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Hours of work polarisation?

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Abstract

We investigate the relationship between hours per worker and employment polarisation. Our core question is whether hours per worker follow the same polarisation patterns as previously observed for employment, measured by either heads or total hours. Using the occupational task index measures of Acemoglu and Autor (2011), we find large relative declines in hours per worker in routine manual jobs – precisely the occupations most negatively affected by employment polarisation from routine-biased technical change. We also find a lower relative decline in hours per worker for non-routine cognitive analytical jobs, which are growing through polarisation. At the same time, hours per worker declined significantly more than the trend for non-routine manual physical occupations. Instead of a polarisation pattern, we find that hours per worker have been declining more in manual jobs (routine manual and non-routine manual physical). These patterns are observed across age, gender and education groups, with few exceptions and changes in intensity. The decline in hours per worker occurred mostly within sectors. Using a wage ranking of occupations instead of occupational task indices, the decline in hours per worker is monotonically related to wages. The results are specific to the European countries and the same patterns are not found using data for the United States.

Key words: job polarisation, hours per worker, routine-biased technical change

JEL codes: J23, J24, O33

Non-technical summary

Employment polarisation has emerged as a prominent feature of labour markets in advanced economies in recent decades. It is characterised by an increase in employment at the bottom and at the top of the skill (or wage) distribution in relation to middle occupations. A hypothesis for the emergence of employment polarisation is the rapidly decline in computer prices that facilitated the replacement of routine tasks by technology. At the same time, technology complemented analytical tasks and the rise of personal services supported employment creation at the bottom. This is the hypothesis of routine-biased technical change (RBTC).

The employment polarisation patterns are well-documented for European countries, the United States and other large economies. Previous analyses on job polarisation have been carried out on employment (both headcount and total hours). In this paper, we analyse the relationship between employment polarisation and hours *per worker*. We aim to answer the following question: have average hours per worker followed the same polarisation patterns as total employment?

The long-term decline in average hours precedes by about a century the employment polarisation patterns which became more apparent only in the 1990s. Nonetheless, there are good reasons to consider that the trend decline in hours per worker is not equal across job tasks. Hours can simply follow the labour demand patterns giving origin to job polarisation. Technology may have changed the degree of substitutability between capital and labour in some occupations.

In carrying out this analysis, we follow the occupational task indices created by Acemoglu and Autor (2011). These indices are based on the Occupational Information Network (O*NET), which for each occupation provides a measure related to work abilities, work activities, work context and skills. An example of an O*NET-measured ability is manual dexterity, an example of an activity is thinking creatively, an example of work context is face to face discussions and an example of a skill is social perceptiveness.

We use three main skill levels split into six different occupational task indices: 1) Low-skilled - non-routine manual tasks, comprised of manual physical tasks (e.g. truck and bus drivers) and manual personal tasks (e.g. hairdressers); 2) Medium-skilled – routine tasks, comprised of manual (e.g. machine operators) and cognitive tasks (e.g. cashiers and ticket clerks); and 3) High-skilled – non-routine cognitive tasks which comprise cognitive analytical tasks (e.g. mathematicians) and cognitive personal tasks (e.g. chief executives). In addition, we investigate hours per worker based on a wage raking of occupations, where we analyse changes in hours per worker in three and six quantiles of the occupation wage distribution.

Further to the occupational task indices, we use a measure of offshorability. The aim is to analyse the evolution in hours per worker in occupations more exposed to competition pressures related to technological developments and globalisation. This measure has been considered in the empirical literature as of secondary importance in relation to the occupational skill indices in explaining employment polarisation patterns.

Our results show that the level and, more importantly, the trend in hours per worker vary considerably across each occupational task index. We find large declines in routine manual jobs – precisely the occupations most negatively affected by employment polarisation from RBTC. Additionally, we find a lower decline in hours per worker for non-routine cognitive analytical jobs, which are growing through polarisation. At the same time, hours per worker declined significantly more than the trend for non-routine manual physical occupations and that decline has not been compensated by an increase in hours per worker in non-routine manual personal jobs. However, for non-routine manual jobs the occupational tasks indices also do not give the typical polarisation patterns for total employment. Overall, instead of a polarisation pattern our results show that hours per work declined more in manual jobs (routine manual and non-routine manual physical).

The hours per worker patterns across occupational task indices remain robust to estimation across age, gender and education, although the intensity may vary and some subtle patterns may emerge. For example, the decline in hours per worker in routine manual jobs and non-routine manual physical jobs is stronger for women. The decline in hours per worker occurs mostly within sectors. The increase in part-time seems important. However, that increase may be partly a consequence of the decline in hours per worker, as the classification into full-time and part-time is self-reported.

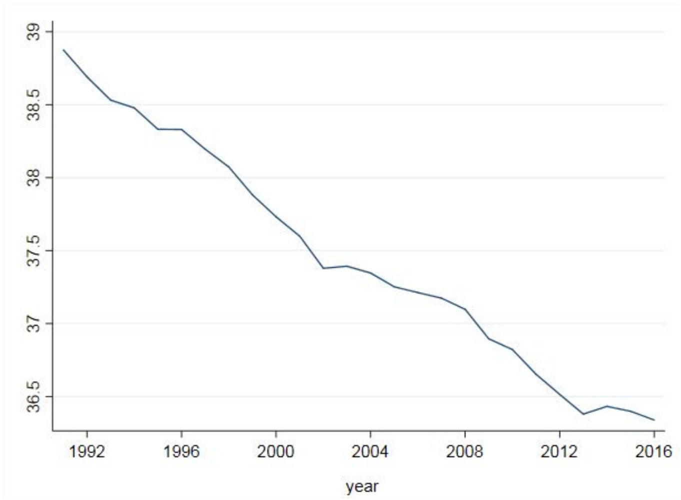
Additionally, we analyse patterns in hours per worker along the wage distribution, instead of the occupational indices. While for total employment we see the typical U-shaped polarisation pattern, for hours per worker the pattern is L-shaped. Phrasing differently, the share of employment declined in middle-wage occupations in relation to bottom and top occupations, whereas hours per worker show a monotonic relationship with wages: hours per worker declined more in low-wage occupations, followed by middle-wage occupations and high-wage occupations have experienced almost no decline in hours per worker. If the wage distribution were partitioned in six quantiles instead of three, we observe a U-shaped pattern for most of the distribution, but with a lower decrease in hours per worker at the top quantile. Thus, contrary to occupational task indices, where hours declined more in the middle, the wage ranking of occupations shows that hours declined more at the bottom.

Overall, our results suggest that patterns in hours per worker exacerbate the impact of polarisation on wage inequality. High-skilled workers increased their share of employment and work relatively more hours, medium-skilled workers saw a decline in the share of employment and a decline in hours per worker and low-skilled workers saw a substantial decrease in hours per workers. The analysis based on the wage ranking of occupations makes this point even clearer: hours per worker declined significantly more in low-paying occupations.

1 Introduction

Employment polarisation has emerged as a widespread phenomenon across advanced economies in the past three decades. It is characterised by a decline in the share of middle-skill jobs and an increase in the share of high- and low-skill jobs (conventionally defined by a one-on-one mapping of wages to skills), leading to the well-known "hollowing-out" of employment. Polarisation has occurred alongside a longer-term decline in the intensive margin of employment (hours per worker) in European economies. Figure 1 shows the evolution of usual weekly average hours of work per worker across EU-15 countries from 1992-2016, which have fallen by almost two and a half hours during that period, generating substantial aggregate effects on total hours in the economy. The fall is not isolated or confined to small groups of countries. Instead, it forms part of a longer term trend of declining hours worked per employed person across European economies. The two labour market trends, while not necessarily sharing causal factors, are likely to have interconnected implications and yet have only been analysed in isolation. We investigate whether hours per worker exhibit polarisation patterns along similar distributional lines as already documented employment polarisation.

Figure 1: Average weekly hours per worker in EU-15 countries, 1992-2016



Source: EU Labour Force Survey, authors' own calculations. Hours refers to usual weekly hours per worker.

The non-monotonic relationship between skills and employment that characterises job polarisation first emerged in the 1990s. For the United States, Acemoglu and Autor (2011) show that the process of employment polarisation occurred largely over two periods. An initial period between 1989 and 1999 was characterised by a strong increase in the share of high-skilled jobs, a smaller increase in the share of low-skilled jobs and a decline in middle-skilled jobs. A second period followed, between 1999 and 2007. where the share of employment grew most in the last third of the wage distribution. With a view to explaining the new employment composition patterns, Autor et al. (2003) developed the hypothesis of routine-biased technical change (RBTC). Traditionally middle-skilled jobs requiring repetitive routine tasks – such as factory production lines or clerical work – are vulnerable to increasing automation and have seen their wages and employment shares decline. Low-skilled jobs, particularly those requiring in-person services – such as cleaning and personal care – are less substitutable for technology and as a consequence their relative employment share has increased slightly. At the other end, high-skilled workers – such as managers and analysts - find their labour complemented by technological progress, increasing their share of employment.

Since the seminal work of Autor et al. (2003), a large body of literature emerged around the theme of employment polarisation. Autor et al. (2006) related the observed employment polarisation in the United States with the changing distribution of in-job task demands related to technological advancement and outsourcing. Goos and Manning (2007) showed evidence of job and wage polarisation in the United Kingdom, while Goos et al. (2009) and Goos et al. (2014) broadened their scope and showed evidence of pervasive job polarisation in 16 European countries. Evidence of job polarisation is also available for other large advanced economies (e.g Coelli and Borland, 2015, for Australia; Green and Sand, 2015, for Canada; Furukawa and Toyoda, 2018, for Japan).

A complementary branch of the literature has focused on specific drivers of employment polarisation. This includes, for example, the role of low-service occupations in the rise of polarisation (Autor and Dorn, 2013), the contribution of ICT to the polarisation of the labour market via an increase in demand for high-skilled labour (Michaels et al., 2014), the types of workers who transit from routine to non-routine cognitive and non-routine manual jobs (Cortes, 2016), the role of specific demographic groups in shaping employment polarisation (Cortes et al., 2017) and the relationship between polarisation patterns and inter-industry wage differentials (Shim and Yang, 2018). More recently, vom Lehn (2019) tests the hypothesis of substitutability and complementarity of different workers with machines and found that patterns of polarisation do not always conform to that hypothesis over time. He hypothesises that more recent technological change could have evolved to replace also analytical tasks.

A key observation is that existing work on employment polarisation focuses on either headcount or total hours worked. To our knowledge, the internal margin of adjustment – hours per worker – has not been analysed, and that is what we study in this paper. Contrary to employment, which has been increasing during our sample, hours per worker are on a long-term declining trend. Employment polarisation and the decline in hours per worker are far apart in time but they may both have, as many other changes in labour markets, a common underlying pattern: technological progress.

Taking the manufacturing sector alone, in the period 1913-1997 hours worked annually per person declined by 31% in the United States, 38% in the United Kingdom, 42% in France and 45% in Germany (Cahuc et al., 2014). The trend has not been uniform over time and across countries. Periods of sharp decline in average hours worked have been followed by periods of stabilisation or even an increase in average hours worked. Average hours worked per person also tend to be substantially higher in low- than in high-income countries (Bick et al. (2018)). Various factors could be at play in the determination of hours worked per person such as, for example, labour laws, unionisation, taxation and home sector productivity. However, Vandenbroucke (2009) argues that these forces appear of secondary importance relative to technology.

The evolution in hours worked also appears to be heterogeneous across skill groups. Since the 1980s, the average hours of low-skilled workers have dropped significantly whereas those of high-skilled workers have remained high (Aguiar and Hurst, 2007 and Boppart and Ngai, 2018). The timing of change in hours worked by educational group coincides with the increase in inequality in wages and consumption (Katz and Autor, 1999); it is also in the neighbourhood of the early stages of the process of job polarisation (Autor et al., 2003).

Our framework models a statistical rather than causal relationship between hours per worker and job polarisation. We ask whether hours per worker follow the same distributional patterns as employment, and less formally investigate possible mechanisms. We also try to infer the possible income distribution consequences of the observed patterns in hours per worker. There are good reasons why polarisation in employment could also affect hours per worker. First, hours per worker could be affected by the same demand forces affecting employment polarisation. Second, technological advancements may change the degree of substitutability between capital and labour. For instance, technological advances have allowed for better monitoring of consumer demand and scheduling of labour. This might be particularly relevant in services sectors.

The value of uncovering a relationship between hours of work and job polarisation is twofold. In a purely mechanical sense, a pattern of hours per worker polarisation would exacerbate already documented employment and wage polarisation. Arguably, it is overall income polarisation – rather than hourly wage or headcount employment - that is of primary concern to policy makers concerned with distributional issues. Total income is the multiplicative function of employment (extensive margin), wages and hours of work (the intensive margin). The third contributing variable – hours – has been absent from the polarisation literature. If hours polarise along similar lines as wages and employment, that would have an exacerbating effect of polarisation. Higher employment with lower hours worked per person in lower-paying occupations together with higher employment with relatively more hours worked per person in high-paying occupations could increase concerns about the quality of jobs at the bottom of the wage distribution and would exacerbate wage inequality.

The second motivating factor for studying patterns in hours per worker is to gain a better understanding of how the relatively new phenomenon of job polarisation is related to the long-term trend decline in hours worked per person. A fundamental difference between the analysis of job polarisation based on employment or total hours and average hours is that while employment and total hours have been increasing, average hours have been declining. An empirical question we attempt to answer is whether hours per worker are declining across all skill levels or they exhibit patterns of polarisation similar to those observed for employment and wages.

