Job polarisation, technological change and routinisation: evidence from Portugal*

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Abstract

This paper provides evidence of job polarisation for Portugal: a country where capital, skills and wages are lower than in EU counterparts. Using data for 1986-2007, we uncover polarisation in employment and wages in the later part of the period. We show a decline in routine occupations, and an increase in abstract occupations. The relative wages for demographic groups holding an early comparative advantage in non-routine tasks increase while those of groups with a comparative advantage in routine tasks decrease. We conclude that polarisation in Portugal is consistent with technology adoption that displace routine intensive occupations.

Keywords: technological change, routinisation, job polarisation, wages

JEL codes: J24, J31, O33

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1 Introduction

In this paper we study job polarisation in Portugal and its causes. Job polarisation is a fairly recent phenomenon characterised by employment growth at both the bottom and the top of the income distribution. Job polarisation has been observed in the U.S. (Autor, Katz and Kearney, 2006) in the late 1980s and 1990s (Acemoglu and Autor, 2011) and in the U.K. for the period between 1975 and 1999 (Goos and Manning, 2007). Polarisation has also been documented in West-Germany (Spitz-Oener, 2006; Dustmann, Ludsteck and Schönberg, 2009) and Northern European countries (Asplund and Barth, 2011). In addition, Michaels, Natraj and Van Reenen (2014) find polarisation for several OECD countries.[1] Goos, Manning and Salomons (2009, 2011) also find evidence of polarisation in Europe as a whole, but not in every single country.[2] 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 (except Italy). High-wage jobs increased their employment shares in all but three of the countries studied.[3]

While the reasons behind job polarisation are still subject to some debate, the main candidate is technology and the so called routinisation hypothesis (first put forward by Autor, Levy and Murnane (2003)) in which technological improvements allow machines to replace workers performing routine tasks. In particular, the increase in computer use in the workplace resulting from the declining price of computer capital has lead to a decrease in the demand for workers performing routine tasks, which tend to be middle skilled. According to this hypothesis, while computers substitute for middle skilled workers, they complement high skilled workers' whose productivity increases with computer capital investment. The majority of workers displaced from middle skilled occupations, unable to secure high paid jobs requiring higher skills, take low paid jobs previously taken by low

[1] The study covers Austria, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, the U.K. and the U.S..

[2] The countries studied are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden and the U.K.

[3] Interestingly enough, the exceptions are Finland, Ireland and Portugal. Their results are not in line with the findings in this paper, most likely due to data differences. Goos, Manning and Salomons (2009, 2011) use the European Labour Force Survey (ELFS), a sample based dataset (0.2% to 3.3% coverage). We use *Quadros de Pessoal* (QP) which is mandatory to the majority of the Portuguese firms, though contrary to ELFS it does not contain information on the self-employed. In addition, since QP coverage of agriculture, mining and fisheries is not mandatory, we exclude the primary sector from our analysis.

skilled workers, leading to a polarisation of jobs in the economy.

Several reasons could explain why certain countries may fail to show evidence of job polarisation, despite experiencing technological change and computerisation. 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, 2011). 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 result in a smaller service sector, which could translate into a different job structure. The timing of technology dissemination and job polarisation 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 labour market trends (Spitz-Oener, 2006; Dustmann, Ludsteck and Schönberg, 2009), which could lead to differences in the timing of polarisation. Differences in the skill composition across countries could also lead to different job structures. A country with a highly skilled workforce could conceivably see most of its workers moving up from middle paid to high paid jobs as a result of computerization. A country with a less skilled workforce like Portugal may have low skilled workers in some of its middle and even higher paid jobs, which could result in less clear cut job polarisation, even if computers displace workers performing routine tasks. In addition, in a country with low capital stock as Portugal, the adoption of computer capital may be limited, specially in a setting of low educational attainment. The existence of a relatively small pool of highly educated workers constraints complementarity gains, and the fact that labor is relatively cheap reduces the potential for substitution between computers and routine task intensive occupations.

In view of the above discussion and the current state of the job polarisation literature, the study of job polarisation in Portugal is of particular interest. Are the market forces created by computerisation likely to generate job polarisation even in countries with lower physical and human capital and 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, low capital stock and share of the service sector, Portugal has experienced job polarisation from the mid-1990s. This provides important evidence that job polarisation is not a phenomenon exclusive of richer economies. By decomposing changes in employment between- and within-industries, we show that employment shifts within industries point to the role of technology as the main driving force behind job polarisation in Portugal. Using O*NET routine and non-routine task measures to classify jobs, we show that the routinisation hypothesis is a robust explanation for the employment and wage patterns observed.

The rest of the paper is organised as follows. Section 2 reviews the extant literature on job polarisation and discusses what different models predict in terms of employment and wage changes and how those can be tested. Section 3 describes the data. Section 4 discusses the Portuguese economic context. Section 5 shows the trends for employment and wages between 1986 and 2007 and Section 6 provides evidence of within and between industry changes in employment. Task measures based on ONET dataset are introduced in Section 7 with a further dissection of employment and wages by task groups. Section 8 presents regressions results and Section 9 concludes.

2 Literature review

Since the early 1960s, the U.S. has seen the stock of capital equipment increasing rapidly alongside a growing trend in the relative demand for skilled workers, suggesting the complementarity of capital equipment and skilled labour (Krusell and Ohanian, 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 – less-skilled workers suffered a decrease in relative wages and demand for the less-skilled decreased in developed countries (Berman, Bound and Griliches, 1994; Berman, Bound and Machin, 1998).[4] 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, especially the U.K. and U.S. (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 have 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).[5]

When Autor, Katz and Kearney (2006) uncovered job polarisation in the U.S. and Goos and Manning (2007) did the same for the U.K., it became clear that SBTC hypothesis could not explain the recent labour market patters alone.[6] Autor, Levy and Murnane (2003); Autor, Katz and Kearney (2006) proposed a nuanced view of the impact of technical change in the labour market according to which technology changes the tasks performed by workers at their jobs which in turn changes the demand for human skills. In their model, technology and skilled labour 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 well-determined rules. They show that the adoption of computers is associated with reduced labour of routine tasks (both cognitive and manual) and increased labour input of non-routine cognitive tasks within industries, occupations and education groups.[7]

Building on Autor, Levy and Murnane (2003), Autor, Katz and Kearney (2006) pro-

[4]There is also some evidence that changes in institutions such as unionisation and minimum wages play a role in explaining the changes observed in the bottom half of the wage distribution (e.g., DiNardo, Fortin and Lemieux (1996)).

[5]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 and Ohanian (2000).

[6]Card and DiNardo (2002) describe additional issues with the SBTC hypothesis

[7]See Spitz-Oener (2006) for similar evidence for Germany.

pose a task-based model with three categories of tasks: abstract, routine and manual, in which college workers perform abstract tasks and high school workers 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.[8] Abstract task workers see their employment and wages rise as computer capital is, for those, a complement and therefore increases their productivity. Finally, non-routine manual task workers employment rise because of the influx of displaced 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 tasks. Even without the education assumption, displaced routine tasks workers should have a stronger comparative advantage in performing manual tasks than in abstract tasks. As a consequence of the influx into manual tasks, the wages of manual workers may drop, but not as much as the wages of workers in routine jobs – the observed wage ratio between routine task workers and non-routine manual workers drops – otherwise workers would not move into manual jobs.

The routinisation hypothesis provides observable implications both in terms of wages and employment changes across the skill distribution. Evidence shows that 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 somewhere in the middle of the wage distribution, as routine jobs tend to be substituted by technology. As for wages, while the wages of the higher skills should increase, the relative changes wages of the middle and low skilled are less obvious because in addition to the direct effect of demand and supply on the various skills, there may also be selection of workers across the various tasks. For example, if workers who keep jobs in routine tasks are particularly skilled, average wages in routine jobs may actually increase relative to the manual jobs.

While in the U.S. wage polarisation has occurred hand in hand with job polarisation (Autor, Katz and Kearney, 2006), Goos and Manning (2007) failed to find wage polarisa-

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

tion in the UK, despite strong evidence of job polarisation. 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 as mentioned above: when hit by demand shocks, job changes do not occur randomly.[9] In particular, Goos and Manning (2007) hypothesise that if those displaced from the middling jobs are less skilled, the average skill of those who remain increases, which could explain the observed wage patterns. 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 labour market polarisation 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 overcome these challenges which uses demographic variables to construct skill groups and which regresses the wage changes of these groups on their task measures at the beginning of the period. Their 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 workers in that group move occupations and tasks or not. In this paper we use a similar empirical strategy to provide evidence of wage trends that are consistent with a task based explanation for polarisation.

3 Data

The main data source used is the *Quadros de Pessoal* (QP). QP is a matched employer-employee dataset created by the Portuguese Ministry of Labour in the 1980s. Every year employers answer a survey with information on personnel and firm characteristics. The dataset covers all Portuguese firms with at least one employee and excludes agriculture, military, public administration and institutionalised or self-employed workers.

QP is a longitudinal dataset covering a period of 21 years from 1986 to 2007 with an average of 1.7 million workers and 220 thousand firms per year.[10] The Ministry of

[9] Another potential explanation is concurrent changes in labour market institutions, such as declines in unionisation and minimum wages.

[10] The latest wave of data available at the time of writing this paper was 2007.

Labour 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, legal structure, the structure of capital (percentage of private, public and foreign capital), initial equity and starting date. For workers, variables include gender, age, schooling, tenure, promotion dates, 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, both male and female. 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.[11] Wages are deflated to the year 1986 using the Consumer Price Index (CPI). 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 defence.[12] Although public administration employs a large number of workers in Portugal, those workers are not fully represented in the sample. Public administration workers account for less than 0.4% of the total number of workers in the sample. We use ISCO88 occupational codes at 2-digit level. Those codes are only available after 1994. To overcome this problem, we employ a simple algorithm that converts the occupational codes prior 1994 to ISCO88 based on the most frequent matches. The same strategy was used to deal with prior 1994 industry codes.

4 Portugal: Economic Context

Portugal is a small economy which joined the European Union in 1986. The entry in the European Union brought this newly formed democracy new trade opportunities as well as an influx of public investment in education and infrastructure. Our analysis starts right at this point in time, 1986, and goes until 2007, which precedes the economic crisis

[11] 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.

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

which lead to the EU/IMF financial assistance program.

