoption resulting from the relatively low levels of human capital, by international standards.

Keywords: technological change; routinization; job polarization; employment; wages

JEL codes: J24, J31, O33

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1 Introduction

Job polarization is a phenomenon characterized by employment growth at both the bottom and the top of the income distribution. Job polarization has been observed in the US (Autor, Katz and Kearney, 2006) in the late 1980s and 1990s (Acemoglu and Autor, 2011) and in the UK for the period between 1975 and 1999 (Goos and Manning, 2007). Polarization has also been documented in West-Germany (Spitz-Oener, 2006; Dustmann, Ludsteck and Schönberg, 2009) and Northern European countries (Asplund et al., 2011; Adermon and Gustavsson, 2015). In addition, Michaels, Natraj and Van Reenen (2014) find polarization for several OECD countries. Goos, Manning and Salomons (2009, 2014) also find evidence of polarization in Europe as a whole, but not in every single country. Using the European Labour Force Survey, they find that the middle paying jobs decreased their employment share while low-paid jobs experienced growth or modest decreases. High-wage jobs increased their employment shares.[1]

Our paper adds to the literature by providing a detailed account of labor market polarization in a country (Portugal) with slow capital accumulation and a relatively small pool of highly educated workers. Our data allows us to document the changing employment patterns of various tasks while separating between routine manual and routine cognitive tasks, a distinction we demonstrate is important at least in a country with slow computer-capital adoption and a small service sector. We are further able to analyze the impact on wages while accounting for compositional changes and document the patterns of occupational mobility across ability quintiles (captured by worker task-spell fixed effects from wage regressions).

While the reasons behind job polarization are still subject to debate, the main candidate is technology and the so called routinization hypothesis, first put forward by Autor, Levy and Murnane (2003), in which technological improvements allow machines to replace workers performing routine tasks. Notwithstanding, several reasons could explain

[1] Their results for Portugal (which we study in this paper) vary according to the period: for 1993-2006, Goos, Manning and Salomons (2009) find a decreasing share in both middle and high-waged jobs (similar to Finland and Ireland), while for 1993-2010, Goos, Manning and Salomons (2014) find increasing share in both low and high-waged jobs, along with a decreasing middle. The latter results are in line with our findings.

why certain countries may fail to show evidence of job polarization, despite experiencing technological change and computerization. First, institutional differences in pay setting could act as counteracting forces in the wage distribution which in turn may affect employment growth of different types of jobs. These include minimum wages and collective bargaining agreements and are unlikely to largely affect the high paid jobs. Second, countries with a large public sector may also present a wage (and occupational) structure less permeable to market forces. Third, if preferences are non-homothetic, differences in the level and distribution of income across countries may result in differences in the occupational structure of employment (Goos, Manning and Salomons, 2014). For example, income elasticity of demand for services is thought to be greater than one (Clark, 1957). In the case of Portugal, its lower GDP per capita relative to the rest of Europe could explain the smaller size of its service sector, which could lead to a non-polarized job structure.

The timing of technology dissemination and job polarization may also differ across countries. For example, Continental Europe appears to have a lag of one decade relative to the Anglo-Saxon countries in terms of their labor market trends (Spitz-Oener, 2006; Dustmann, Ludsteck and Schönberg, 2009). The prevalence of low wages, namely in routine task intensive occupations, combined with the same price of computer capital as in other countries, may limit the gains of substituting workers by machines. In addition, in a country with low capital stock as Portugal, the adoption of computer capital may be limited, especially if combined with a relatively small pool of highly educated workers, constraining complementarity gains. Finally, the relative importance of manufacturing and service industries, and the relative growth of the service industry may affect the way technology disseminates and affects the relative demand for skills in different countries.

In view of the above discussion and the current state of the job polarization literature, the study of job polarization in Portugal is of particular interest. Are the market forces created by computerization likely to generate job polarization even in countries with lower levels of physical and human capital, lower wages and a less developed service sector?

We use *Quadros de Pessoal*, the Portuguese firm census, to show that despite its lower wages, GDP per capita, capital stock and share of the service sector, Portugal has experienced job polarization from the mid-1990s. This provides evidence that job polarization is not a phenomenon exclusive of richer economies. Using routine-cognitive and routine-manual, and non-routine task measures (abstract and manual) to classify jobs, we find support for the routinization hypothesis as an explanation for most of the employment and wage patterns observed. We depart from most of the previous literature which combines all routine jobs in one category, and follow Autor, Levy and Murnane (2003) by separating routine task intensive occupations into routine cognitive and routine manual. This is particularly important for Portugal because each of these sub-categories has differing importance in the service and manufacturing sectors, and Portugal experienced considerable growth in services during our period of analysis.

We define employment cells across worker and firm dimensions to identify the employment trends for cells with comparative advantage in each of the four tasks at the beginning of the period. In doing so, we borrow from the wage estimation methodology of Acemoglu and Autor (2011) and we follow in Autor, Levy and Murnane (2003) footsteps, since they also use cells to look at employment trends. In our wage regressions, we estimate worker task-spell fixed effects to obtain consistent estimates for the trends of each task wage premium. We adapt the methodology of Cortes (2016) to a matched employer-employee dataset, where by computing task-spell fixed effects we mitigate possible biases associated with workers self-selection into occupations.[2] Overall, our results show a sharp increase of both employment and wage premium for abstract tasks relative to manual tasks, along with a decline for routine manual tasks. However, because we unbundle routine tasks into cognitive and manual, we uncover a very modest decline for routine cognitive employment and an increase in their wage premium that does not seem to be caused by self-selection. We claim that even though our results point to routinization as the major cause of job polarization, they show a nuanced form of routinization. The lagging stage of development of the Portuguese economy with low education attainment, hand-in-hand with low computer capital adoption and a large expansion in the services sector from a relatively small share, mean that the relative demand for routine cognitive tasks must have in fact increased for the economy as a whole. Similar trends are observed for more advanced economies (US and Germany) until the 1990s (Black and Spitz-Oener, 2010; Acemoglu and Autor, 2011)

[2] Cortes (2016) uses the sampling survey Panel Study of Income Dynamics for the US.

during which those countries were still having employment growth in routine cognitive activities. Thus, the results for Portugal call for specific education and labor market policies and provide insights for other lagging economies facing similar challenges.

The rest of the paper is organized as follows. Section 2 reviews the extant literature on job polarization and discusses what different models predict in terms of employment and wage changes and how can be tested. Section 3 discusses the Portuguese economic context. Section 4 describes the data. Section 5 shows the trends for employment and wages between 1986 and 2007 and provides evidence of within and between industry changes in employment. Task measures are discussed in Section 6 with a further analysis of employment and wages by task groups. Section 7 presents and discusses regressions' results for employment and wages and Section 8 concludes.

2 Literature review

Since the early 1960s, the US has seen the stock of capital equipment increase rapidly alongside a growing trend in the relative demand for skilled workers, suggesting the complementarity of capital equipment and skilled labor (Krusell et al., 2000). The skill premium – the wage ratio between skilled and unskilled workers – rose particularly rapidly since the late 1970s despite the increase in the supply of skills (Juhn, Murphy and Pierce, 1993). Moreover, the rate of within-industry skill upgrading was concentrated in the most computer intensive sectors of the economy (Autor, Katz and Krueger, 1998). During the 1980s – the decade of the microelectronics revolution – the demand and relative wages for the less-skilled decreased in developed countries (Berman, Bound and Griliches, 1994; Berman, Bound and Machin, 1998). Evidence also shows that changes in institutions such as unionization and minimum wages play a role in explaining the changes observed in the bottom half of the wage distribution (for example, DiNardo, Fortin and Lemieux (1996)). The increase in the demand for skills seems to have been pervasive in developed countries, with documented changes in the wage structure in several countries (Machin and Van Reenen, 1998).

The literature suggests that the changes in wages and employment between the 1960s and the 1980s are related to skills and technological change (Katz and Murphy, 1992; Levy and Murnane, 1992; Bound and Johnson, 1992; Juhn, Murphy and Pierce, 1993). In particular, computer capital seems to have a positive effect on the wages of those workers who use computers in the workplace (Krueger, 1993; DiNardo and Pischke, 1997). This evidence has led to the idea that recent technology developments have been biased towards the most skilled workers in the form of higher employment and wages – the *skill-biased technological change* hypothesis (SBTC hereafter).[3]

When Autor, Katz and Kearney (2006) uncovered job polarisation in the US and Goos and Manning (2007) did the same for the UK, it became clear that SBTC hypothesis could not explain the recent labor market patters alone.[4] Autor, Levy and Murnane (2003) and Autor, Katz and Kearney (2006) proposed a distinct view of the impact of technical change in the labor market according to which technology alters the tasks performed by workers which in turn changes the demand for skills. In their model, technology and skilled labor are still complements, but computer capital substitutes for workers performing routine tasks – tasks that can be programmed into a machine because they follow a set of rules. They show that the adoption of computers is associated with reduced labor in routine tasks and increased labor input in non-routine cognitive tasks within industries, occupations and education groups.

Building on Autor, Levy and Murnane (2003), Autor, Katz and Kearney (2006) propose a task-based model with three categories of tasks: abstract, routine and manual, in which college educated workers perform abstract tasks and workers with high school degrees can substitute between routine and manual tasks. Routine tasks and computer capital are perfect substitutes. Because of the falling price of computer capital, exogenous to the model, computers substitute routine workers, causing a reduction on their employment and, by definition, wages.[5] Abstract task workers see their employment and wages rise as they complement computer capital and therefore their productivity increases. Finally, non-routine manual task workers employment rise because of the influx of displaced workers

[3] See, e.g., Krueger (1993), Berman, Bound and Machin (1998), Machin and Van Reenen (1998), Autor, Katz and Krueger (1998), Acemoglu (1998), Bresnahan (1999), Krusell et al. (2000).

[4] Card and DiNardo (2002) describe additional issues with the SBTC hypothesis. Spitz-Oener (2006) presents similar evidence for Germany.

[5] By definition, the price of computer capital is equal to the wage of routine workers.

from routine tasks. Those routine task workers by assumption cannot perform abstract tasks as they do not hold a college degree, and therefore are pushed into manual task jobs. Even without the education assumption, displaced routine tasks workers should have a stronger comparative advantage in performing manual tasks than in abstract tasks.

Routine jobs are not at the bottom of the wage distribution because those jobs require a certain amount of skills (Goos and Manning, 2007). Therefore, we expect *ceteris paribus* decreasing employment in the middle of the wage distribution, as routine jobs tend to be substituted by technology. As for wages, while the wages of higher skilled workers should increase, the relative changes for the middle and low skilled are less obvious due to the effect of demand and supply on the various skills, as well as the potential selection of workers between those who retain their jobs versus those who are pushed into different jobs.

While in the US wage polarization has occurred hand in hand with job polarization (Autor, Katz and Kearney, 2006), Goos and Manning (2007) failed to find wage polarization in the UK, despite strong evidence of job polarization. They found that wages at the top of the distribution increased relative to the median, but wages at the bottom did not. A possible explanation is non-random selection of workers across jobs: when hit by demand shocks, job changes do not occur randomly.[6] In particular, Goos and Manning (2007) hypothesizes that if those displaced from the middling jobs are less skilled, the average skill of those who remain increases, counteracting the downward pressure in wages from lower demand. In line with their hypothesis, they find evidence of greater educational upgrading in middle than in lower paid jobs. Selection of workers in the process of labor market polarization renders the straightforward wage predictions in Autor, Katz and Kearney (2006) model empirically hard to test.

Acemoglu and Autor (2011) propose an empirical strategy to test whether wage patterns are consistent with the computerization hypothesis in the presence of selection of workers. They use demographic variables to construct skill groups and regress the wage changes of these groups on their task measures at the beginning of the period. Their

[6] Another potential explanation is concurrent changes in labor market institutions, such as declines in unionization and minimum wages (e.g., see discussions in Goos and Manning (2007); Dustmann, Ludsteck and Schönberg (2009); Fernandez-Macias (2012); Adermon and Gustavsson (2015)).

premise is that if the market price of the tasks in which a skill group holds comparative advantage in the beginning of the period declines, such as routine tasks, the relative wage of that skill group should decline, whether those workers move occupations and tasks or not. We extend this empirical strategy to provide evidence of employment trends that are consistent with a task based explanation for polarization. However, another, more direct way to control for self-selection of workers into occupations associated with different tasks is to control directly for unobserved individual characteristics that give workers comparative advantage in certain tasks. To that effect, Cortes (2016) propose a task-spell fixed effect model to estimate the wage premium which we follow in our empirical methodology.

A second hypothesis for polarization is globalization, and in particular offshoring. Computer capital, or more precisely, information and communication technologies, enable firms to take advantage of lower labor costs by making relocation of offshorable jobs possible. In the context of job polarization, the offshoring hypothesis implies that middle paid jobs are delocalized (e.g., customer service clerks, production assemblers or machine operators). Also, some highly-skilled jobs (e.g., code programmers, technicians troubleshooting from call centers or medical imaging technicians) can be delocalized. Thus, both routine and some abstract jobs may be offshorable. As manual jobs often require interpersonal relationships and adaptability, it is more difficult to have them performed by machines or offshored. This is the case for services mainly supplied by manual task-intensive jobs, where the demand for these jobs are almost invariant to the current changes on technology (Autor and Dorn, 2009; Acemoglu and Autor, 2011). The literature establishes that offshorable jobs are at risk in developed economies such as the US (Blinder, 2009; Blinder and Krueger, 2013). Although there is evidence of a decreasing demand for offshorable jobs in many European countries, we show evidence suggesting that Portugal is in fact a modest recipient of offshorable jobs, which is not surprising due to its lower labor costs compared to the rest of Europe.[7] Furthermore, given the partial juxtaposition of offshorable occupations with cognitive and routine occupations, both our framework and data are not suitable to test the offshoring-based hypothesis in conjunction with our main hypothesis of routinization as the main driver of labor market polarization. In any event,

[7] See section 6.2 for a more detailed explanation.

we stress that the descriptive evidence on offshoring for the Portuguese case goes against offshorability being a main driver of the polarization patterns described.

3 Portugal: Economic Context

Our analysis starts in 1986, the year in which Portugal joined the European Union, and goes until 2007, which precedes the economic crisis which lead to the EU/IMF financial assistance program. Though experiencing GDP growth above the European average during those two decades, Portugal still lags behind most western European counterparts in GDP, wages, skills and capital. Table 1 shows Portuguese GDP per capita growing at a higher rate than the rest of Europe, but still not catching up to the other lower performing southern European countries. This difference is even larger if we compare Portuguese GDP per capita with non-southern EU's GDP per capita, which is almost double. Naturally, this is reflected in wages where the average Portuguese wage is approximately half of remaining EU member states' wages.