Our empirical analysis uses the EU-LFS data for the period 1992-2016 for the EU-15 countries.[1] We follow the recommendation of Autor (2013) that researchers use, as far as possible, available measures of tasks classification, and utilise available indices of job task and skill content – particularly routinisation – to explain trends in hours per worker. We use six indices to classify job tasks instead of the common three categories. Non-routine cognitive jobs are divided between analytical and interpersonal; routine jobs are divided between cognitive and manual and non-routine manual jobs are divided between physical and (inter)personal. In particular, we match occupation indices from Acemoglu and Autor (2011) to EU-LFS microdata from 1992 to 2016, focusing on EU-15 countries. In addition, we also use their index of offshorability to account for the potential of outsourcing. The task indices are shown to explain employment and wage polarisation in both the US and the EU. We investigate whether they additionally explain the level and, more importantly, trend in hours per worker.[2]

We find that workers in highly routine manual jobs are working fewer hours relative to other occupations over time – the interaction term between a high degree of routinisation and a time trend is negative and significant. However, this result is only observed for routine manual jobs and is broadly absent for routine cognitive jobs. We also find that workers are working relatively more hours in non-routine cognitive analytical jobs, although the evidence there is somewhat weaker. Taken together, these two patterns give partial support to the hypothesis that hours per worker follow the same polarisation patterns as employment at the top. For non-routine manual jobs the evidence is more mixed. While we observe a relative increase in hours per worker in non-routine manual interpersonal jobs, we see the opposite for non-routine manual physical jobs. The two effects combined make hours per worker for non-routine manual jobs relatively neutral as compared to the trend in hours. However, for non-routine manual jobs the occupational task indices also do not give the typical polarisation patterns for total employment.

Overall, instead of a polarisation pattern, our results show that hours per work declined more in manual jobs (routine manual and non-routine manual physical jobs). Our results remain robust to the partition of the sample between full-time and part-time, between male and female and across education and age groups. Hours worked per person also declined more than the trend in jobs that are highly offshorable. The main patterns are also consistent across the EU-15 countries with few exceptions.

Additionally, we analyse patterns in hours per worker along the wage distribution, instead of the

[1] The EU-15 countries comprise Austria, Belgium, Denmark, France, Finland, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Data exist for all 15 countries for the period 1992-2016, with the exception of Austria, Finland and Sweden where data start in 1995. Further, occupation identifiers are available for Belgium from 1993 and for Finland and Sweden from 1997, and so these countries enter our sample then.

[2] As is standard, we assume skills are increasing in wages. For convenience, we also assume the conventional mapping carries over to tasks, whereby occupations intensive in non-routine cognitive tasks are high-skilled, occupations intensive in routine tasks are middle-skilled, and those intensive in non-routine manual tasks are low-skilled. Throughout the text, we retain this implicit mapping and refer to individuals in jobs with a high content of non-routine cognitive as high-skilled, and similarly for other tasks.

occupational indices. While for total employment we see the typical U-shaped polarisation pattern, for hours per worker the pattern is inverted L-shaped. Put differently, the share of employment declined in middle-wage occupations in relation to bottom and top occupations, whereas hours per worker show a monotonic relationship with wages: hours per worker declined more in low-wage occupations, followed by middle-wage occupations and high-wage occupations have experienced almost no decline in hours per worker. If we partition the wage distribution in six quantiles instead of three, we observe a U-shaped pattern for most of the distribution, but with a lower decrease in hours per worker at the top quantile. Thus, contrary to occupational indices, where hours declined more in the middle, the wage ranking of occupations shows that hours declined more at the bottom.

Taken together, our results suggest that patterns in hours per worker exacerbate the impact of polarisation on wage inequality. High-skilled workers increased their share of employment and work relatively more hours; medium-skilled workers saw a decline in the share of employment and a decline in hours per worker; and low-skilled workers saw a substantial decrease in hours per workers and a smaller increase in their share of employment. The analysis based on the wage ranking of occupations makes this point even clearer: hours per worker declined significantly more in low-paying occupations.

The contributions of this paper are threefold. First and foremost, we document a new stylised fact: trends in hours per worker vary substantially across occupational task indices – taking together the two constituents of each index, at the top (non-routine cognitive) and the middle (routine), hours per worker evolved similarly to employment polarisation patterns, while at the bottom (non-routine manual) they declined. If we instead use a wage rank of occupations, hours per worker decline monotonically with wages. The difference between the two approaches is that the decline in the middle-skill jobs happens via a decline in routine manual jobs which are in fact low paid. This also shows the importance of a finer disaggregation of skills suggested by Acemoglu and Autor (2011), which we employ in this paper. The direct effect of these mechanisms has been to exacerbate overall earnings polarisation. Second, we contribute to the empirical literature relating the long-term decline in hours worked with technological advancement. Third, we provide detailed level country results that show broadly similar patterns across EU-15 countries, and across a variety of demographic groups.

The rest of the paper is structured as follows. Section 2 describes the European Union Labour Force Survey (EU-LFS) data, the construction of the occupational task indices used and shows main descriptive statistics. Section 3 presents baseline results for hours per worker across task indices while Section 4 considers additional contributing factors. The latter includes demographic shifts over the past few decades, offshorability of jobs, part-time employment and industrial change. Section 5 decomposes overall employment polarisation into the hours-per-worker channel and head-count employment channel. Section 6 turns to country-level analysis – the individual EU-15 countries and a comparison with the United States. Section 7 concludes.

2 Data and descriptive statistics

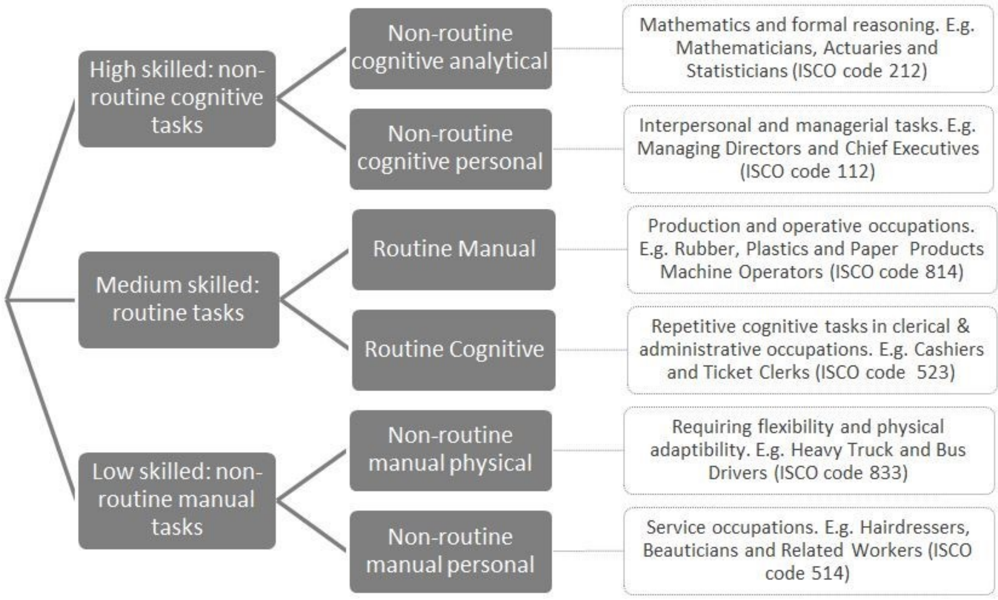
The main dataset used in this paper is the EU Labour Force Survey (EU-LFS). The EU-LFS is a microdataset of repeated cross sections of household level observations (in our case, of annual frequency). As the EU-LFS data are collected based on a harmonised methodology they are suitable for cross-country analyses. Additionally, we use the EU Survey on Income and Living Conditions (EU-SILC) in order to obtain information on wages, as wage variables are missing in our version of the EU-LFS dataset.

Two key variables in our analysis are hours worked per person and individuals' occupations. Hours worked are reported in reference to the week prior to the survey. Individuals are asked about the hours usually worked and the hours actually worked. Differences between the two measures include, among others, overtime or downtime, holidays and sick leave. We focus on working individuals reporting positive usual hours worked per week in the EU-15 countries, during the period 1992-2016, and will only refer to usual hours for the remainder of the paper, unless otherwise stated.

Occupations are codified according to the International Standard Classification of Occupations (ISCO). Each individual worker's occupation is classified with 3-digit ISCO occupation codes: ISCO88 codes for observations up until 2010, and ISCO08 codes for observations from 2011 onwards.[3] The EU-LFS also provides detailed demographic information such as age, gender, education attainment, family status, etc. It also provides other employment information, such as size of firm and, also important for our analysis, the worker's sector of economic activity, according to the Statistical classification of economic activities in the European Community (NACE).

Our analysis centres on measures of occupational skill and task content. We base our analysis on the job skill measures created by Acemoglu and Autor (2011). They use O*NET data on work abilities, work activities, work context and skills to have composite measures to classify each occupation according to their propensity for use of five tasks, and a measure of offshorability. The skill characteristics form three broad groupings - non-routine cognitive, routine, non-routine manual – approximating the top, middle and lower ends of the labour market respectively.

Figure 2: Mapping of skills, tasks and occupations



Much of the polarisation literature explicitly or implicitly finds that three skill categories – high, medium and low - are insufficient to capture structural changes in the labour market, as technological impacts are heterogeneous within each skill grouping. For example, Autor and Dorn (2013) find that the growth in lower skill employment is driven by in-person, service sector jobs. In the middle segment of the labour market, routine manual labour on factory production lines was largely automated in an initial round of RBTC. Arguably, a second round of RBTC, in the form of computerisation, is in the process of replacing routine cognitive jobs, such as cashiers and law clerks. In an attempt to capture richer technological impacts on heterogeneous tasks, we opt for the finer gradation of Acemoglu and Autor (2011). We additionally create a sixth measure that separates lower skilled, non-routine manual jobs into personal services and physical jobs.[4] Figure

[3]Wage analysis is based on 2-digit ISCO occupation codes.

[4]The category of non-routine manual personal is not part of Acemoglu and Autor's 2011 handbook chapter, but it is available in their online data programmes. We have complemented their measures with other O*NET context and ability task measures (Appendix A). We impose a further restriction and remove from the index all occupations with codes below 300 (managers and professionals). This was done because doctors, veterinarians, midwifery professionals and other similar professionals were ranking high in the newly constructed non-routine manual personal index, which made it difficult to distinguish from non-routine analytical personal jobs. The results we report in this paper relate to our modified measure. Results for the original measure by Acemoglu and Autor can be found in Appendix D

2 displays the six task indices, paired by skill level, their corresponding tasks and an example occupation that requires high levels of the relevant index. Throughout the text, we refer to the six task indices as occupational task indices.

The occupations used in Acemoglu and Autor (2011) are the SOC2000 measures and each index is distributed approximately standard normal. We use a number of crosswalks to match the indices to the 3-digit ISCO codes used in the EU-LFS.[5] The final result is a table of ISCO occupation codes and the corresponding values for each of the six indices, for each occupation. A note on terminology: all jobs are characterised by a combination of several different skills and tasks. For brevity, we will refer to jobs characterised by a high content of, e.g., routine cognitive tasks as routine cognitive jobs.

Figure 3: Occupational task indices and personal characteristics

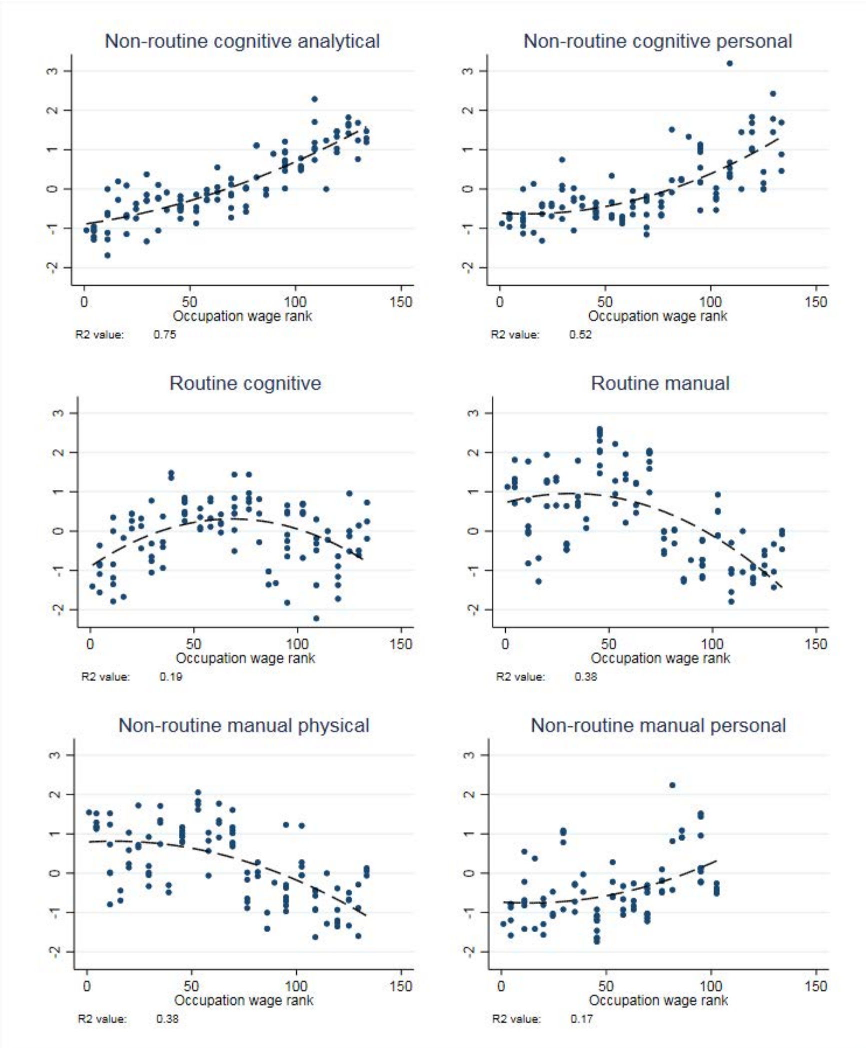
Source: EU-LFS and authors' calculations.