During the period 1986-2007 Portugal experienced two major dips in GDP growth. The first occurred during 1992-1993, which lead to a rise in unemployment from 4.19% in 1991 to 6.85% in 1994 (OECD data). The recession was brief and by 1995 the growth rate returned to approximately 4%, the 1991 level. However in 2000 the GDP growth declined, becoming negative by 2003. In contrast with the previous recession, the effects on unemployment were not short-lived and there was a sharp sustained rise in unemployment from 4.56% in 2001 to 8.92% in 2007, despite positive GDP growth by the end of the period.

Despite the growth experienced in the last two decades, Portugal lags behind most western European counterparts in GDP per capita (Figure 1), wages (Figure 2) and skills (Figure 3). Figure 1 clearly shows Portugal not catching up the rest of Southern European countries in GDP per capita, and even lagging behind in the later part of the period. This difference is even higher if we compare Portugal with non-southern UE, as the Portuguese GDP per capita is almost half of the non-southern EU countries. Naturally, this is reflected in wages, where Portugal lags behind southern Europe and the average wage is approximately half of EU member states' wages. For the share of college education, the difference is even higher, despite the higher rate of growth in the 2000s. A finer look at educational trends for Portugal (Figure 4) shows that the share of tertiary education does not uncover all the educational growth in Portugal during this period. Much of the skill upgrade occurred at the secondary level, with a more than doubling of high school graduates by 2007. 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.

[Figures 1, 2, 3 and 4 about here]

In Figure 5 we plot the share of manufacturing and services between 1986 and 2007. Services comprised just over 40% of employment in 1986, but reached close to 60% by 2007. The magnitude of this sectorial shift is substantial and we will take this into account when interpreting our results.

[Figure 5 about here]

The evidence of Portugal lagging behind other European countries extends to capital stock. As Figure 6 shows, the capital stock per worker of southern European countries is approximately three times less than Scandinavian countries and Continental Europe. Furthermore, Portugal has even less capital per worker than the average southern European country. Since technology investment is likely to depend on the initial technological level, the labor market impact of technology development in Portugal is likely to differ from the one in countries with a higher degree of capital stock. As the total capital includes computer capital, it seems plausible to assume a low stock of computer capital for Portugal. The routinisation model as proposed by 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 and second due to 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.

[Figure 6 about here]

5 Trends in employment and wages

Figure 7 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^{th} percentile compared with the other two. 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 higher inequality increase in the first part of the period, it is from the mid 1990s that one observes wage polarisation, with median wage growth lagging behind growth at the top and the bottom of the distribution.

[Figure 7 about here]

Figure 8 plots the log wage change (relative to the median change) by percentile for the two sub-periods, and confirms the trends identified in Figure 7. 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 polarisation took place from the mid 1990s onwards, but not before.

[Figure 8 about here]

Using employment data, we also find evidence of job polarisation. Figure 9 plots the change in log employment share by skill percentile for two periods: 1986-1994 and 1995-2007.[13] The occupation skill percentile rank is performed for two skill proxy measurements: 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 results for the second period show polarisation of employment: the relative employment in both the bottom and top skill percentiles increases, while in the middle it decreases. polarisation 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 very low education attainment, have wages close to the median wage.[14] However, some of these results could be driven by changes in industrial composition, namely due to the shift from manufacturing to services, and not by technology. In the next section, we decompose employment changes into within and between industry composition effects, to investigate whether the observed trends are likely to be technology related or due to industrial compositional shifts in the economy.

[Figure 9 about here]

[13]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. We use occupations at the 3-digit level. Besides the data constraints, the two periods are inherently different as can observed from the results.

[14]Centeno, Novo and Novo (2014) studies wage inequality in Portugal and show similar patterns.

6 Industrial decomposition of employment

Shifts in the industrial structure can contribute to the above documented job polarisation. For example, if industries that are 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 polarisation could occur. However, if polarisation 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 standard shift-share decomposition (Acemoglu and Autor, 2011) to test whether industrial change can be pointed out as a major explanation for job polarisation.[15] 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 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

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

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 10). 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.[16] The light shaded portion of the bars represents the within-industry changes, while the darker shade portion represents between-industry changes. In addition, we order occupational groups by rank of average wage, with high paid groups on top. For both periods, the light shaded portions of the bars show a polarisation pattern in both periods, with largest within-industry growth in top paid occupations, and largest within-industry decline in middle paid occupations (Office clerks and Operators). In addition, employment polarisation appears to be stronger in the second period, which is consistent with the evidence presented in the earlier figures. Overall, between industry changes (darker shaded portion of the bars) are mostly related with employment shifts from manufacturing to services and affect mostly employment changes in lower paid occupations, both in service occupations and routine operators. While low paid manufacturing occupations decline, low paid services related occupations grow. For the lowest paid occupational groups, the within-industry changes in employment are small in comparison to between-industry changes, and also relative to the other groups, which is consistent with our earlier evidence of stronger employment growth at the upper tail of the wage distribution than the lower tail.

[Figure 10 about here]

We conclude that the within and between industry employment decomposition is broadly consistent with job polarisation due to technological change in both periods, but the magnitude of this phenomenon is larger from 1995 onwards. In addition, between-industry changes in employment among the lowest paid groups associated with the shift from manufacturing to services may partially offset the technology driven effects, resulting in an asymmetrical polarisation pattern, in which the employment growth is lower at bottom

[16] Appendix Table A1 lists 2-digit ISCO occupations by occupational group.

than at the top of the wage distribution.

7 Task measures

7.1 Occupational task measures definition

In order to establish the task content of each occupation's measures, we use the same O*NET descriptors as Acemoglu and Autor (2011).[17] We select the O*NET descriptors that have importance and context scales, both continuous between 1 and 5 (none of the used descriptors are represented in both scales).[18] We apply principal components, by task type, to the O*NET descriptors to reduce the dimension of the descriptors. By construction, the principal components maximise the total variability of the original data.

Each occupation is now represented by a set of task measures. Table 1 summarises the results obtained, displaying the standardised 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), as result of their repetitive work. Most occupations with low intensity in manual tasks also have low values in 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

[17] The O*NET database is the primary project of the O*NET program promoted by the U.S. Department of Labour. 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 U.S. 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.

[18] A detailed list of the descriptors by task type is in Appendix Table A2.

highest value), but with almost null value on routine manual tasks (0.01).

[Table 1 about here]

7.2 Task importance over time

Task measures constitute a vital piece of information to test the routinisation hypothesis. We begin by computing the mean task points by year (we aggregate task points across all observations) to assess its importance over time. The evolution of mean task measures across time (Figure 11) show a sharp reduction in the importance of manual and routine manual tasks consistent with a gradual shift from services to manufacturing. Routine cognitive task importance also exhibits a declining trend, though not as sharp. Abstract task importance increases throughout the period. Overall the results are in line with the routinisation hypothesis: routine tasks (both manual and cognitive) decrease their importance, and cognitive tasks become more pro-eminent. Not explained by routinisation, but by shifts from manufacturing to service industries, manual task importance declines over time. More importantly, routine cognitive task importance, which is more prevalent in service sectors than in manufacturing, exhibits a decline despite the shift towards a service based economy, supporting the routinisation hypothesis.

[Figure 11 about here]

7.3 Employment and wages by task and industry

We further test the routinisation hypothesis by looking at wage and employment trends for four occupational groups based on their task content: abstract, routine cognitive, routine manual and manual. In order to create these four categories, we allocate each occupation to the task for which the occupation ranks highest in intensity.[19] 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

[19] For simplicity we focused on four tasks: non-routine, which we call Abstract (following Autor, Katz and Kearney (2006)), Routine Cognitive, Routine Manual and Manual.

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. In particular, while in the SOC code sales are a category in itself, in the ISCO they are separated in two categories and are aggregated with other service related occupations.[20]

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.

Figure 12 shows the employment share and log wage trends by task intensity for the economy as a whole, manufacturing and services. For both sectors, over 40% of workers fall within the manual category. 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%). Only in manufacturing employment suffers a modest decline in routine manual occupations. 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

[20] 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 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. ISCO 52 Models, salespersons and demonstrators includes cashiers and market vendors, and therefore were classified as routine cognitive. 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.

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.

[Figure 12 about here]

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, there is an actual decline in real wages for abstract occupations, contrasting with the flat trend in the remaining groups, and resulting in a compression of wages. It is also worth noting an increase in routine manual wages relative to manual (and the remaining tasks), especially in services, which suggests that additional factors besides technology and routinisation may be at play in the apparent compression in the bottom half of the wage distribution. Several factors could explain this trend. First, if minimum wages increased over time they could explain some of the compression observed between routine manual and manual wages. That is indeed the case, as shown by Figure 13. It is also clear from the figure that minimum wages are less likely to explain the wage dynamic of the higher paid task groups: abstract and routine cognitive. Second, selection among workers who remain in routine manual occupations may counteract demand effects, as it is possible that the more skilled are the ones retaining their jobs or occupations. Third, compositional effects of occupations within each sector (for example, in terms of seniority or labour market experience) can also distort the results. In order to identify routinisation from potential confounding factors we next present our regression analysis.

[Figure 13 about here]

8 Regression results

We run regressions using gender-age-education-region-industry cells. The cells are defined by gender, five age categories (¡25,25-34,35-44,45-54,55-65), four groups based on years of education (<9 , 9 , 12 , >12), seven regions and eleven industries. Depending on the year, we obtain at least 2582 gender-age-education-region-industry cells. On average, each cell contains 611 workers and the average yearly total employment is 1.7 million workers. [21] For each cell we compute the share of workers allocated to each task (abstract, routine cognitive, routine manual and manual) in 1986. Our variables of interest are the interaction effects between the share of workers in 1986 and time dummies, which capture the trend in employment and wages for cells that hold comparative advantage in t_0 (1986) in a given task. In the regressions we omit manual occupations, which implies that the coefficients of the interaction terms give us the time trends associated with the share of each task relative to the manual share in 1986. This empirical strategy is robust to selective job and occupational changes, since it does not follow workers nor does it look at task shares over time.[22] Our identifying assumption is that if the market price of the tasks in which a skill group holds comparative advantage in 1986 declines due to technology, such as routine cognitive or manual tasks, the relative wage of that skill group should decline, independently of whether workers employed in those tasks have changed or retained their jobs and occupations. Since the observation units are demographic, region and industry cells, this strategy also nets out demographic, region and industry compositional effects. Still, increases in the supply of skills which are considerable in this period, may not be fully accounted for by this empirical strategy, which only considers four education groups in the creation of cell units. This needs to be taken into account when interpreting the results. Similarly, for employment, if a skill group holds a comparative advantage in 1986 in a specific task and the relative demand for this task declines due to technology, employment should decline, assuming the supply of skills is fixed.

