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Routine-Biased Technological Change Does Not Always Lead to Polarisation: Evidence from 10 OECD Countries, 1995-2013

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Routine-biased technological change does not always lead to polarisation: Evidence from 10 OECD countries, 1995 – 2013

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Abstract

This article deals with a central paradox in the occupational polarisation literature: most scholars accept that technological change is biased against routine-intensive occupations, but in many countries, we do not see the pattern of occupational polarisation that the theory usually predicts. I argue and show empirically using a dataset of 10 OECD countries between 1995 and 2013 that technological change is both routine-biased and skill-biased, but that the result of routine-biased technological change may be occupational upgrading rather than polarisation. This is due to differences in occupational routine-wage hierarchies: only where routine occupations cluster around the middle of the wage distribution are we likely to see polarisation. Where routine occupations are concentrated near the bottom of the wage hierarchy, upgrading occupational change is the norm. Based on research on the US, the former has been widely assumed, but it does not hold true in all countries. Overall, this article shows that much previous work on routine-biased technological change and polarisation was built on premises that do not travel well. This underscores the importance of comparative research for building and testing robust general theories.

Keywords: technological change; employment change; polarization; occupational upgrading; routine-bias; occupational wage

1. Introduction

According to the routine-biased technological change (RBTC) hypothesis, in recent years, machines and software have taken over codifiable and repetitive tasks and made redundant many routine workers. Coupled with the argument (or often, as I shall argue, assertion) that these jobs are disproportionately found around the median of the wage distribution, this leads to a predicted pattern of job polarisation: a decline in relative employment in medium-wage routine jobs, accompanied by the growth of high-paying (cognitive non-routine) jobs and low-paying (manual non-routine) service occupations.[1] The widely accepted narrative is thus that RBTC is partly responsible for a growing polarisation of both employment and wages in rich countries. Yet, we are in danger of accepting an incomplete narrative of what happened during the last 30-or-so years.

This article argues that RBTC, alongside continuing skill-biased technological change (SBTC), leads to polarising employment change in some countries and upgrading in others. I propose a refined theoretical model that explains how the relationship between routine tasks and occupational wages shapes which pattern of employment change emerges as a result of RBTC. My analyses, based on 10 OECD countries between 1995 and 2013, first establish that while polarisation has occurred in some countries, others have seen upgrading, contradicting the original RBTC hypothesis and corroborating recent sociological research. I argue that countries differ with regard to where in the wage distribution the most routine-intensive occupations are located and that different patterns of employment change are primarily a function of this: occupational polarisation tends to occur only in countries where routine occupations cluster near the middle of the wage distribution. Where routine occupations command the lowest relative wages, occupational upgrading follows. I go on to show that routine-wage schedules are relatively stable over time, with the pattern conducive to polarisation more prevalent in richer countries.

This article thus bolsters the findings of a recent literature in economic sociology which calls into question a simplistic generalisation of the routine-bias hypothesis, but does so from a different angle. It argues that the mechanism identified in the economics literature does not always lead to polarisation if country-specific characteristics are taken into account. The article proceeds as follows. Section 2 provides a systematic overview of the existing theoretical and empirical literature and section 3 sets out my theoretical argument. Section 4 introduces the data and shows some broad trends. This is followed by an analysis of the task-wage schedules in section 5, and a conclusion in section 6.

[1] Throughout the article, polarisation is used in this way to refer to polarisation of employment in terms of occupational wages. Upgrading is used analogously. Unless otherwise noted, I refer to employment trends in terms of occupations rather than, say, social classes.

2. Literature Overview

2.1 The SBTC and RBTC Models

Investigating the surge in wage inequality in the US throughout the 1980s, economists in the early 1990s found that a substantial part of the increase could be explained by the growing relative demand for more educated, skilled workers (Katz & Murphy, 1992). The skill-biased technological change (SBTC) hypothesis was born and generated substantial research interest in the following years (see, e.g., Berman, Bound, and Griliches 1994; Autor, Katz, and Krueger 1998; Berman, Bound, and Machin 1998). The RBTC hypothesis was likewise formulated based on the US experience in a seminal article by Autor, Levy, and Murnane (2003; hereafter ALM) in an attempt to better understand “what it is that computers do” (p. 1280). They find that computer capital substitutes for workers in performing routine tasks and complements them in nonroutine tasks. The predictions derived from the RBTC hypothesis describe the polarising employment and wage trends in the US in the 1990s and 2000s quite well (Acemoglu & Autor, 2011; Autor, Katz, & Kearney, 2008) and it has since become the predominant way of thinking about technological and occupational change in developed countries in economics.

Sociologists, by contrast, have traditionally looked at social inequalities and changes in the employment structure through the lens of social class (see, e.g., Goldthorpe, Llewellyn, & Payne, 1987; Oesch, 2006). Mostly concerned with social mobility rather than wage inequality, this literature generally shows a long-lasting process of class upgrading, which has however slowed down in recent years (see, e.g., Bukodi & Goldthorpe, 2019 and Goldthorpe, 2013 for evidence for Britain). Technology, while recognised as a driver of changes in the class structure, has been less central to this literature. However, sociologists have increasingly adopted elements of the SBTC framework as a complementary perspective to the traditional class-based analyses (see, e.g., Fernández-Macías, 2012; Oesch, 2013; Oesch & Rodriguez Menes, 2011). This includes a move to occupations as the unit of analysis and an explicit consideration of the factors that determine changes in the occupational structure, including technological progress. The concept of biased technological change has thus arrived in the sociological literature as well.

As the RBTC hypothesis evolved out of the SBTC model, both share a similar logical structure. Technological change itself is often taken to be spurred by the decline of the real price of (computer) capital, which can be assumed to be comparable across developed countries (Autor et al., 2003; Koeniger, Leonardi, & Nunziata, 2007; Spitz-Oener, 2006). Often, this technological change is assumed to be exogenous, but it can also be modelled as an endogenous process (Acemoglu and Autor 2011). The first key difference is implied in the names of the theories: they differ in terms of the occupational attributes that they deem most relevant. In the case of SBTC, it is worker characteristics that matter. Higher skills, usually operationalised with educational attainment, are said to be complemented by new technologies, and occupations which require more skilled workers are expected to expand. If educational expansion does not keep pace in the race with technology, wage premia are expected to increase, giving rise to growing wage inequality (Goldin & Katz, 2008).

In the RBTC model, the focus is on occupational tasks rather than worker characteristics. In the reasoning of ALM, computer capital substitutes for workers in activities that can be accomplished by following explicit rules (these activities ALM call “routine tasks”) and complements workers in carrying out “non-routine” tasks such as problem-solving and complex communications. Thus, employment is expected to contract in occupations where workers perform mostly routine tasks. Employment should grow in non-routine cognitive occupations – essentially high-skilled occupations – where the aforementioned complementarities lead to increased demand, and in simpler non-routine occupations, either through the reallocation of former routine workers or through spillover effects from an increased demand for personal services by the growing group of high-skilled workers (Mazzolari & Ragusa, 2013).

The predictions of the SBTC and RBTC theories regarding employment changes follow from their assumptions on the position of key occupational groups (high-skill and high-routine, respectively) in the wage hierarchy. This can be called the task-wage distribution or task-wage schedule. The SBTC model juxtaposes two types of workers (high-skill and low-skill) and assumes a linear positive relationship between skills and wages. Thus, SBTC predicts straightforward occupational upgrading (Goldin & Katz, 2008). The RBTC argument, on the other hand, distinguishes between low-, medium-, and high-routine workers. While ALM do not develop this aspect in their 2003 paper, Goos & Manning (2007) argue that routine occupations often require medium levels of skill and training and therefore cluster around the middle of the wage distribution. With these medium-wage occupations contracting, the RBTC hypothesis predicts employment polarisation and can rationalise declining wages for medium-wage workers (Acemoglu & Autor, 2011).

Sociologists who have adopted this occupation-based approach point out some important theoretical weaknesses of the models employed by labour economists and refine their predictions. One such weakness is the absence of labour market institutions from the models, even though a large literature, including in other strands of economics, finds these to be important determinants of employment and wage trends (Koeniger et al., 2007; Kristal & Cohen, 2015; Parolin, 2021). Indeed, the prediction of pervasive employment polarisation is predicated on other factors such as unions and employment regulation being either similar across countries or inconsequential. This, of course, stands in stark contrast to the arguments of power resource theory which identifies institutional differences as one of the main drivers of employment and wage trends (Brady, 2009; Korpi, 1983). Furthermore, studies in economics rarely discuss how RBTC relates to other macro trends such as the emergence of the “care economy” or immigration (Dwyer, 2013; Oesch, 2015). Yet, these developments affect the demand for and supply of labour largely beyond the direct effect of technology. Lastly, the RBTC model has been criticised for its sweeping predictions with little regard to country differences (Fernández-Macías, 2012). In light of the cross-sectional variation regarding institutions, immigration, and other factors, it appears unlikely that RBTC would lead to pervasive polarisation regardless of context. Based on these arguments, several sociologists criticise what they consider an overemphasis on technology in some of the labour economics literature. These theoretical disagreements are also reflected in the empirical findings of studies investigating the SBTC and RBTC hypotheses, as the next section shows.

2.2 Empirical Evidence on Employment Change and Technological Change

A multitude of empirical studies in economics and sociology investigate recent changes in the employment structure in relation to SBTC and RBTC.[2] This literature can be summarised as follows. Economists generally agree that there has been widespread polarisation of the employment structure, although there are different views to which degree this is attributable to RBTC. Sociologists, on the other hand, contest the pervasiveness of polarisation, and where they do find evidence for it, question whether RBTC is the only – or even the primary - explanation.

In addition to their landmark 2003 study, ALM have been involved in a number of follow-up articles with other authors on the United States (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Autor et al., 2008). These studies, using data from the Current Population Survey (CPS) with sample sizes reaching into the millions or census data, and measures of occupational tasks based on the Dictionary of Occupational Titles (DOT), invariably report a polarising employment structure. Numerous other economists have also contributed to the evidence regarding employment polarisation in the US, zooming in on different aspects of RBTC based on the ALM framework. For example, Mazzolari & Ragusa (2013) identify increased demand from high-earners for personal services as a contributor to employment growth at the bottom of the wage distribution. Thus, they close one of the gaps in the original framework, which had clear predictions for employment trends at the top and in the middle, but not at the bottom of the wage distribution. Another insightful study by Cortes (2016) tracks the occupational mobility and wage patterns of routine workers in a polarising labour market, thus zooming in on the individual-level ramifications of RBTC. Overall, economists have produced a wealth of evidence that the employment structure in the US has polarised, partly as a result of RBTC. Importantly, the presence of polarisation in the US is not disputed by sociologists – in fact, the sociologists Wright & Dwyer (2003) were among the first to document emerging polarisation in the US in the 1990s. However, both in their 2003 paper and in later studies, Wright and Dwyer argue that RBTC is not the full story behind employment polarisation, pointing to the importance of the care economy in explaining employment growth in low-paying jobs (Dwyer, 2013; Dwyer & Wright, 2019). Their argument is related to that of Mazzolari & Ragusa (2013), showing that RBTC is compatible with processes such as the emergence of the care economy.[3]

Looking beyond the US, the evidence for RBTC-induced polarisation is less clear-cut. A number of economists find employment polarisation in Germany and the United Kingdom, the best-known examples being Spitz-Oener (2006) for Germany and Goos & Manning (2007) for the UK. These studies apply the approach of ALM in different settings and find similar patterns with regard to polarisation. Importantly, Spitz-Oener (2006) also presents direct evidence that computerisation contributed to occupational task changes, offering a look inside the "black

[2] Table A3 in appendix C provides an overview of studies of employment change, categorised by their scope (single-country study or comparative [case] study) and the patterns of employment change which they find.

[3] Table A3 in appendix C also shows that older studies of the US from the 1990s show the pattern of occupational upgrading that is predicted by SBTC, illustrating the shift during the 1990s from upgrading to polarisation (Katz & Murphy, 1992). Finally, two recent studies of the US labour market by Beaudry, Green, and Sand (2014, 2016) find a reversal in the demand for skilled workers as the IT revolution reached maturity around 2000, resulting in downskilling and indicating that the nature of employment change may yet again be changing.

box" of technological change. However, other studies that find similar employment patterns question whether the mechanism is really RBTC. For example, Salvatori (2018) finds that there was job polarisation in the UK, but that RBTC alone cannot explain it. For Germany between 1979 and 1999, Rendall and Weiss (2016) find that even though there was employment polarisation, the regions with the least routine employment had the highest rates of computer adoption, in apparent contradiction to the hypothesis that computers replace routine employment. They point out that the German apprenticeship system produces highly productive routine workers, making it costly to replace them with machinery. This varieties of capitalism-inspired explanation highlights the importance of institutions for employment outcomes. This suggests that even though economists agree that there was polarisation in the UK and Germany, there are doubts whether this can be fully attributed to RBTC.

In addition to these individual-country studies, a small number of comparative studies find a pervasive pattern of employment polarisation (Goos, Manning, & Salomons, 2014; Michaels, Natraj, & Van Reenen, 2014; OECD, 2015). Especially the article on 16 European countries between 1993 and 2010 by Goos, Manning, and Salomons (2014, hereafter GMS) is widely cited in the economics literature and beyond. This paper has been so influential because it purports to show that the processes that have been identified in the US are also at work across Europe, resulting in pervasive job polarisation. However, sociologists have received this study and its claims with scepticism. Fernández-Macías (2012) criticises an earlier version of the study (Goos, Manning, & Salomons, 2009), and shows that its findings depend on a number of questionable methodological choices, only some of which are addressed in the final paper.[4] Thus, when Fernández-Macías (2012) looks at an almost identical sample and time period (EU-15 between 1995 – 2007), he finds job polarisation only in a handful of countries, while a majority show upgrading. Although Germany and the UK are among the countries exhibiting polarisation, this study suggests that polarisation is far from pervasive.

Following the same approach as Fernández-Macías (2012), Eurofound (2014, 31) finds that the overall pattern of employment change in Europe in 2011 – 2013 "was one of upgrading with some polarisation", with more upgrading changes for women and polarisation for men. Eurofound (2017), looking at the period from 2011 – 2016, finds more of the same diversity. Even though these studies only cover a relatively short period that is characterised by exceptional economic circumstances, their findings cast further doubt on the narrative of straightforward polarisation. Fernández-Macías & Hurley (2017) in an important paper go beyond documenting these differences and argue that routine occupations in fact cluster near the bottom of the wage distribution and that RBTC therefore should lead to the same upgrading employment change as SBTC. Where polarisation does occur, they posit that it is not primarily due to technological factors.

[4] The three key differences Fernández-Macías (2012) lists relate to the definition of jobs, the job quality rankings, and the construction of job quality tiers. These are well substantiated critiques which he argues drive the differences in results. Not listed is the exclusion of agricultural and public sector-heavy occupations, even though Fernández-Macías (2012) uses the full working population in his analyses. Only the job quality (i.e., wage) rankings are country-specific in GMS's 2014 paper, and in some of the analyses jobs are defined as occupation-industry cells, but the problems of the uneven job quality tiers and excluded occupations remain. Thus, the 2012 critique for the most part still applies to the 2014 paper.