Figure 3 shows some characteristics of our sample. Weekly hours per worker declined by 2.4

[5]We use a crosswalk from SOC2000 to ISCO88 to transform the indices to ISCO88 codes. Where multiple SOC2000 occupations match ISCO88, we take the weighted mean of each index using the US 2000 Census weights provided by Acemoglu and Autor (2011). To match the indices to ISCO08 codes, we again use a crosswalk from ISCO88 to ISCO08 and take the mean of each index for multiple matches.

hours between 1992 and 2016, primarily in routine manual and non-routine manual jobs. By contrast, hours per worker declined only marginally in routine cognitive and non-routine cognitive analytical jobs. These patterns show the importance of differentiating occupational task indices by more than three categories. The share of part-time work increased across all occupational task indices but more so in routine manual jobs, suggesting that the increase in part-time may have played some role in the accentuated decline in hours per worker in these occupations.[6] The share of part-time is higher among non-routine manual personal tasks, which is also the occupational task index with the largest share of female workers. At the same time, there is no fixed threshold of work-time status; individuals who work sufficiently fewer hours may self-classify as working part-time. In that sense, lower average hours almost mechanically imply more part-time work.

Figure 4: Occupational task indices versus wage ranking



Source: EU-LFS, EU-SILC, index construction data from Acemoglu and Autor (2011), O*NET task data and authors' calculations. Wage ranks are calculated using weighted and pooled 2008 EU-SILC data for EU-15 countries.

Figure 3 also shows the well-known pattern of an ageing workforce and, more importantly for our analysis, that average age increased more in routine jobs. The education shares across the six indices provide additional information of the skills required. Non-routine cognitive tasks are those employing the largest share of highly educated workers. At the bottom, with the lowest shares of

[6]The share of involuntary part-time is higher among part-time workers in routine manual and non-routine manual physical jobs, which is suggestive evidence that part of the decline in hours per worker is demand driven.

highly educated workers, are the non-routine manual physical and routine manual occupations, which are those that display the largest reduction in hours per worker. Routine cognitive jobs stay at the middle of the skill distribution.

Our wage rankings come from individual data from EU-SILC. We construct an hourly wage variable by dividing gross annual employee cash earnings by annual total hours, for both full-time and part-time work, excluding self-employed individuals and family workers, as well as individuals with zero earnings. We pool data across the EU-15 by normalising individual wages by the weighted country average. We then calculate average hourly wages for each of the two-digit ISCO88 occupations in 2008. We use a weighted average using EU-SILC weights, but the unweighted measure is very similar. Other years give similar results, but 2008 gives the largest coverage across countries for the ISCO88 classification. We then link the task indices at the 3-digit ISCO88 with the wage ranking at 2-digit ISCO88, ending up with around 130 occupations for each index, except for non-routine manual personal, which we restrict to not include managerial or professional occupations (100 and 200 level).

Figure 4 displays the relationship between occupational task indices and the occupational wage rank, fitted with a quadratic curve. There is a positive relationship between wages and the level of non-routine tasks. By contrast, routine tasks display the expected inverse U-shaped pattern, highlighting their prevalence in the middle segment of the labour market. The non-routine manual physical index is decreasing in wages, as expected, while the non-routine manual personal is slightly increasing, albeit with a low R^2.

Overall, the descriptive patterns show a more subtle categorisation of the occupational task indices than the usual trichotomy of abstract, routine and manual tasks. In fact, routine manual jobs show characteristics more typical of low-skilled jobs: the share of high-education workers is as low as for non-routine manual physical occupations, as is the wage rank. Conversely, non-routine manual personal occupations appear to be more middle- than low-skilled: the share of high education is similar to routine cognitive jobs, while the wage rank cuts across almost the entire distribution. Indeed, "personal" seems more challenging to pin down using the occupational task indices compared to other jobs - though it emerges clearly that "personal" occupations have a large share of female workers.

3 Baseline results

In this section we estimate a reduced form model to analyse the relationship between the indices discussed in the previous section – known to explain employment and wage polarisation – and weekly hours of work per worker. We are interested primarily in whether the indices can account for the trend in hours per worker, which is decreasing at the aggregate level.

We run the following empirical model:

$$Y_{ikct} = \alpha_0 + \alpha_1 I_i + \alpha_2 t + \alpha_3 I_i * t + \beta X_{ict} + c_c + c_k + \epsilon_{ikct} \tag{1}$$

This specification fits the outcome of interest - hours per worker, Y, for individual i in industry k in country c at time t to an intercept, the index value of the individual's occupation, I_i, a linear time trend t and an interaction between the index in question and the time trend. For ease of interpretation, we convert the continuous index measures into dummy variables that equal one if the occupation has a high index score, above the 66^{th} percentile for occupations in each year, and zero if it has a low score.[7] Coefficient α_1 accounts for level differences between different occupations that occur regardless of any trends, while α_2 controls for the aggregate trend. The main coefficient of interest is α_3, which captures the extent to which hours for occupations in a

[7] We calculate the 66^{th} percentile of each index, each year using the weighted EU-15 LFS observations for the relevant year. This method ensures that for each index, one third of the observations each year will have the dummy variable equal to one. This method thereby abstracts from classification changes over time. As a robustness check, we also repeat the analysis using a constant 66^{th} percentile i.e. the threshold for a given index is the same across years.

given index trend in a way that differs from the aggregate. Given the overall aggregate trend, a positive value for α_3 indicates that occupations with high values of the index in question have exhibited a milder decline, and opposite for a negative value.

Additional covariates include country and industry fixed effects, demographics (gender, age, education) and controls such as firm size, whether the interview was conducted with the person in question or by proxy. Country and industry fixed effects account for time-invariant heterogeneity in average hours worked across countries or industries. Two-way country and industry fixed effects assume the industry effect is identical across countries, while an interacted country-industry fixed effect allows for the possibility of heterogeneity across countries within the same industry. Unless stated otherwise, errors are clustered at the country-industry level, in a total of 240 clusters. All regressions are weighted using EU-LFS weights, as provided by Eurostat.

The results are based on the estimation of specification 1 one time per index on the total sample. We start by analysing the explanatory ability of the non-routine cognitive indices for hours per worker. Table 1 presents baseline regressions of hours per worker on the time trend, a dummy for the individual working in a high index score occupation, the interaction and covariates as specified above. The first three columns refer to the non-routine cognitive analytical index and the final three to the non-routine cognitive personal index. Columns 1 and 4 present results without controls, columns 2 and 5 with the standard controls, country and sector fixed effects, and columns 3 and 6 with controls and country-sector interacted fixed effects.

Table 1: Baseline results for non-routine cognitive (analytical and personal) indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	———— Analytical ————			———— Personal ————		
High Index	2.5290***	1.6709*	2.8334***	2.2450***	1.7544**	3.2951***
	(0.8698)	(0.9351)	(0.7622)	(0.8324)	(0.8500)	(0.6076)
t	-0.1182***	-0.0957***	-0.0818***	-0.1006***	-0.0856***	-0.0790***
	(0.0154)	(0.0137)	(0.0135)	(0.0159)	(0.0118)	(0.0117)
High Index*t	0.0500*	0.0873**	0.0410	-0.0089	0.0352	0.0129
	(0.0272)	(0.0366)	(0.0289)	(0.0275)	(0.0317)	(0.0269)
Constant	37.9281***	39.6241***	41.7552***	38.0525***	39.1187***	41.1743***
	(0.5777)	(1.2525)	(0.5693)	(0.5342)	(1.2703)	(0.5475)
Observations	21561515	16754427	16754427	21561515	16754427	16754427
R-squared	0.0193	0.1575	0.2082	0.0103	0.1530	0.2086
Controls	No	Yes	Yes	No	Yes	Yes
Country FEs	No	Yes	No	No	Yes	No
County-Sector FEs	No	No	Yes	No	No	Yes

Note: All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is 'usual' hours of work.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

High non-routine cognitive analytical and high non-routine cognitive personal jobs are both associated with higher initial hours per worker. The interaction term with the time trend is positive but only weakly significant for the first two specifications for non-routine cognitive analytical jobs. When the most stringent country-sector interaction fixed effects are included, removing more variation, the result becomes insignificant (although the result is statistically significant for most of the EU-15 countries in country-level regressions). Overall, there is some evidence that workers in highly non-routine cognitive analytical occupations work slightly more hours over time relative to other occupations with a low non-routine cognitive analytical index. In contrast,

Table 2: Baseline results for routine (cognitive and manual) indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	———— Cognitive ————			———— Manual ————		
High Index	-2.2284***	-0.2970	-0.9371***	4.9924***	2.6383***	0.9427***
	(0.4875)	(0.4780)	(0.2667)	(0.7305)	(0.4884)	(0.3129)
t	-0.1254***	-0.0878***	-0.0895***	-0.0328**	-0.0228	-0.0380***
	(0.0144)	(0.0161)	(0.0128)	(0.0137)	(0.0139)	(0.0115)
High Index*t	0.0769***	0.0215	0.0187	-0.2083***	-0.1799***	-0.1246***
	(0.0176)	(0.0171)	(0.0131)	(0.0390)	(0.0264)	(0.0192)
Constant	39.4774***	39.2672***	41.1425***	37.1057***	38.3900***	41.2568***
	(0.5409)	(1.1400)	(0.5592)	(0.4864)	(1.1607)	(0.5575)
Observations	21561515	16754427	16754427	21561515	16754427	16754427
R-squared	0.0061	0.1460	0.1946	0.0139	0.1485	0.1961
Controls	No	Yes	Yes	No	Yes	Yes
Country FEs	No	Yes	No	No	Yes	No
County-Sector FEs	No	No	Yes	No	No	Yes

Note: All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is 'usual' hours of work.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the interaction term for high non-routine cognitive personal tasks - such as managerial occupations - is not significantly different from zero across all specifications. It thus appears that such occupations are not experiencing differential trends.

Turning to the analysis of jobs with high routine characteristics, we observe a stark difference in the routine indices between routine cognitive and routine manual occupations (Table 2). Individuals working in high routine cognitive occupations have no statistically distinguishable level or trend differences in hours of work relative to others, once covariates are included. However, high routine manual occupations - those most susceptible to automation - have a strongly negative and significant trend interaction term. Such jobs are reducing their hours per worker relative to other jobs. It appears that the well-documented reduction in employment (headcount and total hours) in routine jobs is matched with employment reductions on the intensive margin too, although that appears to be driven by routine manual jobs only.

Non-routine manual jobs also exhibit contrasting patterns between physical and personal. Table 3 shows a statistically significant negative interaction trend term for high non-routine manual physical occupations, indicating declining hours relative to other occupations. By contrast, results are not statistically significant for high non-routine manual personal jobs. The latter encompass the service sectors growing (in total employment and total hours) with job polarisation. Our results do not show the same patterns for hours. Using the definition in the online programmes underlying the results in Acemoglu and Autor (2011), the interaction term becomes statistically significant when only country fixed effects are used (Appendix D, Table 20).[8]

[8]If a restriction of limiting our definition to occupations above 299 had not been imposed, the interaction term would have been positive, meaning that non-routine manual personal jobs would display increasing hours per worker in relation to other occupations scoring lower in this index. That result did not seem to be picking up trending hours in well-paid occupations categorised as highly non-routine manual personal. Such occupations include doctors, veterinarians and midwifery professionals – all jobs that require in-person, non-routine care work. To test the sensitivity of the results to these professions, we first exclude them from the analysis, or recategorise them as low non-routine manual personal, and find that the results, if anything, strengthen. In addition, we tested the results for the lower half of the wage distribution, omitting all occupations above the median wage. The interaction between the time trend in hours and the dummy for

Table 3: Baseline results for non-routine manual (physical and personal) indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	Physical			Personal		
High Index	4.1315***	1.6831***	0.5127	-4.9628***	-1.6103	-1.2700
	(0.6982)	(0.4911)	(0.3404)	(0.9497)	(1.0041)	(0.9071)
t	-0.0763***	-0.0622***	-0.0683***	-0.1110***	-0.0837***	-0.0866***
	(0.0139)	(0.0152)	(0.0123)	(0.0141)	(0.0151)	(0.0124)
High Index*t	-0.0679**	-0.0658***	-0.0449**	0.0387	0.0017	0.0045
	(0.0287)	(0.0236)	(0.0177)	(0.0305)	(0.0347)	(0.0288)
Constant	37.3183***	38.4413***	41.1664***	39.7527***	39.6616***	41.5287***
	(0.4992)	(1.1758)	(0.6041)	(0.3980)	(1.0881)	(0.5212)
Observations	21561515	16754427	16754427	21831786	16959719	16959719
R-squared	0.0197	0.1470	0.1941	0.0240	0.1483	0.1945
Controls	No	Yes	Yes	No	Yes	Yes
Country	No	Yes	No	No	Yes	No
County-Sector FEs	No	No	Yes	No	No	Yes

Note: All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is 'usual' hours of work.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, our baseline results show only some signs supporting the pattern of polarisation in the intensive margin. Hours per worker are declining across all six skill indices, but the slope varies, leading to differences in the evolution in hours per worker across jobs. On the one hand, we see a typical pattern of polarisation when comparing the evolution of hours per worker among non-routine cognitive analytical (declined less than the trend) and routine manual (declined substantially more than the trend), while the pattern for non-routine manual personal is less clear but tends to be not statistically significant. On the other hand, we do not find statistically significant results for non-routine cognitive personal and routine cognitive tasks, while hours declined more than the trend in non-routine manual physical occupations.