Let Ω_{it} be the natural logarithm of employment (or wage) in cell i at time t. We decompose Ω_{it} into five components. The first component is a vector of yearly time dummies $\mathbf{t_t}$ which serve as a control for macroeconomic conditions. We denote vectorial component $\mathbf{T_{it_0}}$ as the vector of initial employment share in all tasks for cell i in time t_0. Next, we have the interaction term between $\mathbf{T_{it_0}}$ and $\mathbf{t_t}$. Finally, we have a control for cell fixed effects ($\mathbf{X_i}$) and the error term (ϵ_{it}). Thus, our econometric model can be represented as

$$\mathbf{\Omega_{it}} = \mathbf{t_{it}}\alpha + \mathbf{T_{it_0}} \times \mathbf{t_{it}}\gamma + \mathbf{X_i}\beta + \epsilon_{it} \tag{4}$$

[21] Our empirical strategy resembles that of Acemoglu and Autor (2011).

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

In the estimation of the parameters α, γ, β, our interest is in the interaction effect γ. For each duplet of task in 1986 (T_{it_0}) and year t_i there will be a point estimate γ. Note that when estimating Equation 4 for wages, we use cells' employment as weights.

To simplify interpretation of Equation 4 estimation results, we plot the interactions' coefficients in Figure 14 by sector (the full results can be found in the Appendix Tables A4 and A5). The results for the economy (Figure 14) show a clear rise in employment among demographic groups that have a comparative advantage in abstract tasks in 1986, relative to those that have comparative advantage in manual tasks (the omitted group). On the contrary, groups that held comparative advantage in 1986 in routine manual tasks suffered a relative decline in employment, consistent with routinisation (Autor, Katz and Kearney, 2006). The groups with comparative advantage in routine cognitive tasks see their employment increase relative to those with comparative advantage in manual tasks, though by a lower extent than those who have comparative advantage in abstract tasks. This last trend cannot be explained by the routinisation hypothesis. Because we know that service industries have a much larger share of employment in routine cognitive occupations, this could be a result of the shift from manufacturing to services. However that is not the case since this trend holds for both sectors.

[Figure 14 about here]

The fact that workers with comparative advantage in routine cognitive tasks in 1986 experience an employment increase relative to manual across the economy suggests an increase in the supply of workers in those particular cells. This is easily explained by the educational trends described earlier which are not fully accounted for by our empirical strategy. Routine cognitive occupations are performed by workers with middle skills, while manual occupations have lower education levels. We know that from 1986 education levels increased considerably, and the rate of growth in high school graduation surpassed that of college education. The large increase in the supply of middle skilled workers must have more than compensated for any decline in its relative demand, resulting in the positive trend in relative employment in cells with a comparative advantage in routine cognitive occupations.

Regarding wages (panel B of Figure 14), for cells with comparative advantage in abstract occupations in 1986 there is an upward trend for all specifications, with some decline after the 2003 crisis. The same does not hold for the remaining tasks. Cells with comparative advantage in routine cognitive tasks in 1986 experience wage declines, especially in manufacturing. Cells with comparative advantage in routine manual tasks show stable relative wages in manufacturing, but increasing in services. [23]

From our analysis in the previous section (see Figure 13), it was clear that the wages of workers in routine manual tasks are more likely to be affected by the increase in the real minimum wage. This implies that omitting minimum wages from the regression results in an upward bias of the wage trend for routine manual tasks. We therefore re-estimate our regression controlling for a measure of the "toughness" of the minimum wage at the cell level: the ratio of the minimum wage to the 10^{th} wage percentile. Panel C of Figure 14 presents the results of the wage trends with minimum wage controls.[24] The relative wage trends for abstract and routine cognitive tasks remain essentially unchanged, though they become somewhat smaller in magnitude. This suggests a larger overestimation of the wage growth for this task group when minimum wage controls were not included in the regressions, as expected, since this is the lowest paid task group.

Once the effects of minimum wages are taken into account, the wages of routine cognitive tasks decline relative to manual (and abstract) for manufacturing and the economy. For services, routine manual wages still exhibit an increase relative to manual. 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 per-

[23]Contrary to the results for employment where most coefficients are statistically significant (at 10% level), for the wage regressions they are not. Coefficients on the time-dummy interactions with abstract task shares in 1986 are only significant across all specifications from 1994 onwards. Coefficients on the routine manual time-dummy interactions are only significant for services. When controlling for minimum wage toughness, they also become significant in manufacturing after 2002. The routine cognitive interactions are statistically significant for manufacturing and the economy as a whole, and after 2002 for services. And when controls for minimum wages are included, only statistically significance for services changes, occurring mainly between 1994 and 2000.

[24]Relative minimum wage coefficients are negative and statistically significant. Because the minimum wage variable is negatively correlated with cells' mean wage, it is likely to bias of effect of the minimum wage on the wage trend, and to result in an underestimation of the magnitude of the task related wage trends. Despite this potential bias, these regressions support our hypothesis that the routine manual tasks wage trend is the one mostly affected by the omission of the minimum wages. Employment regressions with minimum wage controls are not shown, as the inclusion of minimum wages did not change the task employment trend estimates.

sonal and protective services. Sales, though highly routine, have not yet been substituted by technology in Portugal where internet sales and 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 retail trade in Portugal since it joined the European Union in 1986.

In conclusion, our wage regressions are in line with the routinisation hypothesis – wages in cells with early comparative advantage in abstract and manual occupations increased while those with comparative advantage in routine (cognitive or manual) occupations declined. While the real minimum wage increase may have contributed to the wage growth observed at the bottom of the wage distribution, technology is undoubtedly a major driving force behind the wage polarisation observed.

9 Conclusion

Similar to the U.S., U.K., and continental Europe, Portugal has experienced recent job polarisation. However, we only find evidence of a hollowing out of the middle of the wage distribution from the mid 1990s onwards. Job polarisation has occurred hand-in-hand with wage polarisation – both wages and employment of middle skilled workers suffered a relative decline from 1995 to 2007.

We have also uncovered evidence that job polarisation in Portugal has been technology driven. 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 explain the larger growth in top and bottom paid occupations versus the middle paid. Second, using task measures derived from the Occupational Information Network database (developed by the U.S. Department of Labour) we show an increase in employment in abstract occupations and a decline in employment of routine occupations (manual and cognitive). Third, when controlling for minimum wage effects, demographic-region-industry cell regressions estimate a growing trend for wages in cells with a comparative advantage in abstract and manual occupations in 1986, and a declining trend for wages in cells with a comparative advantage in routine (cognitive and manual) occupations in

1986.

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 labour market polarisation explained by technology advances such as computerisation and automation which displace routine tasks, and complement abstract tasks. Thus, the evidence derived from the Portuguese case adds to the literature by providing a thorough analysis of job and wage polarisation for a developed country below the technological frontier, giving evidence that technology can hit such labour markets in a similar fashion as it hits more advanced economies as the US, UK or Germany.

Our results have significant policy implications, namely for education and employment policies, which 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 the comparatively low levels of education, investments in college education seems 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. This should also be a focus of concern 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 polarisation.

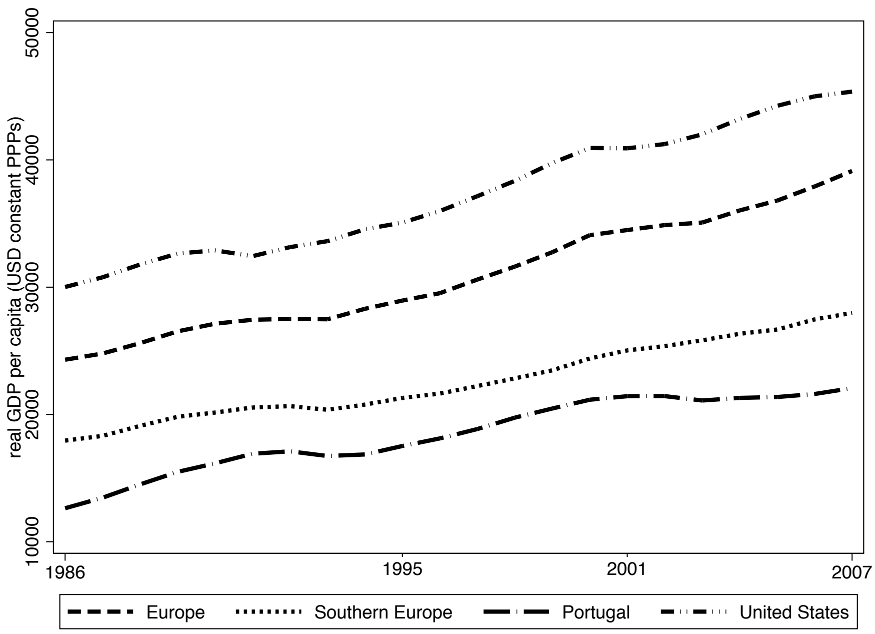

Figure 1: Cross country comparison: GDP per capita

Authors' calculations based on OECD data. Europe: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Luxembourg, the Netherlands, Norway, Sweden and the UK. Southern Europe: Greece, Italy and Spain.

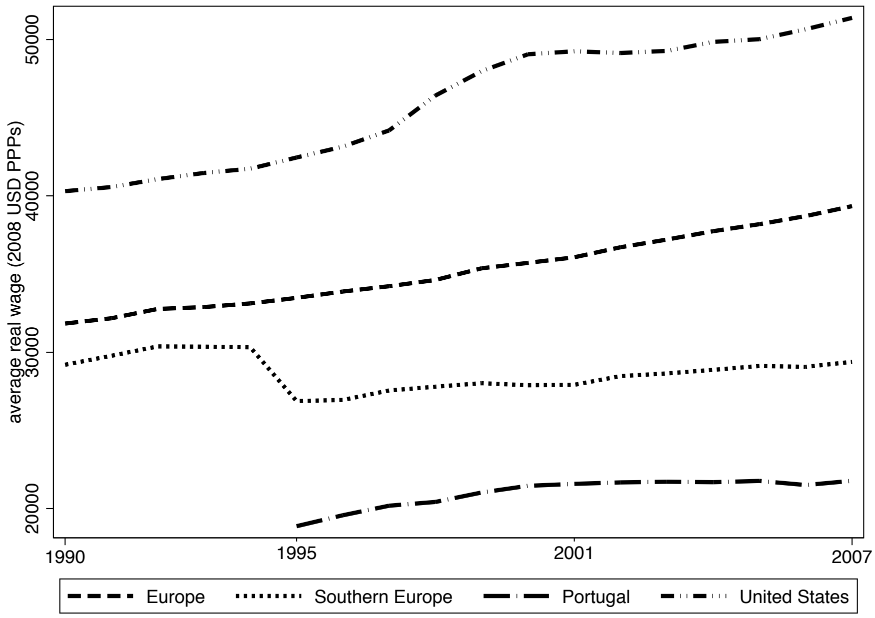

Figure 2: Cross country comparison: mean wages

Authors' calculations based on OECD data. Europe: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Luxembourg, the Netherlands, Norway, Sweden and the UK. Southern Europe: Greece, Italy and Spain.