A number of case studies add to this evidence, even though some of their detailed findings differ. For example, using national labour force surveys, Oesch & Rodriguez Menes (2011) find polarisation in the UK and upgrading in Germany, Spain, and Switzerland in the 1990 – 2008 time frame. Oesch (2013), too, finds dominant upgrading in Denmark, Germany, Spain, and Switzerland in the 1990s and 2000s, and polarisation only in Britain. Oesch & Piccitto (2019) use the EU-LFS for the period from 1992 to 2015 and arrive at very similar results: polarisation in the UK and upgrading in Germany, Spain and Sweden. Finally, E. C. Murphy & Oesch (2018) investigate long-term (1970 – 2010) labour market trends in Ireland and Switzerland and likewise find no evidence for a simple story of upgrading morphing into polarisation. However, while sociologists agree that polarisation has not been as common as claimed by Goos et al. (2014), the example of Germany shows that there is still no consensus as to which countries have experienced it. Using the same data source (EU-LFS), Fernández-Macías (2012) finds polarisation between 1995 and 2007, and Oesch & Piccitto (2019) upgrading between 1992 and 2015. The different time periods certainly play a role, as may other details of the operationalisation.[5]

Generally, sociological studies critical of the technological change literature point to other factors such as the increased labour supply of educated women, low-skill immigration, and labour market institutions as alternative explanations for the observed diverse patterns of employment change. These more nuanced theories already present a serious challenge to simplistic accounts of technological change. With few notable exceptions (e.g. Fernández-Macías & Hurley, 2017), the technical assumptions behind the RBTC model have not been the focus of this literature. This article, on the other hand, argues that even in the absence of an effect from the aforementioned factors, polarisation would not always follow. Its argument is that technological change is indeed biased against routine occupations, but that the rigid assumption that routine occupations are medium-wage has prevented the RBTC model from providing a generalisable account of recent employment trends.

3. A Refined Model of RBTC

The refined model that I propose in this article takes issue with two central claims of the RBTC literature. First, I challenge the notion that RBTC has supplanted SBTC. As sociologists have previously recognised, SBTC and RBTC are not alternatives; rather they are related yet distinct processes that may unfold simultaneously and with varying intensity in different countries (Oesch, 2013; Oesch & Rodriguez Menes, 2011). My model incorporates this insight. Secondly, the assumption that countries' routine-wage schedules are effectively identical does not hold: routine occupations are not everywhere medium-wage (Fernández-Macías & Hurley, 2017),

[5] For example, an interesting recent working paper shows that in the US, the polarising pattern is stronger when agricultural workers are excluded (Cerina, Moro, & Rendall, 2021). Such details are not often discussed but may significantly influence results. For example, Goos et al. (2014) do not provide a justification for excluding agricultural and public sector-heavy occupations, and even papers critical of their approach do not discuss the implications of this practice (Fernández-Macías, 2012). Another area where methodological differences are common is the treatment of non-standard work.

but neither are they always near the bottom, and thus the same technological change may lead to different outcomes based on a country's existing wage hierarchy. Incorporating these insights yields a more encompassing and realistic account of technological and employment change. As I show in the empirical section below, it can explain most of the deviations from the standard RBTC model, but unlike some of the criticisms in the sociological literature, it does so while retaining the basic logic of the framework.

RBTC and SBTC are not mutually exclusive processes: they operate on different occupational characteristics and may have distinct effects on the employment structure. Yet, economists often argue that RBTC has supplanted SBTC, while some sociologists consider lack of polarisation evidence in favour of SBTC over RBTC. This either-or approach does not seem warranted. Instead, I argue that skill-biased upgrading is likely to continue alongside RBTC. For example, Caines, Hoffmann, and Kambourov (2017) show that in the US technological change between 1980 – 2005, and hence employment and wage growth, was biased towards complex tasks in an apparent corroboration of the SBTC hypothesis beyond its original core period in the 1980s. Balsmeier and Woerter (2019) report similar findings for Swiss firms in recent years. Furthermore, many more recent additions to the OECD have not yet reached the level of economic maturity of, say, the US or Germany. Hence, economies like Chile and the Eastern European countries still had some catching up to do in the 1990s and 2000s, which constitute the core period of my analyses. A broader theory of technological change and employment must be able to accommodate these countries – developed but not at the technological frontier – as well. This study is one of the few to include these countries, and insofar as SBTC usually precedes RBTC, we should expect them to experience SBTC during the period of analysis. These considerations suggest that SBTC should not be discarded as part of a general theory of technology and labour market dynamics. I thus follow Oesch (2013) who is one of the few scholars who explicitly investigate SBTC alongside RBTC, but with a larger and more diverse group of countries.

The argument that RBTC results in occupational polarisation is based on the empirical observation that in the US and UK around 1980, routine occupations tended to be medium-wage (Autor et al., 2008; Goos & Manning, 2007). However, there is no iron law which dictates that medium-wage occupations are particularly routine-intensive; unlike with SBTC, there is no strong theoretical expectation where routine occupations should be in the wage hierarchy (Oesch & Piccitto, 2019). Indeed, using refined and updated measures of routine-intensity Fernández-Macías & Hurley (2017) have found that on average in Europe, low-paying occupations tend to be the most routine-intensive, thus directly contradicting Goos et al. (2014). This indicates that the hump-shaped routine-wage curve cannot be as ubiquitous as assumed in the labour economics literature. However, Fernández-Macías & Hurley (2017) do not look at routine-wage distributions in individual countries and it remains an open empirical question how similar they are. That they are identical appears unlikely: Eurofound (2014) shows that there is a significant degree of variation in occupational wage rankings in Europe. It is therefore possible that RBTC primarily affects low-wage occupations in one country and medium-wage occupations in another, resulting in different employment trends when occupations are ranked by their average wage. Hence, a generalisable theory of RBTC should not rely on a common routine-wage schedule across countries for its predictions. Yet, to my knowledge, no other study explicitly takes this into account.

My refined theory of RBTC can be visualised as in figure 1. It assumes that an exogenous force, for example a decline in the price of computer capital, leads to both a rise in the demand for workers performing complex tasks (SBTC) and lower demand for routine workers (RBTC). The key word here is “and”, as previous theories usually focus on only one of these avenues. The crucial novel element is the explicit consideration of the task-wage relationship on a country-by-country basis. In all countries, complexity increases monotonically with the average occupational wage, as depicted on the left of panel B. However, the same is not true for routine task intensity (RTI) and wages. In some countries, RTI is strictly decreasing with increasing wages as posited by Fernández-Macías & Hurley (2017, middle of panel B), while in others, the curve is concave with the highest RTI values for medium-wage occupations as in Autor et al. (2003, right of panel B).

Whether a country experiences upgrading or polarisation thus crucially depends on the routine-wage curve: in scenario 1 of panel A, the complexity-wage curve and the monotonic RTI-wage schedule combine to result in occupational upgrading. Due to the negative correlation between complexity and RTI, SBTC and RBTC reinforce each other, and we see a reallocation from low-wage, low-complexity, high-routine employment to high-paying, complex, non-routine jobs. This scenario is in line with the findings of Fernández-Macías and Hurley (2017). Conversely, polarisation occurs in scenario 2, when the complexity-wage curve is combined with the hump-shaped RTI-wage curve. This is similar to the standard assumption in labour economics (e.g. Goos et al., 2014), although here the continuing importance of skill-bias in technological change is acknowledged. This approach recognises the value of both the routine-bias and skill-bias models and enriches them with insights from the sociological literature. It thus provides a more realistic account of technological and employment dynamics.

Of course, technology is not the only factor that influences employment trends, as the studies discussed above show (see, e.g., Fernández-Macías & Hurley, 2017; D. Oesch, 2015; Wright & Dwyer, 2003). Structural factors such as female and high-skilled labour supply and institutions such as labour unions may have a direct impact on the occupational structure. In the empirical investigation, country-occupation and study-wave fixed-effects will pick up much of the effect of these factors. Importantly for my theory, structural and institutional differences may also play an important role in determining wage hierarchies and may thus be the underlying reason behind the different routine-wage curves. The sociological critiques of the RBTC theory are therefore accounted for in this refined model. An in-depth empirical investigation of these links is beyond the confines of this paper, but the refined model of RBTC provides a roadmap for future research into this issue.

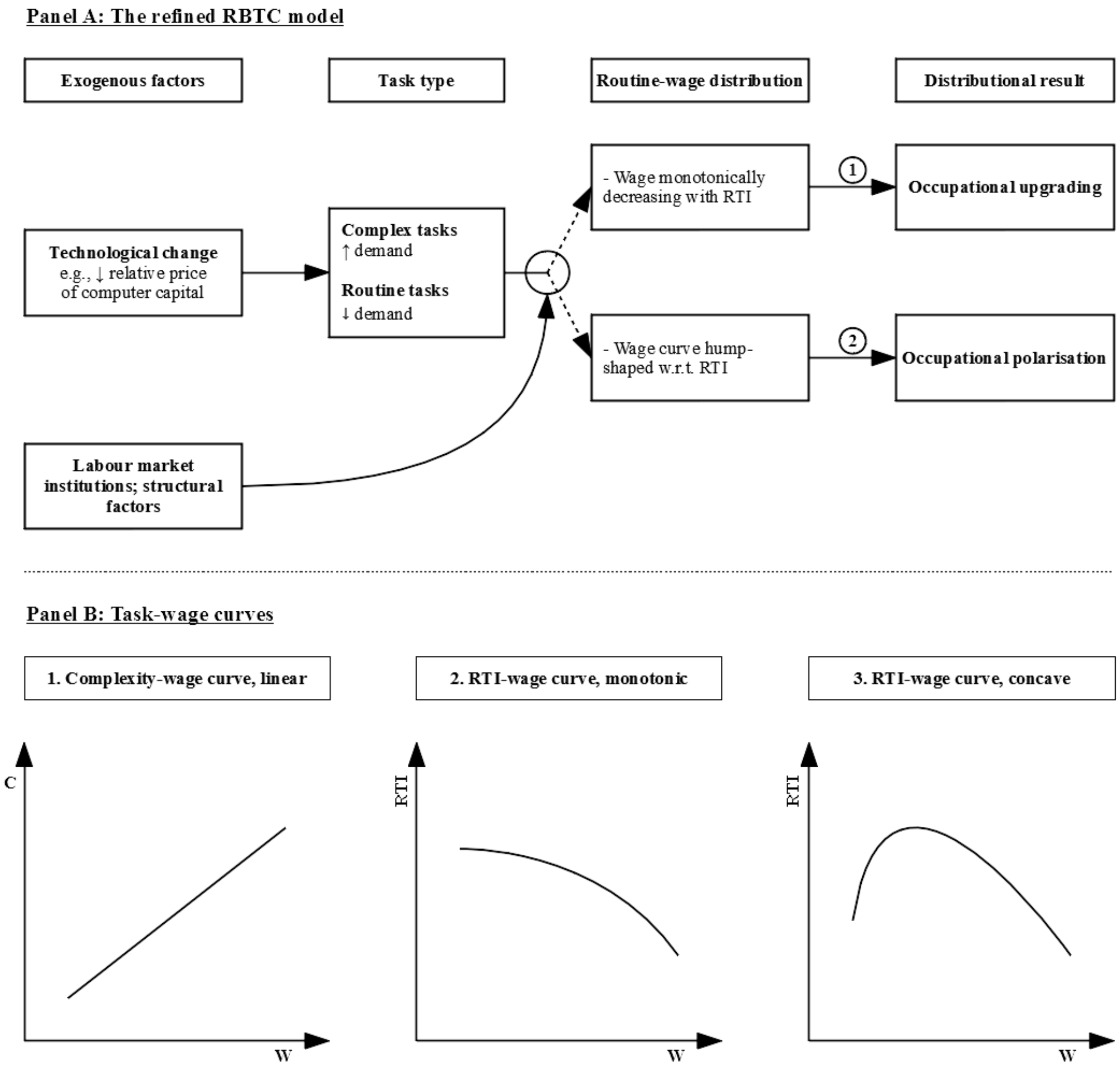

Figure 1: Panel A provides a simple visualisation of the refined RBTC model. Panel B shows the stylised task-wage curves. Panel B1 shows the complexity wage schedule, panel B2 the routine wage schedule in scenario 1 of panel A, and panel B3 shows the routine wage schedule of scenario 2 in panel A under which polarisation occurs.

4. Data

4.1 Employment

The main analytical sample for this study covers 10 countries during the period 1995 – 2013: Chile, Czech Republic, Finland, Germany, Hungary, Luxembourg, Netherlands, Slovenia, Spain, and the United States. I use employment data from the Luxembourg Income Study (LIS). I calculate occupational employment shares at the ISCO-88 2-digit level for 167 country-years covering 27 countries and spanning the time period from 1974 until 2016. From this larger dataset, the sample is selected to include the 10 countries with an uninterrupted time-series for LIS waves IV to IX. The main sample includes all workers, with supplementary analyses looking at working-age full-year full-time workers only. I prepared this dataset by calculating occupational employment shares at the most detailed level of the national occupational classification recorded in the LIS database. Subsequently, I use the crosswalks provided by Mahutga, Curran, and Roberts (2018) to harmonise the data at the 2-digit ISCO-88 level. In doing so, I added 28 additional country-years that were not included in the dataset of Mahutga, Curran, and Roberts (2018) and corrected some coding mistakes. To my knowledge, this constitutes the first comparative dataset of occupational employment shares at the 2-digit ISCO-88 level based on LIS data.

Compared to other data sources, the LIS boasts several strengths that make it appealing for comparative researchers, foremost its geographical and temporal coverage. While other high-quality data sources such as the EU-LFS and EU-SES include only European countries, the LIS data allow me to also analyse non-European countries such as Chile and the United States. Especially the inclusion of the United States, on which much of the existing literature on technological change focuses, is a major advantage. But also Chile, as one of the first non-Western OECD countries, promises to be an enriching addition to comparative datasets. The major downside is that in a number of countries, individuals' occupations were not originally recorded using the ISCO-88 classification and the recoding procedure, although following the admirable and very careful effort by Mahutga, Curran, and Roberts (2018), will inevitably have introduced some measurement error. Furthermore, the LIS sample sizes are highly variable and, on average, small compared to sources like the EU-LFS.[6] As I use only 26 ISCO 2-digit categories, even in countries with a lower sample size, the findings should generally be reliable. However, figure 2 below suggests that employment shares are more volatile in countries with smaller samples, hence this limitation of the LIS data must be kept in mind.

4.2 Labour Income

I follow Mahutga, Curran, and Roberts (2018) and largely work with the LIS variable for annual personal labour income (*pilabour*). This variable includes "cash payments and value of goods and services received from dependent employment, profits/losses and value of goods from self-employment, as well as the value of own consumption" (LIS, 2019). Capital and transfer income are excluded; yet, the problem remains that without information on hours worked our estimates of average occupational wages may be conflated by differences between occupations in average annual hours worked.[7] Individual gross hourly wages would therefore be preferable; however, such detailed data are not available for many of the LIS country-years for which we have occupational data. Thus, to preserve the main advantage of the LIS which is its unmatched geographical and temporal coverage, I work with the annual income variable. Additional analyses in the appendix using hourly wage data suggest that part-time work is not a major driver of the results in the countries in which both wage measures are available. Nevertheless, the lack of hourly wage data is a major drawback of the LIS.

[6] The number of observations used to calculate the employment shares and occupational wages is provided in table A1 in the appendix.
[7] Appendix E contains additional information on the construction of the wage variable.

4.3 Task Content Data

The indices of routine task intensity and task complexity are from Haslberger (2021) and are based on data from waves 3 – 6 of the EWCS in the EU-15 countries. These measures have several advantages over the more commonly used RTI index from Autor and Dorn (2013), and offer further improvements over the approach developed in Eurofound (2014) and Fernández-Macías & Hurley (2017).[8] My definition of routine-intensity closely follows Fernández-Macías & Hurley (2017) and thus focuses on repetitiveness and codifiability, while the complexity index is based on Caines et al. (2017) who define complex tasks as those requiring higher-order skills such as effective communication, abstraction and decision making.[9] Even though the indices are strongly correlated, this problem is less pronounced than in alternative operationalisations such as Fernández-Macías & Hurley (2017).[10] As appendix E explains in greater detail, the internal correlation structure of the indices shows that they are not two sides of the same coin but capture different underlying concepts.