Portugal lags behind the rest of Europe and even other Southern European countries in terms of its share of college graduates, despite its impressive growth. Furthermore, educational trends based on *Quadros de Pessoal* show that much of the Portuguese skill upgrade occurred at the secondary level, with a more than doubling of high school graduates by 2007.[8] This is important for our study, since the increase in the supply of skills in Portugal occurred both in terms of high and medium skills.

Portugal also lags behind other European countries in terms of capital stock. As shown in Table 1, capital stock per worker in southern European countries is approximately three times less than that of Scandinavian countries and Continental Europe. Portugal has less capital per worker than the average of southern European countries. Since technology investments are likely to depend on the initial technological level, the labor market impact of technological change in Portugal is likely to differ from countries with higher capital stock levels. As capital includes computer capital, it seems plausible to assume a relatively low stock of computer capital for Portugal. The routinization model as proposed by

[8] See Appendix Figure A1.

Autor, Katz and Kearney (2006) is less likely to apply to countries with low education, low capital and low wages for two reasons. First, due to the complementarity between computer capital and high-skilled workers which are in less supply than in more advanced economies. Second, the low wages of workers performing mostly routine tasks, which can be lower than the adjusted price of computer capital, making technology investments less profitable.

Table 1: Cross-country descriptive statistics

	real GDP p.c.[1]			**average real wage**[2]			**college education**[3]			**capital**[4]		
	1986	**2007**	δ^*	**1995**	**2007**	Δ	**1999**	**2006**	Δ	**1986**	**2007**	Δ
PT	12,628	22,068	2.7	18,872	21,776	15.4	8.7	13.5	54.9	55.1	102.9	86.7
EU-South	17,943	27,975	2.1	26,876	29,385	9.3	15.9	21.2	33.2	138.7	187.8	35.3
EU-Other	24,298	39,127	2.3	33,477	39,344	17.5	24.4	29.3	20.1	595.3	753.1	26.5
US	30,011	45,361	2.0	42,454	51,385	21.0	35.8	39.5	10.3			

Notes: Authors' calculations. Europe excluding southern countries (EU-Other): Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Luxembourg, the Netherlands, Norway, Sweden and the UK. Southern Europe (EU-South): Greece, Italy and Spain. PT stands for Portugal. δ^* refers to Annual Growth Rate; Δ represents the percentage change; [1]USD constant PPPs (OECD data); [2]2008 USD PPPs (OECD data); [3]Share of college graduates aged between 25-64 (OECD data); [4]Net capital stock at 2010 price per person employed (Mrd ECU/EUR) (annual macro-economic database, AMECO, data).

4 Data

This paper's main data source is *Quadros de Pessoal* (QP), a matched employer-employee dataset created by the Portuguese Ministry of Labor in the 1980s. Employers answer a yearly mandatory survey with information on personnel and firm characteristics. The dataset surveys all Portuguese firms with at least one employee and excludes self-employed workers. QP covers a period of 22 years from 1986 to 2007 with an average of 1.7 million workers and 220 thousand firms per year. Since the focus of this paper is the role of technology in the labor market, we deliberately stop our analyses at 2007 as subsequent years will be contaminated with the economic crisis and the EU/IMF financial assistance program, which are unrelated with our main hypothesis. The Ministry of Labor did not release worker level information for 1990 and 2001, and therefore we have missing data for those two years. Firm-level characteristics include industry, annual sales, location, and starting date. For workers, variables include gender, age, schooling, tenure, job level and occupation (ISCO five-digit codes), hours of work (regular and extra), wages (base wage, regular and irregular bonuses and payments for extra hours of work) and type of contract (if permanent or fixed-term).

We restrict our sample to full-time workers (30 hours per week or 130 hours per month) aged between 16 and 65. We consider that a full-time worker must earn at least 90% of the minimum wage, in which the wage is the sum of base wage plus regular and seniority related bonuses.[9] Wages are deflated to the year 1986 using the Consumer Price Index. We drop workers in occupations and industries associated with the primary sector, as the survey is optional for those. Also, we exclude workers in public administration and defense.[10] Although public administration employs a large number of workers in Portugal, those workers are not fully represented in the dataset (less than 0.4% of the total number of workers in QP). We use ISCO88 occupational codes at 2-digit level, comprising 23 occupations. Those codes are only available after 1994. To overcome this problem, we employ an algorithm that converts the occupational codes prior 1994 to ISCO88 based on the most frequent matches.[11]

5 Trends in employment and wages

Figure 1 shows the evolution in cumulative changes in wages, measured at percentiles 10, 50 and 90. There was a dramatic rise in wage inequality in the 1990s, as top wages rose sharply, while the middle and bottom of the wage distribution experienced a moderate increase. Since 2000 the change in the distribution was much less pronounced, with an only slightly larger growth in the 90$^{\text{th}}$ percentile compared with the other two percentiles. In addition, we can distinguish between two periods, one until the mid 1990s in which wages in the middle of the distribution grow faster than at the bottom and another from the mid 1990s in which there is a convergence between wages at the bottom and the middle of the distribution. According to this figure, despite the inequality increase in the first part

[9]Portuguese minimum wage is set monthly. We impose a 90% lower boundary rather than the minimum wage to allow for data errors and monthly variations that can be present in the dataset. As a robustness check, we have tested several wage cuts ranging from 75% to 90%. The results do not change significantly.

[10]These correspond to the industries (NACE) A, B, C, L and Q, and the occupations (ISCO) 11, 61 and 92.

[11]The algorithm recodes occupations based on the most frequent changes. The procedure is as follows: 1) Let occupation$_j^i$ be the occupation of worker i in year j. 2) Generate the matrix of occupation$_{1994}^i$ and occupation$_{1995}^i$, where the worker i is observed in both 1994 and 1995. 3) Aggregate the results by the mode of occupation$_{1995}^i$. 4) In the case of ties, compute steps (2) and (3) at 3-digits level.

of the period, it is from the mid 1990s that one observes wage polarization, with median wage growth lagging behind growth at the top and the bottom of the distribution.

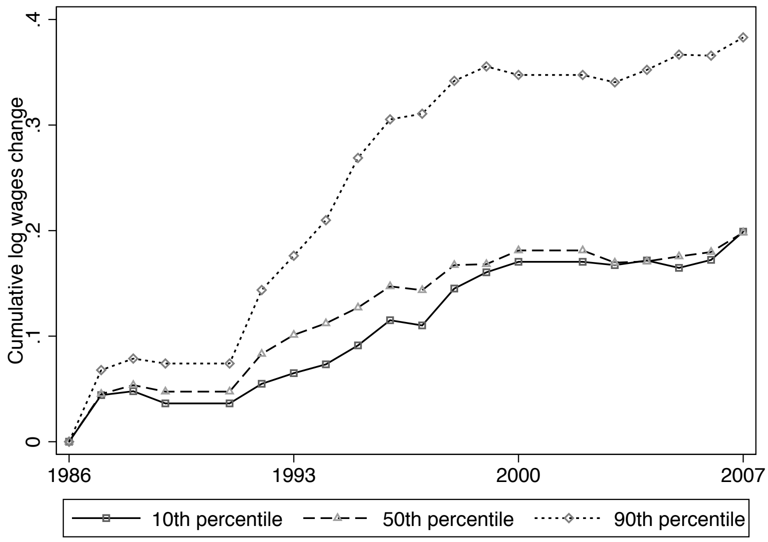

Figure 1: Evolution of cumulative changes by wage percentile, 1986 to 2007
Notes: Wage percentile calculated each year using worker level data (34,770,910 observations).

Figure 2 plots the log wage change (relative to the median change) by percentile for the two sub-periods, and confirms the trends identified in Figure 1.[12] The steeply sloped curve for the first period suggests a strong increase in inequality across the wage distribution, and the u-shaped curve observed in the second period confirms that wage polarization took place from the mid 1990s onwards, but not before.

Using employment data, we also find evidence of job polarization. Figure 3 plots the change in employment share by skill percentile for two periods: 1986-1994 and 1995-2007. The occupation skill percentile rank is performed for two skill proxy measures: mean education years (left panel) and mean wage (right panel). For the first period (1986-1994) the results show an upward sloping curve that is consistent with SBTC – employment share increases for higher skills. In contrast, the second period shows polarization of employment: the relative employment in both the bottom and top skill percentiles increases,

[12] As discussed before there is a change in the occupational codes from 1994 to 1995, and therefore we chose to split the data at that point. Besides the data constraints, the two periods are inherently different as can be observed from the data. A similar figure is obtained by regressing the relative log wage on the wage percentile ranking and its square and estimating the standard errors by applying a standard bootstrapping procedure (coefficients significant at 1% level). For an alternative bootstrapping method see Adermon and Gustavsson (2015).

while in the middle it decreases. Polarization appears stronger in the lower tail when occupations are ranked using mean years of education than mean wages (weighted by employment) suggesting that some occupations, despite having low education attainment, have wages close to the median wage. Our results are in line with those of Goos, Manning and Salomons (2014), where they, using the European Labour Force Survey, find increasing employment shares for the lowest and the highest-paying occupations and decreasing share of the middling occupations during the 1993-2010 period. Further, Centeno and Novo (2014) study wage inequality in Portugal and also find similar patterns.[13]

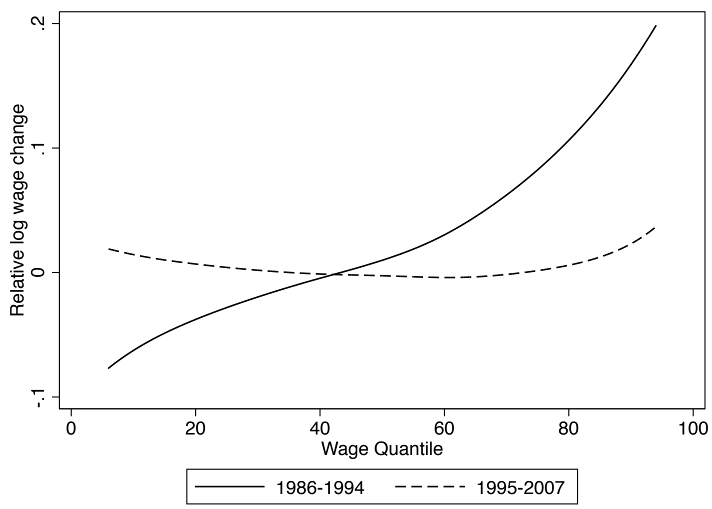

Figure 2: Change in log wage by percentile (relative to the median), 1986-1994 and 1995-2007
Notes: Wage percentiles computed for 1986, 1994, 1995 and 2007 using real wages, the number of observations ranges from 1,231,072 (1986) to 2,345,843 (2007). The results are smoothed using a locally weighted regression (bandwidth 0.8).

[13] Fernandez-Macias (2012) arrive at different results, though the period covered, data and methodology are also different. Their paper offers a discussion of the differences to Goos, Manning and Salomons (2009). In our case, we must stress that unlike the European Labour Force Survey, the QP dataset does not cover the public administration, the primary sector nor the self-employed, notwithstanding our results being in line with Goos, Manning and Salomons (2014).

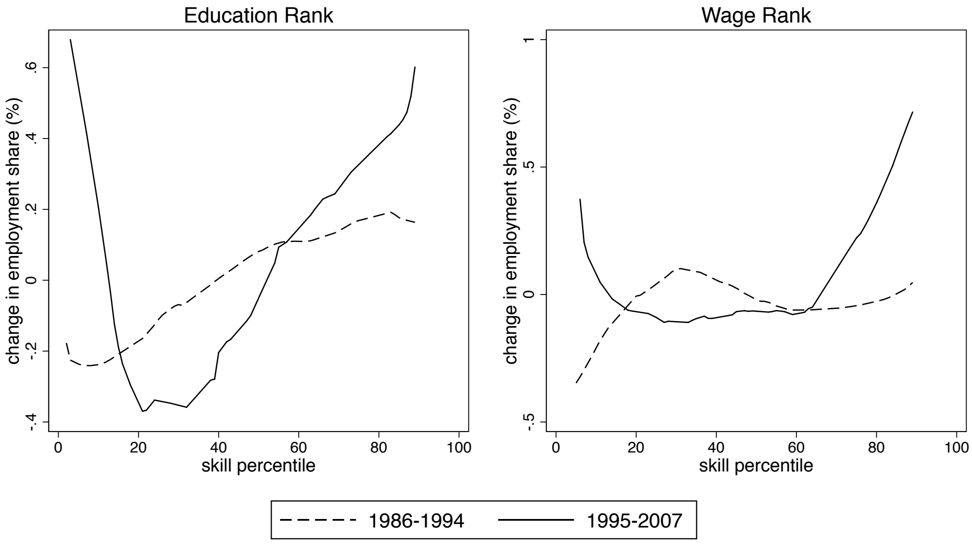

Figure 3: Changes in log employment share by skill percentile, 1986-1994 and 1995-2007
Notes: Skill percentile is the occupation percentile (employment-weighted) considering mean wage rank or mean education years rank. The percentiles are obtained by performing an occupational (3-digits) employment weighted rank for each period's initial year (data at the occupation level, 1,630,578 observations on average per year): 1986 for the first period; 1995 for the second. The results are smoothed using a locally weighted regression (bandwidth 0.8).

Shifts in the industrial structure can contribute to job polarization. For example, if industries more intensive in manual (e.g., construction workers) and abstract (e.g., managerial) occupations grow in employment and industries intensive in routine (e.g., office clerks) occupations decline, job polarization could occur. However, if polarization is being driven by technology changes with a resulting decline in the demand for routine-intensive tasks across the board, we expect *within*-industry changes in employment to explain most of the employment shifts observed, rather than *between* industry changes.