Aggregating into three skill categories, we find patterns consistent with polarisation in non-routine cognitive jobs, and in routine jobs. That, however, is not the case in non-routine manual jobs, as we do not find strong evidence in favour of a relative increase in personal jobs, which in any case would be offset by the decline in physical jobs. Our most robust result is thus the strong relative decline in hours per worker in routine occupations driven by routine manual jobs. Additionally, instead of a polarisation pattern we observe that hours declined more in manual jobs (routine manual and non-routine manual physical jobs).

Our results also show that a finer disaggregation of task classification is important to understand hours per worker patterns across occupations. This finding for hours per worker is consistent with the pattern of employment polarisation uncovered by Fonseca et al. (2018) for Portugal. That paper also distinguishes between routine manual and routine cognitive jobs and shows a sharp decline in routine manual employment but only a modest decline in routine cognitive employment. The authors explain the difference between the two routine jobs by the large expansion

high non-routine manual personal jobs strengthens again, suggesting that the positive interaction trend term is driven by low-paid high non-routine manual personal jobs. Such jobs are exactly the kind of in person services and care work associated with the Autor and Dorn (2013) polarisation in employment and total hours. Results available upon request.

of the service sector, which employs many workers in routine cognitive jobs.

In the following sections we explore in more detail factors that could help explain our results, beyond (or together with) polarisation associated with technical change. In addition to the analysis we will show in the next sections, we undertook a battery of robustness checks on the main results. First, we replicated all central results with an alternative measure of hours of work: actual hours worked rather than usual hours. Actual hours can vary from usual due to annual leave, sick leave, public holidays and overtime, among other reasons. On average, actual hours are lower than usual hours in levels but the trend remains comparable over time. We replicated the baseline regressions using actual hours of work and found no qualitative changes to the results. In addition, we varied the hours criterion for sample inclusion, at time including or removing observations with zero hours worked, and at others including only those who worked a minimum number of hours (e.g. 5 hours). These checks yielded broadly the same results as the baseline. Second, we implemented a variety of fixed effects, including country level, industry level and industry-country level interaction. The latter is the most stringent - by retaining only within country industry variation - and as such causes standard errors to increase for some results. The point estimates are, however, essentially unchanged - reassuringly suggesting that failing to remove country-industry fixed effects does not introduce noticeable bias (in the remaining sections we use country-industry fixed effects).

4 Potential contributing factors

Routine-biased technical change may be only one of several contributing factors to the patterns in hours per worker uncovered in our baseline results. From 1992-2016, several demographic shifts have taken place in the European labour markets. Most notable are the ageing of the workforce, the increased participation of women, and the increased level of education. In addition, international trade and global supply chains have increased over the same period. Occupations that require little face-to-face interaction have been vulnerable to offshorability, and this may in turn have affected hours of work. Related to both globalisation and technical change, changes in industrial structure and reallocation have occurred over the relatively long period covered in this paper. The distinction between occupational change (jobs and tasks) and industrial change (type of output) is thus important. Moreover, there has been an increasing trend towards part-time work. We consider the impacts of demographic change, offshorability, industrial change and trends in part-time work in turn below.

4.1 Demographic trends

We analyse separately three main demographic changes that impacted the European labour markets during the time frame of our analysis: an ageing work force, increased participation of women in the labour market and an ever-more educated workforce.

4.1.1 Age trends: ageing population

Existing work (Autor and Dorn, 2009) finds an increase in the average age of workers in shrinking industries. The outcome is likely a consequence of a standard stock-flow phenomenon – new, younger workers are less likely to enter shrinking industries while older workers, with built-up human capital, remain. From a different perspective, Moreno-Galbis and Sopraseuth (2014) argue that ageing populations can explain the increase in demand for services. Ageing could then be an additional factor that complements technological change in explaining the increase in demand for services via the change in the relative prices of goods and services, as argued by Autor and Dorn (2013). We investigate whether our main results are observed along age and cohort lines.

Descriptive statistics from our sample show that individuals work more hours, on average, as they age but there is some concavity to the age profile.

We segment first the sample on both age (at the time of survey) and date of birth. The former compares 25 year olds in 1992 with 25 year olds in 2016, while the latter tracks two different generations – those born between 1953 and 1967, ("Baby Boomers" – oldest aged 65 at end of sample) and 1968 and 1980 ("Generation X" – youngest aged 18 at start of sample) – across time. We then repeat the same regressions from specification 1 as for the baseline results. Selected tables are presented in Appendix C, Tables 11-13. Within each of the segmented samples the regression results are similar to the overall results and to each other. Put differently, the hours polarisation patterns within age and cohort groups are the same relative to each other and the overall population. The result implies that our baseline results are also observed within age group.

However, the above within-group analysis ignores any group reallocation across occupations. We also regress occupation average age on index specific intercepts and time trends. The results show that occupations with high degrees of routine manual tasks have a lower age than the average occupation but are also growing older over time, relative to other occupations. In short, those occupations have reduced hours of work but increasing average ages. The reverse is true for growing industries – those with high non-routine cognitive tasks and high non-routine personal tasks. In addition to their average hours increasing, their average age is becoming younger.

Taken together, the results suggest that while we do observe shrinking industries "getting old", as per Autor and Dorn (2009), the reallocation across occupations is not driving the hours patterns. Each group is experiencing hours-per-worker patterns trending along routinisation lines.

4.1.2 Gender: increasing female labour force participation

The past two decades have seen a substantial increase in female participation in the labour market. Women accounted for 46% of employment in 2016, up from 41% in 1992, but more impressively, they have accounted for 70% of the employment growth during this period. At the same time, they work, on average, fewer hours than men (Figure 3). A question remains as to whether the increase in female labour participation can explain patterns in hours per worker, rather than just the overall hours trends.

We estimate specification (1) for women and men separately for each of the six skill indices. The declining patterns of hours per worker across skill indices do not seem to differ substantially between men and women, but some interesting patterns emerge with the split of the sample. Selected tables are presented in Appendix C, Tables 14-16, for the specification with country-sector fixed effects. Within non-routine cognitive jobs, both women and men have a positive interaction term, meaning that hours per worker in these occupations are declining less than the overall declining trend in hours per worker, but the result is never significant. For routine cognitive tasks, there is a statistically significant positive coefficient for men only; for routine manual tasks, instead, the steep overall decline occurs for both men and women, but the coefficient is much stronger for women than it is for men. Similarly, for non-routine manual physical tasks the faster decline in hours worked per person is stronger for women than men. For high non-routine manual personal occupations the positive coefficient of the interaction term is determined by female, but remain not statistically significant. If we instead use the Acemoglu and Autor (2011) definition, then the coefficient is positive for female and negative for male and statistically significant for both (Table 21).

The decline in hours per worker for women is then an important driving force for the strong decline in hours per worker in routine manual jobs. Taking these results together one can conclude that there may be some additional composition effects from women entering the labour market in certain occupations, but within each group hours per worker patterns tend to conform with the patterns identified for the whole sample.

4.1.3 Education: increasing educational attainment

The most surprising finding of the polarisation literature was that, contrary to previous decades, technological change was not simply skill-biased, but routine-biased; as such, occupational content was a more important predictor of employment loss than skill (captured in years of education). At the same time, it remains true that most employment gains have come at the occupations mostly typical of the highest skilled categories. Educational attainment was steadily increasing over our sample period. Here we examined whether higher educational attainment is behind our baseline results, or whether our baseline results are also observed within each educational category. We split the sample across three education categories: individuals with low education have achieved a lower secondary school education or less; medium education refers to senior secondary school qualification or some tertiary education; and high education refers to an undergraduate degree or above. We then estimate specification 1 for each category for each of the six skill indices. As before, this approach does not take into account between group changes but is only suggestive of within group patterns.

The stratification of our sample into three education categories sheds further light on our baseline results. For the non-routine cognitive tasks we find no statistically significant results, meaning that within each group hours per worker decline at broadly the same rate as for other task indices (Table 17). More importantly – our main result -, the strong decline in routine manual jobs is not driven by education. Hours per worker are declining faster in routine manual jobs than in other jobs for all education groups (Table 18). By contrast, education does play a role in the observed decline in hours per worker in non-routine manual physical jobs. The estimated decline is driven by high education workers (Table 19). For non-routine manual personal tasks, results are not statistically significant but the coefficient turns negative for high-education workers. With the Acemoglu and Autor (2011) definition, there is a relative increase in hours per worker for low and medium education while hours per worker decline for workers with high education (Table 22).

4.2 Offshorability

Technological progress, particularly in the area of information and communication, has made it easier to outsource tasks previously performed by middle-skilled workers. In particular, jobs that require little face-to-face interaction, or other on-site requirements, are more at risk of outsourcing. Blinder and Krueger (2013) estimated that about 25% of jobs in the United States could be offshored. Oldenski (2014) found that offshorability has contributed to relative employment gains among high-skilled and relative losses in middle-skilled workers. Goos et al. (2014) have found that offshorability is a contributing, albeit second-order, driver of employment polarisation.

To investigate the impact of offshorability on hours of work, we match the measure of offshorability created by Acemoglu and Autor (2011) to the EU-LFS dataset using the same series of crosswalks for our six earlier task measures.[9] The index measures the potential for offshoring in an occupation based on the task requirements, rather than the actual degree of offshoring. Analysing the relationship between the offshorability index and average wage we conclude that the potential for offshorability cuts across the entire wage distribution: the quadratic relationship between the offshorability index and average wages is essentially flat with an R-squared value of only 4%. Similar to the analysis for the task skill indices, we regress hours per worker on an intercept and time trend specific to highly offshorable occupations. Errors are clustered at the country-industry level and a variety of fixed effects and controls are used. The key results, given in Table 4, conform

[9] Measures of offshorability can vary widely and there is no consensus about the ideal measure. For example, Blinder and Krueger (2013) report three measures of offshorability based on microdata: one self-reported, another being a combination of self-reported measures made internal consistent, and a last and preferable measure by the authors which is based on the assessment of the coders trained by the authors. Using a different approach Firpo et al. (2011) construct three measures based on O*NET. They consider that occupations are more offshorable if: 1) they require little face-to-face communication; 2) they do not require on-site presence; 3) they do not require decision making. Our measure of offshorability based on Acemoglu and Autor (2011) is more closely correlated with the second measure of Firpo et al. (2011).

Table 4: Baseline results for offshorability index

	(1)	(2)	(3)
	Hours per worker		
High Index	-0.4611	1.4272***	0.7517*
	(0.5150)	(0.5145)	(0.3980)
t	-0.0990***	-0.0606***	-0.0699***
	(0.0144)	(0.0148)	(0.0112)
High Index*t	-0.0040	-0.0522**	-0.0375**
	(0.0224)	(0.0228)	(0.0171)
Constant	38.8962***	38.9168***	41.0480***
	(0.5409)	(1.1347)	(0.5263)
Observations	21561515	16754427	16754427
R-squared	0.0039	0.1469	0.1941
Controls	No	Yes	Yes
Country FE	No	Yes	No
Country-Sector FE	No	No	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Offshorability is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the offshorability index.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to the hours of work polarisation narrative once the full set of controls are added: occupations that have a high degree of offshorability, known to be associated with wage and employment polarisation, have decreasing hours per worker relative to less offshorable occupations. This shows up as a negative and significant coefficient interaction term between time and high offshorability.

In sum, occupations that are highly exposed to technological change and globalisation are experiencing declining average hours. Our results support the view that the intensive margin of employment (hours per worker) seems to be an important adjustment margin for such occupations.

4.3 Industrial change

Another important driver of hours per worker could be changing industrial structure, whereby rising sectors tend to be characterised by lower average work hours than contracting sectors. If that is the case, our framework is simply capturing the fact that these rising sectors have a higher composition of expanding skills than contracting skills (i.e. at the poles rather than the middle), and not necessarily the results of divergence across skills per se. While it is not possible to fully disentangle these effects, we attempt to shed light into this issue by separating the within- and between-effects at the sectoral level. In other words, we compare the evolution of average hours from 1992 to 2016 within each 1-digit sector to the shift of employment between sectors, using a standard shift-share analysis.

As the sectoral classification of LFS changed from NACE1 to NACE2 in 2008, it is not straightforward to perform a decomposition for the whole sample, so we instead consider the two subperiods. For the 1992-2007 period, out of a fall of 4% in average (usual) hours worked (from 38.8 to 37.2), 2.8% was attributed to the within-sector component, around 70% of the total. Results for the 2008-2016 period are very similar: approximately 72% of the average (usual) hours decline from

37.1 to 36.3 (1.96%) is a result of a fall within sectors, and only 27% from sectoral shifts. Taking the whole period together, and matching NACE2 to NACE1 sectors (at the letter level) gives a very similar picture, as can be seen in Table 5, Panel A.