I use an index based on data from the EU-15 countries throughout the main body of the article; however, using country-specific measures does not substantively change the conclusions for European countries. Applying measures based on an entirely European sample to the US and Chile is certainly not unproblematic, as is the fact that the task data are measured between 2000 and 2015 and thus during the period of analysis. However, compared to the prevailing practice of using an index based on the American Dictionary of Occupational Titles from 1977 for all countries and periods, my approach undoubtedly promises more robust insights. Indeed, I show in Haslberger (2021) that in most cases, a pooled index will rank occupations in a country more similarly to that country's actual ranking than applying the ranking of another individual country in the sample. It therefore appears highly likely that such a pooled measure will also exhibit better out-of-sample performance than a measure from any one country-year.

4.4 Employment Trends by Occupational Wage

This section presents data on employment trends by occupational wage and establishes that there is indeed an empirical puzzle: there is no universal pattern of employment change that conforms to a simple reading of either the SBTC or RBTC theory. Panel A of table 1 provides an overview similar to that in Goos, Manning, and Salomons (2014), with occupations ordered and divided roughly into terciles based on their average occupational wage. Unlike GMS, I include all occupations whereas they exclude agricultural occupations and what appear to be occupations with heavy public sector involvement (ISCO groups 11, 23, 33, 61, and 92).[11] Comparing my table to that in GMS, we find that the ranking of occupations in terms of their

[8] For a detailed description of the indices and a discussion of their advantages, please refer to appendix E.

[9] I apply here a task-based definition of the SBTC argument. Normally, the SBTC literature focuses on levels of education (see, e.g., Goldin and Katz 2008). However, insofar as higher levels of education prepare individuals to perform more cognitively complex tasks, this should lead to similar conclusions.

[10] Haslberger (2021) shows that at the 2-digit level the correlation between the routine and cognitive indices of Fernández-Macías & Hurley (2017) is -0.86, whereas in my proposal it is -0.73 (-0.62 using country-specific measures).

[11] The excluded occupations cumulatively account for almost 10 percent of total employment. Senior officials and teaching professionals fall into the highest-earning tercile; the other three groups are among the lowest-paid. While there may be valid reasons for this exclusion, they are not made explicit in GMS.

average wage is highly similar: the rank-order correlation with the 21 2-digit occupations that are included in GMS is 0.98.

While the ordering in terms of wages is almost identical, there are substantial differences in routine scores and employment trends. Above all, middling occupations do not stand out as disproportionately high-routine in my data. It appears that the statement, "routine occupations cluster around the middle of the wage distribution" is, at least at this level of generality, misleading.[12] My data furthermore show that what mainly distinguishes middling from low-wage occupations is their higher average complexity, while they are fairly similar in terms of routine-intensity. It therefore seems likely that greater complexity explains much of the wage premium in middling occupations. Most importantly, table 1 provides no evidence for pervasive employment polarisation if we use the full set of occupations. Middling and low-paying occupations both saw sizeable employment reductions, while high-paying occupations were the only group to expand their employment share in 2013 compared to 1995. This finding is robust to looking at quintiles or more arbitrarily defined groups as in GMS; in fact, with quintiles the average changes look even more clearly upgrading.[13] However, further analyses, reported in table A4 in appendix C, reveal a gendered pattern of (tentative) upgrading for women and polarisation for men, as recorded in Eurofound (2014). On average, these results therefore suggest that occupational change was largely upgrading in terms of wages.

If we instead plot the trajectory of high-, medium-, and low-wage occupations in individual countries, we see a diversity of patterns that is consistent with my refined theory. In figure 2 below, I ranked occupations by their average wage in the respective country in the first period for which I have data and then classified them so as to represent as close as possible to one third of employment.[14] The graphs indicate that neither the upgrading nor the polarisation narrative can explain employment trends across the developed world. The United States and Germany are textbook examples of employment polarisation, as employment in high-wage occupations increased strongly and low-wage employment grew moderately in both countries, at the expense of medium-wage occupations. Yet, only Luxembourg and The Netherlands also experienced growing high-wage and low-wage employment at the expense of middling occupations.

In five of the remaining six countries, both medium- and low-wage employment shares declined, resulting in an upgrading employment structure. Chile and Spain experienced relatively straightforward upgrading of the occupational structure. These countries, of course, are latecomers to the club of liberal democracies and as such had to catch up economically to countries like the US. Czech Republic and Slovenia also experienced a strongly upgrading

[12] In GMS, the discrepancy between middling and low-paying occupations in terms of RTI is inflated by classifying the high-routine groups 82 and 74 as middling occupations, despite them belonging to the lowest-paying third. High-routine group 81 is classified as a middling occupation in GMS even though it is in the top-earning tercile. This swells the medium-wage group to comprise the 22nd to 68th percentiles of occupational wages. It is only by using cut-off points in a strategic manner and excluding the aforementioned occupations that GMS achieve the stark contrasts in their analysis. Moreover, the high routine-intensity of middling occupations in GMS is driven largely by the implausibly high RTI score for office clerks who, as previous research has argued, have seen their range of tasks expand to be a far cry from the high-routine occupation of the past (see also Haslberger 2021).

[13] See appendix C.

[14] With 26 ISCO codes, tercile shares even in the initial period are never exactly 33.3 percent.

pattern since the 1990s, the recent dip in high-wage employment largely being an artefact of the change to ISCO-08. Again, this appears consistent with a story of economic catch-up after democratisation. In Finland, low-wage employment was marginally lower in 2013 than in 1995, while medium-wage employment declined more substantially and high-paying jobs expanded. Hungary is the only outlier in that the data show occupational downgrading. This is in line with Eurofound (2017) who also find downgrading in Hungary from 2011 – 2016; my findings suggest that this was in fact a more durable process.

The overall picture is compounded by the change from ISCO-88 to ISCO-08 that happened in many European countries around 2010. Despite the use of the official crosswalk in Mahutga, Curran, and Roberts (2018), a significant discontinuity cannot be avoided and we see a sudden dip in the employment share of high-wage occupations accompanied by a jump in the share of low-wage occupations. The example of Germany, where we have annual data, shows that this is not a trend but a one-off effect, as previous trends continue afterwards. The findings for Hungary, and to a lesser extent Spain, Luxembourg, and the Netherlands, may furthermore be more volatile due to low sample sizes in some waves. For example, in Spain the 1995 wave includes only 1144 respondents, compared to over 10000 in later waves, and shows a marked jump compared to surrounding waves. The overall trend of occupational upgrading, however, is unaffected by this.

To summarise, the analyses presented here suggest that occupational upgrading was the most common pattern in a range of developed countries, with a sizeable minority of countries experiencing polarisation – among them the two largest and best-studied economies in the sample, Germany and the US.[15] RBTC as commonly understood cannot explain these diverse experiences, so there is indeed a puzzle that my refined theory can address.

[15] If the appraisal of employment changes is limited to the period 1995 – 2013 and occupations are allocated to terciles based on their wages in 1995, Finland exhibits a polarising pattern as well while the trend in the US can be described as weak polarisation, with strong employment growth in high-wage occupations, strong declines in middling occupations, and essentially constant employment in low-wage occupations (see figure A11 in appendix C). The appendix also contains figures showing smoothed employment changes across the wage distribution which likewise show upgrading on average, but diverse patterns across countries.

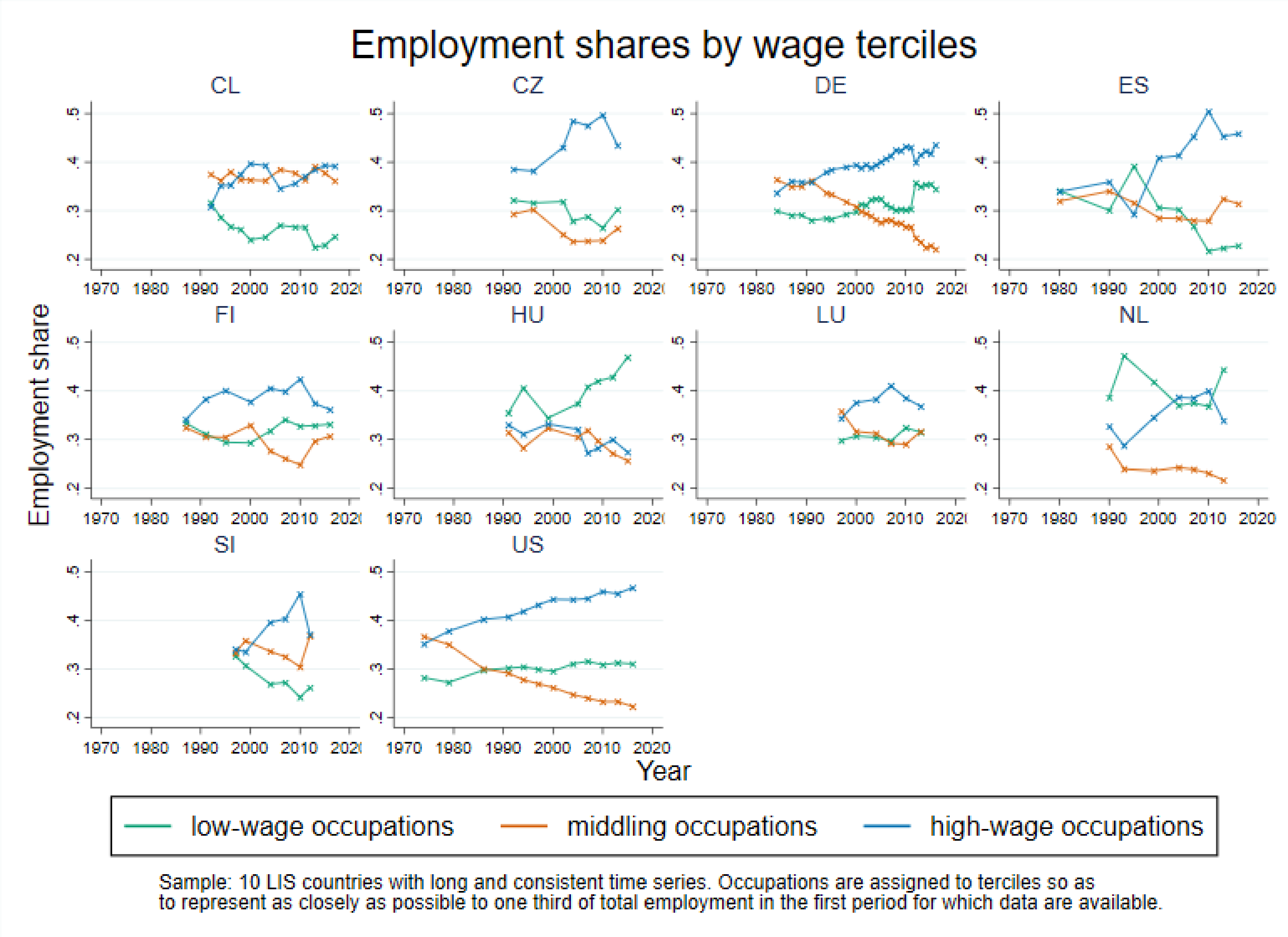

Figure 21: Employment changes by wage terciles in 10 LIS countries.

Table 1: Average Wage, Routine, and Complexity Rankings

PANEL A: WAGE RANKING

ISCO-88 CODE	EMP 1995	EMP 2013	Δ%	RTI SCORE	COMP. SCORE
12	3.19	3.01	-0.18	-0.22	0.47
21	3.30	4.88	1.58	-0.19	0.61
11	0.41	0.43	0.02	-0.34	0.49
22	1.66	2.32	0.66	-0.07	0.38
24	3.82	5.71	1.88	-0.23	0.49
23	4.23	4.23	-0.01	-0.33	0.23
31	3.37	3.02	-0.35	-0.07	0.48
13	3.86	3.34	-0.53	-0.09	0.07
34	7.43	8.77	1.32	-0.17	0.34
81	1.31	1.15	-0.16	0.30	-0.20
High wage	**32.58**	**36.87**	**4.29**	**-0.16**	**0.35**
72	6.25	5.25	-1.01	0.13	0.04
83	4.51	4.23	-0.28	0.06	-0.41
73	1.24	0.90	-0.34	0.23	-0.08
32	2.82	3.61	0.79	-0.02	0.19
41	9.45	9.06	-0.42	-0.02	0.26
71	5.57	4.49	-1.09	0.27	-0.12
33	1.15	1.55	0.39	0.17	0.01
42	2.61	2.77	0.15	0.39	-0.29
Med. wage	**33.61**	**31.86**	**-1.75**	**0.08**	**0.02**
82	3.92	3.45	-0.47	-0.32	0.15
74	3.14	1.79	-1.35	0.34	-0.28
51	7.17	9.17	1.99	0.03	-0.22
61	2.01	1.56	-0.46	0.08	-0.35
93	3.49	2.61	-0.88	0.25	-0.49
52	5.24	5.26	0.01	-0.05	-0.30
91	6.61	6.80	0.18	0.14	-0.63
92	2.23	0.62	-1.62	0.21	-0.56
Low wage	**33.81**	**31.27**	**-2.54**	**0.14**	**-0.38**

PANEL B: RTI RANKING

ISCO-88 CODE	RTI SCORE	EMP 1995	EMP 2013	Δ%
11	-0.34	0.41	0.43	
23	-0.33	4.23	4.23	
33	-0.32	1.15	1.55	
24	-0.23	3.82	5.71	
12	-0.22	3.19	3.01	
21	-0.19	3.30	4.88	
34	-0.17	7.43	8.77	
13	-0.09	3.86	3.34	
31	-0.07	3.37	3.02	
22	-0.07	1.66	2.32	
Low RTI	**-0.19**	**32.43**	**37.26**	**+4.84**
52	-0.05	5.24	5.26	
41	-0.02	9.45	9.06	
32	-0.02	2.82	3.61	
51	0.03	7.17	9.17	
83	0.06	4.51	4.23	
61	0.08	2.01	1.56	
Med. RTI	**0.00**	**31.20**	**32.89**	**+1.69**
72	0.13	6.25	5.25	
91	0.14	6.61	6.80	
42	0.17	2.61	2.77	
92	0.21	2.23	0.62	
73	0.23	1.24	0.90	
93	0.25	3.49	2.61	
71	0.27	5.57	4.49	
81	0.30	1.31	1.15	
74	0.34	3.14	1.79	
82	0.39	3.92	3.45	
High RTI	**0.23**	**36.37**	**29.85**	**-6.52**

PANEL C: COMPLEXITY RANKING

ISCO-88 CODE	COMP. SCORE	EMP 1995	EMP 2013	Δ%
21	0.61	3.30	4.88	
24	0.49	3.82	5.71	
11	0.49	0.41	0.43	
31	0.48	3.37	3.02	
12	0.47	3.19	3.01	
22	0.38	1.66	2.32	
34	0.34	7.43	8.77	
41	0.26	9.45	9.06	
High comp.	**0.39**	**32.64**	**37.20**	**+4.57**
23	0.23	4.23	4.23	
32	0.19	2.82	3.61	
33	0.15	1.15	1.55	
13	0.07	3.86	3.34	
72	0.04	6.25	5.25	
42	0.01	2.61	2.77	
73	-0.08	1.24	0.90	
71	-0.12	5.57	4.49	
81	-0.20	1.31	1.15	
51	-0.22	7.17	9.17	
Med. Comp.	**-0.01**	**36.21**	**36.46**	**+0.26**
74	-0.28	3.14	1.79	
82	-0.29	3.92	3.45	
52	-0.30	5.24	5.26	
61	-0.35	2.01	1.56	
83	-0.41	4.51	4.23	
93	-0.49	3.49	2.61	
92	-0.56	2.23	0.62	
91	-0.63	6.61	6.80	
Low comp.	**-0.43**	**31.16**	**26.33**	**-4.82**

Note: The wage ranking is based on pooled average wages at the beginning of the period (1995).