We perform a shift-share decomposition (Acemoglu and Autor, 2011) to test whether industrial change can be pointed out as a major explanation for job polarization.[14] We decompose the total change in employment share of each occupation j over the time interval t (ΔE_{jt}) into two parts: the first is the change in occupational employment share due to changes in the industry shares or *between* industry (ΔE_{jt}^{B}); the second captures the change in employment share due to *within*-industry shifts (ΔE_{t}^{W}). Equation 1 expresses

[14] An alternative approach to calculate shifts in the industry can be found in Berman, Bound and Griliches (1994).

this relationship,

$$\Delta E_{jt} = \Delta E_{jt}^{B} + \Delta E_{jt}^{W} \tag{1}$$

The changes in employment from Equation 1 can be computed as expressed in Equations 2 and 3,

$$\Delta E_{jt}^{B} = \sum_{k} \Delta E_{kt} \lambda_{jkt} \tag{2}$$

$$\Delta E_{jt}^{W} = \sum_{k} \Delta \lambda_{jkt} E_{kt} \tag{3}$$

In Equation 2, $\Delta E_{kt} = E_{kt_1} - E_{kt_0}$ is the change in employment share for industry k over time interval $t = \{t_0; t_1\}$ and $\lambda_{jkt} = (\lambda_{jkt_1} + \lambda_{jkt_0})/2$ is the average employment share in industry k for occupation j over the same time interval. Similarly, for Equation 3, $\Delta\lambda_{jkt} = \lambda_{jkt_1} - \lambda_{jkt_0}$ is the variation of industry k's employment share for occupation j during the time interval t and $E_{kt} = (E_{kt_1} + E_{kt_0})/2$ is average employment share of industry k in the given time interval.

We decompose employment changes for our broad occupational categories for two time periods: 1986-1994 and 1995-2007 (Figure 4). We consider seven broad occupational groups. The top paid-groups are 1) Managerial and health professions and 2) Technical and professional; the middle paid include 3) Office clerks and 4) Operators; and the bottom paid consist of 5) Sales, ticket clerks and other services, 6) Personal and protective services and 7) Routine operators (Appendix Table A1 lists 2-digit ISCO occupations by occupational group). The light shaded portion of the bars represents the within-industry changes, while the darker shade portion represents between-industry changes. We order occupational groups by rank of average wage, with high paid groups on top.

Both graphs in Figure 4 exhibit within and between-industry changes in the occupation groups' employment shares. For both periods, the light shaded portions of the bars show a larger within-industry growth in top paid occupations, and largest within-industry decline in middle paid occupations (Office clerks and Operators). This pattern of within-industry change appears to be stronger in the second period, which is consistent with the descriptive evidence on job polarization presented in the earlier figures. Overall, between-industry changes (darker shaded portion of the bars) are related with employment shifts from manufacturing to services and affect mostly employment changes in lower paid occupations.

While low paid manufacturing occupations decline, low paid services related occupations grow. To be consistent with our earlier evidence of stronger employment growth at the upper tail of the wage distribution than at the lower tail, these industry shifts most likely cancel each other out, resulting in small employment growth among the low paid. In other words, between industry decline in routine operators, mostly associated with manufacturing, has a similar magnitude (5.9%) of the between industry increase in personal and protective services, and sales, ticket clerks and other services (5.6%), which are mostly service occupations. For the lowest paid occupational groups, the within-industry changes in employment are small in comparison to between-industry changes. Interestingly, in the second period, the within-industry shifts among the low paid are consistent with the routinization hypothesis showing increases in personal and protective services, and small declines in routine operators and sales, ticket services and other services, which are more likely to be of a routine nature.

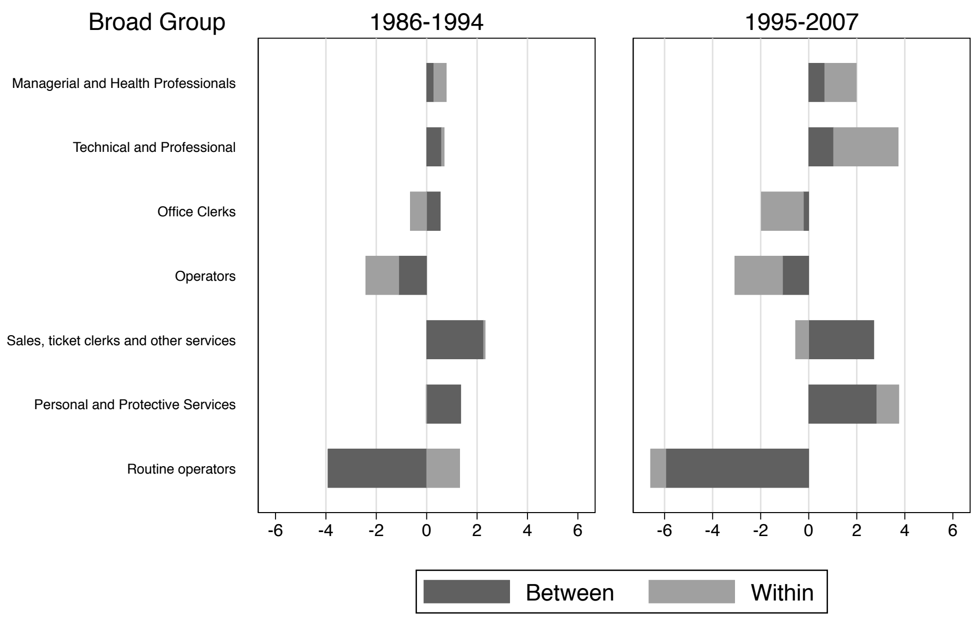

Figure 4: Changes in employment share by occupation groups: within and between industry decomposition
Notes: Each bar represents the change in employment share (in percentage points). Decomposition is performed for 11 industry breakdown (D, E, F, G, H, U, J, K M, N and O).

6 Employment, wages and task measures

6.1 Occupational task measures definition

In order to further investigate whether routinization is driving the job polarization documented in the previous sections, we use the O*NET descriptors (Goos, Manning and Salomons, 2009; Acemoglu and Autor, 2011) to find the task content of each occupation, allocating to each occupation their predominant task.[15] We select the O*NET descriptors that have importance and context scales, both between 1 and 5 (a detailed list of the descriptors by task type is in Appendix Table A2). We apply principal components by task type to the O*NET descriptors to reduce the dimension of the descriptors. The principal components maximize the total variability of the original data by construction.

With this methodology, each occupation is represented by a set of task measures. While most studies consider three tasks – abstract, routine and manual – we propose to unbundle routine into routine cognitive and routine manual. As it will become self-evident in the analysis that follows, the two routine type of tasks have markedly different characteristics and presumably are subject to differentiated effects of technological change. Table 2 summarizes the results obtained, displaying the standardized principal components (mean 0 and standard deviation 1) for each task measure and the total variability of the original data explained by the principal component. Managerial, science and health-related occupations are the ones that require the most abstract skills. *Physical, mathematical and engineering science professional* is the most abstract-intensive occupational group, with 1.62 scale points. By contrast, *sales and services elementary occupations* (e.g., housekeeping) are the ones that require less abstract skills (-1.85 points), whilst they are more intensive in routine manual and manual skills (0.23 and 0.09 respectively). *Office clerks* have the highest measure in routine cognitive importance (1.13), while *machine operators and assemblers* are, as expected, the ones with the highest importance in routine manual (2.20 points). Most occupations with low intensity in manual tasks also have low values in

[15]The O*NET database is the primary project of the O*NET program promoted by the US Department of Labor. The database provides information about occupations in several dimensions (we use version 15.0). We converted 854 SOC codes into 27 ISCO codes using the 2007 US employment data as weights. A SOC to ISCO crosswalk was kindly provided by Maarten Goos, Alan Manning and Anna Salomons to whom we are thankful.

Table 2: Task importance measures

Occupation	ISCO	Abstract	Routine Cognitive	Routine Manual	Manual
Small enterprises & corporate managers	12+13	1.01	-0.01	-1.32	-1.20
Physical, mathematical and eng. science prof.	21	1.62	0.62	-1.10	-1.09
Life science and health professionals	22	1.37	0.63	-0.38	-0.38
Teaching professionals	23	1.30	-0.41	-1.75	-2.12
Other professionals	24	1.39	0.02	-1.76	-1.96
Physical and eng. science associate prof.	31	0.89	0.43	-0.07	-0.09
Life science and health associate prof.	32	0.24	0.49	-0.11	-0.10
Teaching associate professionals	33	-0.08	-1.09	-1.72	-2.42
Other associate professionals	34	0.75	0.78	-1.44	-1.93
Office clerks	41	-0.41	1.13	-0.57	-1.01
Customer services clerks	42	-0.69	0.49	-0.37	-1.06
Personal and protective services workers	51	-0.88	-0.41	-0.34	-0.25
Models, salespersons and demonstrators	52	0.43	0.02	-1.03	-0.81
Extraction and building trades workers	71	-0.24	-0.37	0.66	1.90
Metal, machinery and related trades workers	72	0.11	0.03	0.01	1.88
Precision, handicraft, print. and rel. trades work.	73	-0.09	0.22	1.54	0.41
Other craft and related trades workers	74	-0.90	0.00	1.46	0.53
Stationary-plant and related operators	81	-0.27	0.12	1.62	1.20
Machine operators and assemblers	82	-0.53	-0.04	2.20	1.25
Drivers and mobile-plant operators	83	-0.60	-0.23	1.01	2.97
Sales and services elementary occupations	91	-1.85	-1.12	0.23	0.09
Laborers in mining, const., manuf. and transp.	93	-0.70	-0.27	0.91	1.53
(%) Total Variability Explained		89%	65%	87%	81%

Notes: Task importance measures obtained using principal components of several O*NET measures. The scores are standardized to mean 0 and standard deviation 1.

routine manual tasks. When the routine manual measure approaches the mean (0 points) the relationship is not as straightforward. For instance, *metal, machinery and related trade workers* are highly intensive in manual tasks (1.88 points, the second highest value), but with almost null value on routine manual tasks (0.01).

We further allocate each occupation to the task for which the occupation ranks highest in intensity. Let occupation i in task j have rank ij. Occupation i is more intensive in task j if rank $ij >$ rank ik with $k \neq j$. The process was straightforward for all occupations, but four. For one of these exceptions, the occupation ranked equally high in two tasks (ISCO 51). For the remaining exceptions, we had to look at the occupations in the finer categories to improve the match between the codes given that O*NET is based on the SOC code and certain ISCO categories do not offer a perfect match for SOC.[16]

[16]The exceptions to the rank rule were: *Life science and health associate professionals* (ISCO 32), *Personal and protective services workers* (ISCO 51), *Models, salespersons and demonstrators* (ISCO 52) and *Sales and services elementary occupations* (ISCO 91). ISCO 51 ranked equally high in two tasks, so we had to make a judgment call. The remaining exceptions resulted from differences between the SOC and ISCO codes, and correspond to occupations which rank high in two or more tasks, and in which the disaggregated occupations fit best in a task other than the highest ranking. In particular, ISCO 32

Our exact aggregation can be found in Table A3 in the appendix. This table also includes summary statistics by ISCO occupation, such as mean wages and wage growth in 1986-2007, employment share in 1986 and changes in employment share over the same period. It is worth noting that wage growth was highest for the life sciences and health related occupations and lowest for *customer services clerks*, with a 2% wage decline in the period. Employment grew highest among personal and protective services, managers and other professionals and lowest among office clerks, routine operators and operators.

6.2 Employment by task intensity

Figure 5 shows the employment share trends by task for the economy, manufacturing and services where each occupation is assigned the task with the highest intensity. For both sectors, over 40% of workers fall within the manual category and this percentage stays relatively flat throughout the period. Routine manual tasks are more predominant in manufacturing (ranging from 34% to 40%) than in services (13% to 16%) with a modest decline in manufacturing. The opposite is true for routine cognitive tasks: they are more prevalent in services than in manufacturing. Their share is at most 14% in manufacturing and at least 28% in services. Though this share seems to decline in both sectors, the decline is more pronounced for services, and modest for manufacturing. It is therefore interesting that for the economy as a whole, routine cognitive occupations' decline is very slight due to the expansion of service industries in which the share of these occupations is higher. Abstract occupations rise steadily in both sectors, but because services have a higher share of abstract task intensive occupations, the economy as a whole experiences a higher increase due to the expansion of service employment.

The O*NET allows the identification of those occupations whose tasks are offshorable.

Life science and health associate professionals includes health specialists such as optometrists, dieticians and physiotherapists which fit better in the abstract category than in the routine cognitive. Because ISCO 52 *Models, salespersons and demonstrators* includes occupations that are heterogeneous in their task content, we perform a finer task assignment. We classify ISCO 52 as manual, with the exception of sales representatives and cashiers. Because these two cases do not fit in the manual category, we assign sales representatives to routine cognitive category and cashiers as routine manual. Finally, ISCO 91 Sales and services elementary occupations includes doormen, janitors, security, cleaning and dry services and maids, which are often referred in the literature as good examples of occupations hard to replace with technology. These were classified as manual. Note that despite including "salespersons" in the title, ISCO 91 contains fewer sales occupations (only street vendors) than ISCO 52, hence they were allocated to different categories.

As discussed in the literature review, Portugal does not seem to follow the decreasing demand for offshorable jobs observed in more advanced economies. In Appendix Figure A2 provide evidence of this by showing an uptrend in offshorable jobs in Portugal.[17] Thus, in the case of Portugal we rule out an offshoring-based hypothesis to explain the observed polarization. Since offshorable occupations coincide with sub-groups of occupations intensive in abstract and routine cognitive tasks, using the O*NET to disentangle the effects of offshorability from routinization would be difficult and would require either additional data or a different methodological approach to identify jobs that had been actually offshored. Some of the employment and wage effects that we attribute to routinization may therefore be also partly due to an influx of offshorable jobs, making this an important topic for further research.