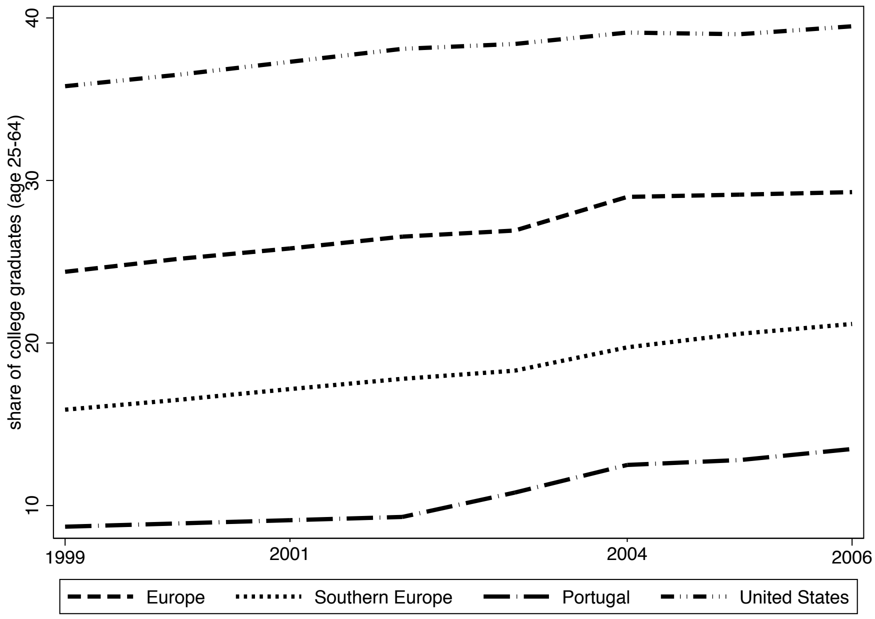

Figure 3: Cross country comparison: education

Authors' calculations based on OECD data. Europe: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Luxembourg, the Netherlands, Norway, Sweden and the UK. Southern Europe: Greece, Italy and Spain.

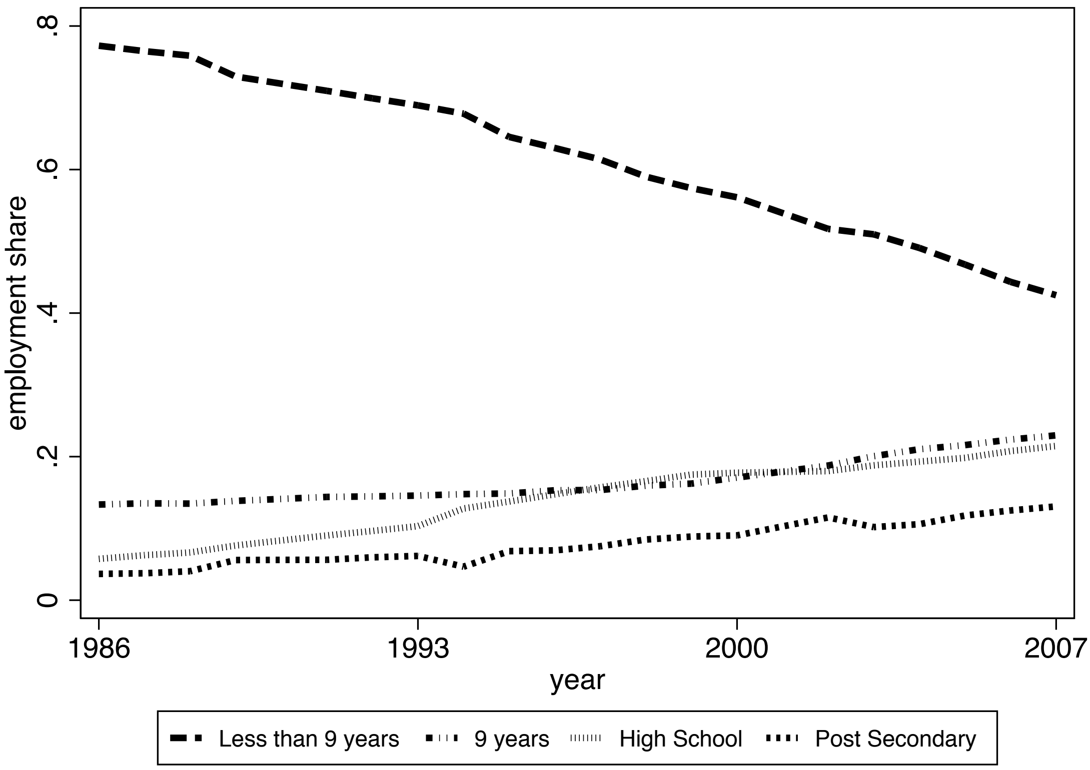

Figure 4: Education trends

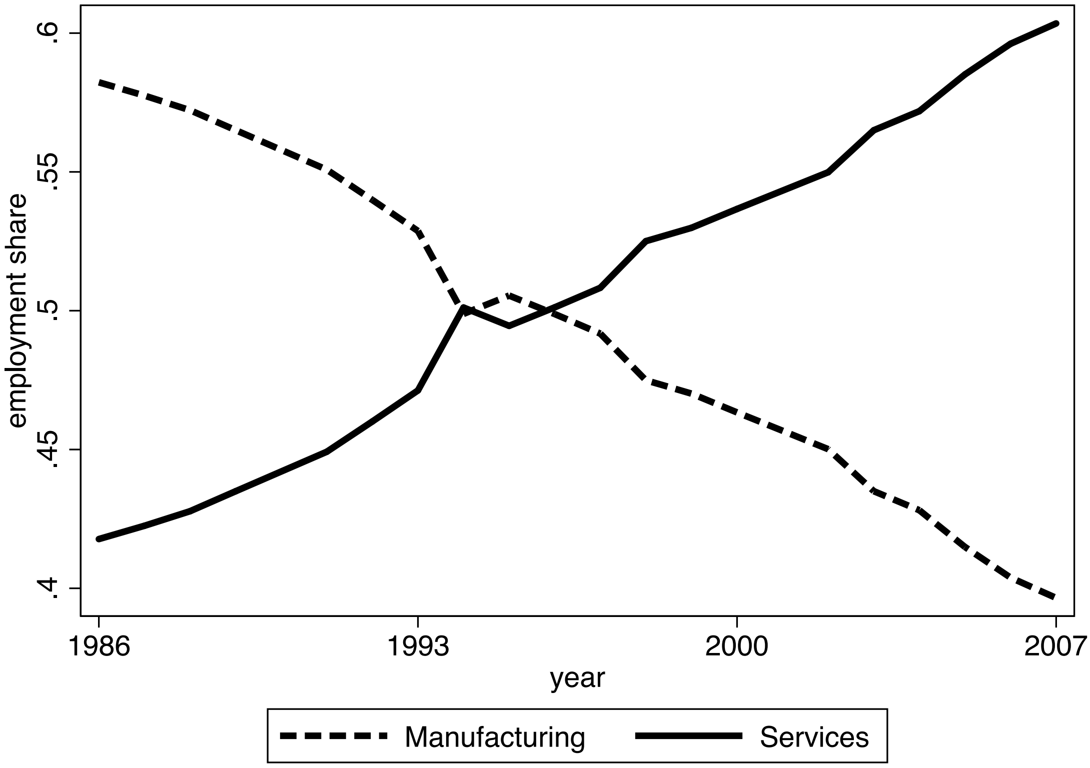

Figure 5: Employment share evolution of manufacturing and services

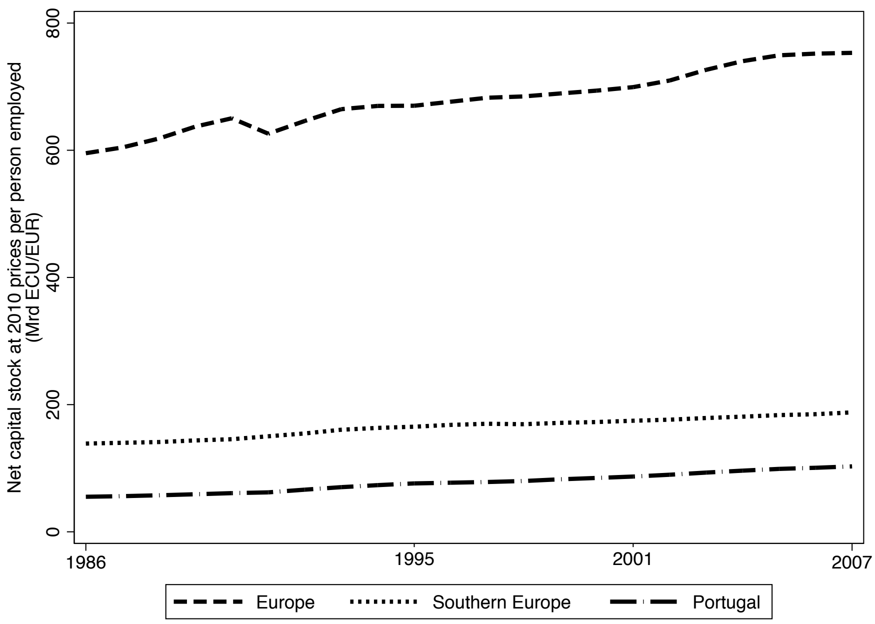

Figure 6: Cross country comparison: Capital stock

Authors' calculations based on annual macro-economic database (AMECO) of the European Commission's Directorate General for Economic and Financial Affairs. Europe: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Luxembourg, the Netherlands, Norway, Sweden and the UK. Southern Europe: Greece, Italy and Spain.