4.5 Continuing SBTC in the Data

This section presents evidence for the first element of my refined model: simultaneous skill-biased and routine-biased technological change. Independent of where in the wage distribution these occupations are located, RBTC requires that routine-intensive occupations decline and low-routine occupations grow, and SBTC entails that complex occupations expand while simple occupations contract. In panels B and C of table 1, we see that employment change between 1995 and 2013 was indeed highly skill- and routine-upgrading. Occupations are ordered by their task requirements, from least to most routine-intensive in the panel in the middle, and from most to least complex in the panel on the right. Occupations scoring low on RTI or high on complexity increased their cumulative employment share by almost 4.8 and 4.6 percent, respectively. Total employment in occupations with average RTI and complexity scores did not change much, with small increases of 1.7 and 0.3 percent, while the most routine-intensive and the least complex occupations lost almost 6.5 and 4.8 percent of cumulative employment, respectively. Of course, many simple occupations are also routine-intensive, but there are several exceptions to this pattern which show that the measures are only partly collinear. The linear patterns largely hold if we divide occupations more finely into quintiles, as can be seen in appendix C. This finding is similar to Oesch (2013) who also finds evidence for both RBTC and SBTC if occupations are divided into task and skill terciles. However, he concludes that employment change has corresponded to RBTC in Britain and Spain and to SBTC in Denmark, Germany, and Switzerland, while this article argues that RBTC, properly understood, can account for employment changes in upgrading countries as well.

Simple regression analyses provide further support for a linear relationship between tasks and employment shares. In table 2, I regress occupational employment shares on the RTI and complexity measures, first for all workers and FYFT workers and then for women and men separately. I interact the task measures with a linear time-trend to deal with the fact that they are constant over time. All regressions also include country-occupation and year fixed-effects.[16] With this, I follow Goos, Manning, and Salomons (2009, 2014) who use a similar approach to estimate the effect of task content on labour demand. My results in panel A largely confirm the findings of GMS. Routine-intensity has a stable and highly statistically significant negative association with occupational employment (column 1). The coefficient on task complexity is positive and marginally statistically significant if entered alone (column 2); however, in a "horse-race", the coefficient on RTI retains its size and statistical significance, while task complexity loses both (column 3). Running the models for FYFT workers only leads to very similar results, albeit less precisely estimated. It appears, therefore, that the trends for non-standard workers were not fundamentally different than for FYFT workers, alleviating some of the concerns articulated above.[17] Running the models separately for women and men in panel B yields similar findings; interestingly, the estimated coefficient sizes are larger and more robust for women. Hence, we can conclude that RTI and task complexity are associated with

[16] Besides institutional and supply-side factors, the fixed-effects may pick up some of the effect of technology, making the coefficients on RTI and complexity lower-bound estimates. I owe this point to an anonymous reviewer.
[17] Table A5 in the appendix shows virtually identical results in a larger sample of all countries with LIS data from 1995 – 2016, and in the case of FYFT workers, shows significant results where the main analysis does not.

employment trends in the ways my theory would predict. The regression results suggest, however, that the effect of routine-intensity is the quantitatively more important one.

Table 2: Tasks and Employment Demand

	PANEL A: BY WORKER STATUS					
	ALL WORKERS			FYFT WORKERS ONLY		
DV: Employment share	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
Time-trend interacted with:						
RTI	-0.84***		-1.08***	-0.62**		-0.60
	(0.31)		(0.41)	(0.31)		(0.37)
Complexity		0.21*	-0.19		0.22	0.02
		(0.11)	(0.13)		(0.16)	(0.19)
Observations	1,558	1,558	1,558	1,558	1,558	1,558
Country-occupations	260	260	260	260	260	260
R-squared	0.077	0.029	0.083	0.076	0.068	0.076
	PANEL B: BY SEX					
	WOMEN			MEN		
DV: Employment share	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)
Time-trend interacted with:						
RTI	-1.19**		-1.56**	-0.61**		-0.67*
	(0.48)		(0.67)	(0.28)		(0.38)
Complexity		0.25	-0.28		0.22*	-0.05
		(0.19)	(0.27)		(0.12)	(0.15)
Observations	1,533	1,533	1,533	1,555	1,555	1,555
Country-occupations	260	260	260	260	260	260
R-squared	0.073	0.035	0.079	0.059	0.044	0.059

*Note: All point estimates (and standard errors in parentheses) are multiplied by 100. Robust standard errors are clustered by country-occupation. All occupations are weighted by their initial employment share in 1995. All regressions include country-occupation fixed-effects and wave fixed-effects. Sample: 10 LIS countries 1995 – 2013. *** p<0.01, ** p<0.05, * p<0.1*

5. The Task-Wage Schedules

The crucial novelty in my refined theory is the mechanism that leads from the observed patterns of technological change to the observed patterns of employment change in terms of wages. We have just seen that technological change has been both skill-biased and routine-biased in recent years. This section first confirms that the relationship between occupational complexity and wages is indeed monotonic and positive in all countries. It then shows that there are two distinct types of relationship between occupational wages and RTI: one linear or monotonic, as found in Fernández-Macías and Hurley (2017), and the concave ("hump-shaped") relationship that has formed the backbone of the traditional RBTC theory as in Goos, Manning, and Salomons (2014), as depicted in figure 1 above. I also show that the shape of the task-wage curves within countries is relatively constant over time, even as individual occupations sometimes change their position.

Since the different shapes of the distributions are best illustrated graphically, I fit fractional-polynomial prediction plots for each of the 163 country-years which provide employment and wage data in my LIS dataset. I use the *fpfitci* command in Stata in its default configuration, that is, a second-degree polynomial estimated with *regress*. The use of a fractional polynomial function serves to better detect nonlinearities where they arise, while remaining relatively agnostic regarding the functional form of the relationship. We can thus determine whether a relationship is linear or not without having to fit different equations and comparing fit statistics. I show that both patterns do indeed arise, and that the two stylised patterns in figure 1 capture the overwhelming majority of cases in my dataset.[18] Note that the task measures are calculated from data for the period 2000 – 2015, while LIS employment data extend further back in many countries. Yet, this is an assumption that has to be made if we want to move away from using DOT data that predates the LIS data and is based on the US only – surely a much stronger assumption than the one made here.

As mentioned above, I do not exclude non-standard workers, who are known to be disproportionately female, concentrated in certain occupational groups such as service occupations, and to have become more numerous in many countries.[19] Of course, non-standard workers tend to have lower annual labour incomes, all else being equal. Including these workers means that my task-wage curves may be influenced by between-occupation differences and within-occupation changes in patterns of non-standard work. It nevertheless seems to me preferable to include non-standard workers in the analysis. Excluding them would introduce a different kind of bias into the country-comparisons, as non-standard work is an important feature of the labour market, the overall prevalence which varies between countries and has generally increased. Excluding non-standard workers would mean disregarding an ever-increasing proportion of the workforce. Figures A13 to A17 in the appendix show that the results are generally robust to the exclusion of non-standard workers or to the use of hourly wages, where available.

5.1 The Complexity-Wage Schedule

We start with the complexity-wage schedule, which is the more straightforward of the two task-wage schedules. Human capital theory predicts that wages increase linearly, by and large, with complexity or skill demands (see, e.g., K. M. Murphy and Topel 2016). There is indeed a large literature which shows that workers who perform complex tasks are rewarded in the labour market, and that more complex jobs require a higher level of skills, usually proxied by education (see, e.g., Goldin and Katz 2008). There may be some exceptions to this pattern related to gender issues; for example, there is some evidence that jobs which require medium levels of skills and training but are traditionally associated with women tend to have lower average wages than lower-skilled jobs which are traditionally associated with men (Tahlin, 2019). Overall, however, that more complex jobs command higher wages, is uncontentious.

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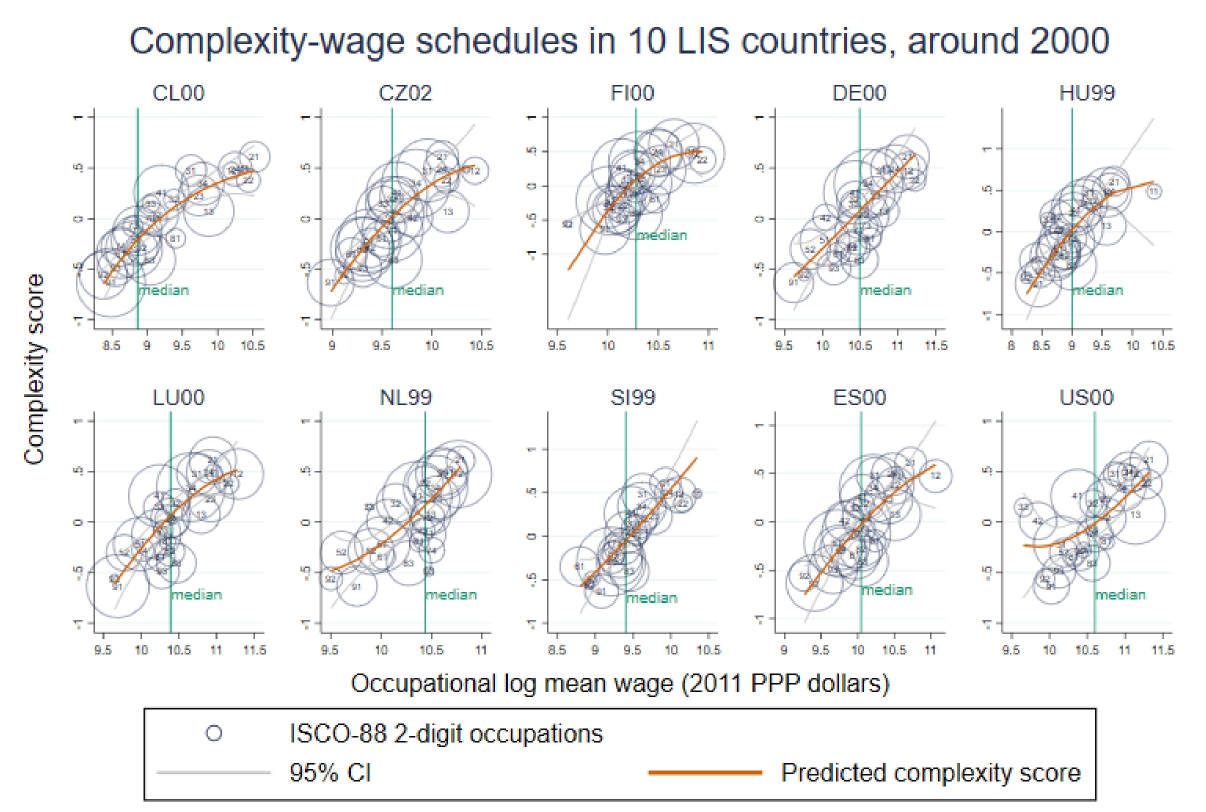
[18] Deviations from the proposed patterns appear to be due mostly to measurement error in very small occupations where wages may be measured imprecisely.

[19] Nevertheless, part-time work did not expand uniformly. According to Wright and Dwyer (2003), the share of part-time employment decreased in the US during the long expansion of the 1990s. OECD (2015) likewise finds decreasing rates of part-time employment in Nordic countries and Spain for the period covered by this study.

Figure 3 investigates this line of argument and illustrates the complexity-wage curve in my 10-country sample in LIS wave V, which corresponds to the year 2000. For reasons of space, I cannot present the complexity-wage schedules for all available 163 country-years here, but detailed results are available upon request. My analyses show precisely what theory predicts: there is a clear positive relationship between complexity and wages. Moreover, this relationship is approximately linear in most countries, and it is monotonically increasing in all countries except the US. There, it is only the exceptionally low pay of teaching associate professionals that introduces a nonmonotonicity at the bottom of the distribution; if ISCO group 33 is excluded the complexity-wage curve is monotonically increasing in the US as well.[20] The remaining panels of figure 3 show that the postulated relationship between task complexity and wages hold in a wide range of circumstances. For example, in Czech Republic and Chile – two countries with historical trajectories very different from those of Germany and the US – the pattern is just as in panel C of figure 1. Overall, therefore, it is very clear that there is a straightforward positive relationship between the complexity of the tasks performed and the remuneration received.



Note: This graph uses the EU-15 complexity measures and LIS data from the year closest to 2000.

[20] I suspect that this has to do with the official crosswalks from the US SOC classifications to ISCO. The only SOC groups partly assigned to ISCO group 33 are childcare workers (4600), teacher assistants (2540), and other education, training and library workers (2550) – in most other classifications at least some actual teachers are classified as associate teaching professionals, boosting average wages of the group. Interestingly, the position of group 33 in the US wage hierarchy does not change if we look at full-year full-time workers and hourly wages only. In a few other cases the linear relationship is distorted by an occupation which is assigned an implausibly low or high average wage – in some cases more than an entire log point from the next lowest- or highest-earning occupation. Such differences are arguably due to measurement error in small samples and should not be seen to undermine the general pattern in the data.

Figure 3: The complexity-wage schedule around 2000. Employment and wage data from LIS wave V (2000 or nearest year).

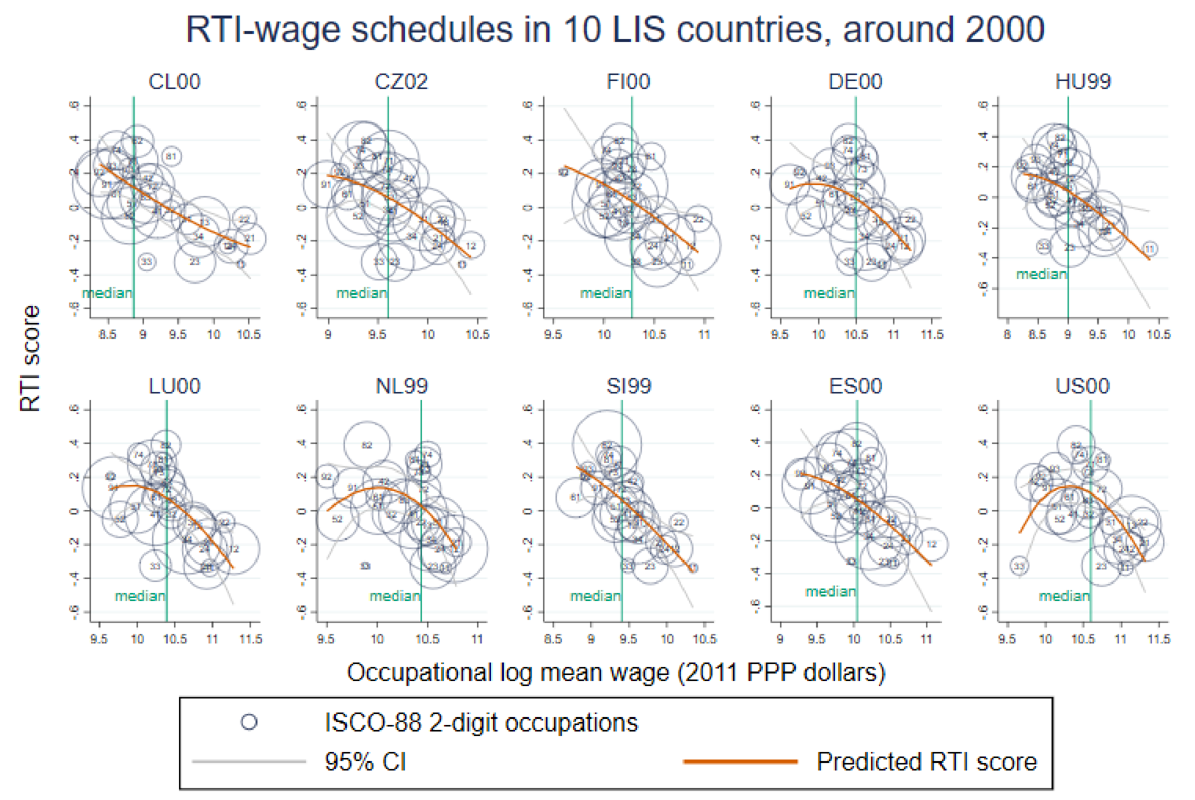
5.2 The Routine-Wage Schedule

Moving on to the routine-wage schedule, my graphical analyses confirm that there is no universal pattern, in contrast with the complexity-wage schedule. In some countries, routine occupations do cluster predominantly around the middle of the wage distribution as the polarisation argument would predict. However, other countries show the monotonic, linear or near-linear relationship which is associated with occupational upgrading as postulated by Fernández-Macías & Hurley (2017). Figure 4 illustrates this for the year 2000. Perhaps most importantly, the textbook examples of employment polarisation, Germany and the US, both exhibit the hump-shaped pattern. This also helps to explain how the idea that routine occupations tend to be medium-wage could gain such widespread acceptance without proper scrutiny: early and influential studies of RBTC often focused on these two countries (see, e.g., Autor, Levy, and Murnane 2003; Spitz-Oener 2006; Antonczyk, Deleire, and Fitzenberger 2018). In the US, the hump-shape is more pronounced, and although it is again to a significant extent driven by ISCO group 33, it is robust to excluding associate teaching professionals from the analysis.