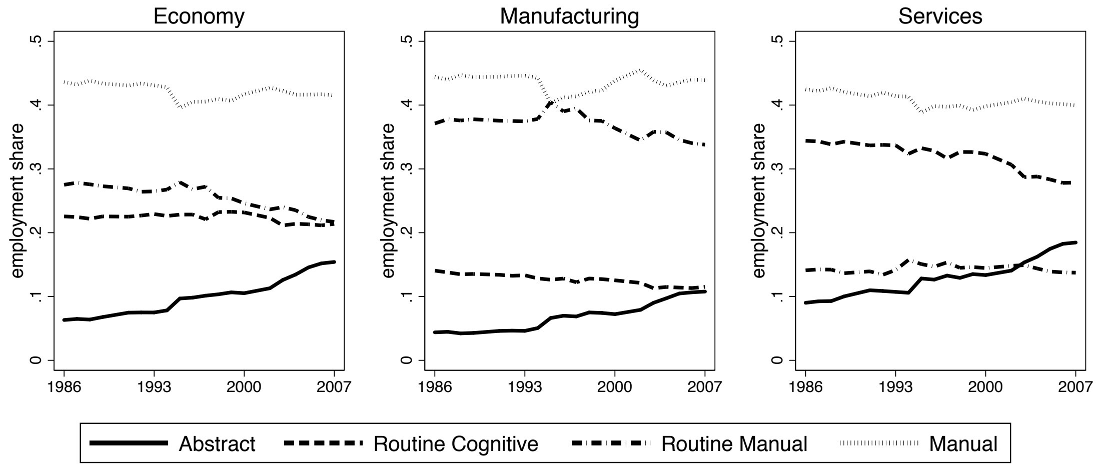

Figure 5: Employment share evolution by task and sector

6.2.1 How likely are workers to change tasks between two periods?

Table 3 presents the transition matrix between tasks for the whole period (1986-2007) as well as transition to non-employment and show that most individuals remain in the same task (more than 77% by task) or go to the non-employment pool (more than 11%).[18]

[17] Consistent with our findings, van Welsum and Reif (2005) show that the Trade balance for Portugal in the categories "other business services" and "computer and information services" as a percentage of GDP, a very rough measure of offshorability, was close to zero during the period 1995-2003, with a small increase from a slight negative to a slight positive balance, suggesting that Portugal may have become a very modest recipient of offshorable jobs after 2001.

[18] Transitions are calculated between two consecutive periods in which the worker is observed in the dataset. For example, if a worker is missing in one year, and the year after returns to the same task,

In addition, there are no major differences across tasks in the percentage of those who move out of a task, out of the data, or to another task. Between any two periods the percent of workers transitioning out of our data to unemployment (or to an uncovered sector) is around 12% for all task categories except manual for which the percentage is 14.2%. Looking at those workers who switch tasks, we can see that abstract workers switch mostly to routine cognitive (5.9%), while routine cognitive workers transitions occur more frequently to abstract (3%) and manual (4.8%). However, most routine manual workers who switch do so to manual (6.5%), suggesting that their skills are not sufficient to perform or learn how to perform abstract tasks. We also found transition flows between manual and routine tasks, as most manual workers who switch tend to end up performing routine tasks (3% routine cognitive and 3% routine manual). Overall, the figures show low task mobility patterns, along with a low degree of upgrade for tasks associated with higher wage premium, circumscribed to a small percentage of transitions from routine cognitive to abstract. In addition, there is no evidence that workers in routine occupations experience higher probability of becoming unemployed or switch out of their task more often, suggesting that much of job polarization likely occurs through job market entrants. This may be the result of the high labor market rigidity due to collective bargaining and firing restrictions in place during this period.[19] The results from the wage regressions will allow us to characterize further these mobility patterns, detailing how the task premia has changed during the period.

we consider him a stayer. We define non-employment when a worker leaves the dataset which is just a rough approximation, since we cannot track whether workers switch to unemployment or to a job not covered by our data (primary sector, self-employed or public administration). Using a subsample of the Portuguese Labour Force Survey that most closely replicates our QP data, we inspect workers' transitions to non-employment, and find that less than one-third move to other jobs not covered by the QP dataset and the remaining move to either unemployment or leave the labor market. This suggests that the number of our transitions to non-employment may be overestimated by close to 30%.

[19]During the period under study, Portugal has been characterized by a high degree of employment protection, high collective bargaining coverage (86% in 2007, according to OECD), wage rigidity and labor market segmentation (see, e.g., Addison, Portugal and Vilares (2016); Blanchard (2007); Carneiro, Portugal and Varejão (2014) for more details).

Table 3: Transition matrix – 1986-2007

From ↓ / To →	**Abstract**	**Routine Cog.**	**Routine Man.**	**Manual**	**Non-emp.**
Abstract	77.0%	5.9%	1.1%	3.5%	12.5%
Routine Cognitive	3.0%	79.1%	1.7%	4.8%	11.4%
Routine Manual	0.8%	2.4%	78.7%	6.5%	11.6%
Manual	1.3%	3.0%	3.0%	78.5%	14.2%

Notes: Each cell in the matrix is calculated as the percentage of transitions from task i to task j for all workers observed across the years as a percentage of all workers originally in task i.

6.3 Wages by task intensity

Figure 6 shows the evolution of log wage by task for the economy as a whole, manufacturing and services. Abstract intensive occupations experience the sharpest rise in wages, widening the gap between abstract intensive and the remaining occupations until the 2003 crisis. From 2003 onwards, real wages decline in abstract occupations, contrasting with the flat trend in the remaining groups. It is also worth noting an increase in routine manual wages (the lowest paid) relative to manual (and the remaining tasks), especially in services, which suggests that additional factors besides technology and routinization may be at play in the apparent compression in the bottom half of the wage distribution.

Several factors could explain the rise of workers' wages in routine manual occupations. First, the decline in routine manual occupations may have occurred in a non-random way, leading to selection among workers who remain in routine manual occupations, as it is possible that the more skilled are the ones retaining their occupations. Second, if minimum wages increased over time they could explain some of the compression observed between routine manual and manual wages. Figure 7 shows that the minimum wage increased over time towards the 10^{th} percentile of the wage distribution for each task and is therefore likely to have impacted the wage growth of routine manual and manual tasks including the wage convergence observed.

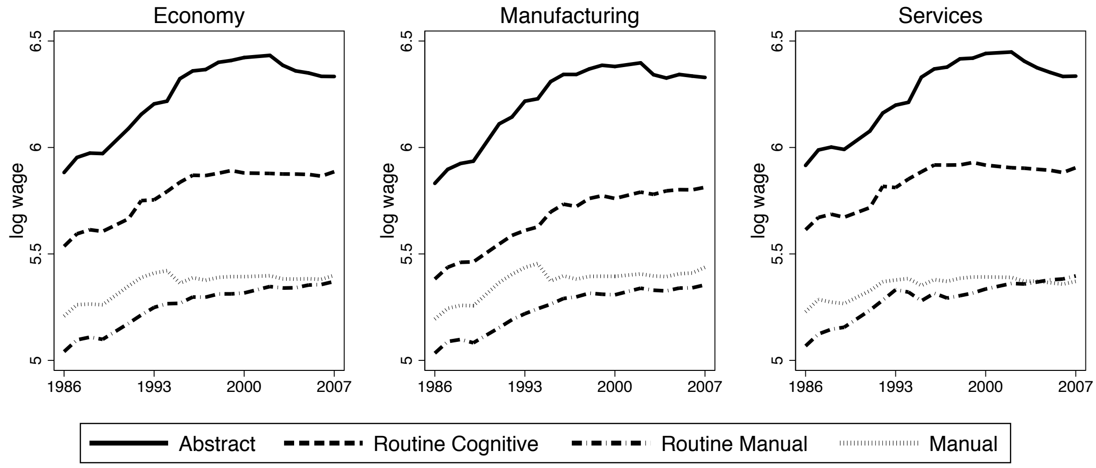

Figure 6: Wage evolution by task and sector

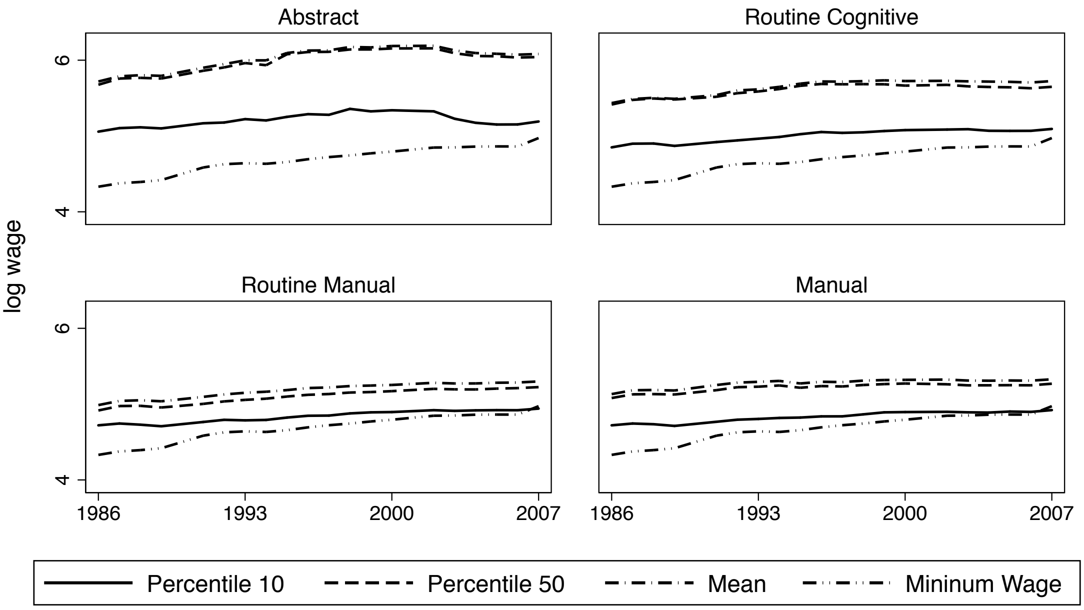

Figure 7: Task wage percentiles and minimum wage

7 Routinization hypothesis

Is the job polarization observed so far due to the routinization hypothesis? In this section, we aim at answering this question by empirically testing the hypothesis for employment and wages.

7.1 Evidence from employment

To empirically test for the effects of routinization hypothesis on employment while controlling for confounding factors, we resort to cells constructed using age, education, tenure, region and industry variables in resemblance to Autor, Levy and Murnane (2003) methodology for employment and Acemoglu and Autor (2011) methodology for wages. For each cell, we compute the share of workers allocated to each task (abstract, routine cognitive, routine manual and manual) at the beginning of the period (1986 or 1995), along with yearly cell employment. Thus, the unit of observation is the log employment in each cell, which is regressed against their task measures at the beginning of the period. The variables of interest are the interaction between the share of workers in beginning of the period and time dummies. The interaction terms capture the trend in employment for cells that hold comparative advantage in t_0 (1986 or 1995) on a given task.

The underlying identification assumption is that, for a fixed relative supply of skills (cell skill composition in beginning of the period), a decline in the price of computer capital reduces the employment of skill groups that hold comparative advantage in the initial period in tasks replaced by computers, and increases the employment of skill groups that hold comparative advantage in the first period in tasks that exhibit complementarity with computer capital. This is true whether workers have changed or retained their jobs and occupations throughout the period. For example, if a skill-industry-region cell has a relatively high share of routine manual workers in beginning of the period, we expect this cell's employment to grow less over time than employment in a cell that has a comparative advantage in abstract skills at the beginning of the period. Since the observation units are demographic, region and industry cells, this strategy also nets out compositional effects along these dimensions.[20] Still, increases in the supply of skills, considerable in this period, may not be fully accounted for by this empirical strategy, which only considers three education groups in the creation of cell units. This will be taken into account when interpreting the results.

Formally, we define the natural logarithm of employment Ω_{it} in cell i at time t as:

$$\Omega_{it} = t_t\boldsymbol{\alpha} + T_{it_0} \times t_t\boldsymbol{\beta} + c_i + \omega_{it} \tag{4}$$

where T_{it_0} is the matrix of initial employment share in abstract, routine cognitive and routine manual tasks for cell i in time t_0 – manual tasks are the omitted group. The vector of yearly time dummies t_t controls for macroeconomic conditions. The cell fixed effects c_i control for remaining unobserved heterogeneity arising from each cells' attributes, i.e., it nets out persistent differences across cells unrelated with their initial distribution of tasks. Our coefficients of interest are the point estimates $\boldsymbol{\beta}$ from the interaction term $T_{it_0} \times t_t$, which capture the trend in employment for cells that hold comparative advantage in t_0 (1986 or 1995) in a given task, relative to manual.

We apply fixed-effects (within) estimation to Equation 4. The estimation is performed separately for each period (1986-1994 and 1995-2007), since polarization is observed mostly in the latter. In addition, splitting the estimation in two periods, reduces the time span covered in each regression, which mitigates biases from changes in workers' skills composition, along with possible attrition biases resulting from reporting errors. We omit manual occupations, which implies that the coefficients of the interaction terms give us the time trends associated with the initial share of each task relative to the manual share. Cells are defined by gender, age (<25, 25-34, 35-44, 45-54, 55-65), education (less than high school, high school, college), job tenure (≤2, >2), regions (NUTS 2) and industries (11 industries breakdown) and are our units of observation. Depending on the year, we obtain at least 2,986 gender-age-education-tenure-region-industry cells. On average, each cell contains 419 workers and the average yearly total employment is 1.6 million workers.

To simplify interpretation of Equation 4 estimation results, we plot the interaction

[20] See Acemoglu and Autor (2011) for a more formal discussion of the selection issue.

coefficients for the two periods in Figure 8 by sector, where we include the 95% confidence interval around each point estimate (estimated coefficients are in Appendix Table A4). For both periods, the results for the economy as a whole show a clear rise in employment among demographic groups that have a comparative advantage in abstract tasks in the initial period, relative to those that have comparative advantage in manual tasks (the omitted group). On the contrary, groups that initially held comparative advantage in routine manual tasks suffered a relative decline in employment in both periods, consistent with routinization (Autor, Katz and Kearney, 2006). Regarding the growth in relative employment of the groups with comparative advantage in routine cognitive tasks it is positive in the first period (1986-1994) and negative towards the end of the second period (the coefficients before 2003 are not significant at the 10% level). The fact that cells with a comparative advantage in routine cognitive tasks experience negative employment growth in the second period only is in line with our previous descriptive statistics showing evidence of polarization for the second period only, and points to technology as the likely cause for the relative thinning of middle paid employment.

When broken down by sector (Figure 8) the results for the first period (1986-1994) are broadly similar to those for the economy. In the second period (1995-2007), similar trends are present across sectors, with a few differences in magnitude. Employment in cells with comparative advantage in abstract accelerates faster for services, while the decline of groups that held comparative advantage in routine manual tasks declines faster in manufacturing, especially after 2002. For both sectors, routine cognitive coefficients are not significant in the beginning of the period, but are negative at the end, especially for services. These results suggest that the demands forces resulting from routinization impacts employment of the various tasks with different intensity in the two sectors.