Table 5: Sectoral changes of hours worked

Panel A: Shift-share decomposition

Period	Total % change	Within	Between	Interaction	Absolute change	Initial period	Final period
1992-2007	-4.02	-2.82	-0.88	-0.29	-1.56	38.76	37.20
2008-2016	-1.96	-1.41	-0.54	-0.02	-0.73	37.12	36.39
1998-2016	-4.59	-3.41	-0.98	-0.20	-1.75	37.78	36.39
1992-2016	-6.11	-4.19	-1.20	-0.71	-2.37	38.76	36.39

Panel B: Correlation of sectoral hours changes with tasks

	NR Cognitive		Routine		NR Manual		Offshore
	Analytical	Personal	Cognitive	Manual	Physical	Personal	
1992-2007	0.748	0.348	0.420	-0.147	-0.097	0.279	-0.019
2008-2016	0.876	0.506	0.317	-0.307	-0.203	0.449	-0.048
1998-2016	0.756	0.378	0.349	-0.113	-0.063	0.282	-0.059
1992-2016	0.682	0.290	0.289	-0.084	-0.013	0.185	0.007

Overall, the bulk of the hours decline can be accounted for by a decline within each sector, rather than industrial change. This result provides further support to our hypothesis that technological change, manifesting through occupational polarisation, also drives the hours decline. Another way to see this is to relate hours decline for each sector with our task content measures. Panel B of Table 5 shows the correlation of the change in usual hours worked over different time intervals with the sectoral average of each of our content measures (over the whole period covered). The change in hours worked is most highly correlated with the non-routine cognitive analytical task content, implying that sectors with a high content of such tasks showed the highest increase in hours (equivalently, the lowest reduction). The opposite holds for sectors characterised by a high concentration of routine manual and non-routine manual physical tasks. Indeed, for the 2008-2016 period, the only industries with increasing average usual hours were the ICT sector, utilities, and education, all considered part of the knowledge economy. The ICT sector and education have much higher than average share of occupations with high non-routine analytical content.

4.4 Work-time status

Another potential driver of our results may be a rise in part-time employment, a prominent feature of labour markets in Europe during the period studied, as the share of part-time workers in the labour force in the EU-15 countries grew from only 16% in 1995 to 24% in 2016. Of course, the rise of part-time work is itself, at least to some extent, part and parcel of lower average hours. A sufficient reduction in hours may be such that individuals switch from full- to part-time status. That is true whether there is a pre-defined threshold or whether work-time status is self-reported (as it is in the LFS). The forces then that have allowed for workers to work fewer hours on average may have also partially contributed to the rise of part-time work (together of course with changing societal norms, such as higher female participation).

In Table 6, we repeat our main exercise separately for full- and part-time workers, shown in Panels A and B respectively. For both highly non-routine cognitive occupations, the results are diametrically antithetical. There is a relative increase in hours for part-time workers in these occupations, relative to no effect for full-time workers. This is consistent with the idea that some individuals work fewer hours and drop off the full-time group, raising average hours in the part-time group. The same pattern holds for occupations with high non-routine manual personal

Table 6: Full versus part-time status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hours per worker						
	NR Cognitive		Routine		NR Manual		Offshore
	Analytical	Personal	Cognitive	Manual	Physical	Personal	
Panel A - FT workers							
High Index	1.843***	2.330***	-1.871***	0.087	0.314	-0.824***	-0.911***
	(0.403)	(0.461)	(0.262)	(0.243)	(0.298)	(0.303)	(0.218)
t	-0.032***	-0.033***	-0.046***	-0.023*	-0.029**	-0.039***	-0.049***
	(0.008)	(0.008)	(0.013)	(0.012)	(0.013)	(0.011)	(0.012)
High Index * t	0.008	0.008	0.027**	-0.037***	-0.026**	0.002	0.027***
	(0.017)	(0.020)	(0.013)	(0.011)	(0.012)	(0.013)	(0.007)
Constant	53.37***	53.03***	52.97***	53.19***	52.98***	53.29***	53.08***
	(0.51)	(0.50)	(0.57)	(0.56)	(0.58)	(0.56)	(0.55)
Panel B - PT workers							
High Index	0.039	-0.0687	1.131***	2.866***	1.479***	-0.245	1.594***
	(0.468)	(0.404)	(0.310)	(0.471)	(0.535)	(0.346)	(0.331)
t	0.0112	0.003	0.028*	0.075***	0.044***	0.011	0.051***
	(0.014)	(0.012)	(0.015)	(0.012)	(0.012)	(0.011)	(0.015)
High Index * t	0.081***	0.066***	-0.010	-0.206***	-0.106***	0.049**	-0.075***
	(0.022)	(0.022)	(0.018)	(0.026)	(0.030)	(0.020)	(0.019)
Constant	11.44***	11.30***	11.02***	10.16***	10.86***	10.98***	10.49***
	(0.86)	(0.86)	(0.86)	(0.84)	(0.81)	(0.82)	(0.87)

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. All regressions include controls for age, educational level, sex, size of firm, proxy interview, marital status, and country-sector fixed effects. Industry controls are 1 digit NACE. High Offshorability is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the offshorability index. FT regressions have 13,362,253 observations and PT regressions have 3,344,858 observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

content. As shown in the next section, these three task groups are the ones that have gained in employment shares over the past two decades.

By contrast, for the two main losers in employment, routine manual and non-routine manual physical-intensive occupations, average hours exhibit a relative decline for both full- and part-time workers, although the magnitude is much stronger for part-time. For routine cognitive-intensive occupations, in turn, average hours show a relative increase in full-time workers, but no effect for part-time workers. Finally, for the offshorable occupations, the index-trend interaction term is positive and significant for full-time, and negative and significant for part-time.

Overall, for growing occupations, the decline in average hours is driven by a combination of lower hours for full-time workers and a rising share of part-time workers, likely also comprised of formerly full-time workers who work sufficiently less to reclassify their work-time status.[10] For shrinking occupations, both types of workers work fewer hours. The reduction of average hours attributable to lower hours for full-time workers is around ⅓, depending on the initial date.[11] It should be noted that these figures most likely underestimate the within effect. The fluid boundary between part- and full-time work and the likely truncation below of the distribution of hours for full-timers, there is a likely underestimate of the true reduction of full-time hours. Indeed, not only have average hours for part-timers risen, but this increase is driven by higher hours at the upper half of the distribution (75^{th} percentile).

[10] In the absence of panel data, this hypothesis is untestable. However, the hours decline for full-time workers comes from a compression at the right tail; average hours for those working less than 50 hours a week have not changed from 2004 to 2016. Assuming the decline is not limited to the top, it is possible that such behaviour occurs.

[11] This number is constructed comparing the actual reduction in average hours versus the one that would have occurred had the employment shares of full- and part-time workers remained constant. A shift-share analysis to gauge the importance of each margin is not very informative, since average hours for part-time workers rose during the period studied.

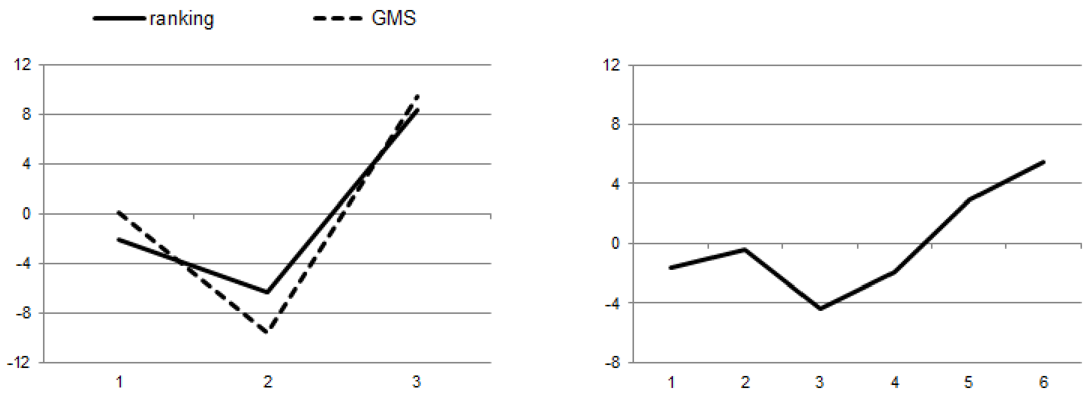
5 Employment and hours polarisation?

We have shown that falling hours per worker in Europe exhibit some of the main patterns of RBTC, with large reductions in hours worked for routine manual and some increase in non-routine cognitive analytical (both in relative terms). At the same time, other patterns we found do not necessarily conform to the trichotomy of abstract, routine and manual tasks. Routine cognitive tasks have exhibited little, if any, reduction in hours worked, and non-routine manual physical tasks have exhibited a reduction as large as routine manual. Here we examine how the higher-dimension approach we take compares with what is already established in the literature.

The dashed line in the left panel of Figure 5 replicates the analysis of Goos et al. (2014) (henceforth GMS), who show the evolution of employment shares for four low, nine middle and eight high-paying occupations (based on 2-digit ISCO88 classification). The pattern closely resembles the familiar U-shaped pattern identified in GMS qualitatively.[12] The solid line in the left panel repeats the same exercise, but instead of manually classifying occupations into categories, we group occupations into three quantiles, based on wage ranking in 2008, normalised for each country, with almost identical results.[13] The right panel instead uses a breakdown into six quantiles, and shows that the bottom ⅙ of the wage distribution also experiences a small reduction in employment.

Figure 5: Change in employment share by wage category, % share of total employment, 1992-2010

(a) Three categories (b) Six categories



Source: EU-LFS and authors' calculations. GMS uses the categorization of Goos et al. (2014) into low-, middle- and high-paying occupations. Ranking refers to the classification into quantiles by occupation wage ranking in 2008. The left chart is based on a breakdown into three quantiles, and the right chart into six. Employment is measured by aggregate hours.

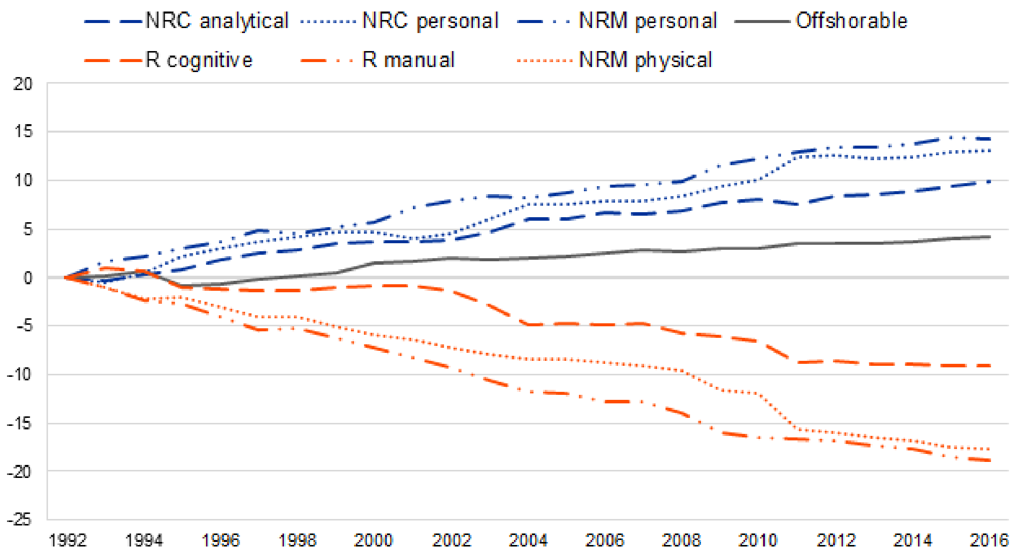
We then examine whether the patterns identified for average hours also hold for total employment. Figure 6 shows the task content of the mean job in the sample, from 1992-2016, for each of our 6 categories, plus offshorability, standardized to zero in 1992. Our aim is to identify the overall employment trends without imposing any structure on the classification (as we do in our main analysis where we classify the top third of each task-intensity into our high-content categories). The results are quite stark: the decline of routine manual (and secondarily cognitive) and non-routine manual physical content in the job-pool is substantial. Conversely, equally substantial is the increase in the non-routine cognitive personal (and secondarily analytical) and non-routine

[12] Some quantitative differences remain. Namely, we find no increase at the lower end, while GMS do. There are two possible reasons for this discrepancy. First, our 1992 sample does not include Austria, Belgium, Finland and Sweden; if instead our initial year is 1998, the first year of data for all our 15 countries, the pattern is identical to GSM. Second, GSM use a different sample for Germany. Note that we also include codes 61 and 92 (agricultural and fisheries workers) to the low-wage category for GMS. Without these sectors there is indeed an increase in employment at the low end.

[13] We use EU-SILC for occupational wages, which start in 2004 but have good coverage for all countries in 2008. We do not expect the ranking to fluctuate substantially, and the similarity with the GMS classification is reassuring.

manual personal tasks in the content of the average job. While the increasing categories are in line with the trichotomous classification, the decline in non-routine manual physical content is not; there seems to be a stark difference in the employment trends within the non-routine manual category, for physical and personal, for employment levels (shown here) and average hours worked. This is also reflected in the right panel of Figure 5; the bottom category, which has exhibited a fall in employment, has a high content of both routine manual and non-routine manual physical tasks.

Figure 6: Evolution of task content, 1992-2016 (1992=0)



Source: EU-LFS and authors' calculations. Each line shows the task content of the mean job in the sample, for each task.