A total of four countries exhibit the concave relationship between RTI and wages: Germany, the United States, Luxembourg, and The Netherlands. This is interesting insofar as those are the four countries with the highest median wages in my sample. On the other hand, countries with lower median wages or where occupational upgrading was particularly pronounced such as Czech Republic or Chile (presumably due to a catch-up process after the end of the Communist/ Pinochet regimes) show a clear quasi-linear monotonic relationship between RTI and wages, as was hypothesised in panel B of figure 1. This is *prima facie* evidence to suggest that the level of economic development may play a role in determining the nature of the routine-wage schedule.

The lack of hourly earnings data constitutes a major disadvantage of the LIS for this type of analysis. The patterns described here pertain to all workers and annual wages, which leaves open the possibility that the results are influenced by patterns of part-time work. For example, Germany and the Netherlands have very high rates of female part-time employment and, together with Finland, the highest overall female employment rates. Appendix C shows analyses with samples restricted to FYFT workers aged between 18 and 65 and hourly wages. Figure A13 shows that in the four countries with data on gross hourly wages in 2000, the patterns shown here are weaker, especially in the Netherlands and the US, but overall intact. Figures A14 to A16 illustrate that this holds true not only in 2000, but also at the beginning and at the end of the period of analysis. Likewise, we see in figure A17 that of the five countries with information on worker status in 2000, only in Germany do the results for annual wages change when the sample is restricted to FYFT workers. We can therefore be confident that the results are not predominantly driven by differences in the prevalence of non-standard work, although not in every country the findings are fully robust to using hourly wages or excluding non-standard workers. Nevertheless, the role of non-standard work and gender differences certainly deserves additional scrutiny in further research. It is furthermore important to note that very similar results obtain when the RTI measures of Autor & Dorn (2013) that GMS rely on are used. As figure A18 shows, the concave RTI-wage schedule is clearly visible in Germany, Luxembourg, the Netherlands and the United States. In Czechia and Spain, a nascent concave shape is visible while in the remaining countries the monotonic relationship prevails. Thus, even with the more widely known measures of Autor & Dorn (2013), the results described above hold. This shows that the findings are not driven by the choice of routine measure, as the more commonly used routine measure yields very similar results.

Which shape the RTI-wage schedule takes conforms remarkably well to the overall patterns of employment change that I discussed above. The four countries with concave RTI-wage schedules all experienced employment polarisation (scenario 2). Of the six countries with a (largely) monotonic RTI-wage curve, five experienced occupational upgrading (scenario 1). The exception here is Hungary which has experienced occupational downgrading where upgrading would be expected and thus does not conform to any of the scenarios.[21] This constitutes strong evidence in favour of my theory, as 9 out of 10 cases align with its predictions.



Note: This graph uses the EU-15 RTI measures and LIS data from the year closest to 2000.

[21] The curious case of Hungary can largely be explained by the employment expansion and wage gains in the service occupations of group 51. Personal and protective services workers moved from the 16th to the 61st wage percentile between 1991 and 2015, while expanding their employment share from 2.9 percent to 10.6 percent. This accounts for much of the increase in apparent low-wage employment in figure 2. Therefore, the supposed pattern of occupational downgrading may be better understood as wage upgrading for service occupations. The volatility in Hungary of employment shares and relative wages may in turn have to do with the very low sample size compared to all other countries in the analysis.

Figure 4: The RTI-wage schedule around 2000. Employment and wage data from LIS wave V (2000 or nearest year).

5.3 RTI-Wage Curves and Occupational Wage Rankings Over Time

It is furthermore important to point out that the shape of the task-wage curves appears to be a relatively constant country-characteristic, even as individual occupations move up or down the wage hierarchy. Figure 5 shows the development of the RTI-wage curve in the US, which has the longest time-series in the LIS, from 1974 – 2016. The concave curve is somewhat less pronounced in later years but is clearly present throughout. Equivalent figures for a further 16 countries are provided in appendix D. There are of course minor fluctuations, but instances where the shape of the RTI-wage curve changes substantially over time are rare. One example is Spain, where a monotonic RTI-wage curve slowly gives way to a marginally concave one over time. Indeed, where there is sustained and gradual change, as also in Slovenia, it is always towards the concave relationship. This may indicate that the concave RTI-wage relationship is characteristic of richer and more technologically advanced countries.

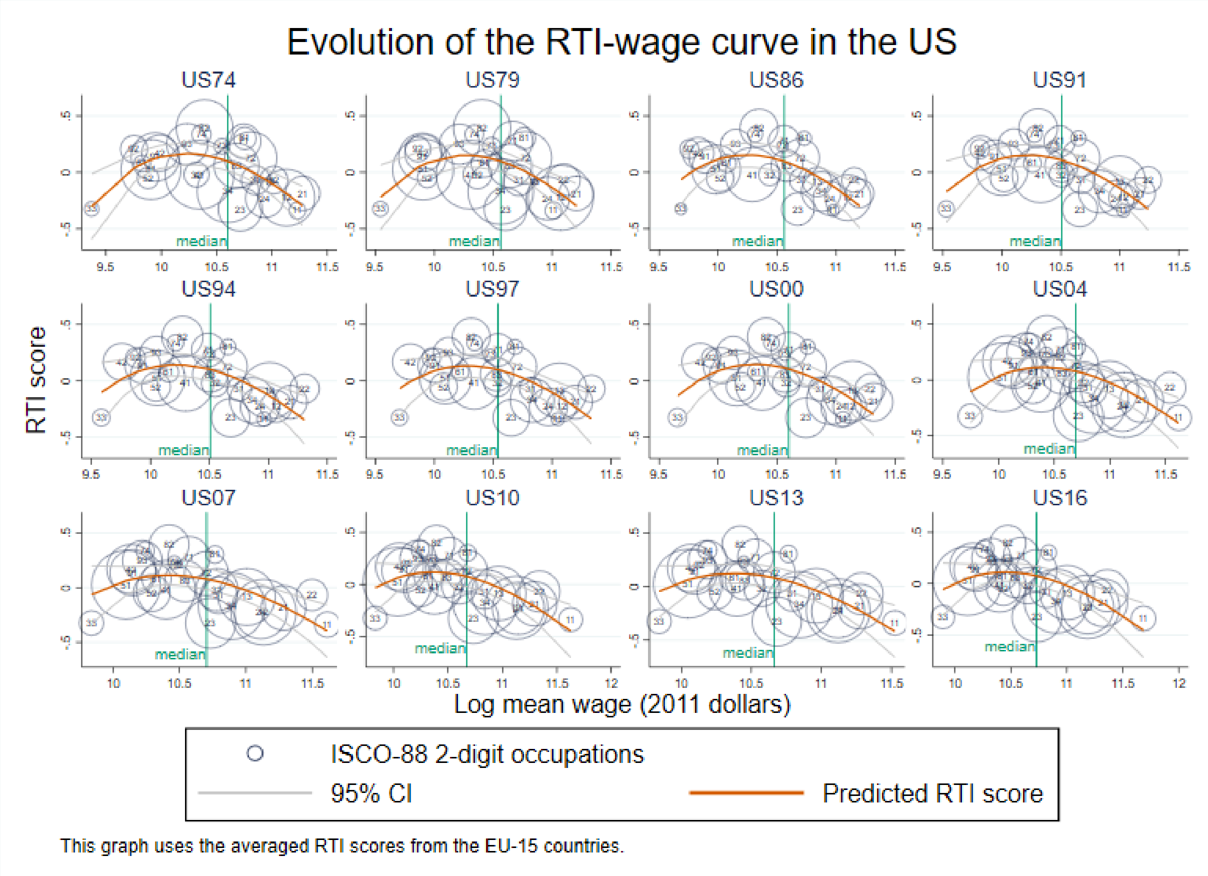


Figure 5: The evolution of the RTI-wage curve in the US from 1974 – 2016.

Since the RTI measure does not change over time, all changes in the RTI-wage curve are due to a combination of changing employment shares and occupations moving up or down the wage hierarchy. Substantial employment changes towards higher-paid occupations have already been documented in this article. Large changes in the shape of the RTI-wage curve likely require positional changes in the wage hierarchy as well. In particular, a shift from the linear to the hump-shaped pattern could be the result of the relative wages of routine-intensive occupations increasing over time, or those of a subset of low-to-medium-routine occupations decreasing, or both. The following analyses provide some clarity on this issue.

Table 3 shows the three highest-paying and lowest-paying occupations in each country in my sample in 1995 and 2013. We see that the top three occupations are more similar across countries than the bottom three. This is not surprising, as the differences in the RTI-wage distribution that we are trying to explain are at the bottom end. Incidentally, in the countries with concave RTI-wage curves, service workers (major group 5) appear to be more heavily represented at the bottom than in countries with monotonic curves, where elementary occupations (major group 9) account for most of the three lowest-wage occupations. This is what we would expect, as service occupations are less routine-intensive than elementary occupations. In contrast, there is an overall convergence at the top end of the wage distribution. This indicates that while the top jobs have become more similar across countries, country-specific factors continue to heavily influence the low-wage sector.[22] Thus, despite the relative stability of the RTI-wage curves, occupational wage hierarchies have been far from static. We see in the example of the US that legislators and senior officials (group 11) only become the highest paid occupational group in the early 2000s, after overtaking health professionals (group 22) who had in turn previously overtaken science professionals (group 21) in the early 1990s.

Table 3: Highest- and Lowest-Earning Occupations

Country	1995	2013	Country	1995	2013
Chile	21, 22, 12 93, 91, 92	21, 22, 12 74, 91, 92	**Hungary**	11, 12, 13 93, 92, 91	21, 22, 11 93, 91, 92
Czech Republic	12, 11, 13 93, 92, 91	11, 12, 21 93, 91, 92	**Luxembourg**	12, 11, 21 52, 92, 91	12, 24, 11 52, 92, 91
Germany	11, 12, 21 92, 52, 91	11, 12, 21 51, 91, 92	**Netherlands**	11, 12, 21 51, 52, 91	11, 12, 21 93, 92, 91
Spain	12, 21, 31 61, 91, 92	11, 12, 21 51, 91, 92	**Slovenia**	11, 22, 12 91, 93, 92	11, 12, 22 91, 92, 61
Finland	11, 12, 23 13, 61, 92	11, 12, 22 52, 91, 92	**United States**	22, 21, 12 92, 42, 33	11, 22, 21 42, 51, 33

Note: This table shows the three ISCO-88 codes with the highest (top line) and with the lowest (bottom line) average wage for each country in 1995 and 2013. The occupational codes are: 11: legislators and senior officials; 12: corporate managers; 13: general managers; 21: physical, mathematical and engineering science professionals; 22: life science and health professionals; 23: teaching professional; 24: other professionals; 31: physical and engineering science associate professionals; 33: teaching associate professionals; 42: customer service clerks; 51: personal and protective services workers; 52: models, salespersons and demonstrators; 61 market-oriented skilled agricultural and fishery workers; 74: other craft and related trades workers; 91: sales and

[22] Furthermore, the United States' wage structure is exposed as somewhat of an outlier. Nowhere else are teaching associate professionals (group 33) and customer services clerks (group 42) among the lowest earners. As stated above, this does not appear to be driven by part-time employment.

services elementary occupations; 92: agricultural, fishery and related labourers; 93: labourers in mining, construction, manufacturing and transport. For the full list of ISCO codes, see appendix A.

For reasons of space, additional detailed analyses of wage changes and the ramifications for RTI wage curves are relegated to appendix B. Table A2 provides a full overview how occupations are distributed across and have moved between wage terciles in individual countries. From this distribution matrix, no obvious systematic differences are apparent between countries with a concave RTI-wage curve and countries without. What is apparent, however, is that professionals and health and teaching associate professionals (groups 32 and 33) have generally improved their positions as well as, interestingly, operators (groups 81 and 82). The losers have been other associate professionals (group 34) and above all trades workers (major group 7). Thus, among the winners and losers are both high- and low-routine occupations. There is a fruitful avenue for future research in zooming in on these occupations to investigate which factors, beyond their routine-intensity, have affected their wage trajectory.

Another issue is that theoretically, the movements of 2-digit occupations up and down the wage hierarchy may represent genuine changes in relative wages as well as compositional changes within the relatively broad 2-digit ISCO categories. It is possible that occupational wages have remained unchanged at the 4-digit level, but, for example, employment growth in higher-earning 4-digit occupations has driven up the average wage of the broader 2-digit group. To assess this possibility, I investigate compositional changes within 2-digit occupations in the two countries that originally report 4-digit ISCO-88 data, Chile and Germany. The findings, reported in figure A1, dispel the notion that compositional changes at the 4-digit level might be responsible for wage trends at the 2-digit level. At least in Chile and Germany, therefore, it is not the case that 2-digit occupations have moved up or down the wage distribution because of disproportionate employment growth in higher- or lower-earning 4-digit occupations. These additional analyses shed some light on the underlying complexities of occupational wage hierarchies as they interact with routine intensity to form RTI-wage curves.

6. Conclusion

This article takes a critical look at the RBTC argument and proposes a refined theoretical framework to understand the diverse patterns of employment change in countries exposed to very similar technologies. In this framework, an exogenous technological shock leads to an increase in the demand for workers performing complex tasks and a decrease in the demand for workers performing routine tasks. SBTC and RBTC may therefore be at work simultaneously. While task complexity is positively associated with the occupational wage, there are two possible patterns regarding routine-intensity: either routine occupations cluster around the middle of the wage distribution, or the lowest paid occupations are also the most routine-intensive ones. As a result of this, both occupational upgrading and polarisation may emerge as a result of RBTC. My analyses find empirical support for all components of this refined model, using a novel dataset of 10 countries with employment and wage data from the LIS and task measures based on the EWCS. Thus, the article makes an important theoretical and empirical contribution to the study of technological and occupational change.