7.2 Evidence from wages

In order to test the routinization hypothesis for wages, we rely on wage regressions where we include the main task performed by the worker. However, including tasks dummies in the wage equation rises endogeneity concerns since workers can self-select into occupations based on characteristics not observed by the econometrician. In particular, as technology

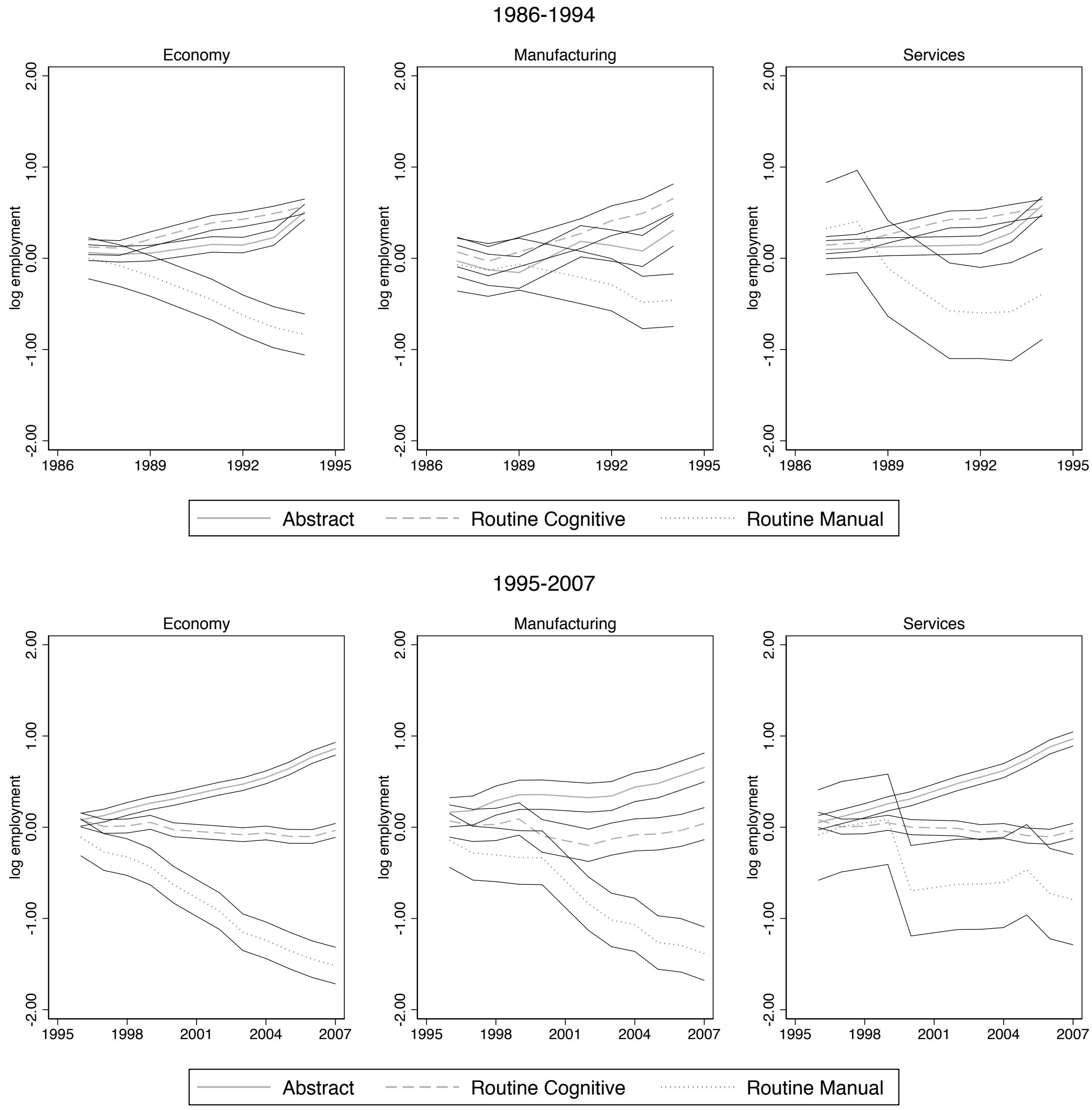

Figure 8: Employment trends based on initial task share by sector

Notes: Estimations performed for gender-age-education-tenure-region-industry cells. The estimates displayed are only for the iteration effect of Equation 4: share of workers in a given task and in a given cell in beginning of the period (1986 or 1995) interacted with time dummies. Model contains fixed effects for cells. A 95% confidence band is represented around each trend of coefficients (solid black lines). Estimated coefficients from Appendix Table A4.

substitutes for workers performing routine tasks, workers who continue to perform those tasks can in theory either be of lower or higher ability conditional on selecting into that task (higher if they are successful in retaining jobs in occupations that have become increasingly scarce, lower if those with higher ability in routine tasks have transferable skills and are able to successfully move to jobs with abstract tasks). To overcome selection bias, we follow Cortes (2016) whose identification strategy relies on directly controlling for task-specific ability by including task-spell fixed effects in the wage regression. The task-spell fixed effects control for workers' unobserved ability in each task that they are employed, mitigating the problem of self-selection of workers into tasks according to their task-specific ability and allow us to identify a consistent estimate of the task premia over time, under reasonable assumptions.[21] Formally, let log wage w_{it} of worker i in time t to be described by:

$$w_{it} = \sum_j T_{ijt}\theta_{jt} + \sum_j T_{ijt}\gamma_{ij} + Z_{it}\boldsymbol{\xi} + \epsilon_{it} \tag{5}$$

where T_{ijt} is the task indicator function that is one when worker i selects into task j at time t and zero otherwise, θ_{jt} is the task-time fixed effect, and γ_{ij} are worker task-spell fixed effect. By construction, the task-time fixed effect – our variable of interest – can be thought as the interaction of task and time dummies and the worker task-spell fixed effect as the interaction of worker fixed effects with task dummies. Finally, Z_{it} is a vector including year fixed effects and controls for region (NUTS2). Those control variables are by assumption not specific to any tasks or skills and are orthogonal to the error term ϵ. We apply a fixed-effects (within) estimation at the worker task-spell level and for all the specifications we cluster the standard errors at the worker level.

We plot the task-time fixed effects coefficients (θ_{jt}) in Figure 9 by sector and period (see Appendix Table A5 for the estimated coefficients). Similar to the employment regressions, we add the 95% confidence interval for the point estimates. Manual tasks are the comparison group. The wage results show an upward trend for the abstract relative wage

[21] The estimation method assumes that: the unobserved skills and their returns do not change over time; workers know their skills and idiosyncratic shocks to the wages do not affect the task choice. For the formal details about the model deduction and its empirical implementation see Cortes (2016)

premium for all specifications. The routine cognitive relative wage premium also follows an upward trend, though less steep. The routine manual relative wage premium declines in the first period (1986-1994) for the economy and for manufacturing, but increases modestly for services. In the second period (1995-2007), the routine manual wage premium is still negative and declining for the economy and for manufacturing, and for services it exhibits a modest decline that recovers by the end of the period.

While the upward trend in the relative wage premium of abstract tasks and the declining trend in the relative wages of routine manual tasks in manufacturing and for the economy are in line with the routinization hypothesis, the increasing trend in the wage premium for routine cognitive tasks and the lack of a negative trend in the wage premium of routine manual for services is not. Before discussing how these results can in fact be compatible with a nuanced form of the routinization hypothesis, we first run a number of robustness checks to address potential sources of biases that could have impacted our wage estimates.

7.2.1 Robustness checks

In this section we perform a series of robustness checks to our wage regressions to lessen possible remaining biases such as due to heterogeneity and omitted variables.[22] We first address heterogeneity by allowing worker characteristics to vary over time. Formally, we add to Equation 5 worker time-varying observable characteristics and their interactions with task fixed effects. This specification not only reduces omitted variable bias, but the interaction variables allow the returns to skills to be task-specific, thus relaxing the assumption that task specific ability is invariant with time, as we had in our previous estimations. To account for that, we include categorical variables for age (<25, 25-34, 35-44, 45-54 and >55 years old) and education (less than high school, high school and college). Because workers can sort themselves into different types of firms, we include the firm characteristics where the worker is employed: firm size (less than 9, 10-49, 50-249 and more than 250 employees) and industry (11 dummies). Finally, to account for task specific human capital, we add a quadratic function for the task tenure (the seniority in

[22] For the sake of simplicity we only present the results for the economy, as the results by sector are similar to those obtained before.

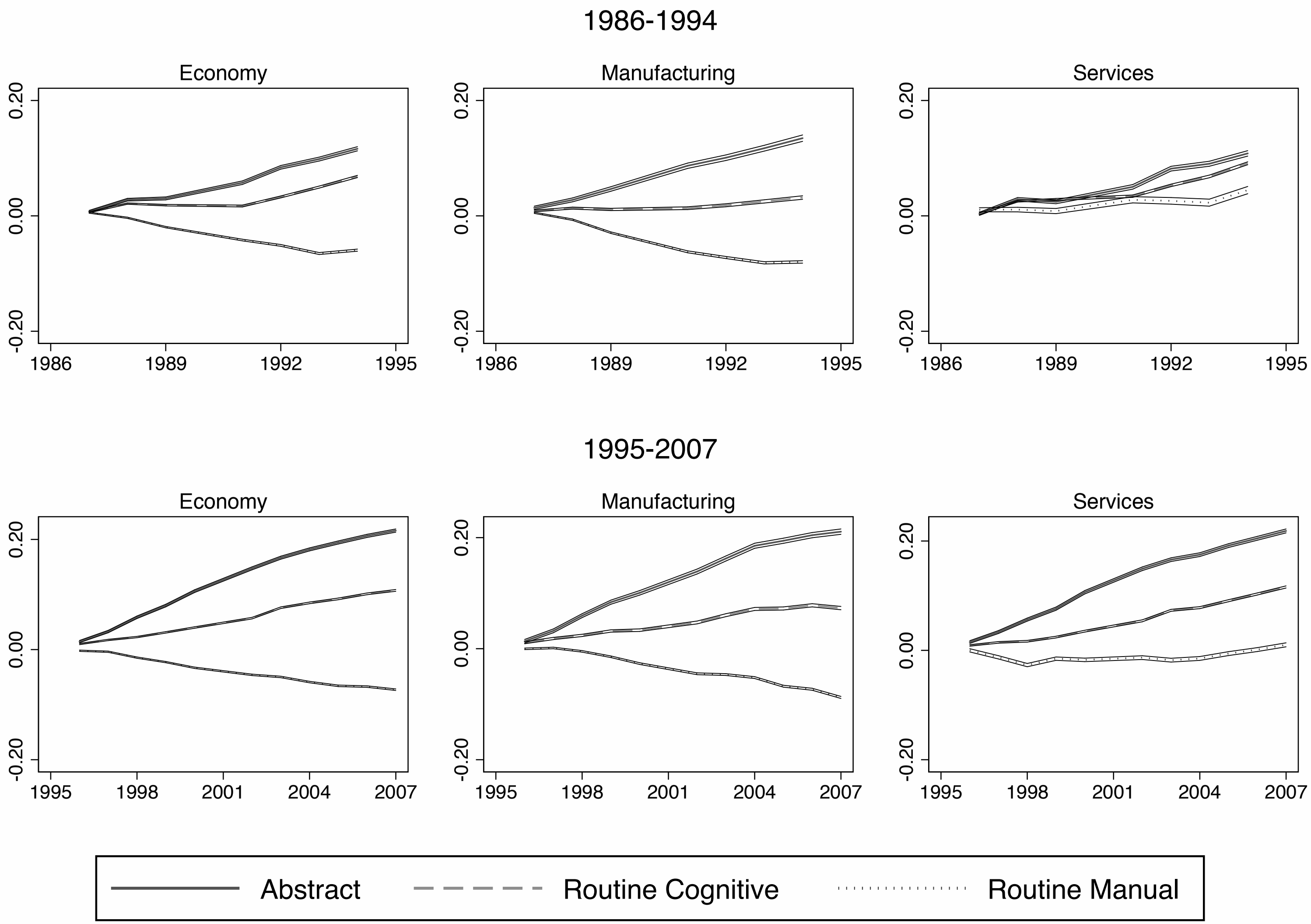

Figure 9: Task wage premium by sector

Notes: Worker level estimations of Equation 5. The coefficients plotted correspond to task-year dummies (task-time fixed effects θ_{jt}). Model contains worker task-spell fixed effects. A 95% confidence band is represented around each trend of coefficients (solid black lines). Estimated coefficients from Appendix Table A5.

a certain task). Panel A of Figure 10 presents the interaction coefficients between time and tasks fixed effects (as in Figure 9) – the task-time fixed effect – when we add all the above worker time-varying characteristics simultaneously (we also estimated separate wage regressions adding each of these additional variables and their interaction with the task fixed effects separately, but our results remained stable). The results reveal similar trends for the task wage premium when comparing with the main results obtained with Equation 5, with the exception of the routine manual trend which becomes flatter for the economy (by sector the differences among the coefficients are almost null).

Our earlier discussion of the minimum wage (see Figure 7) suggested that wages in routine manual tasks, being the lowest paid, are more likely to be affected by the increase in the real minimum wage that took place during the period. This implies that omitting minimum wages could possibly result in a bias of the relative wage premia for routine manual tasks. To account for minimum wage effects, we re-estimate our regressions controlling for a measure of the "toughness" of the minimum wage at the cell level where cells are defined as in Equation 4 (employment regressions) using age, gender, education, tenure, region and industry dummies. Our measure uses the ratio of the minimum wage to the 10^{th} wage percentile of each cell. Panel B of Figure 10 presents the results of the wage trends with the minimum wage controls, along with the time-varying worker firm characteristics (and their interaction with the task fixed effects) included in the specification of Panel A. The controls for age, education, task tenure, firm size and industry and the interactions of these variables with the dummies for the tasks (as in Panel A) present a stronger robustness check. The estimated trends are similar to those obtained before, suggesting that the rise of minimum wage does not cause any substantial bias in the previous estimates.