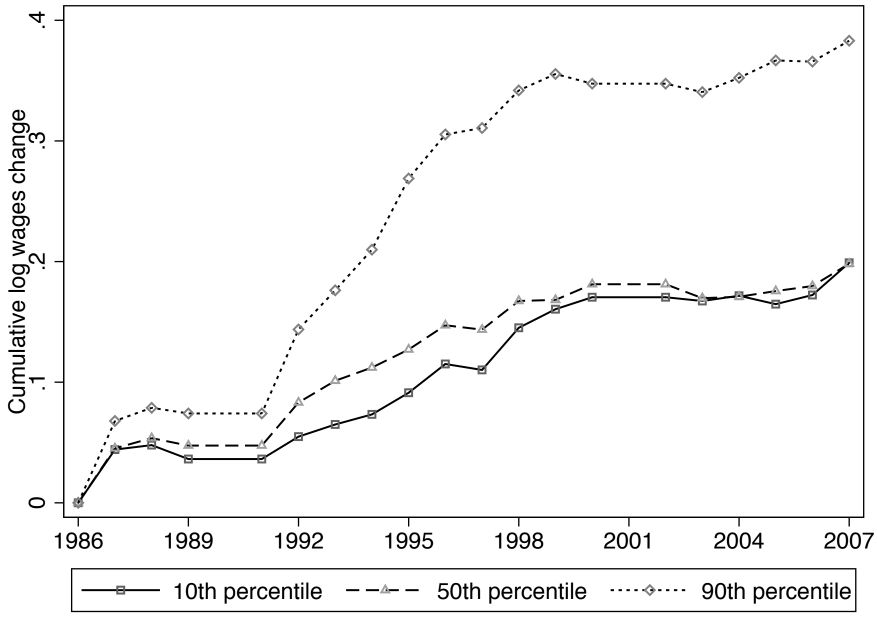

Figure 7: Evolution of cumulative changes by wage percentile, 1986 to 2007

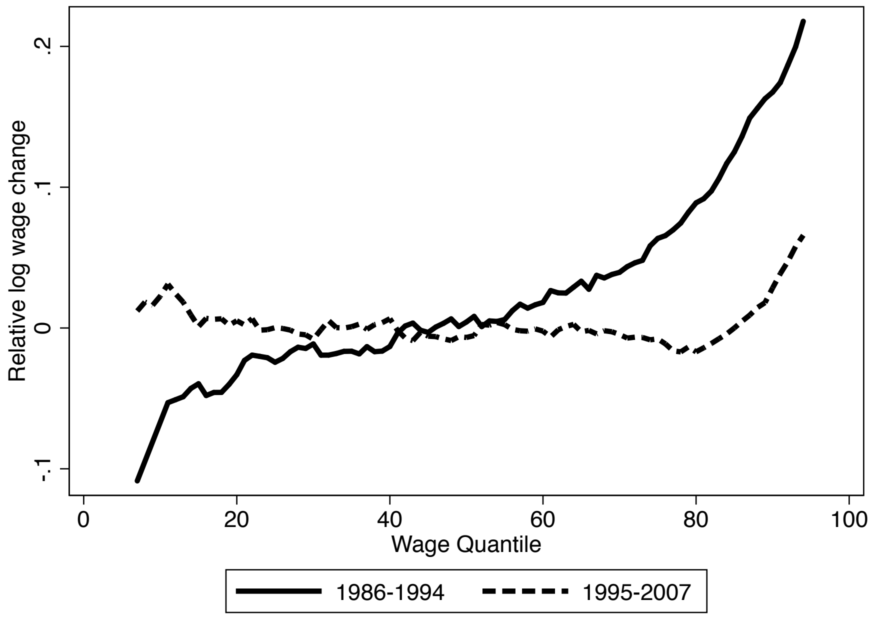

Figure 8: Change in log wage by percentile (relative to the median), 1986-1994 and 1995-2007

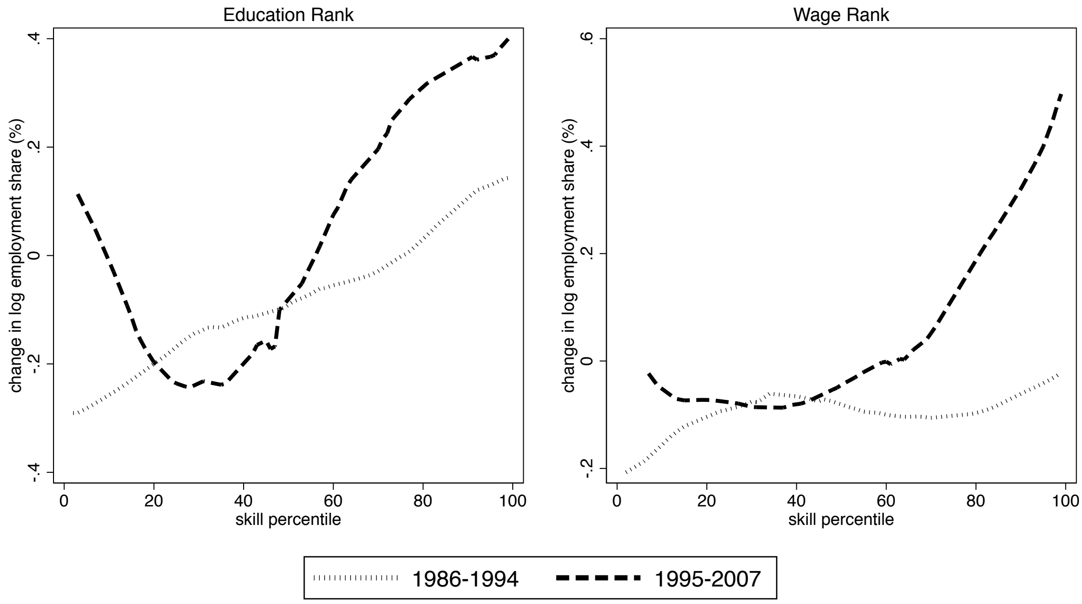

Figure 9: Changes in log employment share by skill percentile, 1986-1994 and 1995-2007
Skill percentile is the occupation percentile (employment-weighted) considering mean wage rank or mean education years rank. The percentiles are obtained by performing an occupational (3-digits) employment weighted rank for each period's initial year: 1986 for the first period; 1995 for the second. The results are smoothed using a locally weighted regression (bandwidth 0.8).

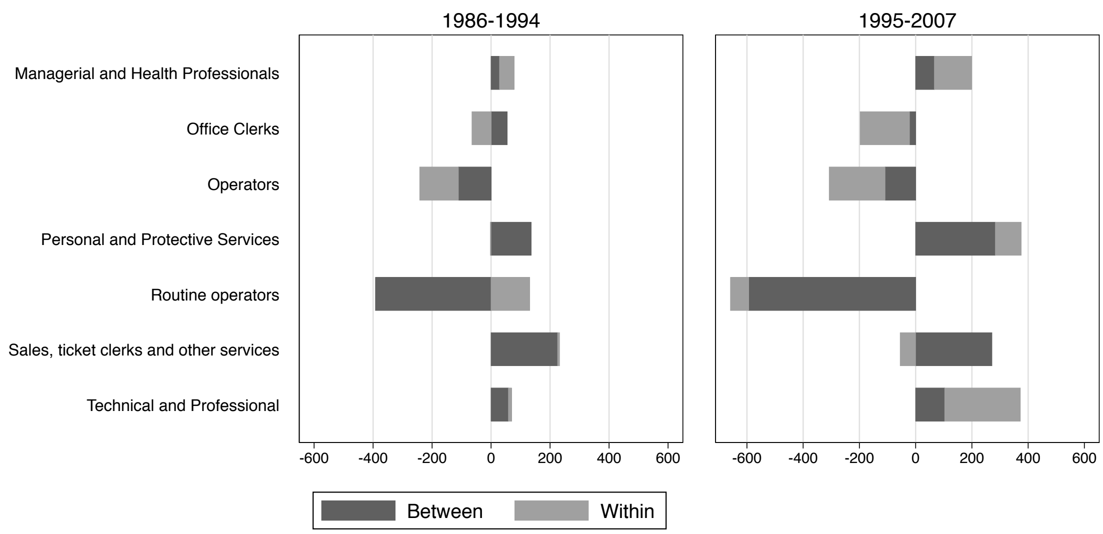

Figure 10: Changes in employment share by occupation groups: within and between industry decomposition
Each bar represents the change in employment share (in percentage points).