The key empirical finding is that routine occupations either cluster near the middle or near the bottom of the wage distribution in a way that is relatively constant over time but differs systematically between countries. In the former cases, occupational polarisation usually emerges, as posited in the labour economics literature (Acemoglu & Autor, 2011; Goos & Manning, 2007; Goos et al., 2014). However, in countries where routine occupations earn the lowest wages, occupational upgrading has been the norm. In contrast to other authors who have concluded from this that these countries have experienced SBTC (e.g. Oesch, 2013), I argue that their experience is compatible with RBTC if differences in the routine-wage schedules are taken into account. Furthermore, unlike Fernández-Macías & Hurley (2017) who posit that RBTC in Europe generally results in occupational upgrading and that polarisation, where it does occur, is therefore primarily due to other factors, I show that RBTC can lead to polarisation in the countries where the assumptions of Autor et al. (2003) and Goos et al. (2014) are met. In future research on technological change and employment dynamics, scholars should take this finding into account – my analyses suggest that one can no longer simply assume, as many labour economists do, that routine occupations are predominantly medium-wage. Nor are they always low-wage, as some sociologists argue. Hence, employment polarisation is not a necessary consequence of routine-biased technological change, and the upgrading employment changes in many countries are compatible with RBTC, properly understood.

Thus, this article makes several contributions to the scientific debate about how recent technological changes have affected the labour market. It provides a much-needed comparative angle that is not limited to European countries and adds nuance to the debate about the nature of recent technological change. Most importantly, my refined theory can accommodate the different patterns of employment change that have been observed in advanced economies, as RBTC and SBTC are shown to operate simultaneously. Thus, the "myth" of pervasive polarisation has been further debunked (Oesch & Piccitto, 2019), and a plausible explanation for the concomitance of RBTC and occupational upgrading presented.

Currently, the analysis is limited by the nature of the underlying datasets. The LIS, being neither register data nor labour force survey data, does not allow to fully account for part-time work due to missing information on hourly earnings or worker status in many datasets. The smaller sample sizes also necessitate a higher level of aggregation of the occupational codes, compared to some other studies (e.g. Fernández-Macías & Hurley, 2017; Wright & Dwyer, 2003). Future research should therefore attempt to replicate the findings for the countries for which better data are available.

Nevertheless, the findings of this article open up ample opportunities for further investigation. The next step in this research agenda will be to investigate which structural and institutional factors drive the differences in wage hierarchies which this article uncovered and thereby tighten the link to the extant sociological literature. For example, higher levels of robotisation may contribute to a smaller and better paid routine manufacturing workforce, and thus to employment polarisation. Similarly, labour unions may improve the relative wage position of highly unionised occupational groups. Finally, the aforementioned differences in female labour force participation and part-time work may affect wage hierarchies. To which extent this is the case and what in turn causes these differences deserves greater scrutiny. Despite the large sociological literature on occupational stratification (see, e.g., Liu & Grusky, 2013; Mouw & Kalleberg, 2010; Williams, 2017), the drivers of differences in occupational wage hierarchies are poorly understood yet crucial for the comparative analysis of employment trends. Furthermore, the differential impacts of technological change on women and men deserve greater attention, as previous research emphasises the importance of female-dominated care work for understanding recent employment trends (Dwyer, 2013; Oesch, 2013). In any case, this article offers important insights for the study of occupational change and interesting directions for future research.

Bibliography

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics* (Vol. 4b, pp. 1043–1171). Elsevier B.V. https://doi.org/10.1016/S0169-7218(11)02410-5

Antonczyk, D., DeLeire, T., & Fitzenberger, B. (2018). Polarization and rising wage inequality: Comparing the U.S. and Germany. *Econometrics*, *6*(20), 1–33. https://doi.org/10.3390/econometrics6020020

Autor, D., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, *103*(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D., Katz, L. F., & Kearney, M. S. (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics*, *90*(2), 300–323. https://doi.org/10.1162/rest.90.2.300

Autor, D., Katz, L. F., & Krueger, A. B. (1998). Computing Inequality: Have Computers Changed the Labor Market? *The Quarterly Journal of Economics*, *113*(4), 1169–1213.

Autor, D., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. *Research Policy*, *48*(8), 103765. https://doi.org/10.1016/j.respol.2019.03.010

Beaudry, P., Green, D. A., & Sand, B. M. (2014). The Declining Fortunes of the Young Since 2000. *American Economic Review: Papers & Proceedings*, *104*(5), 381–386. https://doi.org/10.1257/aer.104.5381

Beaudry, P., Green, D. A., & Sand, B. M. (2016). The Great Reversal in the Demand for Skill and Cognitive Tasks. *Journal of Labor Economics*, *34*(1), S199–S247. https://doi.org/10.1086/682347

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

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

Brady, D. (2009). *Rich Democracies, Poor People: How Politics Explain Poverty*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195385878.001.0001

Bukodi, E., & Goldthorpe, J. H. (2019). *Social Mobility and Education in Britain: Research, Politics and Policy*. Cambridge: Cambridge University Press.

Caines, C., Hoffmann, F., & Kambourov, G. (2017). Complex-task biased technological change and the labor market. *Review of Economic Dynamics*, *25*, 298–319. https://doi.org/10.1016/j.red.2017.01.008

Cerina, F., Moro, A., & Rendall, M. (2021). *A Note on Employment and Wage Polarization in* *the U.S.* (No. 15797).

Cortes, G. M. (2016). Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data. *Journal of Labor Economics*, *34*(1), 63–105. https://doi.org/10.1086/682289

Dwyer, R. E. (2013). The Care Economy? Gender, Economic Restructuring, and Job Polarization in the U.S. Labor Market. *American Sociological Review*, *78*(3), 390–416. https://doi.org/10.1177/0003122413487197

Dwyer, & Wright. (2019). Low-Wage Job Growth, Polarization, and the Limits and Opportunities of the Service Economy. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *5*(4), 56. https://doi.org/10.7758/rsf.2019.5.4.02

Eurofound. (2014). *Drivers of recent job polarisation and upgrading in Europe: European Jobs Monitor 2014*. Luxembourg: Publications Office of the European Union.

Eurofound. (2017). *Occupational change and wage inequality: European Jobs Monitor 2017*. Luxembourg. https://doi.org/10.2806/332137

Fernández-Macías, E. (2012). Job Polarization in Europe? Changes in the Employment Structure and Job Quality, 1995-2007. *Work and Occupations*, *39*(2), 157–182. https://doi.org/10.1177/0730888411427078

Fernández-Macías, E., & Hurley, J. (2017). Routine-biased technical change and job polarization in Europe. *Socio-Economic Review*, *15*(3), 563–585. https://doi.org/10.1093/ser/mww016

Goldin, C., & Katz, L. F. (2008). *The Race between Education and Technology*. Cambridge, MA: Harvard University Press.

Goldthorpe, J. H. (2013). Understanding - And misunderstanding - Social mobility in Britain: The entry of the economists, the confusion of politicians and the limits of educational policy. *Journal of Social Policy*, *42*(3), 431–450. https://doi.org/10.1017/S004727941300024X

Goldthorpe, J. H., Llewellyn, C., & Payne, C. (1987). *Social mobility and class structure in modern Britain* (2nd ed.). Oxford: Clarendon Press.

Goos, M., & Manning, A. (2007). Lousy and Lovely Jobs : The Rising Polarization of Work in Britain. *The Review of Economics and Statstics*, *89*(1), 118–133.

Goos, M., Manning, A., & Salomons, A. (2009). Job Polarization in Europe. *American Economic Review: Papers & Proceedings*, *99*(2), 59–63. https://doi.org/10.1257/aer.99.2.58

Goos, M., Manning, A., & Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, *104*(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Haslberger, M. (2021). Rethinking the measurement of occupational task content. *Economic and Labour Relations Review*.

Katz, L. F., & Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, *107*(1), 35–78. https://doi.org/10.2307/2118323

Koeniger, W., Leonardi, M., & Nunziata, L. (2007). Labor Market Institutions and Wage

Inequality. *Industrial and Labor Relations Review*, *60*(3), 340–356.

Korpi, W. (1983). *The Democratic Class Struggle*. London: Routledge & Kegan Paul.

Kristal, T., & Cohen, Y. (2015). What do computers really do? Computerization, fading pay-setting institutions and rising wage inequality. *Research in Social Stratification and Mobility*, *42*, 33–47. https://doi.org/10.1016/j.rssm.2015.07.001

Luxembourg Income Study (LIS) Database, http://www.lisdatacenter.org (multiple countries; {28.04.2020}). Luxembourg: LIS.

Luxembourg Income Study (LIS) Database. (2019). Generic Codebook: LIS Database (2019 Template). LIS. Retrieved from https://www.lisdatacenter.org/frontend#/home

Liu, Y., & Grusky, D. B. (2013). The payoff to skill in the third industrial revolution. *American Journal of Sociology*, *118*(5), 1330–1374. https://doi.org/10.1086/669498

Mahutga, M. C., Curran, M., & Roberts, A. (2018). Job tasks and the comparative structure of income and employment: Routine task intensity and offshorability for the LIS. *International Journal of Comparative Sociology*, *59*(2), 81–109. https://doi.org/10.1177/0020715218765218

Mazzolari, F., & Ragusa, G. (2013). Spillovers from high-skill consumption to low-skill labor markets. *The Review of Economics and Statstics*, *95*(1), 74–86.

Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT Polarized Skill Demand? Evidence From Eleven Countries Over Twenty-Five Years. *The Review of Economics and Statstics*, *96*(March), 60–77. https://doi.org/10.1162/REST_a_00366

Mouw, T., & Kalleberg, A. L. (2010). Occupations and the structure of wage inequality in the united states, 1980s to 2000s. *American Sociological Review*, *75*(3), 402–431. https://doi.org/10.1177/0003122410363564

Murphy, E. C., & Oesch, D. (2018). Is Employment Polarisation Inevitable? Occupational Change in Ireland and Switzerland, 1970-2010. *Work, Employment and Society*, *32*(6), 1099–1117. https://doi.org/10.1177/0950017017738944

Murphy, K. M., & Topel, R. H. (2016). Human Capital Investment, Inequality and Economic Growth. *Journal of Labor Economics*, *34*(2), S99–S127. Retrieved from http://www.nber.org/papers/w21841

OECD. (2015). *In It Together: Why Less Inequality Benefits All*. Paris.

Oesch, D. (2006). Coming to grips with a changing class structure: An analysis of employment stratification in Britain, Germany, Sweden and Switzerland. *International Sociology*, *21*(2), 263–288. https://doi.org/10.1177/0268580906061379

Oesch, D. (2013). *Occupational Change in Europe: How Technology and Education Transform the Job Structure*. Oxford: Oxford University Press. https://doi.org/10.1093/acprof

Oesch, D. (2015). Welfare regimes and change in the employment structure: Britain, Denmark and Germany since 1990. *Journal of European Social Policy*, *25*(1), 94–110. https://doi.org/10.1177/0958928714556972

Oesch, D., & Piccitto, G. (2019). The Polarization Myth: Occupational Upgrading in Germany, Spain, Sweden, and the UK, 1992-2015. *Work and Occupations*, *46*(4), 441–469. https://doi.org/10.1177/0730888419860880

Oesch, D., & Rodriguez Menes, J. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990–2008. *Socio-Economic Review*, *9*, 503–531.

Parolin, Z. (2021). Automation, Occupational Earnings Trends, and the Moderating Role of Organized Labor. *Social Forces*, *99*(3), 921–946. https://doi.org/10.1093/sf/soaa032

Rendall, M., & Weiss, F. J. (2016). Employment polarization and the role of the apprenticeship system. *European Economic Review*, *82*, 166–186. https://doi.org/10.1016/j.euroecorev.2015.11.004

Salvatori, A. (2018). The anatomy of job polarisation in the UK. *Journal for Labour Market Research*, *52*(8), 1–15. https://doi.org/10.1186/s12651-018-0242-z

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *Journal of Labor Economics*, *24*(2), 235–270. https://doi.org/10.1086/499972

Tahlin, M. (2019). *Polariseringsmyten - Försvinner verkligen de medelkvalificerade jobben?* Stockholm.

Williams, M. (2017). Occupational Stratification in Contemporary Britain: Occupational Class and the Wage Structure in the Wake of the Great Recession. *Sociology*, *51*(6), 1299–1317. https://doi.org/10.1177/0038038517712936

Wright, E. O., & Dwyer, R. E. (2003). The patterns of job expansions in the USA: a comparison of the 1960s and 1990s. *Socio-Economic Review*, *1*, 289–325.

Appendix

Appendix A: ISCO-88 codes and Summary Statistics

Below are the ISCO-88 codes at two-digit level.

11	Legislators and senior officials
12	Corporate managers
13	General managers
21	Physical, mathematical and engineering science professionals
22	Life science and health professionals
23	Teaching professionals
24	Other professionals
31	Physical and engineering science associate professionals
32	Life science and health associate professionals
33	Teaching associate professionals
34	Other associate professionals
41	Office clerks
42	Customer services clerks
51	Personal and protective services workers
52	Models, salespersons and demonstrators
61	Market-oriented skilled agricultural and fishery workers
62	Subsistence agricultural and fishery workers (*subsumed under 61 where present*)
71	Extraction and building trades workers
72	Metal, machinery and related trades workers
73	Precision, handicraft, printing and related trades workers
74	Other craft and related trades workers
81	Stationary-plant and related operators
82	Machine operators and assemblers
83	Drivers and mobile-plant operators
91	Sales and services elementary occupations
92	Agricultural, fishery and related labourers
93	Labourers in mining, construction, manufacturing and transport

Sample sizes

Country	Survey wave					
	~1995	~2000	~2004	~2007	~2010	~2013
CL	46001	80079	87443	97126	76054	85897
CZ	30652	8476	4373	11454	8616	7564
DE	6484	11886	10907	10345	16012	13708
ES	1144	5057	13511	14099	11468	10482
FI	9144	11997	11966	12195	9829	11610
HU	1579	1819	1745	1624	1550	1599
LU	2624	2737	3934	4362	6020	4265
NL	4847	4742	10155	11639	11496	11052
SI	3064	5208	4682	4687	4685	4071
US	67989	101879	96077	95475	89275	61859

Table A 1: Sample sizes used to compute the employment shares.

Appendix B: Wage Changes and Compositional Changes at the 4-digit Level

This appendix discusses in greater detail the issues mentioned at the end of section 5: the changes in countries' wage structures and possible compositional changes at the 4-digit ISCO-88 level. We start by providing a full overview how occupations are distributed across and have moved between wage terciles in individual countries between 1995 and 2013. From the distribution matrix in table A2, no systematic differences are apparent between countries with a concave RTI-wage curve and countries without. In the aforementioned case of Hungary, the position of service workers (group 51) in the wage hierarchy changed substantially without much altering the RTI-wage curve. Similarly, the declining relative position of groups 71 and 73 in Czech Republic has had no visible implications for the RTI-wage curve, as a glance at appendix D can verify. In Spain, which has seen the most movement of occupations between wage terciles between 1995 and 2013 according to the table, there has been a trend towards a marginally concave RTI-wage curve in recent years. It is therefore difficult to draw conclusions for individual countries.

What is apparent, however, is that professionals and health and teaching associate professionals have generally improved their positions as well as, interestingly, operators (major group 8). The biggest losers have been other associate professionals (group 34) and trades workers (major group 7). Thus, among the winners and losers are both high- and low-routine occupations, and even occupations of the same major group (groups 32 and 33, versus groups 31 and 34). Clearly, routine-intensity alone cannot explain the reshuffling of the wage hierarchy that has taken place between 1995 and 2013. There is a fruitful avenue for future research in zooming in on these occupations and investigate which factors, beyond their routine-intensity, have affected their wage trajectory.