Due to selective mobility of workers between tasks, estimations of task returns over time are likely to be biased. For example, growth in returns to abstract tasks may be downward biased if workers from routine cognitive tasks who are able to switch to abstract occupations are of lower skill than the mean skills of incumbents in abstract occupations. Following Cortes (2016) methodology, results in panels C and D account for this selection, by including in the wage regression a set of dummies that maps all transitions to the current task (zero represents no transition and is the baseline). Including this set of dummies that maps all transitions in the wage regressions aims to measure the transition cost associated with workers switch to the current task given their task in the previous period. Because the costs can vary depending on the task of origin and destination, as some tasks may require more similar skills than others, adding a set of dummies that maps all transitions allows the cost function to cover all task pair combinations. We present two specifications accounting for the switching costs: one adding switching dummies to our main model (panel C) for all pairwise transitions, and another where we add both the switching dummies and the worker time-varying characteristics (and their interactions with task fixed effects) as in the wage regression found in panel A. Despite that overall 36% of worker switch jobs within the whole period, the results are similar to those before, thus discarding any serious bias that task switching might induce in our results. In addition to switching costs, we additionally run the specification of panel A by splitting the sample between workers who switch task (panel E) and those who do not switch task (panel F). The results for switchers are identical to the ones found before. For non-switchers, the regression results do not show clear trends for the first period as most coefficients for routine manual and routine cognitive are not significant. For the second period, as found before, the results show abstract and routine cognitive wage premiums increasing, though the latter are less pronounced. In addition, routine manual wage premium declines less than in previous regressions. While the trends for routine tasks premiums are less pronounced, we do not find evidence contradicting the results found in our previous estimations.

As a final robustness check, we extend Cortes (2016) empirical methodology, which uses dummies to capture task wage premiums, by using instead the continuous task measures from which the task dummies were created (see Table 2). Each occupation has now a vector of task intensities, with a value for each task category. Reducing each occupation to a unique task as we have done so far, while appealing for its simplicity, reduces the richness of variation offered by the O*NET descriptors and could result in measurement error and biased estimations. By replacing, in Equation 5, the task indicator function (T_{ijt}) from the first interaction by the task continuous measures (C_{ijt}) and comparing the results obtained to the original ones, we are able to assess the magnitude of such potential

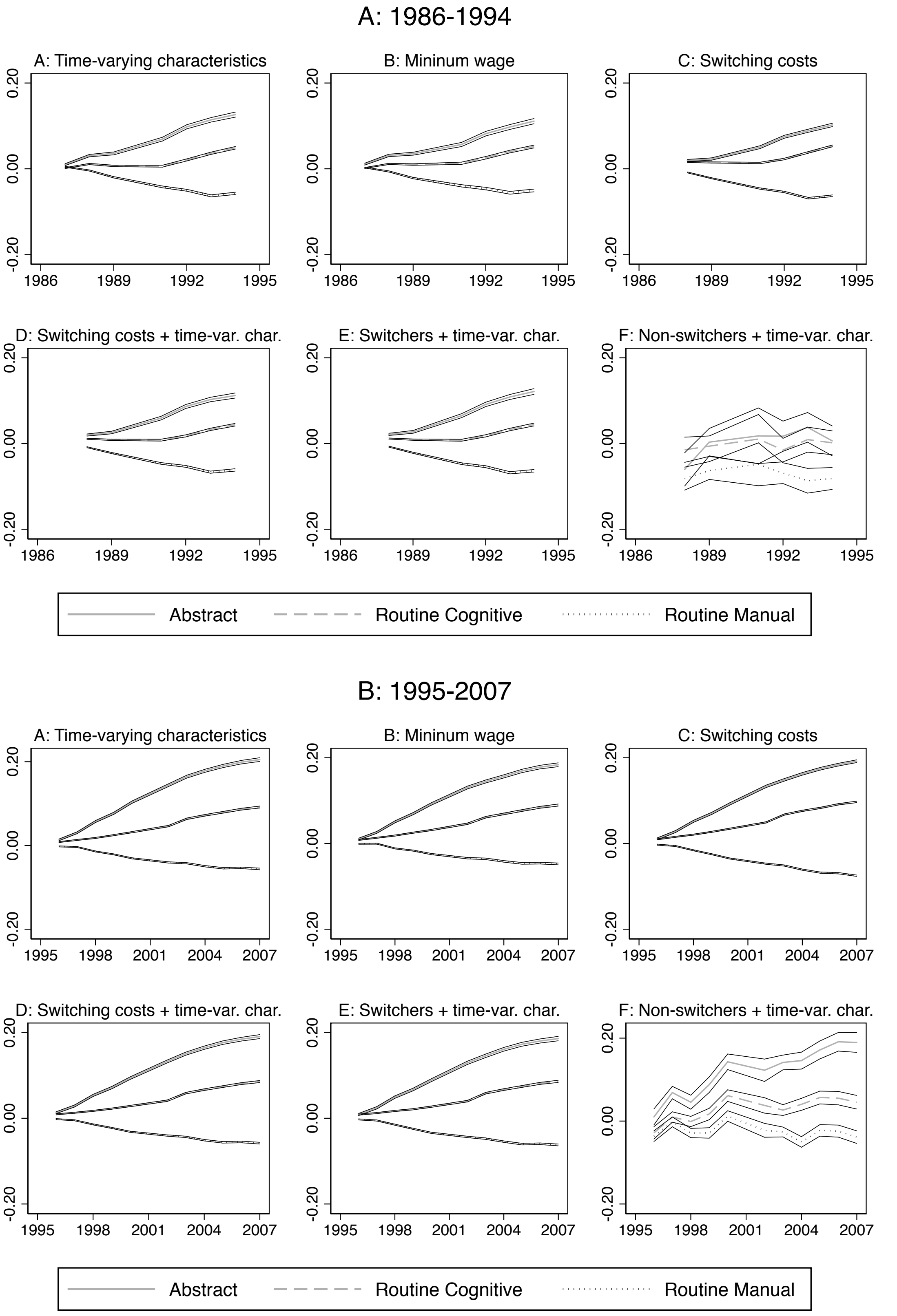

Figure 10: Robustness checks to task wage premia estimations

Notes: Worker level estimations with worker task-spell fixed effects as in Equation 5 with additional control variables as indicated in each panel's title (see main text for description). The coefficients plotted correspond to task-year dummies (task-time fixed effects θ_{jt}). A 95% confidence band is represented around each trend of coefficients (solid black lines).

bias.[23]

Formally, the equation to be estimated becomes:

$$w_{it} = \sum_j C_{ijt}\theta_{jt} + \sum_j T_{ijt}\gamma_{ij} + Z_{it}\boldsymbol{\xi} + \epsilon_{it} \tag{6}$$

where Z_{ijt} represents the same control variables from Equation 5 - year and regions fixed effects, and where the coefficients of interest are given by the vector θ_{jt} of task-time fixed effects, which capture the average returns to the continuous measures of task intensity over time.

In Figure 11 we plot the coefficients from the interaction of the continuous task measures at the worker level with time dummies. The trends shown are similar to those obtained with task dummies, despite the fact that the coefficients do not hold the same interpretation regarding their magnitude given that continuous measures of task intensity are based on the O*NET descriptors, which contain both positive and negative values and cannot be interpreted as percentages.

Overall, the robustness checks performed show that our estimations of the task wage premiums (based on Equation 5) are rather robust to different specifications and are not greatly affected in magnitude by potential biases caused by the omission of time-varying characteristics, minimum wage variables, switching costs and selection in task transitions as well as our simplified measurement of task intensity. Since the estimated trends remain unchanged, so do our interpretation and conclusions.

[23] However, it is important to note that the downside of using continuous measures of task intensity is that in reality, task intensity may not be truly continuous nor possible to unbundle, causing discontinuities that could bias the estimation results.

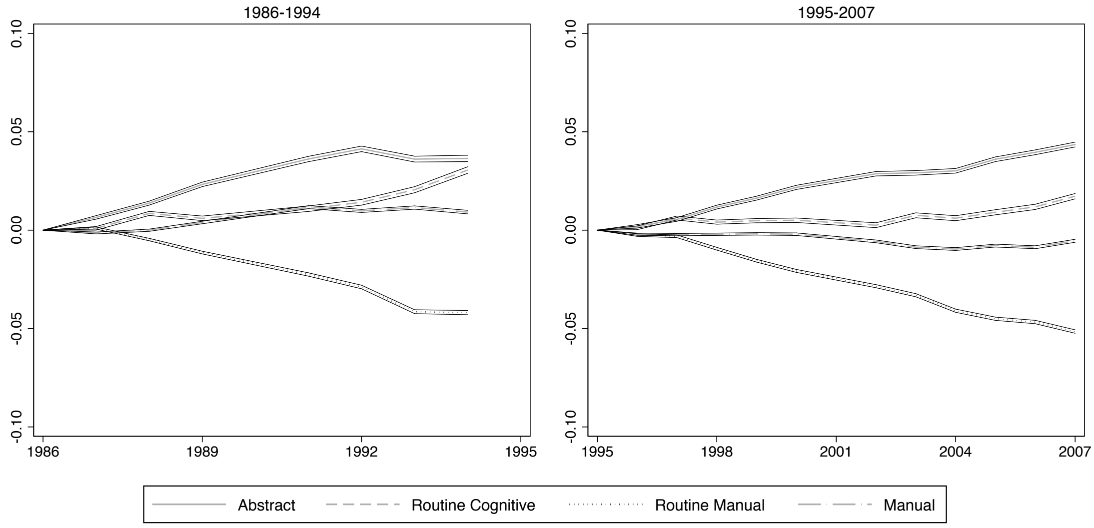

Figure 11: Robustness checks to task wage premium estimations – continuous measures
Notes: Worker level estimations of Equation 6. The coefficients plotted θ_{jt} correspond to the interaction between continuous task measures and year dummies. Model contains worker task-spell fixed effects. A 95% confidence band is represented around each trend of coefficients (solid black lines).

7.3 Transitions between tasks

The task-spell fixed effect estimated in the wage regressions can be considered a time invariant measure of worker's specific task ability (Cortes, 2016). Thus, an ability rank can be obtained by computing yearly quintiles for each task. We use these quintiles to characterize the workers' transitions between tasks, as well as to assess the magnitude of possible self-selection across tasks. In Figure 12, we plot all possible switches from worker's i observed task in t to task in $t + 1$. The ability quintiles are obtained from estimating Equation 5, to which the worker time-varying characteristics were added.[24] Thus, for each pair of two different tasks in t and $t+1$, we calculate the workers' distribution across quantiles for the task in time t. For example, for all workers who switch from Routine Cognitive to Abstract between two consecutive years (Panel B), 11.4% come from the 1st quintile, 14.0% from the 2nd quintile, 17.3% from the 3rd quintile, 20.3% from the 4th quantile and the remaining 37.0% from the 5th quintile of Routine Cognitive in period t.

The results for the four panels show that workers who do not switch tasks are al-

[24]We prefer the specification where we control for the observable workers' characteristics – age, education, task tenure, firm size and industry dummies and their interactions with the task dummies as in the robustness check presented in Panel A. However, we also computed the ability quintiles without controlling for worker time-varying characteristics and the results are similar.

most evenly spread across the five quantile for all possible transitions (the percentage of non-switchers is represented by diamond shapes). The results from Panel A show that low ability workers are the ones who often switch from Abstract task to other tasks, while high ability workers have lower likelihood to switch to other tasks, especially Routine Manual and Manual tasks. Workers switching from Routine Cognitive (Panel B) to Routine Manual and Manual are often ranked as low ability, whereas those who move to Abstract occupations are predominantly high ability (5th quintile). Panel C shows relative low association between ability and switching from Routine Manual to Manual, as those switches occur with a similar frequency across the ability distribution. Yet, switching from Routine Manual to Abstract is much more frequent for high ability workers' and the same applies for those switching from routine manual to routine cognitive, though to a lesser extent. Workers who switch from Manual (Panel D) to Abstract are mostly high ability, while low ability workers switch more frequently to Routine Manual.

Overall, the results show that transitions between tasks follow a pattern based on workers' specific task ability. Higher ability workers tend to move to tasks holding higher wage premiums – evident by the transitions from all tasks to Abstract coming mainly from the top of the ability distributions. Lower ability tend to move to tasks holding lower wage premiums – evident by the transitions from Abstract and Routine Cognitive to Routine Manual and Manual coming mainly from the bottom of the ability distributions. These results confirm the need to control for selection among workers transitioning between tasks in our regression analysis, despite our results suggesting that selection bias does not affect the robustness of our results.

7.4 Discussion

Our findings suggest that the abstract tasks' wage premium relative to manual have experienced a sharp increase between 1986 and 2007, while the premium for routine manual tasks has dropped for the economy and manufacturing, in line with the routinization hypothesis. In the service sector, routine manual wages exhibit a stable trend (slightly negative until 2005) relative to manual even when additional controls are included, which could go against the routinization hypothesis which would predict a declining trend. A

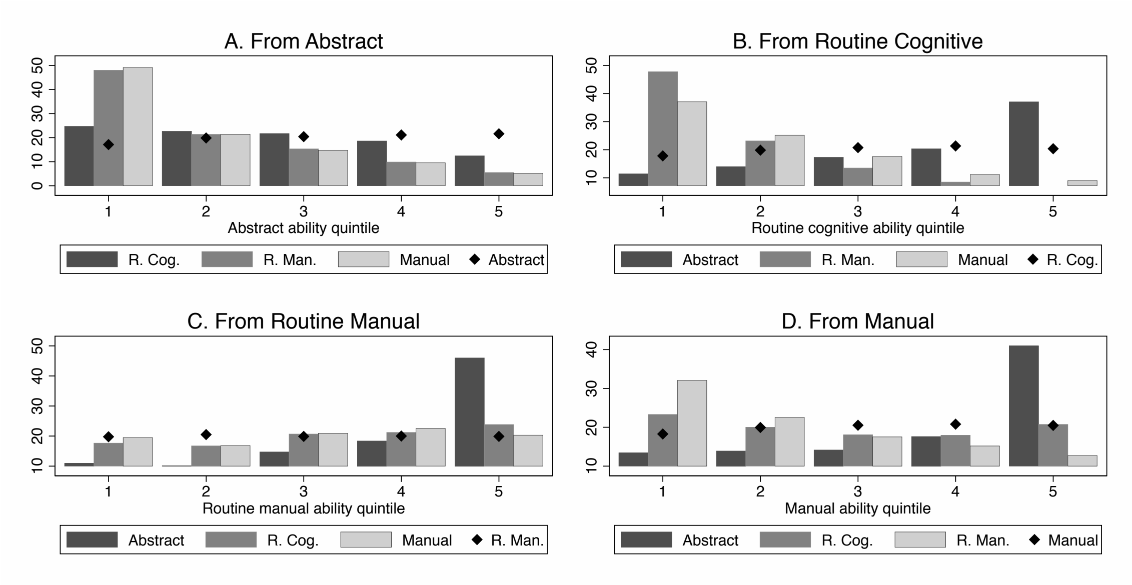

Figure 12: Share of task switches by ability quintiles
Notes: Ability quantiles are obtained ranking the worker task-spell fixed effects by year. The fixed effects are obtained from estimation of Equation 5 in which we include additional control variables for time-varying characteristics.

closer look at the occupational make up of these tasks allows us to explain this apparent contradiction. Routine manual tasks in services are comprised of mostly sales persons and cashiers (in terms of employment), while the majority of manual employment in services consists of personal and protective services. Sales, though highly routine, have not yet been substituted by technology in Portugal where internet sales and the use of self-checkouts are still very incipient. These results are consistent with an increase in the demand for sales workers, which is not surprising due to the dramatic expansion of services, and in particular retail trade since Portugal joined the European Union in 1986.