The common trends for total employment and average hours across each occupational task index is summarised in Table 7, where we show the evolution of total employment shares and average hours for the occupations with a high content of each task, as defined previously. We see that while average hours fell across tasks, they fell more for those tasks that suffered employment losses. It should be noted that when calculating the total employment shares, we fix the task content cut-offs at their levels in 1992; we cannot let the cut-off vary by year, otherwise there would not be meaningful variation in employment shares across time. On the other hand, the cut-off for average hours does vary by year; since fewer jobs had, for instance, high non-routine cognitive analytical content in 1992 than in 2016, using a fixed cut-off may classify into the high non-routine cognitive analytical content category jobs that we would not necessarily consider as possessing this attribute.[14] Conversely, shrinking occupations, such as those with high routine manual content may not be classified as such using a fixed cut-off, even though they would meet conventional criteria to be classified as such.[15]

We then consider how average hours evolve by wage categories, to gauge whether the U-shaped pattern of employment holds. The left panel of Figure 7 repeats the analysis of Figure 5 for the GMS classification and the ranking based on wages by occupation in 2008, for three quantiles. We see that in this case, the choice of classification does play a role in the results. In the GMS classification, there is a hump-shaped response: the fall in hours is higher for the lowest-paid occupations, then for the highest, and the smallest reduction is shown by the middle categories. However, using a quantile-based ranking using three quantiles, we see an inverse L-shaped pattern, with the losses in average hours being monotonically negatively related to wages. As such,

[14] Examples include medical technicians, technical/medical sales professionals, credit and loan officers, insurance and sales representative, broadcasting technicians, travel consultants, and electrical installers and servicers.

[15] Examples include bank tellers and related clerks, cashiers and ticket clerks, vehicle repairers.

Table 7: Evolution of employment share and average hours

	NR Cognitive analytical	NR Cognitive personal	Routine cognitive	Routine manual	NR Manual physical	NR Manual personal	Offshorable
	Share of total employment in jobs with high content of each task						
1992	31.5	33.0	30.6	32.6	33.6	15.6	30.1
1998	34.9	37.1	30.2	31.1	32.4	16.5	31.8
2007	39.2	41.2	28.7	27.8	29.3	16.4	33.3
2016	38.7	43.0	30.2	23.1	24.6	19.6	39.6
1992-2010	8.9	10.2	-2.7	-6.9	-6.1	1.6	3.4
1992-2016	7.2	10.0	-0.4	-9.5	-9.0	4.0	9.5
	Average hours in jobs with high content of each task						
1992	40.3	39.1	37.2	40.9	40.9	35.4	38.0
1998	40.1	39.9	36.9	40.3	40.5	34.3	37.8
2007	39.7	39.3	36.8	39.3	39.4	32.8	37.0
2016	38.4	36.9	36.0	36.1	37.8	33.7	35.8
1992-2010	-0.9	-0.1	-0.8	-3.8	-2.1	-2.5	-0.9
1992-2016	-1.9	-2.2	-1.2	-4.8	-3.2	-1.7	-2.2

while employment may be polarising, with more jobs created at high- and low-wage occupations, average hours are falling more in low-wage occupations.

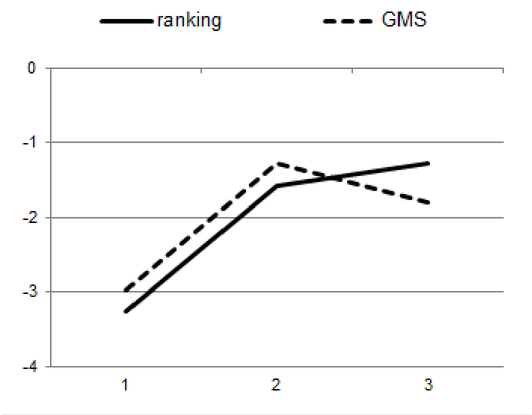
As it appears that the results for average hours are sensitive to the wage classification, we further consider the distribution of hours losses using a six quantile wage grouping in the right panel of Figure 7, which shows an inverse U-shaped pattern of average hours losses until the 83^{rd} percentile and lower losses thereafter. The overall conclusion remains with finer categorisations, namely that, by and large, there is no polarisation in hours losses, but rather lower losses at higher wages. That is, while employment gains are characterized by a U-shaped pattern, hours losses are characterized by an inverse L-shaped pattern.

Since the literature typically considers total hours as a measure of total employment when considering polarisation, it follows that this pattern is at least partially driven by changes in the patterns of average hours. An interesting exercise is to consider whether the polarisation pattern would differ were it not for the change in the hours pattern. Figure 8 repeats the exercise of Figure 5 but now considers the wage ranking classification for an aggregate employment measure based on heads, as well as total hours. While both of these broadly follow the same pattern, the main differences are in the low- and high-wage categories. For the low-wage category, the change in hours-based employment share is almost 2 percentage points (pp) lower than in the heads definition, reflecting the fact that average hours have fallen for routine manual and non-routine manual physical tasks. For the high category, higher average hours reflect a gain in employment share of over 1 pp more with the total hours measure.[16] The six-quantile ranking reveals that the additional gain at the top with the total hours measure is driven by the very top, where the employment share gain is over 1.2pp higher with the total hours measure.

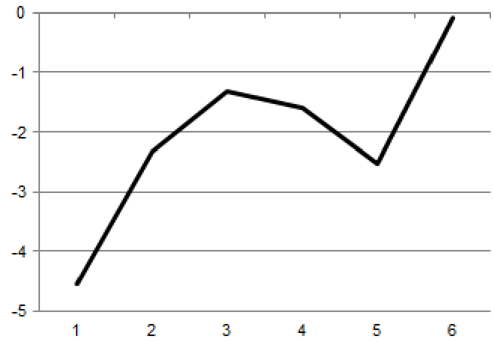
[16] Absolute differences are less important, as they are quite sensitive to the classification used. With the updated version of the GMS classification defined above, a 2.1pp gain in employment share for the low group with the heads definition is 0.1 with the total hours definition. With the original GMS classification these figures are 3.5 and 1.9, respectively.

Figure 7: Change in average hours by wage category, 1992-2010

(a) Three categories



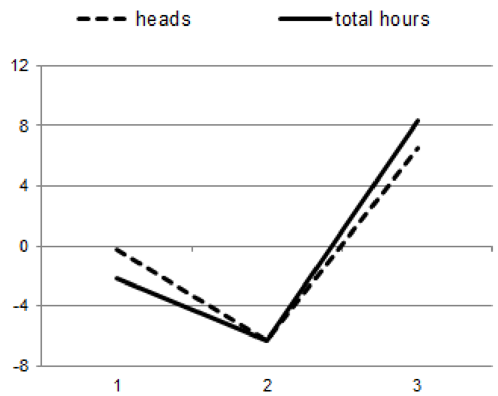
(b) Six categories



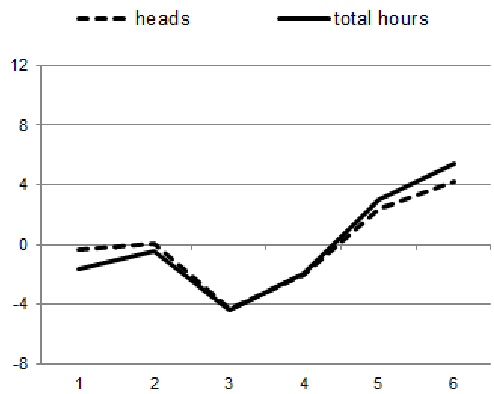
Source: EU-LFS and authors' calculations. GMS use the categorization of Goos et al. (2014) into low-, middle- and high-paying occupations. Ranking refers to the classification into quantiles by occupation wage ranking in 2008. The left chart is based on a breakdown into three quantiles, and the right chart into six. Employment is measured by aggregate hours.

Figure 8: Employment growth by wage category, % share of total employment, 1992-2010

(a) Three categories



(b) Six categories



Source: EU-LFS and authors' calculations. The left chart is based on a breakdown into three quantiles, and the right chart into six. Total hours refers to employment being measured by aggregate hours, while heads uses a headcount measure.

6 Country comparisons

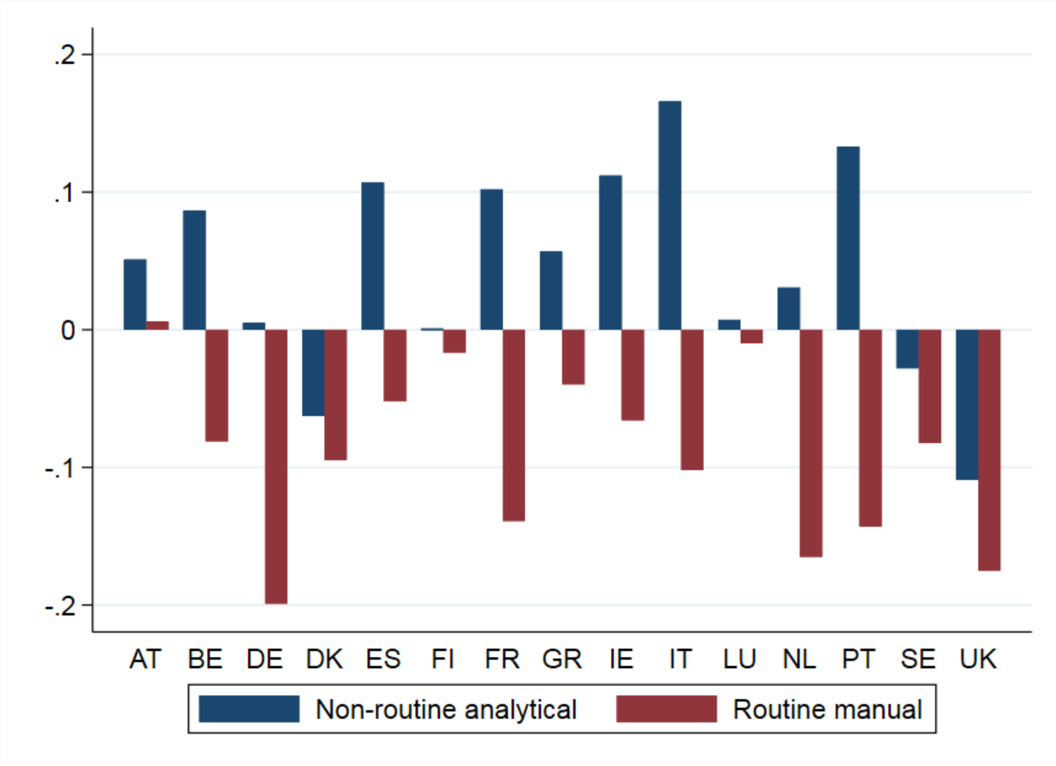
In this section we analyse country specific patterns on the polarisation of hours worked per person. First, we analyse whether the results obtained for the aggregation of the EU-15 countries hold for most of the individual countries. Then, we analyse whether the patterns uncovered for the EU-15 countries are also observed for the United States.

6.1 Individual EU-15 countries

The level and developments of hours worked per person across the EU-15 countries are very heterogeneous (e.g. Ohanian and Raffo 2012). Thus, it is important to carry out a country level analysis to determine whether the results obtained for the EU-15 are common to most individual countries or are driven just by a few. We carry out the same analysis as for our baseline results to each of the EU-15 countries. Here we focus on our baseline results relating to non-routine cognitive analytical jobs and routine manual jobs. Table 23 in Appendix E shows the results for all six indices and offshorability.

The results described in Section 4 are broadly consistent across countries. A visual representation is very helpful to summarise the main results by country. Hours per worker in routine manual jobs are declining faster than trend hours in all countries with the exception of Austria. For non-routine cognitive analytical jobs, hours per worker are increasing in most countries with the exception of Denmark, Sweden and the UK, while estimates are not statistically significant for Germany, Finland and Luxembourg (Figure 9).

Figure 9: Country specific results



Source: EU-LFS and authors' calculations. All results statistically significant with exception of DE, FI and LU for non-routine analytical tasks.

This results show that our baseline results are observed for a large set of countries and not driven by just a set of a few countries. In particular, the decline in hours per worker in routine manual jobs is very robust. However, more research is necessary to uncover the reasons for different patterns across countries for the other indices.

6.2 United States

We extend our analysis to compare the EU-15 hours per worker across occupational task indices with the US labour market. The US has not experienced the large decline in average hours of work since the Great Recession, in contrast to Europe. It has, however, exhibited well documented employment and wage polarisation. The lack of a decline in average hours does not, by itself, preclude hours polarisation: routine jobs may reduce their average hours but be outweighed by high skilled and low-skilled hours increases.

We repeat our analysis for the US using the Current Population Survey (CPS) – the US equivalent to the EU-LFS. Interestingly enough, the baseline results presented in Tables 8, 9 and 10 uncover the polar opposite to the EU-15 results. Highly routine occupations - both routine cognitive and routine manual - have experienced increasing hours trends relative to other occupations. This is in direct contrast to the strongly negative routine manual results for EU-15 countries. Also contrasting the EU results are the negative and significant interaction trends for high skilled, non-routine analytical occupations and the lower-skilled non-routine manual personal occupations. Both of these had positive hours trends relative to other occupations in the EU.[17]

The results are robust to a variety of clustering and fixed effects specifications (industry, state, industry-state interactions), and sample inclusion criteria (strictly positive hours worked, zeros, and minimum hours).