There is another major caveat that has to be addressed in order to strengthen confidence in my findings. It is possible that stronger employment growth in 4-digit occupations with wages above the mean for the respective 2-digit occupation, rather than genuine wage increases, are responsible for the upward movement of an occupation in the wage hierarchy, and vice versa. There are two countries in my sample for which we can assess this possibility in a straightforward manner: Chile and Germany. Both countries report 4-digit ISCO-88 data to the LIS, which have been aggregated to 2-digit level for the main analyses. We can thus investigate the relationship between employment changes at the 4-digit level and the extent to which the wage of a 4-digit occupations deviates from the 2-digit mean. For this analysis I focus on the period 1995 – 2010 (1996 – 2011 for Chile) in order to avoid the confounding influence of the switch from ISCO-88 to ISCO-08.

If we plot the change in employment share and the deviation from the 1995 2-digit mean wage of 4-digit occupations in panel A of figure A1, we see a cross-shaped pattern in both countries. While most occupations, including all large 4-digit occupations, line up on a more or less vertical line around zero deviation from the 2-digit mean wage, there is a less densely populated horizontal line of small 4-digit occupations with more or less constant employment shares and large deviations from the 2-digit average wage. If employment expansion of higher-earning 4-digit occupations was behind the trends at the 2-digit level, we would expect the occupations to be organised around a diagonal line from the bottom left to the top right corner of the graphs. Instead, there is no relationship between employment changes and deviations from the 2-digit mean wage, regardless of whether we look at absolute or relative employment changes and whether or not we control for initial employment.

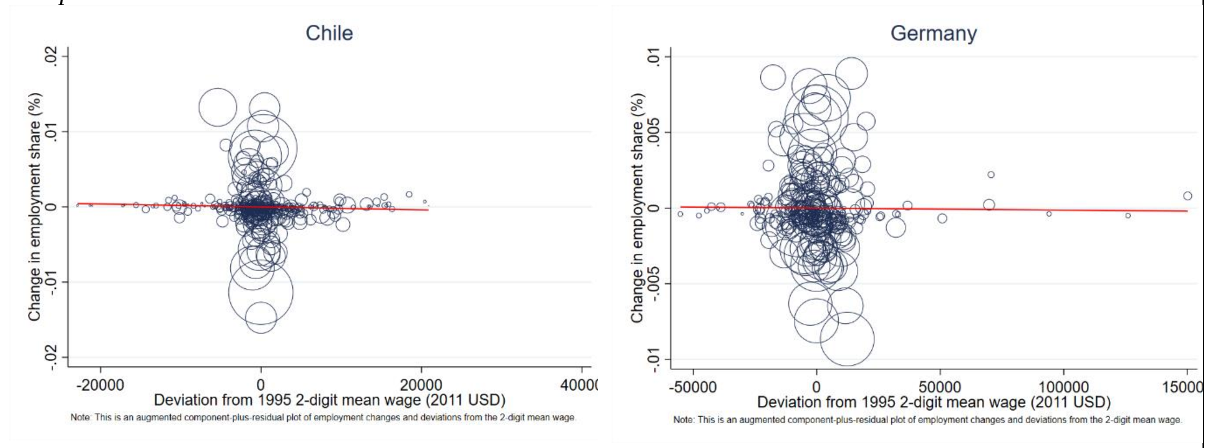
The impression that compositional changes are not the driving force behind occupational wage trend is reinforced by the analysis of counterfactual wage changes at the 2-digit level in panel B of figure A1. For this analysis I calculated hypothetical 2-digit wages for a scenario in which the shares of 4-digit occupations making up a 2-digit group remained unchanged while 4-digit wages were allowed to develop as they did. As Autor, Katz, and Kearney (2008) explain, the validity of this exercise rests on the partial equilibrium assumption that changes in labour market quantities do not affect labour market prices. This runs counter to economic intuitions and findings, but the analysis is nevertheless worthwhile because it can serve as a kind of sanity check. We see that the actual and counterfactual wage changes are very similar for most occupations, regardless of whether we look at Chile which has seen strong overall real wage growth or Germany, where real wage growth has in fact been negative between 1995 and 2010. Repeating the same exercise holding constant wages and only allowing 4-digit employment shares to change, we see in panel C that the counterfactuals bear little resemblance to the actual changes during this period. This indicates that 2-digit wages would have developed very similarly in the absence of compositional changes at the 4-digit level, and that wage changes at the level of detailed occupations are really behind the majority of wage increases and declines of larger occupational groups.

Overall, the findings for Chile and Germany, while showing that limited compositional changes at the 4-digit level have taken place, do not support the conclusion that these account for the patterns we see at the 2-digit level. Wage changes at the 2-digit level overwhelmingly reflect genuine wage changes, rather than compositional changes, at the 4-digit level. The LIS data do not allow us to perform a similar analysis for every country in the sample, but the very clear results in the case of Chile and Germany should provide some reassurance that compositional changes at the 4-digit level are not a major issue. The findings discussed here provide a starting point for further analyses into the role of wage and compositional changes in determining changes in the employment structure.

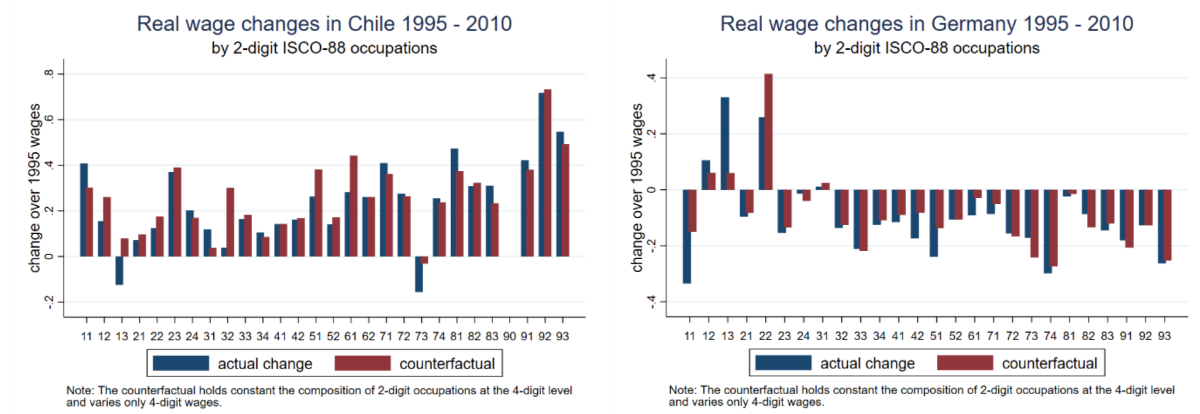
Table A 2: Distribution of Occupations Across Wage Terciles, 1995 and 2013, and Changes

	1995										2013										Change									
ISCO code	**CL**	**CZ**	**FI**	**DE**	**HU**	**LU**	**NL**	**SI**	**ES**	**US**	**CL**	**CZ**	**FI**	**DE**	**HU**	**LU**	**NL**	**SI**	**ES**	**US**	**CL**	**CZ**	**FI**	**DE**	**HU**	**LU**	**NL**	**SI**	**ES**	**US**
11	3	3	3	3	3	3	3	3	2	3	3	3	3	3	3	3	3	3	3	3	0	0	0	0	0	0	0	0	1	0
12	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	0	0	0	0	0	0	0
13	3	3	1	2	3	2	3	3	3	3	3	3	3	3	3	2	3	3	2	3	0	0	2	1	0	0	0	0	-1	0
21	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	0	0	0	0	0	0	0
22	3	3	2	3	3	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	1	0	0	1	1	0	0	0
23	3	3	3	3	3	3	3	3	3	2	3	3	3	3	3	3	2	3	3	2	0	0	0	0	0	0	-1	0	0	0
24	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	0	0	0	0	0	0	0
31	3	3	3	3	3	3	3	3	3	3	3	3	2	3	3	3	3	2	3	2	0	0	-1	0	0	0	0	-1	0	-1
32	3	2	2	1	2	2	1	3	2	2	3	3	3	1	2	3	2	3	3	2	0	1	1	0	0	1	1	0	1	0
33	2	2	3	1	1	1	1	2	2	1	2	3	2	1	3	3	2	3	3	1	0	1	-1	0	2	2	1	1	1	0
34	3	3	3	3	3	3	3	3	3	3	3	3	2	2	3	2	2	3	3	2	0	0	-1	-1	0	-1	-1	0	0	-1
41	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	-1	0	0	0	0	0	0	0	0	-1
42	2	2	1	1	2	2	1	3	2	1	2	1	1	2	2	2	1	2	2	1	0	-1	0	1	0	0	0	-1	0	0
51	2	1	1	1	1	1	1	2	2	1	2	1	1	1	2	1	1	1	1	1	0	0	0	0	1	0	0	-1	-1	0
52	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	0	0	0	0	0	0	0	0	0
61	1	1	1	1	2	1	1	2	1	1	1	1	1	2	1	1	1	1	2	1	0	0	0	1	-1	0	0	-1	1	0
71	2	3	1	2	2	1	2	2	3	2	2	1	1	2	1	1	1	1	2	2	0	-2	0	0	-1	0	-1	-1	-1	0
72	2	2	2	2	2	2	2	2	3	2	2	2	2	2	3	2	2	2	2	2	0	0	0	0	1	0	0	0	-1	0
73	2	3	2	2	3	2	2	1	2	2	1	1	2	1	2	2	1	2	2	2	-1	-2	0	-1	-1	0	-1	1	0	0
74	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	-1	0	0	0	0	0	0
81	3	1	3	2	2	2	3	1	3	2	3	2	3	3	3	2	3	2	3	2	0	1	0	1	1	0	0	1	0	0
82	2	1	2	1	1	2	2	1	2	1	2	2	2	2	1	2	3	2	3	2	0	1	0	1	0	0	1	1	1	1
83	3	2	2	1	2	2	2	2	3	2	3	2	2	1	2	1	1	1	2	2	0	0	0	0	0	-1	-1	-1	-1	0
91	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
92	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
93	1	1	1	1	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	-1	0	0	-1	0
															Absolute sum of changes						**3**	**9**	**7**	**8**	**8**	**7**	**9**	**10**	**11**	**4**

Panel A: Change in employment share of 4-digit occupation and deviation from mean wage of 2-digit occupation



Panel B: Actual and counterfactual real wage changes at the 2-digit level, constant 4-digit employment shares



Panel C: Actual and counterfactual real wage changes at the 2-digit level, constant 4-digit wages

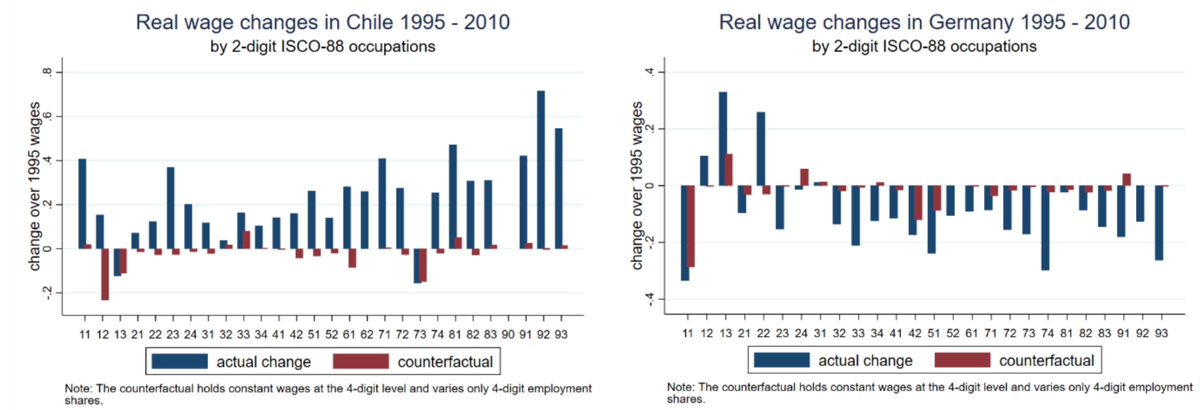


Figure A 1: Panel A shows the relationship between employment changes and wage deviations at the 4-digit level, panel B shows actual and counterfactual wage changes in 2-digit occupations if the employment shares of 4-digit occupations had remained constant at their 1995 values, and panel C repeats the same exercise varying 4-digit employment shares and holding constant 4-digit wages.

Appendix C: Additional Tables and Figures

Table A3 shows an overview of studies of employment change, categorised by their scope (single-country study or comparative [case] study) and the patterns of employment change which they find. Firstly, the table shows that single-country studies are more numerous than comparative studies, and that the US accounts for a large share of this literature. Secondly, among the single-country studies, the findings lean heavily towards polarisation, while comparative studies more often report upgrading. Finally, economists tend to find employment polarisation, while economic sociologists (and more institutionally minded economists) find more diverse, but predominantly upgrading patterns of employment change.

Table A4 shows a simple model of employment change regressed on log annual wages and the share of full-year, full-time (FYFT) workers in 1995 which suggests a somewhat ambiguous picture. In the 10-country sample, just looking at the wage variables, employment changes appear more polarising than upgrading. Running the models separately for women and men, we see that the overall polarisation is driven by men while for women there is a statistically insignificant tendency towards upgrading. If we control for the FYFT share, the quadratic relationship gives way to a linear one, but since data on status in employment are only available for 5 of the 10 countries, the results are not directly comparable.[23] An important takeaway from these regressions is that the coefficient on the share of FYFT workers is negative and statistically significant (except for women only), which suggests that non-standard employment has expanded more strongly than standard employment.[24] The results for women and men separately are similar to the 10-country model. In my data, therefore, we see a gendered pattern of (tentative) upgrading for women and polarisation for men, as recorded in Eurofound (2014).

Table A5 extends the analyses in table 2 of the main article by expanding the sample in panels A and B to include not only the 10 countries with consistent time-series used in the article, but all available LIS country-years between 1995 and 2016. The results are in line with, and in fact slightly stronger than, the smaller sample. In panel C, I control for the share of FYFT workers in each occupation in the countries for which this information is available. Again, the relationship between RTI and occupational employment shares is robust and appears not to be driven by differences in non-standard work.

Figure A2 depicts the increase in social scientific publications on polarization mentioned in the literature overview. Figures A3 – A5 show employment changes by wage, RTI, and complexity quintiles. It shows the upgrading patterns largely intact. Figures A6 and A7 show the result of a locally smoothed regression of average changes in employment shares on the mean occupational wage percentile. They show a precipitous decline in employment up until the 20th wage percentile, small declines until roughly the 65th percentile, and a marked increase in the top tercile or so. While the trend is not linear, it is almost monotonic, except for a small dip around the median wage. Thus, this graphical analysis is in line with the findings from table 2.

[23] Rerunning the models in columns 1 – 4 with only the 5 countries included in columns 5 – 8, the results are insignificant.

[24] According to OECD (2015), the expansion of part-time employment has itself contributed to employment polarisation across countries, but a more detailed analysis of this nexus is beyond the scope of this article.

However, additional analyses by country and with different start and end points in figures A8 – A10 show considerable diversity.

Figure A11 shows the patterns of employment change in the 10-country sample for the period from 1995 – 2013. There are some differences compared to figure 2 in the main text owing to the different start date. This means that some occupations fall in a different wage tercile than in figure 2, especially in countries where the time series starts much earlier, as discussed in the text. Figure A12 shows employment trends by wage tercile an expanded sample of all LIS countries with data in multiple waves.