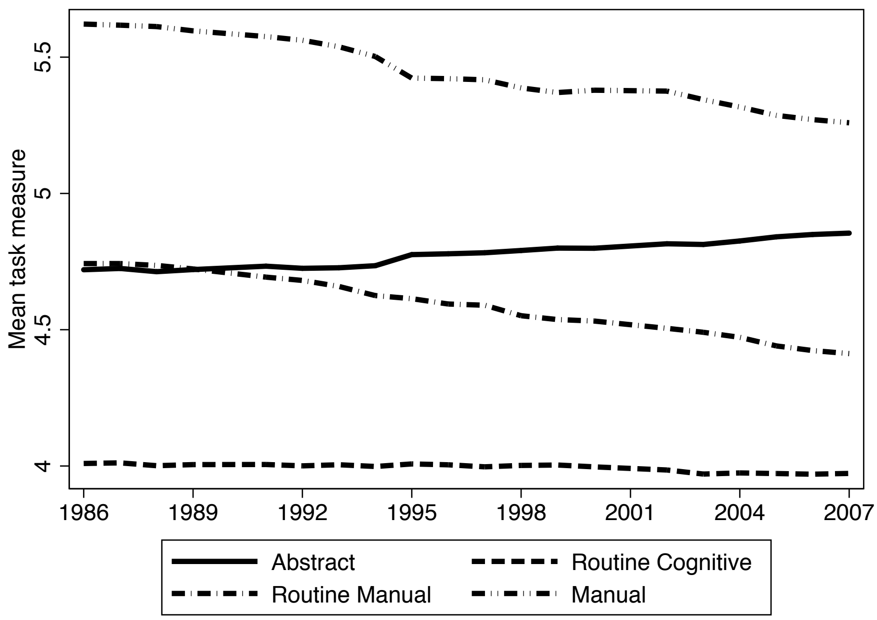

Figure 11: Mean task importance by year

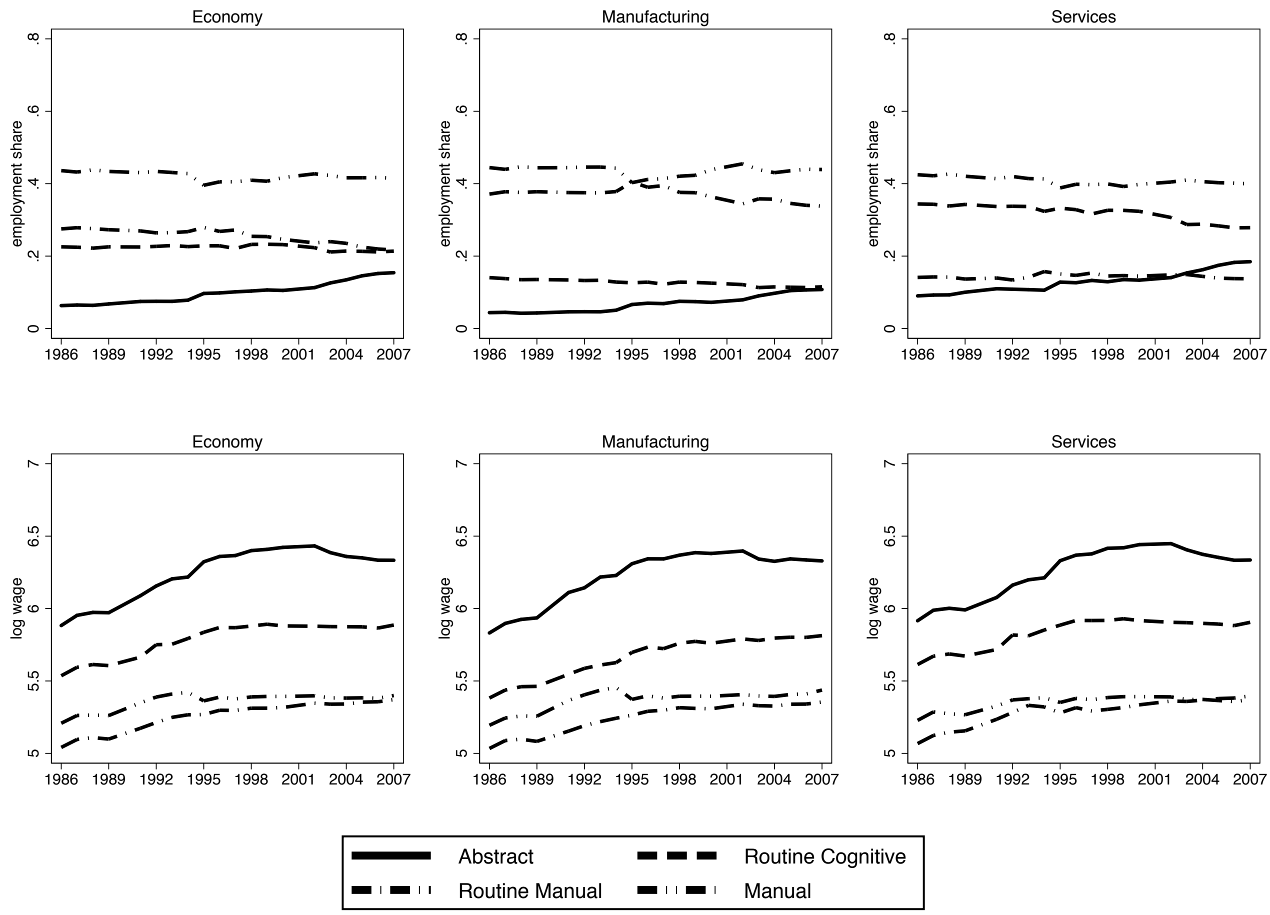

Figure 12: Employment share and log wage evolution by task and sector

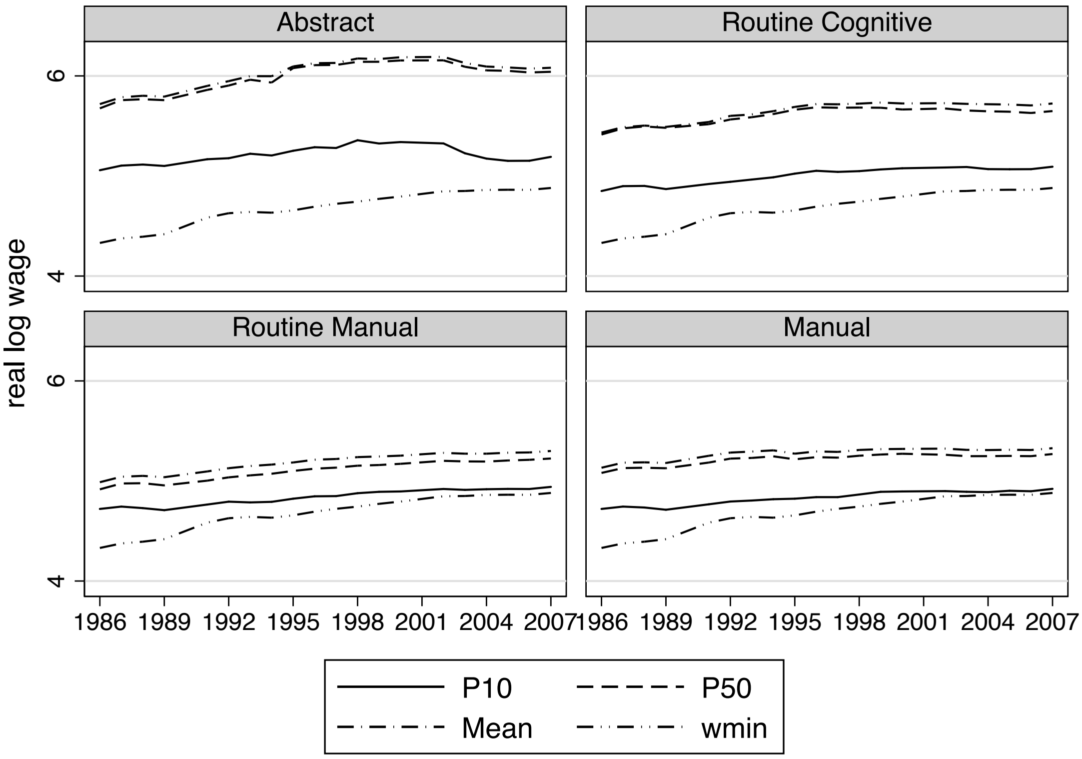

Figure 13: Task wage percentiles and real minimum wage

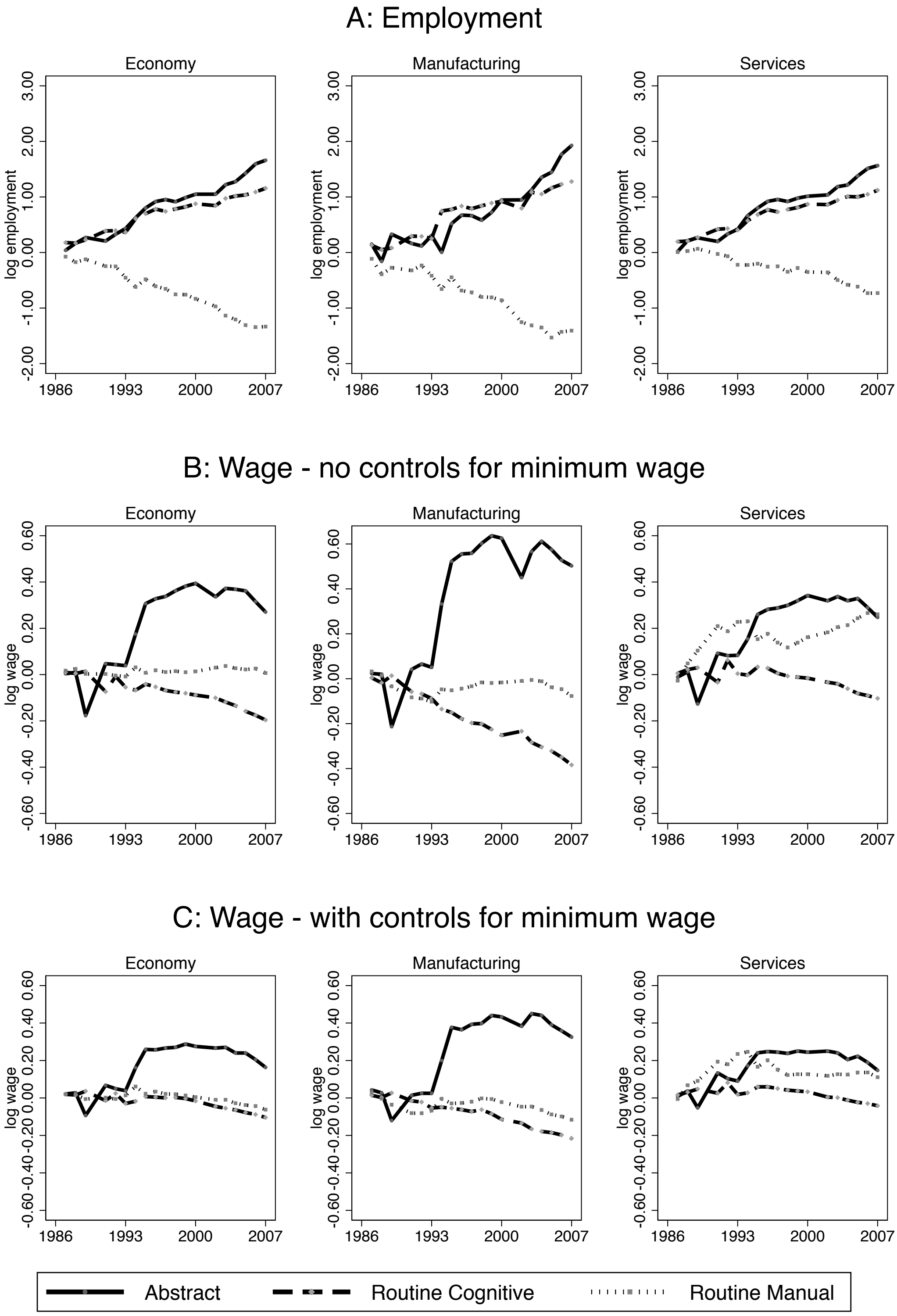

Figure 14: Task 1986 estimation for wages and employment by sector

Notes: Estimations performed for gender-age-education-region-industry cells. The estimates displayed are only for the iteration effect: task 1986 times time dummies. Task stands for the share of workers in a given task in 1986. Model contains fixed effects for cells. Wage estimations weighted by cells' employment. For more details see Appendix Tables A4 and A5.