Table 8: US results for non-routine cognitive (analytical and personal) indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	Analytical			Personal		
High Index	5.0834***	3.2788***	3.3540***	5.0665***	3.7217***	4.3557***
	(0.1891)	(0.1291)	(0.1190)	(0.2217)	(0.1697)	(0.1508)
t	-0.0445***	-0.0641***	-0.0498***	-0.0471***	-0.0675***	-0.0494***
	(0.0135)	(0.0099)	(0.0076)	(0.0168)	(0.0122)	(0.0086)
High Index*t	-0.0296**	-0.0241**	-0.0430***	-0.0230	-0.0186	-0.0287**
	(0.0141)	(0.0104)	(0.0090)	(0.0170)	(0.0141)	(0.0127)
Constant	37.6631***	33.1511***	36.0557***	37.6752***	33.0519***	36.1736***
	(0.1971)	(0.4420)	(0.4716)	(0.2306)	(0.4857)	(0.4691)
Observations	1683460	1641808	1641808	1683460	1641808	1641808
R-squared	0.0288	0.0902	0.1082	0.0294	0.0951	0.1179
Controls	No	Yes	Yes	No	Yes	Yes
State FEs	No	Yes	Yes	No	Yes	Yes
Sector FEs	No	No	Yes	No	No	Yes

All regressions weighted with CPS weights, and standard errors clustered at state-sector level. Controls: age, educational level, sex, size of firm, marital status. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index in that year. Sample is individuals working non-zero hours in the CPS sample from 1995-2016.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The contrasting results between the US and Europe may not be too surprising. We posit that the differences are possibly due to employment regulations governing firms' labour adjustment. US employment law does not contain the same labour protections, particularly with regard to firing restrictions, as European employment law. As a result, it is less costly for American firms to reduce headcounts of workers in shrinking industries. European firms, by contrast, must perhaps

[17] For non-routine manual personal tasks the results for the US comprise all occupations while for the EU-15 they concern only ISCO codes above 299.

Table 9: US results for routine (cognitive and manual) indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	Cognitive			Manual		
High Index	-2.3558***	-1.2937***	-1.9043***	-1.4834***	-1.1819***	-1.8206***
	(0.1261)	(0.1341)	(0.1077)	(0.2475)	(0.1832)	(0.1415)
t	-0.0791***	-0.1009***	-0.0868***	-0.0582***	-0.0843***	-0.0850***
	(0.0134)	(0.0098)	(0.0062)	(0.0104)	(0.0087)	(0.0063)
High Index*t	0.0723***	0.0606***	0.0387***	0.0115	0.0181	0.0390***
	(0.0101)	(0.0101)	(0.0083)	(0.0167)	(0.0132)	(0.0114)
Constant	40.2408***	33.5315***	36.9692***	39.9215***	34.0500***	37.9422***
	(0.1917)	(0.4641)	(0.4692)	(0.1524)	(0.4564)	(0.4770)
Observations	1683460	1641808	1641808	1683460	1641808	1641808
R-squared	0.0039	0.0824	0.1034	0.0029	0.0826	0.1026
Controls	No	Yes	Yes	No	Yes	Yes
State FEs	No	Yes	Yes	No	Yes	Yes
Sector FEs	No	No	Yes	No	No	Yes

All regressions weighted with CPS weights, and standard errors clustered at state-sector level. Controls: age, educational level, sex, size of firm, marital status. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index in that year. Sample is individuals working non-zero hours in the CPS sample from 1995-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: US results for non-routine manual (physical and personal) indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	Personal			Physical		
High Index	1.9452***	1.2127***	1.9347***	0.4366**	0.1581	-0.5700***
	(0.1628)	(0.1434)	(0.1397)	(0.1810)	(0.1573)	(0.1341)
t	-0.0092	-0.0568***	-0.0571***	-0.0457***	-0.0748***	-0.0690***
	(0.0130)	(0.0083)	(0.0052)	(0.0133)	(0.0093)	(0.0066)
High Index*t	-0.1323***	-0.0676***	-0.0357***	-0.0264**	-0.0177*	-0.0130
	(0.0114)	(0.0100)	(0.0097)	(0.0128)	(0.0103)	(0.0088)
Constant	38.7755***	32.8718***	36.4226***	39.2958***	33.1101***	37.3402***
	(0.1794)	(0.4541)	(0.4667)	(0.1963)	(0.4720)	(0.4928)
Observations	1683460	1641808	1641808	1683460	1641808	1641808
R-squared	0.0019	0.0822	0.1032	0.0008	0.0818	0.1013
Controls	No	Yes	Yes	No	Yes	Yes
State FEs	No	Yes	Yes	No	Yes	Yes
Sector FEs	No	No	Yes	No	No	Yes

All regressions weighted with CPS weights, and standard errors clustered at state-sector level. Controls: age, educational level, sex, size of firm, marital status. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index in that year. Sample is individuals working non-zero hours in the CPS sample from 1995-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

rely more on intensive margin hours adjustments. An additional hypothesis possibly underlying the results is the marketisation of home production which occurred earlier in the US and explains much of the EU-US employment and hours gap (e.g. Freeman and Schettkat 2005).

7 Conclusion

In this paper we analysed whether hours per worker were an additional margin of employment polarisation. Our results suggest a relation between hours per worker and employment polarisation patterns. The level and, more importantly, the trend in hours per worker vary considerably across each occupational task index. This is a new fact that has not been previously considered in the polarisation literature.

We find large declines in routine manual jobs – precisely the occupations most negatively affected by employment polarisation from RBTC. Additionally, we find a lower decline in hours per worker for non-routine cognitive analytical jobs, which are growing through polarisation. At the same time, hours per worker declined significantly more than the trend for non-routine manual physical occupations and that decline has not been compensated by an increase in hours per worker in non-routine manual personal jobs. However, for non-routine manual jobs the occupational task indices also do not give the typical polarisation patterns for total employment. Overall, instead of a polarisation pattern our results show that hours per worker declined more in manual jobs (routine manual and non-routine manual physical).

Our results remain robust to estimation across age, gender and education groups, although the intensity may vary and some subtle patterns may emerge. For example, the decline in hours per worker in routine manual jobs and non-routine manual physical jobs is stronger for women. The decline in hours per worker occurs mostly within sectors. The increase in part-time seems important. However, that increase may be partly a consequence of the decline in hours per worker, as the classification into full-time and part-time is self-reported.

Using a wage ranking of occupations instead of the occupational task indices, the decline in hours per worker is monotonically related to wages. First, the results we obtained for employment changes using a wage ranking is a U-shaped curve, in line with the empirical literature. However, when the wage ranking is divided in six quantiles instead of three, we observe that the bottom quantile experiences employment losses similar to the middle. Second, hours per worker appear monotonically related to wages: using three quantiles of the wage ranking of occupations we observe a sharper decline in the bottom quantile, a milder decline in the middle and almost no decline at the top; using six quantiles for the wage ranking of occupations we observe an inverse U-shaped pattern for most of the distribution, but with lower decrease in hours per worker in the top quantile. Thus, while employment gains are characterised by a U-shaped pattern, the decline in hours per worker is characterised by an inverse L-shaped pattern.

Taken together, these results suggest that patterns in hours per worker exacerbate the impact of employment polarisation on wage inequality. High-skilled workers increased their fraction of employment and work relatively more hours, medium-skilled workers saw a decline in the share of employment and a decline in hours per worker and low-skilled workers saw a substantial decrease in hours per worker. The analysis based on the wage ranking of occupations makes this point even clearer: hours declined significantly more in low-paying occupations.

The patterns in hours per worker uncovered for the EU-15 aggregate are observed in most of each of the individual countries. The results for the United States are fundamentally different. We tentatively suggest that labour market institutions can play a role. In addition, the earlier marketisation of household production in the United States can additionally help to explain the differences found between the EU-15 and the Unites States.

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Appendix A O*NET tasks used to construct indices

Sourced from Acemoglu and Autor (2011): O*NET task measures used in this paper are composite measures of O*NET importance scales of work abilities, work activities, work context and skills:

Non-routine cognitive: Analytical

- 4.A.2.a.4 Analyzing data/information
- 4.A.2.b.2 Thinking creatively
- 4.A.4.a.1 Interpreting information for others

Non-routine cognitive: Interpersonal

- 4.A.4.a.4 Establishing and maintaining personal relationships
- 4.A.4.b.4 Guiding, directing and motivating subordinates
- 4.A.4.b.5 Coaching/developing others

Routine cognitive

- 4.C.3.b.7 Importance of repeating the same tasks
- 4.C.3.b.4 Importance of being exact or accurate
- 4.C.3.b.8 Structured v. Unstructured work (reverse)

Routine manual

- 4.C.3.d.3 Pace determined by speed of equipment
- 4.A.3.a.3 Controlling machines and processes
- 4.C.2.d.1.i Spend time making repetitive motions

Non-routine manual physical

- 4.A.3.a.4 Operating vehicles, mechanized devices, or equipment
- 4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls
- 1.A.2.a.2 Manual dexterity
- 1.A.1.f.1 Spatial orientation

Non-routine manual interpersonal – adapted from Acemoglu and Autor (2011).

- 2.B.1.a Social Perceptiveness
- 4.C.1.a.2.l Face-to-face discussions (Added by current authors)
- 4.A.4.a.5 Assisting and Caring for Others (Added by current authors)

Offshorability

- 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.C.1.a.2.l Face-to-face discussions (reverse)
- 4.A.1.b.2 Inspecting Equipment, Structures, or Material (reverse)
- 4.A.3.a.2 Handling and Moving Objects (reverse)
- 4.A.3.b.4 0.5*Repairing and Maintaining Mechanical Equipment (reverse)
- 4.A.3.b.5 0.5*Repairing and Maintaining Electronic Equipment (reverse)

Appendix B Top 10 of occupations for each skill index, ordered

Non-routine Cognitive Analytical		Non-routine Manual Personal	
212	Mathematicians, actuaries and statisticians	112	Managing Directors and Chief Executives
261	Legal professionals	342	Sports and Fitness Workers
112	Managing Directors and Chief Executives	133	Information and Communications Technology Services Managers
252	Database specialists and systems administrators	122	Sales, Marketing and Development Managers
211	Physicists, chemists and related professionals	143	Other Services Managers
251	Software and applications developers and analysts	134	Professional Services Managers
225	Veterinarians	222	Nursing and Midwifery Professionals
231	University and higher education teachers	233	Secondary Education Teachers
216	Architects, Planners, Surveyors and Designers	322	Nursing and Midwifery Associate Professionals
214	Engineering professionals	132	Manufacturing, Mining, Construction and Distribution Managers
Routine Cognitive		**Routine Manual**	
523	Cashiers and Ticket Clerks	814	Rubber, Plastic and Paper Products Machine Operators
431	Numerical Clerks	834	Mobile Plant Operators
421	Tellers, Money Collectors and Related Clerks	815	Textile, Fur and Leather Products Machine Operators
422	Client Information Workers	752	Wood Treaters, Cabinet-makers and Related Trades Workers
324	Veterinary Technicians and Assistants	812	Metal Processing and Finishing Plant Operators
251	Software and Applications Developers and Analysts	817	Wood Processing and Papermaking Plant Operators
413	Keyboard Operators	816	Food and Related Products Machine Operators
441	Other Clerical Support Workers	811	Mining and Mineral Processing Plant Operators
541	Protective Services Workers	961	Refuse Workers
821	Assemblers	813	Chemical and Photographic Products Plant and Machine Operators

Non-routine Manual Physical		Non-routine Manual Personal	
833	Heavy Truck and Bus Drivers	322	Nursing and Midwifery Associate Professionals
835	Ships' Deck Crews and Related Workers	342	Sports and Fitness Workers
834	Mobile Plant Operators	531	Child Care Workers and Teachers' Aides
723	Machinery Mechanics and Repairers	514	Hairdressers, Beauticians and Related Workers
931	Mining and Construction Labourers	532	Personal care workers in health services
831	Locomotive Engine Drivers and Related Workers	341	Legal, social and religious associate professionals
741	Electrical Equipment Installers and Repairers	541	Protective services workers
811	Mining and Mineral Processing Plant Operators	325	Other health associate professionals
961	Refuse Workers	511	Travel attendants, conductors and guides
711	Building Frame and Related Trades Workers	516	Other personal services workers

Non-routine Manual Personal (Acemoglu and Autor definition)		Offshoring	
233	Secondary Education Teachers	952	Street and related sales and service workers
222	Nursing and Midwifery Professionals	431	Numerical Clerks
322	Nursing and Midwifery Associate Professionals	251	Software and applications developers and analysts
232	Vocational Education Teachers	212	Mathematicians, actuaries and statisticians
342	Sports and Fitness Workers	241	Finance professionals
261	Legal professionals	112	Managing Directors and Chief Executives
235	Other teaching professionals	261	Legal professionals
263	Social and religious professionals	215	Electrotechnology engineers
511	Travel attendants, conductors and guides	264	Authors, journalists and linguists
531	Child Care Workers and Teachers' Aides	331	Financial and mathematical associate professionals

Appendix C Additional tables

C.1 Age

Table 11: Baseline regressions with sample stratified along age lines - non-routine cognitive

	(1)	(2)	(3)	(4)
	Hours per worker			
	—- Analytical —-		—– Personal —–	
	Younger	Older	Younger	Older
High Index	2.9047***	4.2682***	3.3435***	4.4218***
	(0.6380)	(0.8704)	(0.5133)	(0.7733)
t	-0.0833***	-0.0324*	-0.0731***	-0.0313**
	(0.0130)	(0.0167)	(0.0118)	(0.0154)
High Index * t	0.0304	0.0187	-0.0215	-0.0105
	(0.0244)	(0.0321)	(0.0263)	(0.0336)
Constant	41.6335***	50.7438***	40.8304***	49.7384***
	(0.6122)	(1.7956)	(0.6120)	(1.8354)
Observations	3741843	2209524	3741843	2209524
R-squared	0.1326	0.1614	0.1294	0.1583
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Baseline regressions with sample stratified along age lines - routine