This study, in contrast with most empirical studies, unbundles the wage premium for routine tasks into two categories: manual and cognitive. This distinction allows us to uncover an upward wage trend for routine cognitive tasks, together with a very modest declining employment. The declining demand for routine tasks as they are replaced by technology, would put a downward pressure on this task group's wages. However, the rapid expansion of the service sector, which has led to an increase in employment in sales, ticket clerks & other services (a specific occupational category associated with routine cognitive tasks), is the likely explanation for the observed upward trend in wages and modest employment decline observed for routine cognitive tasks. These results seem to be a direct consequence of the initial lower development of the service sector and low educational levels for the Portuguese economy during this period which may have delayed some technological investments. In fact, similar patterns for employment have been reported earlier for Germany (Black and Spitz-Oener, 2010) and the US (Acemoglu and Autor, 2011), where routine cognitive tasks' employment rose until 1990, supporting the consistency of our results with the routinization hypothesis. Lessons from more advanced economies also suggest that the Portuguese wages and employment in occupations focusing on routine cognitive tasks are likely to suffer more in the future.

8 Conclusion

Similar to the US, UK, and continental Europe, Portugal has experienced recent job polarization, with a hollowing of employment around the middle of the wage distribution from the mid 1990s onwards. Job polarization has occurred hand-in-hand with wage polarization – both wages and employment of middle skilled workers suffered a relative decline from 1995 to 2007.

We have also uncovered evidence that job polarization in Portugal has been technology driven, though in a nuanced form. First, despite the large industry movements observed due to a shift from manufacturing to service industries, it is the within-industry employment changes in occupations that account for the larger growth in top and bottom paid occupations versus the middle paid, ruling out industry shifts as the major cause of job polarization. Second, using task measures derived from the Occupational Information Network database (developed by the US Department of Labor) our descriptive statistics show an increase in employment in abstract-intensive occupations in both manufacturing and services and a decline in routine manual-intensive occupations, but only in the second period for manufacturing, where these occupations are much more predominant. Routine cognitive-intensive occupations also show a declining trend for both sectors, though it is very slight for manufacturing and more pronounced in the service sector, especially in the second period. However, since the share of the service sector has increased dramatically between 1986 and 2007, and routine cognitive occupations are much more predominant in services than manufacturing, the overall employment for routine-cognitive occupations shows hardly any decline throughout the period. These trends suggest that the dramatic shift between manufacturing and services observed during this period is likely to have had a strong impact in the relative demand for the two types of routine tasks.

Third, when controlling for several confounding variables, the employment regression estimates for the first period reveal a growing trend for cells with a comparative advantage in abstract and routine cognitive occupations at the beginning of the period, and a declining trend in cells with a comparative advantage in routine manual occupations, relative to manual occupations. However, for the second period, the trend for cells with a comparative advantage in routine cognitive tasks is reverted, and some coefficients become negative towards the end of the period, consistent with the routinization hypothesis. Our regression results thus confirm that routinization is the likely cause behind job market polarization which is only observed in the second half of the period under analysis.

Fourth, our results for the task wage premium reveal somewhat similar patterns to those from employment: a rise in the premium for abstract tasks, and a decline for routine manual tasks, relative to manual task wages. However, the routine cognitive wage premia boasts a positive trend in both periods, suggesting that despite the considerable increase in the supply of middle skills (especially high school graduates) observed during this period, the relative growth in demand for these skills was even larger. This is mainly explained by the remarkable expansion of the services sector, with its large share of routine cognitive jobs. In addition, the fact that Portugal has lower human capital levels than more advanced economies, has likely lead to slower computer capital adoption with a relatively lower replacement of some routine cognitive jobs. An example of this is the still incipient use of self-checkouts and internet based retail trade.

Overall, our findings overwhelmingly support the routinization hypothesis for the Portuguese case, with the exception of the routine cognitive group which does not follow the expected wage trends. Because similar patterns can be found for more advanced countries (e.g., US and Germany) before 1990, this supports our claim that this is likely due to the Portuguese lagging development, especially in terms of the size of its service sector and education levels.

The Portuguese case shows that a country lagging in GDP per capita, wages, education and capital stock relative to many of its European counterparts can experience similar patterns of labor market polarization explained by technology advances such as computerization and automation which displace routine tasks, and complement abstract tasks. Yet, its manifestation is more nuanced, with differing impacts on routine cognitive and routine manual tasks. The evidence derived from the Portuguese case adds to the literature by providing a thorough analysis of job and wage polarization for a developed country below the technological frontier, highlighting the importance of unbundling routine tasks into cognitive and manual, which have different relevance in manufacturing and services, at a time where rapid shifts between these two sectors are taking place. Our findings provide evidence that technology can hit these labor markets in a similar fashion as more advanced economies such as the US, UK or Germany, though with a lag.

Our results suggest that education and employment policies should promote the acquisition of non-routine skills likely to sustain a comparative advantage in the near future. In the case of Portugal, and given its comparatively low levels of education, investments in college education seem warranted. The mismatch between the supply and demand for skills due to the technological change is one of the probable causes for the high prevalence of long-term unemployment, representing more than 50% of total unemployment in the last decade. In addition, the disappearing of middle paid jobs may bring about the weakening of social ties associated with the thinning of the middle class, which is likely to be intensified in the future decades, as the adoption of computer technology expands. This should also be taken into account in the design of policies with redistributive implications (such as those aimed at reducing the budget deficit) that may affect disproportionally individuals and families at the various sections of the wage distribution, and exacerbate the potential negative consequences of job polarization.

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References

Acemoglu, Daron. 1998. "Why do new technologies complement skills? Directed technical change and wage inequality." *Quarterly Journal of Economics*, 113(4): 1055–1089.

Acemoglu, Daron, and David H Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics.* , ed. Orley Ashenfelter and David E Card, 1043–1171. Amsterdam:Elsevier Inc.

Addison, John T, Pedro Portugal, and Hugo Vilares. 2016. "Unions and Collective Bargaining in the Wake of the Great Recession: Evidence from Portugal." *British Journal of Industrial Relations*, 55(3): 551–576.

Adermon, Adrian, and Magnus Gustavsson. 2015. "Job Polarization and Task-Biased Technological Change: Evidence from Sweden, 1975-2005." *Scandinavian Journal of Economics*, 117(3): 878–917.

Asplund, Rita, Erling Barth, Per Lundborg, and Kjersti Misje Nilsen. 2011. "Polarization of the Nordic Labour Markets." *Finnish Economic Papers*, 24(2): 87–110.

Autor, David H, and David Dorn. 2009. "This Job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure." *American Economic Review*, 99(2): 45–51.

Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118(4): 1279–1333.

Autor, David H, Lawrence F Katz, and Alan B Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113(4): 1169–1213.

Autor, David H, Lawrence F Katz, and Melissa S Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review*, 96(2): 189–194.

Berman, E, J Bound, and Steve Machin. 1998. "Implications of Skill-Biased Technological Change: International Evidence." *Quarterly Journal of Economics*, 113(4): 1245–1279.

Berman, E, J Bound, and Z Griliches. 1994. "Changes in the Demand for Skilled Labor within U. S. Manufacturing: Evidence from the Annual Survey of Manufactures." *Quarterly Journal of Economics*, 109(2): 367–397.

Black, Sandra E, and Alexandra Spitz-Oener. 2010. "Explaining women's success: technological change and the skill content of women's work." *Review of Economics and Statistics*, 92(1): 187–194.

Blanchard, Olivier. 2007. "Adjustment within the euro. The difficult case of Portugal." *Portuguese Economic Journal*, 6(1): 1–21.

Blinder, Alan S. 2009. "How many US jobs might be offshorable?" *World Economics*, 10(2): 41–78.

Blinder, Alan S, and Alan B Krueger. 2013. "Alternative measures of offshorability: a survey approach." *Journal of Labor Economics*, 31: S97–S128.

Bound, John, and George Johnson. 1992. "Changes in the structure of wages in the 1980's: an evaluation of alternative explanations." *American Economic Review*, 82(3): 371–392.

Bresnahan, Timothy F. 1999. "Computerisation and Wage Dispersion: An Analytical Reinterpretation." *Economic Journal*, 109(456): 390–415.

Carneiro, Anabela, Pedro Portugal, and José Varejão. 2014. "Catastrophic job Destruction During the Portuguese Economic Crisis." *Journal of Macroeconomics*, 39(PB): 444–457.

Centeno, Mário, and Álvaro A Novo. 2014. "When supply meets demand: wage inequality in Portugal." *IZA Journal of European Labor Studies*, 3(1): 1–23.

Clark, Colin. 1957. *The Conditions of Economic Progress.* London:Macmillan.

Cortes, Guido Matias. 2016. "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data." *Journal of Labor Economics*, 34(1): 63–105.

DiNardo, John E, and Jorn-Steffen Pischke. 1997. "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" *Quarterly Journal of Economics*, 112(1): 291–303.

DiNardo, John, Nicole M Fortin, and Thomas Lemieux. 1996. "Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach." *Econometrica*, 64(5): 1001–1044.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg. 2009. "Revisiting the German Wage Structure." *Quarterly Journal of Economics*, 124(2): 843–881.

Fernandez-Macias, Enrique. 2012. "Job Polarization in Europe? Changes in the Employment Structure and Job Quality, 1995-2007." *Work and Occupations*, 39(2): 157–182.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job Polarization in Europe." *American Economic Review*, 99(2): 58–63.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review*, 104(8): 2509–2526.

Goos, Maarten, and Alan Manning. 2007. "Lousy and lovely jobs: The rising polarization of work in Britain." *Review of Economics and Statistics*, 89(1): 118–133.

Juhn, Chinhui, Kevin M Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy*, 101(3): 410–442.

Katz, Lawrence F, and Kevin M Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics*, 107(1): 35–78.

Krueger, Alan B. 1993. "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989." *Quarterly Journal of Economics*, 108(1): 33–60.

Krusell, Per, Lee E Ohanian, José-Víctor Ríos-Rull, and Giovanni L Violante. 2000. "Capital-skill complementarity and inequality: A macroeconomic analysis." *Econometrica*, 68(5): 1029–1053.

Levy, Frank, and Richard J Murnane. 1992. "US earnings levels and earnings inequality: A review of recent trends and proposed explanations." *Journal of Economic Literature*, 30(3): 1333–1381.

Machin, Steve, and J Van Reenen. 1998. "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries." *Quarterly Journal of Economics*, 113(4): 1215–1244.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years." *Review of Economics and Statistics*, 96(1): 60–77.

Spitz-Oener, Alexandra. 2006. "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure." *Journal of Labor Economics*, 24(2): 235–270.

van Welsum, Desirée, and Xavier Reif. 2005. "Potential Offshoring: Evidence from Selected OECD Countries." *Brookings Trade Forum*, 165–194.

Appendix

Table A1: Broad occupational groups

Broad Occupational Groups	ISCO	Occupation
Technical and professional	21	Physical, mathematical and engineering science professionals
	23	Teaching professionals
	24	Other professionals
	31	Physical and engineering science associate professionals
	33	Teaching associate professionals
	34	Other associate professionals
Managerial and health professionals	12+13	Small enterprises & corporate managers
	22	Life science and health professionals
	32	Life science and health associate professionals
Office clerks	41	Office clerks
Personal and protective services	51	Personal and protective services workers
Sales, ticket clerks and other services	42	Customer services clerks
	52	Models, salespersons and demonstrators
	91	Sales and services elementary occupations
Routine operators	73	Precision, handicraft, printing and related trades workers
	74	Other craft and related trades workers
	81	Stationary-plant and related operators
	82	Machine operators and assemblers
Operators	71	Extraction and building trades workers
	72	Metal, machinery and related trades workers
	83	Drivers and mobile-plant operators
	93	Laborers in mining, construction, manufacturing and transport

Table A2: O*NET descriptor and scale type by task

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

Notes: O*NET measures selected for construction of each task measures following Acemoglu and Autor (2011). By reverse we mean that the scale has been transformed in order for the lower values to be at the top and for the higher values be at the bottom. For simplicity we focused on four tasks: Analytical, which we call Abstract (to borrow Autor, Katz and Kearney (2006) terminology), Routine Cognitive, Routine Manual and Manual. If we included an interpersonal category, occupations high in interpersonal tasks can either be also high in abstract tasks or in manual or routine manual tasks, and therefore it is not straightforward how to interpret the interpersonal task content in face of the routinization hypothesis.