Table 1: Task importance measures

Occupation	ISCO	Non-routine 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.

Appendix A Tables

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: Analytical (Abstract)		
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
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	R. Man.	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.

Table A4: Employment regression results

	(1)	(2)	(3)
Dep. Var.		**log employment**	
Sector	Economy	Manufacturing	Services
1987	0.009	-0.004	0.009
	(0.040)	(0.086)	(0.045)
1988	0.114**	0.171*	0.099*
	(0.040)	(0.087)	(0.045)
1989	0.204***	0.215*	0.198***
	(0.040)	(0.087)	(0.045)
1991	0.309***	0.249**	0.324***
	(0.040)	(0.087)	(0.045)
1992	0.377***	0.291***	0.402***
	(0.040)	(0.087)	(0.045)
1993	0.443***	0.308***	0.482***
	(0.040)	(0.087)	(0.045)
1994	0.374***	0.174*	0.434***
	(0.040)	(0.087)	(0.045)
1995	0.451***	0.262**	0.507***
	(0.040)	(0.086)	(0.045)
1996	0.463***	0.308***	0.507***
	(0.040)	(0.086)	(0.045)
1997	0.634***	0.441***	0.687***
	(0.040)	(0.086)	(0.045)
1998	0.713***	0.511***	0.770***
	(0.040)	(0.086)	(0.045)
1999	0.773***	0.523***	0.843***
	(0.040)	(0.086)	(0.044)
2000	0.867***	0.593***	0.942***
	(0.040)	(0.086)	(0.044)
2002	1.054***	0.889***	1.093***
	(0.040)	(0.085)	(0.045)
2003	1.027***	0.743***	1.103***
	(0.040)	(0.085)	(0.044)
2004	1.070***	0.780***	1.145***
	(0.040)	(0.086)	(0.044)

Continued...

	(1)	(2)	(3)
2005	1.119***	0.828***	1.194***
	(0.040)	(0.086)	(0.044)
2006	1.124***	0.775***	1.218***
	(0.040)	(0.086)	(0.045)
2007	1.063***	0.709***	1.157***
	(0.040)	(0.086)	(0.045)
Abstract 1986 ×			
1987	0.040	0.150	0.018
	(0.075)	(0.201)	(0.080)
1988	0.166*	-0.158	0.215**
	(0.075)	(0.204)	(0.080)
1989	0.270***	0.329	0.264***
	(0.075)	(0.207)	(0.080)
1991	0.206**	0.163	0.198*
	(0.075)	(0.205)	(0.080)
1992	0.329***	0.117	0.335***
	(0.074)	(0.207)	(0.079)
1993	0.431***	0.305	0.417***
	(0.074)	(0.204)	(0.079)
1994	0.624***	0.004	0.662***
	(0.074)	(0.207)	(0.079)
1995	0.802***	0.520*	0.801***
	(0.074)	(0.205)	(0.079)
1996	0.917***	0.673**	0.920***
	(0.074)	(0.205)	(0.079)
1997	0.953***	0.664**	0.954***
	(0.074)	(0.205)	(0.079)
1998	0.913***	0.581**	0.918***
	(0.074)	(0.203)	(0.079)
1999	0.988***	0.723***	0.979***
	(0.074)	(0.201)	(0.079)
2000	1.050***	0.945***	1.014***
	(0.074)	(0.201)	(0.079)
2002	1.049***	0.948***	1.037***
	(0.074)	(0.201)	(0.079)
2003	1.220***	1.127***	1.185***

Continued...

	(1)	(2)	(3)
	(0.074)	(0.201)	(0.079)
2004	1.276***	1.353***	1.216***
	(0.074)	(0.201)	(0.079)
2005	1.426***	1.446***	1.377***
	(0.073)	(0.201)	(0.079)
2006	1.595***	1.767***	1.512***
	(0.074)	(0.201)	(0.079)
2007	1.660***	1.926***	1.564***
	(0.074)	(0.201)	(0.079)
Routine manual 1986 ×			
1987	-0.075	-0.114	0.006
	(0.127)	(0.211)	(0.170)
1988	-0.174	-0.392	0.026
	(0.127)	(0.210)	(0.171)
1989	-0.124	-0.274	0.066
	(0.127)	(0.212)	(0.169)
1991	-0.246	-0.323	-0.028
	(0.127)	(0.211)	(0.169)
1992	-0.251*	-0.234	-0.067
	(0.127)	(0.212)	(0.169)
1993	-0.454***	-0.418*	-0.222
	(0.126)	(0.210)	(0.169)
1994	-0.621***	-0.658**	-0.225
	(0.127)	(0.210)	(0.170)
1995	-0.483***	-0.447*	-0.202
	(0.126)	(0.209)	(0.169)
1996	-0.608***	-0.685**	-0.256
	(0.126)	(0.209)	(0.170)
1997	-0.655***	-0.717***	-0.250
	(0.126)	(0.209)	(0.169)
1998	-0.754***	-0.800***	-0.348*
	(0.126)	(0.209)	(0.169)
1999	-0.759***	-0.809***	-0.278
	(0.126)	(0.209)	(0.169)
2000	-0.834***	-0.859***	-0.352*
	(0.126)	(0.209)	(0.169)

Continued...

	(1)	(2)	(3)
2002	-0.971***	-1.255***	-0.358*
	(0.126)	(0.208)	(0.169)
2003	-1.137***	-1.311***	-0.496**
	(0.126)	(0.208)	(0.169)
2004	-1.206***	-1.351***	-0.582***
	(0.126)	(0.209)	(0.169)
2005	-1.307***	-1.532***	-0.615***
	(0.126)	(0.208)	(0.169)
2006	-1.345***	-1.429***	-0.731***
	(0.126)	(0.209)	(0.169)
2007	-1.335***	-1.408***	-0.731***
	(0.126)	(0.209)	(0.169)
Routine Cognitive 1986 ×			
1987	0.179**	0.130	0.196**
	(0.059)	(0.125)	(0.066)
1988	0.169**	0.050	0.207**
	(0.058)	(0.125)	(0.066)
1989	0.228***	0.081	0.272***
	(0.059)	(0.125)	(0.066)
1991	0.387***	0.294*	0.419***
	(0.059)	(0.126)	(0.066)
1992	0.395***	0.290*	0.432***
	(0.058)	(0.126)	(0.065)
1993	0.363***	0.252*	0.403***
	(0.058)	(0.125)	(0.066)
1994	0.607***	0.747***	0.572***
	(0.058)	(0.125)	(0.066)
1995	0.699***	0.775***	0.682***
	(0.058)	(0.124)	(0.065)
1996	0.781***	0.836***	0.769***
	(0.058)	(0.124)	(0.065)
1997	0.740***	0.789***	0.731***
	(0.058)	(0.124)	(0.065)
1998	0.785***	0.840***	0.775***
	(0.058)	(0.124)	(0.065)
1999	0.823***	0.890***	0.809***

Continued...

	(1)	(2)	(3)
	(0.058)	(0.124)	(0.065)
2000	0.877***	0.922***	0.869***
	(0.058)	(0.123)	(0.065)
2002	0.844***	0.795***	0.863***
	(0.058)	(0.123)	(0.065)
2003	0.973***	1.085***	0.942***
	(0.058)	(0.123)	(0.065)
2004	1.016***	1.053***	1.009***
	(0.058)	(0.124)	(0.065)
2005	1.037***	1.161***	1.001***
	(0.058)	(0.123)	(0.065)
2006	1.088***	1.228***	1.047***
	(0.058)	(0.123)	(0.065)
2007	1.157***	1.277***	1.121***
	(0.058)	(0.124)	(0.065)
Constant	3.473***	4.097***	3.265***
	(0.012)	(0.025)	(0.014)
R^2-adjusted	0.918	0.924	0.916
F-statistic	630	92	562
Observations	50687	12619	38068

Notes: Regression results for gender-age-education-region-industry cells. Each task is the task's employment share in 1986. Manual is the omitted category. Wage estimations weighted by cells' employment. Huber-White robust standard errors are reported. Model contains fixed effects for cells.

Table A5: Wages regression results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.		**log wage**			**log wage**	
		without minimum wage controls			with minimum wage controls	
Sector	Economy	Manufacturing	Services	Economy	Manufacturing	Services
1987	0.047***	0.041***	0.057***	0.043***	0.039***	0.049***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1988	0.064***	0.072***	0.054***	0.072***	0.084***	0.057***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1989	0.075***	0.092***	0.049***	0.108***	0.126***	0.083***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1991	0.169***	0.207***	0.112***	0.286***	0.343***	0.216***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1992	0.202***	0.248***	0.137***	0.344***	0.406***	0.272***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1993	0.242***	0.287***	0.176***	0.387***	0.447***	0.313***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1994	0.254***	0.294***	0.197***	0.370***	0.419***	0.308***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1995	0.235***	0.271***	0.183***	0.367***	0.414***	0.310***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1996	0.258***	0.297***	0.204***	0.404***	0.457***	0.341***
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.006)
1997	0.262***	0.293***	0.218***	0.425***	0.472***	0.371***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
1998	0.271***	0.294***	0.233***	0.436***	0.472***	0.393***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
1999	0.278***	0.299***	0.242***	0.457***	0.492***	0.414***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
2000	0.284***	0.306***	0.246***	0.484***	0.528***	0.434***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
2002	0.287***	0.313***	0.246***	0.537***	0.592***	0.479***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
2003	0.280***	0.309***	0.235***	0.539***	0.596***	0.479***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
2004	0.282***	0.304***	0.241***	0.554***	0.609***	0.495***

Continued...