	(1)	(2)	(3)	(4)
	Hours per worker			
	—- Cognitive —-		—- Manual —	
	Younger	Older	Younger	Older
High Index	-2.0383***	-2.2006***	2.0963***	3.1891***
	(0.3613)	(0.3745)	(0.3921)	(0.5554)
t	-0.1118***	-0.0547***	-0.0624***	0.0180
	(0.0151)	(0.0144)	(0.0126)	(0.0144)
High Index * t	0.0623***	0.0390**	-0.1003***	-0.2008***
	(0.0175)	(0.0170)	(0.0224)	(0.0309)
Constant	40.7816***	50.1531***	39.4683***	48.6488***
	(0.6457)	(1.9100)	(0.6980)	(1.9206)
Observations	3741843	2209524	3741843	2209524
R-squared	0.1182	0.1428	0.1167	0.1422
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Baseline regressions with sample stratified along age lines - non-routine manual

	(1)	(2)	(3)	(4)
	Hours per worker			
	—– Physical —–		—– Personal —-	
	Younger	Older	Younger	Older
High Index	2.4243***	2.8672***	-2.3102***	-3.3677***
	(0.4614)	(0.6288)	(0.8280)	(1.1271)
t	-0.0832***	-0.0299*	-0.0904***	-0.0644***
	(0.0128)	(0.0163)	(0.0130)	(0.0131)
High Index * t	-0.0492**	-0.0728***	-0.0035	0.0650
	(0.0208)	(0.0260)	(0.0299)	(0.0407)
Constant	38.7660***	48.1199***	41.3585***	50.8499***
	(0.7630)	(1.9367)	(0.6556)	(2.0225)
Observations	3741843	2209524	3794069	2228632
R-squared	0.1197	0.1430	0.1196	0.1432
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2 Gender

Table 14: Baseline regressions with sample stratified along gender lines - non-routine cognitive

	(1)	(2)	(3)	(4)
	Hours per worker			
	—- Analytical —-		—- Personal —-	
	Female	Male	Female	Male
High Index	2.9570***	2.4960***	2.6978***	3.5570***
	(1.0006)	(0.5438)	(0.7407)	(0.5402)
t	-0.0752***	-0.0877***	-0.0827***	-0.0773***
	(0.0206)	(0.0105)	(0.0174)	(0.0106)
High Index * t	0.0542	0.0326	0.0307	0.0020
	(0.0385)	(0.0198)	(0.0309)	(0.0242)
Constant	35.7355***	42.6126***	34.9511***	42.1078***
	(0.9896)	(0.5160)	(1.0092)	(0.5239)
Observations	7800573	8953854	7800573	8953854
R-squared	0.1572	0.1138	0.1532	0.1194
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 15: Baseline regressions with sample stratified along gender lines - routine

	(1)	(2)	(3)	(4)
	Hours per worker			
	—- Cognitive —-		—- Manual —-	
	Female	Male	Female	Male
High Index	0.1940	-1.7092***	2.8824***	-0.2462
	(0.3842)	(0.2155)	(0.4888)	(0.2425)
t	-0.0710***	-0.0996***	-0.0179	-0.0619***
	(0.0188)	(0.0127)	(0.0149)	(0.0135)
High Index * t	-0.0096	0.0419***	-0.2684***	-0.0515***
	(0.0188)	(0.0119)	(0.0320)	(0.0129)
Constant	34.8137***	42.1432***	34.4231***	42.5968***
	(0.9307)	(0.5634)	(0.9209)	(0.5379)
Observations	7800573	8953854	7800573	8953854
R-squared	0.1415	0.1016	0.1465	0.1012
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Baseline regressions with sample stratified along gender lines - non-routine manual

	(1)	(2)	(3)	(4)
	Hours per worker			
	—- Physical —-		—- Personal —-	
	Female	Male	Female	Male
High Index	1.9800***	-0.3299	-0.8496	-1.3211
	(0.4901)	(0.2741)	(0.7523)	(0.9165)
t	-0.0616***	-0.0732***	-0.0802***	-0.0869***
	(0.0159)	(0.0147)	(0.0158)	(0.0123)
High Index * t	-0.1089***	-0.0267*	0.0049	-0.0122
	(0.0314)	(0.0141)	(0.0296)	(0.0236)
Constant	34.3051***	42.6849***	35.2386***	42.2921***
	(0.9264)	(0.5703)	(0.7979)	(0.5367)
Observations	7800573	8953854	7846974	9112745
R-squared	0.1420	0.1001	0.1422	0.0987
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.3 Education

Table 17: Baseline regressions with sample stratified along education - non-routine cognitive

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	——— Analytical ———			——— Personal ———		
	Low	Mid	High	Low	Mid	High
High Index	4.9619***	2.8143***	2.8265***	4.6360***	4.0738***	3.3599***
	(1.1206)	(0.6866)	(0.6825)	(0.5753)	(0.7001)	(0.6549)
t	-0.0939***	-0.0849***	-0.0228	-0.1000***	-0.0789***	-0.0016
	(0.0160)	(0.0112)	(0.0176)	(0.0148)	(0.0115)	(0.0117)
High Index * t	0.0065	0.0244	0.0229	-0.0095	-0.0497	-0.0024
	(0.0467)	(0.0250)	(0.0239)	(0.0252)	(0.0322)	(0.0283)
Constant	39.3707***	44.6373***	43.6233***	39.1210***	44.0347***	42.7427***
	(0.5843)	(0.4598)	(0.9699)	(0.5668)	(0.4626)	(0.8291)
Observations	4945745	7384674	4424008	4945745	7384674	4424008
R-squared	0.2629	0.2107	0.1815	0.2620	0.2116	0.1820
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Baseline regressions with sample stratified along education - routine

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	——— Cognitive ———			——— Manual ———		
	Low	Mid	High	Low	Mid	High
High Index	-0.4515	-1.2496***	-2.2887***	0.9152**	-0.1222	-0.6108
	(0.3016)	(0.2867)	(0.5821)	(0.3760)	(0.2943)	(0.4560)
t	-0.1278***	-0.1185***	-0.0218	-0.0372**	-0.0653***	-0.0140
	(0.0139)	(0.0144)	(0.0238)	(0.0163)	(0.0141)	(0.0172)
High Index * t	0.0677***	0.0601***	-0.0102	-0.1185***	-0.0634***	-0.1003***
	(0.0167)	(0.0146)	(0.0280)	(0.0238)	(0.0188)	(0.0235)
Constant	40.3039***	44.8883***	42.9483***	39.4692***	45.0335***	44.2822***
	(0.5724)	(0.4366)	(1.0153)	(0.6274)	(0.4210)	(0.9760)
Observations	4945745	7384674	4424008	4945745	7384674	4424008
R-squared	0.2473	0.1975	0.1742	0.2484	0.1990	0.1684
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Baseline regressions with sample stratified along education - non-routine manual

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours per worker					
	——— Physical ———			——— Personal ———		
	Low	Mid	High	Low	Mid	High
High Index	-0.0638	-0.4136	-0.3730	-0.7455	-1.3270	-2.2299***
	(0.3555)	(0.3428)	(0.4946)	(1.2181)	(0.8603)	(0.6462)
t	-0.1168***	-0.0916***	-0.0160	-0.1180***	-0.1019***	-0.0250
	(0.0164)	(0.0132)	(0.0174)	(0.0130)	(0.0151)	(0.0184)
High Index * t	0.0187	0.0021	-0.0698***	0.0697	0.0287	-0.0422
	(0.0216)	(0.0171)	(0.0232)	(0.0430)	(0.0270)	(0.0272)
Constant	39.8746***	44.9661***	44.3864***	40.1727***	45.0066***	43.5932***
	(0.6365)	(0.4649)	(0.9950)	(0.5512)	(0.4394)	(1.0307)
Observations	4945745	7384674	4424008	4976773	7463390	4519556
R-squared	0.2468	0.1972	0.1667	0.2463	0.1972	0.1719
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D Non-routine manual personal Definition of Acemoglu and Autor (2011)

Table 20: Baseline

	(1)	(2)	(3)	(4)
	Hours per worker			
High Index	-3.1303***	-0.9984**	-0.5236	-0.5120
	(0.5991)	(0.4760)	(0.4660)	(0.4615)
t	-0.1036***	-0.0850***	-0.0860***	-0.0878***
	(0.0130)	(0.0133)	(0.0112)	(0.0108)
High Index*t	-0.0171	0.0140	0.0411**	0.0267
	(0.0267)	(0.0225)	(0.0208)	(0.0198)
Constant	39.3242***	39.3638***	42.3381***	41.3666***
	(0.4231)	(1.1248)	(0.7431)	(0.5124)
Observations	21831786	16959719	16959719	16959719
R-squared	0.0132	0.1462	0.1705	0.1932
Controls	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	No
Sector FE	No	No	Yes	No
Country-Sector FE	No	No	No	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Age and Gender

	(1)	(2)	(3)	(4)
	Hours per worker			
	—Age—		—Gender—	
	younger	older	female	male
High Index	-1.0136**	-1.6268**	-0.7760	0.1131
	(0.4987)	(0.6999)	(0.6304)	(0.3008)
t	-0.0910***	-0.0581***	-0.0863***	-0.0865***
	(0.0120)	(0.0114)	(0.0149)	(0.0120)
High Index * t	0.0035	0.0477	0.0510*	-0.0299*
	(0.0205)	(0.0332)	(0.0268)	(0.0170)
Constant	40.8567***	50.2047***	35.0262***	42.1684***
	(0.6234)	(1.9759)	(0.8779)	(0.5394)
Observations	3794069	2228632	7846974	9112745
R-squared	0.1140	0.1396	0.1416	0.0971
Controls	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Education and FT/PT Status

	(1)	(2)	(3)	(4)	(5)
	Hours per worker				
	—Education—			—Status—	
	low	mid	high	FT	PT
High Index	0.1550	-0.4186	-1.0393*	-0.3378	0.0239
	(0.5415)	(0.3101)	(0.5302)	(0.2438)	(0.4780)
t	-0.1145***	-0.1026***	-0.0248	-0.0378***	0.0189
	(0.0126)	(0.0125)	(0.0182)	(0.0108)	(0.0120)
High Index * t	0.1034***	0.0644***	-0.0634**	-0.0088	0.0380
	(0.0316)	(0.0217)	(0.0260)	(0.0127)	(0.0274)
Constant	40.0030***	44.7952***	43.4015***	53.1620***	10.9220***
	(0.5262)	(0.4017)	(1.0088)	(0.5503)	(0.8640)
Observations	4976773	7463390	4519556	13555103	3356901
R-squared	0.2474	0.1967	0.1683	0.1465	0.1369
Controls	Yes	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes	Yes

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E Country-level results

Table 23: Country results - coefficient on interaction term only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NRCA	NRCP	RC	RM	NRMP	NRMI	Off
AT	0.0511***	−0.0303***	0.0360***	0.0061*	0.0733***	−0.0560***	−0.0699***
BE	0.0867***	0.0825***	−0.0355***	−0.0811***	−0.0146***	−0.0535***	−0.0631***
DE	0.0051	−0.0686***	0.0465***	−0.1990***	−0.0538***	0.0713***	−0.1150***
DK	−0.0627***	−0.0344***	−0.0217***	−0.0947***	0.0248***	0.0417***	−0.1120***
ES	0.1070***	0.0097***	0.0136***	−0.0520***	0.0250***	−0.1010***	−0.0401***
FI	0.0005	−0.0791***	0.0390***	−0.0166**	0.0411***	−0.0129*	−0.0366***
FR	0.1020***	0.1020***	−0.0320***	−0.1390***	−0.0383***	−0.0062*	−0.0654***
GR	0.0569***	0.0257***	0.0636***	−0.0397***	−0.0292***	0.0031	0.0222***
IE	0.1120***	0.0238***	0.0259***	−0.0658***	−0.0420***	−0.1360***	0.0979***
IT	0.1660***	0.1080***	0.0390***	−0.1020***	−0.0143***	−0.0447***	−0.0417***
LU	0.0072	−0.0358***	−0.0061	−0.0099*	0.0292***	−0.0879***	0.0172***
NL	0.0306***	−0.0416***	−0.0464***	−0.1650***	−0.1150***	0.0242***	0.0033
PT	0.1330***	0.1020***	0.0520***	−0.1430***	−0.0712***	0.0405***	0.0227***
SE	−0.0282***	−0.1010***	−0.0110***	−0.0823***	−0.0085***	0.0038	−0.0552***
UK	−0.1090***	−0.0763***	0.0088***	−0.1750***	−0.1130***	0.0972***	−0.0450***

All regressions weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. The coefficient is from the interaction term of the High Index with the trend. High Index is a dummy that takes value 1 if the occupation is above the 66^{th} percentile for the index. Sample is individuals working non-zero hours in EU-15 countries from 1998-2016.
NRCA=Non-routine cognitive analytical, NRCP=Non-routine cognitive personal, RC=Routine cognitive, RM=Routine manual, NRMP=Non-routine manual - physical,
NRMI=Non-routine manual - personal, Off=Offshorability
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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