Table A3: Allocation between occupations and tasks

ISCO	Occupation	Task	Education 1986	Education 2007	Wage 1986 real	Wage 2007 real	Wage 2007 nom.	Emp. share 1986	%Change real wage all	%Change real wage manuf	%Change real wage serv	Δemp. share 1986-2007 (p.p.) all	Δemp. share 1986-2007 (p.p.) manuf	Δemp. share 1986-2007 (p.p.) serv
Technical and Professional														
21	Physical, mathematical and eng. science prof.	Abstract	14	16	450	669	2049	0.2	49	59	30	1.8	0.8	1.0
24	Other professionals	Abstract	11	15	317	543	1661	0.4	71	94	64	2.1	0.3	1.8
23	Teaching professionals	Abstract	14	15	410	493	1509	0.0	20	0	20	0.4	0.0	0.4
31	Physical and eng. science associate prof.	Abstract	8	12	332	446	1366	2.7	34	50	19	1.3	0.3	1.1
34	Other associate professionals	R. Cog.	8	12	327	510	1562	3.5	56	57	54	2.3	0.0	2.3
33	Teaching associate professionals	Abstract	7	13	201	323	988	0.5	61	48	70	0.4	-0.1	0.5
Managerial and Health Professionals														
12+13	Small enterprises & corporate managers	Abstract	10	12	458	744	2277	2.1	62	46	71	2.0	0.4	1.6
22	Life science and health professionals	Abstract	9	16	265	550	1683	0.2	108	120	109	0.6	0.0	0.5
32	Life science and health associate prof.	Abstract	8	12	192	329	1008	0.2	71	87	70	0.5	0.0	0.5
Office Clerks														
41	Office clerks	R. Cog.	8	11	240	321	981	16.3	33	43	24	-3.6	-3.3	-0.4
Personal and Protective Services														
51	Personal and protective services workers	Manual	5	8	173	198	606	5.3	14	-4	15	5.0	0.0	5.0
Sales, ticket clerks and other services														
42	Customer services clerks	R. Cog.	7	10	238	233	713	2.7	-2	7	-2	0.2	-0.3	0.5
52	Models, salespersons and demonstrators	(*a*)	6	9	159	224	687	5.3	41	56	40	1.5	-0.2	1.7
91	Sales and services elementary occupations	Manual	4	7	163	195	596	4.9	19	18	19	2.4	-0.8	3.2
Routine operators														
73	Precision, handicraft, print. and rel. trades work.	R. Man.	4	7	193	236	722	1.3	23	22	22	-0.4	-0.4	0.0
74	Other craft and related trades workers	R. Man.	4	6	131	180	551	10.6	37	35	44	-2.6	-2.8	0.2
81	Stationary-plant and related operators	R. Man.	4	7	195	297	910	1.7	53	63	-7	-0.5	-0.7	0.2
82	Machine operators and assemblers	R. Man.	4	7	167	234	717	8.6	40	42	23	-3.8	-4.1	0.3
Operators														
71	Extraction and building trades workers	Manual	4	6	205	228	699	8.6	12	14	-1	-0.7	-0.3	-0.4
72	Metal, machinery and related trades workers	Manual	5	7	203	269	825	9.6	32	34	30	-3.3	-2.6	-0.7
83	Drivers and mobile-plant operators	Manual	4	7	207	262	801	4.7	27	29	23	0.2	-0.7	0.9
93	Laborers in mining, const., manuf. and transp.	Manual	4	7	149	194	595	10.4	30	33	26	-5.77	-4.12	-1.65

Notes: Tasks are grouped as: Non-routine Cognitive Abstract, Routine Cognitive, Routine Manual and Non-routine Manual. Education is measured by mean years of formal education. Wages are the mean wages in euros in a given year. Real wage refers to wage deflated to 1986 using CPI. %Change represents the percentage change in mean wage. Δemp. share is the change in employment change expressed in percentage points. (*a*) We split occupation 52: *Sales Representatives* are assigned to Routine Cognitive, *Cashiers* to Routine Manual, and the remaining occupations are Manual. In 2007, *Sales Representatives* represent 46% and *Cashiers* 34% of the total employment in ISCO 52.

Table A4: Employment regression results - task interactions

	Economy			Manufacturing			Services		
	Abstract	**Rout. Cog.**	**Rout. Man.**	**Abstract**	**Rout. Cog.**	**Rout. Man.**	**Abstract**	**Rout. Cog.**	**Routine Man.**
Period 1									
1987	0.062	0.123**	-0.000	-0.030	0.069	-0.070	0.144**	0.095	0.326
	(0.044)	(0.042)	(0.115)	(0.087)	(0.083)	(0.148)	(0.048)	(0.051)	(0.257)
1988	0.044	0.113**	-0.080	-0.126	-0.032	-0.128	0.169***	0.110*	0.403
	(0.044)	(0.041)	(0.116)	(0.087)	(0.082)	(0.148)	(0.048)	(0.050)	(0.286)
1989	0.057	0.209***	-0.193	-0.156	0.069	-0.065	0.260***	0.127*	-0.110
	(0.044)	(0.041)	(0.114)	(0.088)	(0.082)	(0.145)	(0.048)	(0.050)	(0.267)
1991	0.152***	0.389***	-0.455***	0.187*	0.271**	-0.210	0.426***	0.140**	-0.576*
	(0.043)	(0.041)	(0.115)	(0.087)	(0.083)	(0.147)	(0.047)	(0.050)	(0.267)
1992	0.145***	0.428***	-0.624***	0.140	0.413***	-0.290*	0.435***	0.148**	-0.599*
	(0.043)	(0.041)	(0.114)	(0.087)	(0.083)	(0.146)	(0.047)	(0.050)	(0.255)
1993	0.227***	0.490***	-0.756***	0.080	0.492***	-0.484***	0.496***	0.278***	-0.584*
	(0.043)	(0.041)	(0.115)	(0.087)	(0.082)	(0.146)	(0.047)	(0.050)	(0.274)
1994	0.508***	0.570***	-0.835***	0.305***	0.655***	-0.459**	0.552***	0.578***	-0.393
	(0.043)	(0.041)	(0.115)	(0.086)	(0.081)	(0.147)	(0.047)	(0.049)	(0.254)
R^2-overall			0.248			0.107			0.297
F-statistic			374.87			53.691			333.669
Observations			22660			5859			16801
Period 2									
1996	0.083*	0.080*	-0.111	0.164*	0.068	-0.145	0.050	0.081	-0.085
	(0.036)	(0.039)	(0.103)	(0.081)	(0.090)	(0.150)	(0.040)	(0.042)	(0.253)
1997	0.128***	0.009	-0.271**	0.183*	0.020	-0.284	0.116**	0.007	0.006
	(0.036)	(0.039)	(0.103)	(0.081)	(0.090)	(0.150)	(0.040)	(0.042)	(0.253)
1998	0.201***	0.014	-0.327**	0.293***	0.031	-0.302*	0.181***	0.011	0.046
	(0.036)	(0.039)	(0.102)	(0.082)	(0.090)	(0.150)	(0.040)	(0.042)	(0.253)
1999	0.264***	0.054	-0.431***	0.355***	0.091	-0.331*	0.257***	0.049	0.087
	(0.036)	(0.039)	(0.102)	(0.082)	(0.091)	(0.150)	(0.040)	(0.042)	(0.253)
2000	0.309***	-0.027	-0.629***	0.358***	-0.095	-0.335*	0.312***	0.001	-0.696**
	(0.036)	(0.039)	(0.102)	(0.082)	(0.091)	(0.150)	(0.040)	(0.042)	(0.253)
2002	0.424***	-0.063	-0.920***	0.324***	-0.198*	-0.838***	0.478***	-0.013	-0.626*
	(0.036)	(0.039)	(0.102)	(0.081)	(0.090)	(0.150)	(0.039)	(0.042)	(0.253)
2003	0.472***	-0.082*	-1.151***	0.343***	-0.129	-1.016***	0.549***	-0.054	-0.624*
	(0.036)	(0.039)	(0.102)	(0.081)	(0.090)	(0.149)	(0.039)	(0.042)	(0.253)
2004	0.547***	-0.063	-1.238***	0.439***	-0.084	-1.070***	0.621***	-0.041	-0.604*
	(0.036)	(0.039)	(0.102)	(0.080)	(0.090)	(0.149)	(0.039)	(0.042)	(0.253)
2005	0.644***	-0.100*	-1.349***	0.480***	-0.073	-1.263***	0.742***	-0.091*	-0.466
	(0.036)	(0.039)	(0.102)	(0.081)	(0.090)	(0.150)	(0.039)	(0.042)	(0.253)
2006	0.771***	-0.102**	-1.447***	0.567***	-0.034	-1.295***	0.880***	-0.104*	-0.727**
	(0.036)	(0.039)	(0.102)	(0.081)	(0.090)	(0.149)	(0.039)	(0.042)	(0.253)
2007	0.860***	-0.035	-1.515***	0.655***	0.039	-1.385***	0.969***	-0.040	-0.793**
	(0.036)	(0.039)	(0.102)	(0.081)	(0.090)	(0.149)	(0.039)	(0.042)	(0.253)
R^2-overall			0.431			0.249			0.495
F-statistic			851.237			105.984			807.932
Observations			44383			11092			33291

Notes: Dependent variable is the log employment at gender-age-education-tenure-region-industry cells. Fixed-effects regression results. The coefficients shown are from the interaction between time dummies and task's employment share. Manual is the omitted category. Model contains fixed effects for cells and year dummies. Huber-White robust standard errors in parentheses. * 10% significant, ** 5% significant and *** 1% significant.

Table A5: Wage regression results - task wage premium

	Economy			**Manufacturing**			**Services**		
	Abstract	**Rout. Cog.**	**Rout. Man.**	**Abstract**	**Rout. Cog.**	**Rout. Man.**	**Abstract**	**Rout. Cog.**	**Routine Man.**
Period 1									
1987	0.007***	0.006***	0.006***	0.014***	0.009***	0.005***	0.003*	0.004***	0.011***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
1988	0.028***	0.021***	-0.003***	0.028***	0.013***	-0.007***	0.029***	0.025***	0.011***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
1989	0.030***	0.019***	-0.020***	0.047***	0.011***	-0.029***	0.024***	0.028***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
1991	0.058***	0.017***	-0.042***	0.087***	0.013***	-0.062***	0.050***	0.034***	0.028***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
1992	0.084***	0.033***	-0.051***	0.101***	0.018***	-0.072***	0.082***	0.053***	0.026***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
1993	0.098***	0.050***	-0.065***	0.117***	0.025***	-0.081***	0.090***	0.068***	0.023***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
1994	0.116***	0.068***	-0.059***	0.135***	0.032***	-0.080***	0.108***	0.091***	0.045***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)
R^2-overall			0.204			0.195			0.218
F-statistic			23935.712			13687.273			10426.085
Observations			9914606			5546849			4367757
Period 2									
1996	0.014***	0.010***	-0.002***	0.013***	0.011***	-0.000	0.015***	0.009***	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
1997	0.033***	0.018***	-0.004***	0.032***	0.018***	0.001	0.034***	0.015***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
1998	0.059***	0.023***	-0.015***	0.059***	0.024***	-0.005***	0.056***	0.017***	-0.027***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
1999	0.080***	0.031***	-0.023***	0.084***	0.032***	-0.015***	0.076***	0.024***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2000	0.106***	0.040***	-0.033***	0.101***	0.033***	-0.027***	0.106***	0.035***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2002	0.148***	0.057***	-0.046***	0.139***	0.047***	-0.045***	0.149***	0.054***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2003	0.167***	0.076***	-0.050***	0.162***	0.060***	-0.047***	0.166***	0.073***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2004	0.182***	0.085***	-0.059***	0.185***	0.072***	-0.052***	0.175***	0.078***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2005	0.195***	0.092***	-0.066***	0.194***	0.072***	-0.068***	0.192***	0.091***	-0.006**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2006	0.206***	0.101***	-0.067***	0.204***	0.078***	-0.073***	0.205***	0.103***	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
2007	0.216***	0.108***	-0.073***	0.211***	0.073***	-0.088***	0.219***	0.116***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
R^2-overall			0.128			0.102			0.153
F-statistic			13110.385			4855.254			8501.514
Observations			23164871			10431802			12733069

Notes: Dependent variable is the log wage. Worker level estimations of Equation 5. The coefficients correspond to task-year dummies (task-time fixed effects θ_{jt}). Model contains worker task-spell fixed effects and controls for region. Standard errors in parentheses and clustered by worker. * 10% significant, ** 5% significant and *** 1% significant.

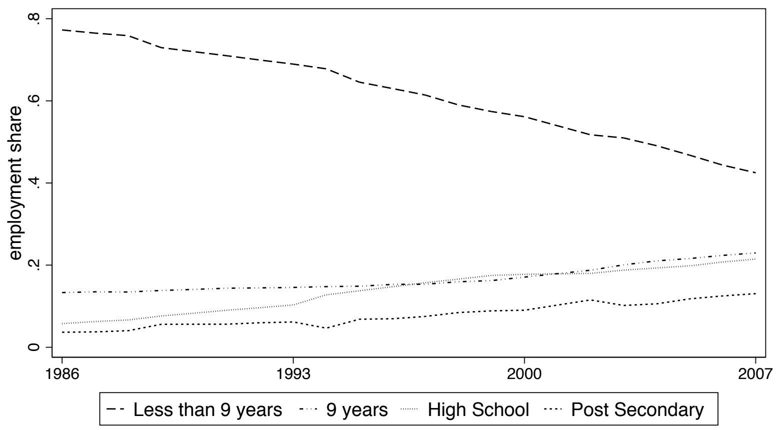

Figure A1: Education trends

Notes: Authors' calculations based on *Quadros de Pessoal* data.

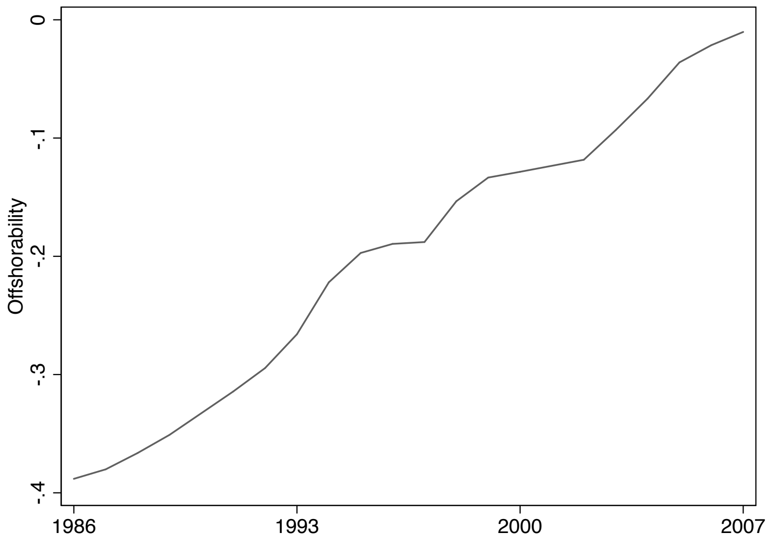

Figure A2: Offshorability measure evolution

Notes: Offshorability measure is obtained by retaining the first principal component of the following O*NET descriptors: 4.C.1.a.2.l - Face-to-Face Discussions (reverse); 4.A.4.a.8 - Performing for or Working Directly with the Public (reverse); 4.A.4.a.5 - Assisting and Caring for Others (reverse); 4.A.3.a.2 - Handling and Moving Objects (reverse); 4.A.1.b.2 - Inspecting Equipment, Structures, or Material (reverse); 4.A.3.b.5 - Repairing and Maintaining Electronic Equipment (reverse); 4.A.3.b.4 - Repairing and Maintaining Mechanical Equipment (reverse). The procedure is the same as performed for tasks in section 6. The offshoring is assigned to workers based on their occupations. The plot is based on offshoring mean value calculated using *Quadros de Pessoal* data by year.