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
2005	0.290***	0.322***	0.240***	0.562***	0.624***	0.496***
	(0.005)	(0.008)	(0.006)	(0.004)	(0.007)	(0.006)
2006	0.290***	0.329***	0.233***	0.563***	0.628***	0.493***
	(0.005)	(0.008)	(0.006)	(0.004)	(0.007)	(0.006)
2007	0.312***	0.357***	0.248***	0.585***	0.652***	0.513***
	(0.005)	(0.008)	(0.007)	(0.004)	(0.007)	(0.006)
Abstract 1986 ×						
1987	0.004	0.023	-0.011	0.021	0.043	0.008
	(0.024)	(0.050)	(0.028)	(0.020)	(0.039)	(0.023)
1988	0.010	0.020	0.012	0.027	0.027	0.037
	(0.024)	(0.050)	(0.027)	(0.020)	(0.039)	(0.023)
1989	-0.177***	-0.214***	-0.127***	-0.094***	-0.121***	-0.052*
	(0.023)	(0.046)	(0.026)	(0.019)	(0.036)	(0.022)
1991	0.047*	0.041	0.092***	0.067***	0.014	0.134***
	(0.023)	(0.047)	(0.026)	(0.019)	(0.036)	(0.022)
1992	0.043	0.066	0.082**	0.050**	0.025	0.103***
	(0.022)	(0.047)	(0.025)	(0.018)	(0.037)	(0.021)
1993	0.039	0.051	0.083***	0.039*	0.025	0.090***
	(0.022)	(0.046)	(0.025)	(0.018)	(0.036)	(0.021)
1994	0.175***	0.333***	0.154***	0.162***	0.200***	0.172***
	(0.022)	(0.048)	(0.025)	(0.018)	(0.038)	(0.021)
1995	0.307***	0.523***	0.260***	0.259***	0.377***	0.241***
	(0.021)	(0.045)	(0.024)	(0.017)	(0.035)	(0.020)
1996	0.328***	0.555***	0.282***	0.257***	0.364***	0.248***
	(0.021)	(0.045)	(0.024)	(0.017)	(0.035)	(0.020)
1997	0.338***	0.558***	0.288***	0.267***	0.393***	0.245***
	(0.021)	(0.044)	(0.023)	(0.017)	(0.035)	(0.019)
1998	0.362***	0.602***	0.299***	0.270***	0.398***	0.238***
	(0.020)	(0.044)	(0.023)	(0.017)	(0.034)	(0.019)
1999	0.382***	0.637***	0.319***	0.288***	0.441***	0.251***
	(0.020)	(0.043)	(0.023)	(0.017)	(0.034)	(0.019)
2000	0.394***	0.626***	0.342***	0.275***	0.433***	0.244***
	(0.020)	(0.043)	(0.022)	(0.016)	(0.033)	(0.019)
2002	0.336***	0.450***	0.319***	0.267***	0.383***	0.250***
	(0.020)	(0.041)	(0.022)	(0.016)	(0.032)	(0.019)

Continued...

	(1)	(2)	(3)	(4)	(5)	(6)
2003	0.373***	0.566***	0.337***	0.270***	0.451***	0.241***
	(0.020)	(0.042)	(0.022)	(0.016)	(0.033)	(0.018)
2004	0.369***	0.612***	0.319***	0.240***	0.440***	0.205***
	(0.019)	(0.041)	(0.022)	(0.016)	(0.032)	(0.018)
2005	0.362***	0.575***	0.329***	0.240***	0.390***	0.223***
	(0.019)	(0.041)	(0.022)	(0.016)	(0.032)	(0.018)
2006	0.315***	0.528***	0.290***	0.204***	0.358***	0.190***
	(0.019)	(0.041)	(0.021)	(0.016)	(0.032)	(0.018)
2007	0.270***	0.503***	0.247***	0.163***	0.325***	0.147***
	(0.019)	(0.041)	(0.021)	(0.016)	(0.032)	(0.018)
Routine manual 1986 ×						
1987	0.017	0.032	-0.027	0.020*	0.029*	-0.006
	(0.011)	(0.016)	(0.021)	(0.009)	(0.013)	(0.018)
1988	0.024*	0.013	0.048*	0.017	-0.004	0.068***
	(0.011)	(0.016)	(0.021)	(0.009)	(0.013)	(0.018)
1989	0.003	-0.034*	0.103***	-0.006	-0.036**	0.091***
	(0.011)	(0.016)	(0.021)	(0.009)	(0.013)	(0.018)
1991	0.003	-0.083***	0.209***	0.001	-0.081***	0.194***
	(0.011)	(0.016)	(0.021)	(0.009)	(0.012)	(0.017)
1992	-0.004	-0.089***	0.187***	-0.006	-0.082***	0.180***
	(0.011)	(0.016)	(0.021)	(0.009)	(0.012)	(0.017)
1993	-0.008	-0.102***	0.228***	0.014	-0.067***	0.235***
	(0.011)	(0.016)	(0.021)	(0.009)	(0.013)	(0.017)
1994	0.031**	-0.048**	0.230***	0.061***	-0.004	0.246***
	(0.011)	(0.016)	(0.020)	(0.009)	(0.013)	(0.017)
1995	0.008	-0.052**	0.153***	0.022*	-0.029*	0.166***
	(0.011)	(0.016)	(0.020)	(0.009)	(0.012)	(0.017)
1996	0.019	-0.044**	0.177***	0.034***	-0.027*	0.201***
	(0.011)	(0.016)	(0.020)	(0.009)	(0.012)	(0.017)
1997	0.011	-0.034*	0.138***	0.022*	-0.020	0.151***
	(0.010)	(0.016)	(0.020)	(0.009)	(0.012)	(0.017)
1998	0.014	-0.017	0.117***	0.020*	-0.002	0.122***
	(0.011)	(0.016)	(0.020)	(0.009)	(0.012)	(0.017)
1999	0.010	-0.019	0.138***	0.013	-0.006	0.127***
	(0.010)	(0.016)	(0.020)	(0.009)	(0.012)	(0.017)
2000	0.013	-0.017	0.162***	0.004	-0.022	0.127***

Continued...

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.010)	(0.015)	(0.019)	(0.008)	(0.012)	(0.016)
2002	0.030**	-0.010	0.182***	-0.010	-0.047***	0.118***
	(0.010)	(0.015)	(0.019)	(0.008)	(0.012)	(0.016)
2003	0.037***	-0.006	0.205***	-0.010	-0.046***	0.127***
	(0.010)	(0.015)	(0.019)	(0.008)	(0.012)	(0.016)
2004	0.027**	-0.012	0.214***	-0.028***	-0.065***	0.125***
	(0.010)	(0.016)	(0.019)	(0.008)	(0.012)	(0.016)
2005	0.022*	-0.038*	0.243***	-0.038***	-0.088***	0.136***
	(0.010)	(0.016)	(0.019)	(0.009)	(0.012)	(0.016)
2006	0.026*	-0.047**	0.266***	-0.043***	-0.099***	0.136***
	(0.011)	(0.016)	(0.019)	(0.009)	(0.012)	(0.016)
2007	0.007	-0.077***	0.260***	-0.062***	-0.117***	0.111***
	(0.011)	(0.016)	(0.020)	(0.009)	(0.013)	(0.017)
Routine Cognitive 1986 ×						
1987	0.010	0.004	0.005	0.019*	0.014	0.016
	(0.011)	(0.027)	(0.013)	(0.009)	(0.021)	(0.011)
1988	0.005	-0.018	0.022	0.016	0.003	0.031**
	(0.011)	(0.027)	(0.013)	(0.009)	(0.021)	(0.011)
1989	0.014	0.013	0.030*	0.036***	0.027	0.048***
	(0.011)	(0.026)	(0.013)	(0.009)	(0.020)	(0.011)
1991	-0.074***	-0.058*	-0.033**	-0.014	-0.015	0.026*
	(0.011)	(0.025)	(0.012)	(0.009)	(0.020)	(0.010)
1992	-0.008	-0.068**	0.062***	0.024**	-0.022	0.081***
	(0.011)	(0.025)	(0.012)	(0.009)	(0.020)	(0.010)
1993	-0.055***	-0.088***	0.004	-0.030***	-0.054**	0.019
	(0.011)	(0.025)	(0.012)	(0.009)	(0.020)	(0.010)
1994	-0.067***	-0.135***	-0.002	-0.018*	-0.049*	0.028**
	(0.011)	(0.025)	(0.012)	(0.009)	(0.020)	(0.010)
1995	-0.041***	-0.150***	0.033**	0.007	-0.055**	0.059***
	(0.010)	(0.024)	(0.012)	(0.009)	(0.019)	(0.010)
1996	-0.053***	-0.178***	0.027*	0.004	-0.063***	0.060***
	(0.010)	(0.024)	(0.012)	(0.009)	(0.019)	(0.010)
1997	-0.068***	-0.197***	0.006	0.001	-0.072***	0.050***
	(0.010)	(0.024)	(0.012)	(0.008)	(0.018)	(0.010)
1998	-0.076***	-0.201***	-0.007	0.003	-0.062***	0.042***
	(0.010)	(0.024)	(0.012)	(0.008)	(0.018)	(0.010)

Continued...

	(1)	(2)	(3)	(4)	(5)	(6)
1999	-0.081***	-0.226***	-0.011	-0.003	-0.085***	0.037***
	(0.010)	(0.023)	(0.011)	(0.008)	(0.018)	(0.010)
2000	-0.089***	-0.252***	-0.015	-0.016*	-0.114***	0.033***
	(0.010)	(0.023)	(0.011)	(0.008)	(0.018)	(0.010)
2002	-0.101***	-0.234***	-0.033**	-0.045***	-0.134***	0.005
	(0.010)	(0.023)	(0.011)	(0.008)	(0.018)	(0.009)
2003	-0.118***	-0.284***	-0.040***	-0.055***	-0.165***	0.002
	(0.010)	(0.023)	(0.011)	(0.008)	(0.018)	(0.009)
2004	-0.134***	-0.305***	-0.061***	-0.064***	-0.178***	-0.012
	(0.010)	(0.022)	(0.011)	(0.008)	(0.018)	(0.009)
2005	-0.159***	-0.322***	-0.081***	-0.078***	-0.185***	-0.023*
	(0.010)	(0.022)	(0.011)	(0.008)	(0.017)	(0.009)
2006	-0.176***	-0.350***	-0.091***	-0.088***	-0.198***	-0.030**
	(0.010)	(0.022)	(0.011)	(0.008)	(0.017)	(0.009)
2007	-0.196***	-0.384***	-0.103***	-0.104***	-0.216***	-0.042***
	(0.010)	(0.022)	(0.011)	(0.008)	(0.017)	(0.009)
min wage/p10 (logs)				-3.840***	-4.382***	-3.471***
				(0.025)	(0.050)	(0.028)
Constant	5.266***	5.171***	5.355***	8.687***	9.125***	8.412***
	(0.002)	(0.003)	(0.002)	(0.022)	(0.045)	(0.025)
R^2-adjusted	0.971	0.970	0.972	0.993	0.995	0.991
F-statistic	941	375	533	5593	3122	2740
Observations	50687	12619	38068	50687	12619	38068

Notes: Regression results for gender-age-education-region-industry cells. Each task is the task's employment share in 1986. Manual is the omitted category. Wage estimations weighted by cells' employment. Huber-White robust standard errors are reported. Model contains fixed effects for cells.

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