Furthermore, figures A13 to A16 show the RTI-wage curves in the countries for which the LIS provides information on gross hourly wages. These figures show broadly robust patterns, although there are minor deviations. Reassuringly, however, not only in 2000, but also earlier and later in the period of analysis, most countries show the same kind of RTI-wage curve as with annual income data in 2000. In figure A17, the RTI-wage curves are plotted using annual labour income like in the main body of the paper, but the sample is restricted to FYFT workers only. This constitutes an alternative approach to addressing the problem of the wage variable. Figure A17 likewise shows the overall robustness of the patterns postulated in the main article, as only Germany exhibits a differently shaped RTI-wage curve. Finally, figure A18 depicts the RTI-wage curves with the routine measures of Autor and Dorn (2013), showing very similar patterns as with my measures. This confirms that the results of my study are not driven by the choice of routine measure.

Table A 3: Studies of Employment Change and Their Findings.

Findings/ Type of study	**Unambiguous polarisation**	**Dominant polarisation**	**Dominant upgrading**	**Unambiguous upgrading**	**Other**
Single-country studies	<u>DE:</u> Dustmann, Ludsteck, & Schönberg, 2009 Rendall & Weiss, 2016 <u>ES:</u> Anghel, De la Rica, & Lacuesta, 2014 Sebastian, 2018 <u>PT:</u> Fonseca, Lima, & Pereira, 2018 <u>SE:</u> Heyman, 2016 <u>UK:</u> Goos & Manning, 2007 Cortes & Salvatori, 2016 <u>US:</u> Autor et al., 2003 Autor, Katz, & Kearney, 2006 Autor & Dorn, 2013 Mazzolari & Ragusa, 2013 Cortes, 2016 Cortes, Jaimovich, & Siu, 2017 Siegel & Bárány, 2018	<u>DE:</u> Spitz-Oener, 2006 <u>SE:</u> Adermon & Gustavsson, 2015 <u>UK:</u> Gallie, 1991 Salvatori, 2018 <u>US:</u> Acemoglu & Autor, 2011	<u>CH:</u> Balsmeier & Woerter, 2019	<u>SE:</u> Tahlin, 2019 <u>US:</u> Katz & Murphy, 1992 Berman et al., 1994 Katz & Autor, 1999 Acemoglu, 2002	<u>Downskilling:</u> <u>US:</u> Beaudry, Green, & Sand, 2014 Beaudry, Green, & Sand, 2016
Comparative studies	Goos et al., 2009 Goos et al., 2014 Michaels et al., 2014 OECD, 2015	Naticchioni, Ragusa, & Massari, 2014 Antonczyk, DeLeire, & Fitzenberger, 2018 Cirillo, 2018 Mahutga, Curran, & Roberts, 2018 Jerbashian, 2019	Oesch & Rodriguez Menes, 2011 Fernández-Macías, 2012 Eurofound, 2014, 2017 Fernández-Macías & Hurley, 2017 E. C. Murphy & Oesch, 2018	Berman et al., 1998 Oesch & Piccitto, 2019	

Table A 4: Occupational Wages and Employment Change, 1995 – 2013

DV: ΔEmployment 1995-2013	(1) All workers	(2) All workers	(3) Women only	(4) Men only	(5) All workers	(6) All workers	(7) Women only	(8) Men only
1995 log annual wage	0.107**	0.008*	0.016	0.139**	0.083	0.024**	0.026	0.172**
	(0.047)	(0.003)	(0.009)	(0.050)	(0.066)	(0.006)	(0.014)	(0.057)
1995 squared log annual wage	-0.005*			-0.007**	-0.003			-0.007*
	(0.002)			(0.003)	(0.003)			(0.003)
1995 FYFT share					-0.070**	-0.069**	-0.073	-0.055*
					(0.020)	(0.019)	(0.038)	(0.022)
Observations	260	260	252	260	130	130	127	130
R-squared	0.061	0.052	0.067	0.071	0.093	0.091	0.072	0.094

Standard errors clustered by country in parentheses. All occupations are weighted by their initial employment share in 1995. All regressions include a constant and country-dummies. Sample: same as in table 2 (columns 1 – 4)/DE, ES, FI, NL, US (columns 5 – 8).*** p<0.01, ** p<0.05, * p<0.1

Table A 5: Tasks and employment demand.

PANEL A: BY WORKER STATUS						
		ALL WORKERS			ALL FYFT WORKERS	
DV: Employment share	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
Time-trend interacted with:						
RTI	-0.604***		-0.838***	-0.432*		-0.590**
	(0.200)		(0.267)	(0.231)		(0.296)
Complexity		0.133	-0.182*		0.082	-0.125
		(0.083)	(0.103)		(0.123)	(0.155)
Observations	2,930	2,930	2,930	2,930	2,930	2,930
Country-occupations	597	597	597	597	597	597
R-squared	0.053	0.025	0.059	0.025	0.019	0.026
PANEL B: BY SEX						
		ALL WOMEN			ALL MEN	
DV: Employment share	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)
Time-trend interacted with:						
RTI	-0.858***		-1.190***	-0.457**		-0.559**
	(0.311)		(0.447)	(0.203)		(0.273)
Complexity		0.158	-0.252		0.142	-0.078
		(0.141)	(0.204)		(0.091)	(0.117)
Observations	2,891	2,891	2,891	2,923	2,923	2,923
Country-occupations	597	597	597	597	597	597
R-squared	0.063	0.038	0.068	0.042	0.032	0.043

PANEL C: ACOUNTING FOR NON-STANDARD EMPLOYMENT			
	(C1) All workers	(C2) All workers	(C3) All workers
FYFT share	-0.007	-0.008	-0.007
	(0.006)	(0.006)	(0.006)
Time-trend interacted with:			
RTI	-.774***		-.974***
	(0.219)		(0.285)
Complexity		0.183	-0.149
		(0.121)	(0.149)
Observations	933	933	933
Country-occupations	182	182	182
R-squared	0.068	0.031	0.072

*Note: All point estimates (and standard errors in parentheses) are multiplied by 100. Robust standard errors are clustered by country-occupation. All occupations are weighted by their initial employment share in 1995. All regressions include country-occupation fixed-effects and wave fixed-effects. Sample: all LIS countries 1995 – 2016 (panels A and B), all countries with FYFT data 1995 – 2016 (panel C). *** p<0.01, ** p<0.05, * p<0.1*

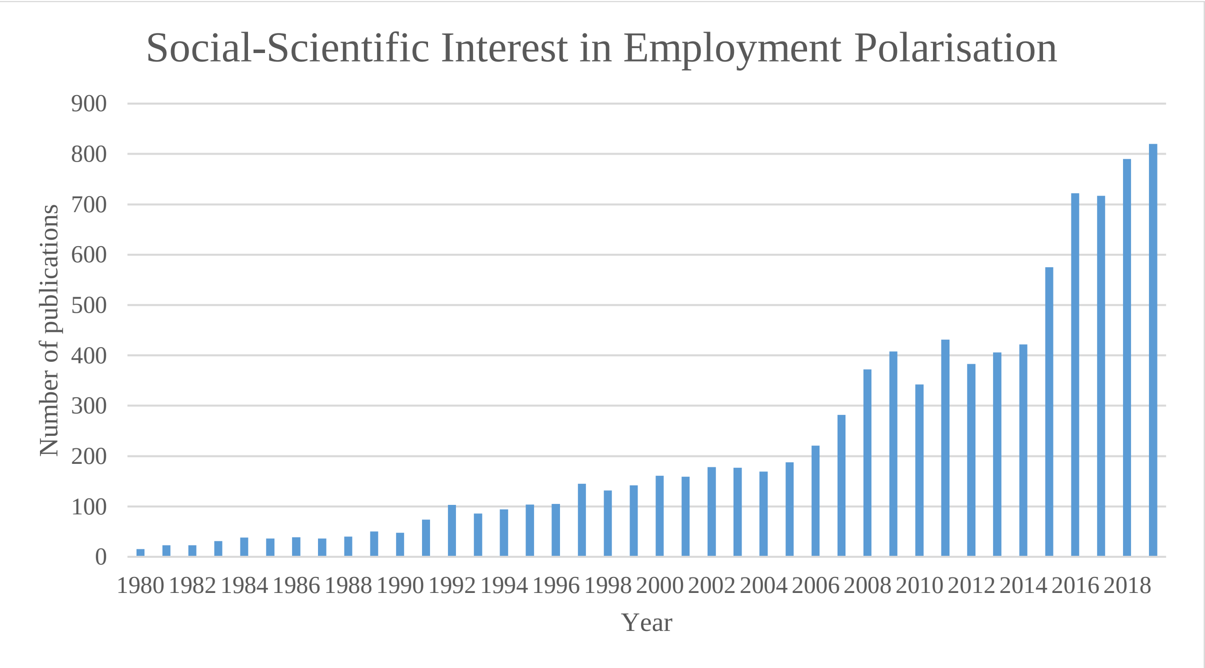


Figure A 2: This chart shows the results of a Web of Science search for publications in economics, sociology, political science, and interdisciplinary social sciences containing the following keywords: 'technological change', 'employment polarisation', 'employment polarization', 'automation'.

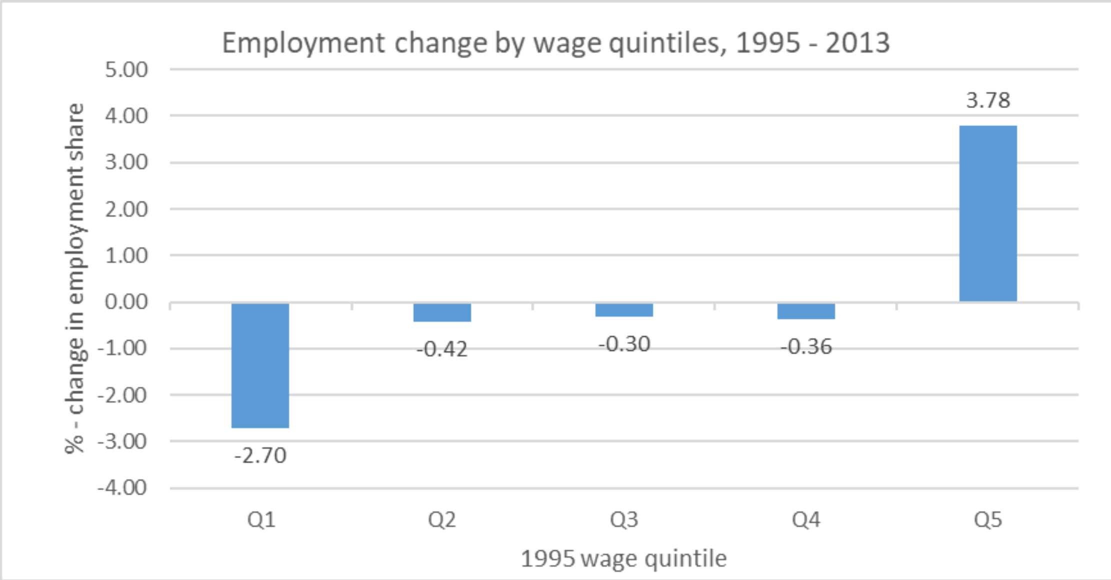


Figure A 3: Employment change by wage quintiles in the 10-country sample.

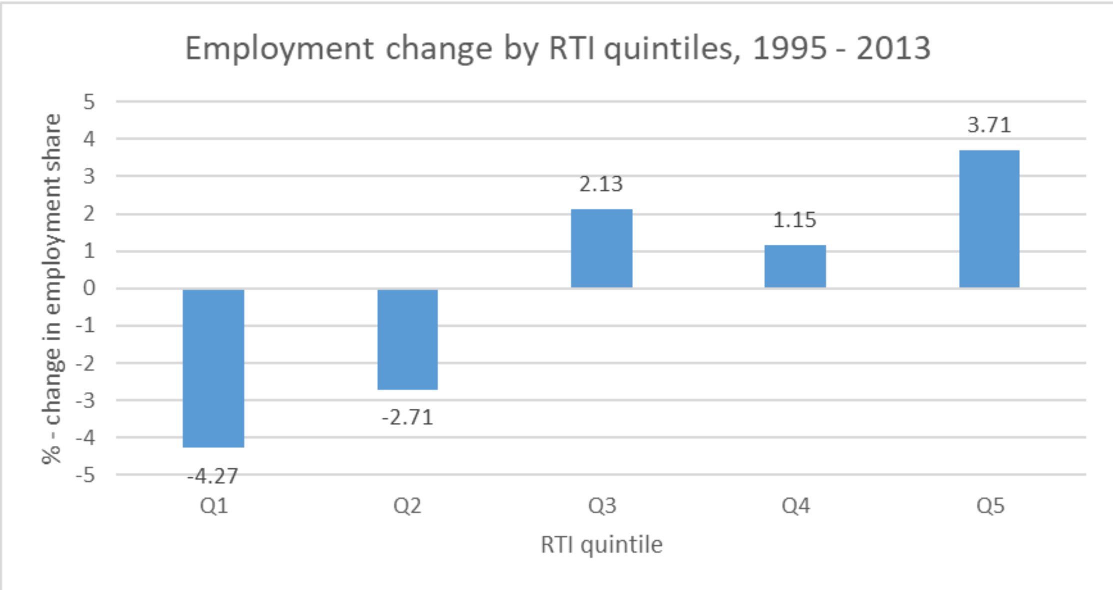


Figure A 4: Employment change by RTI quintiles in the 10-country sample.

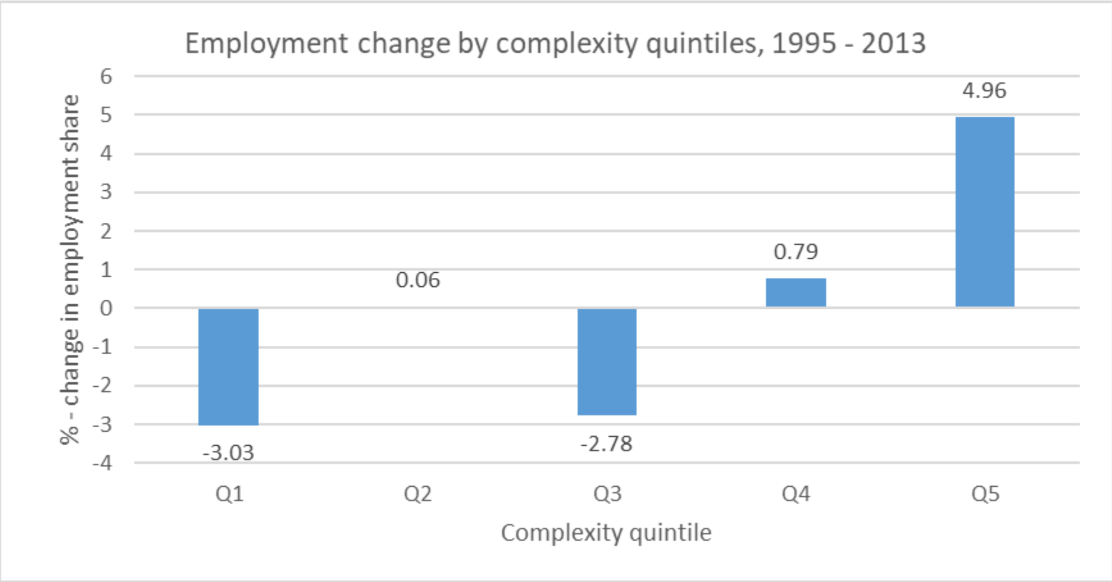


Figure A 5: Employment change by complexity quintile in the 10-country sample.

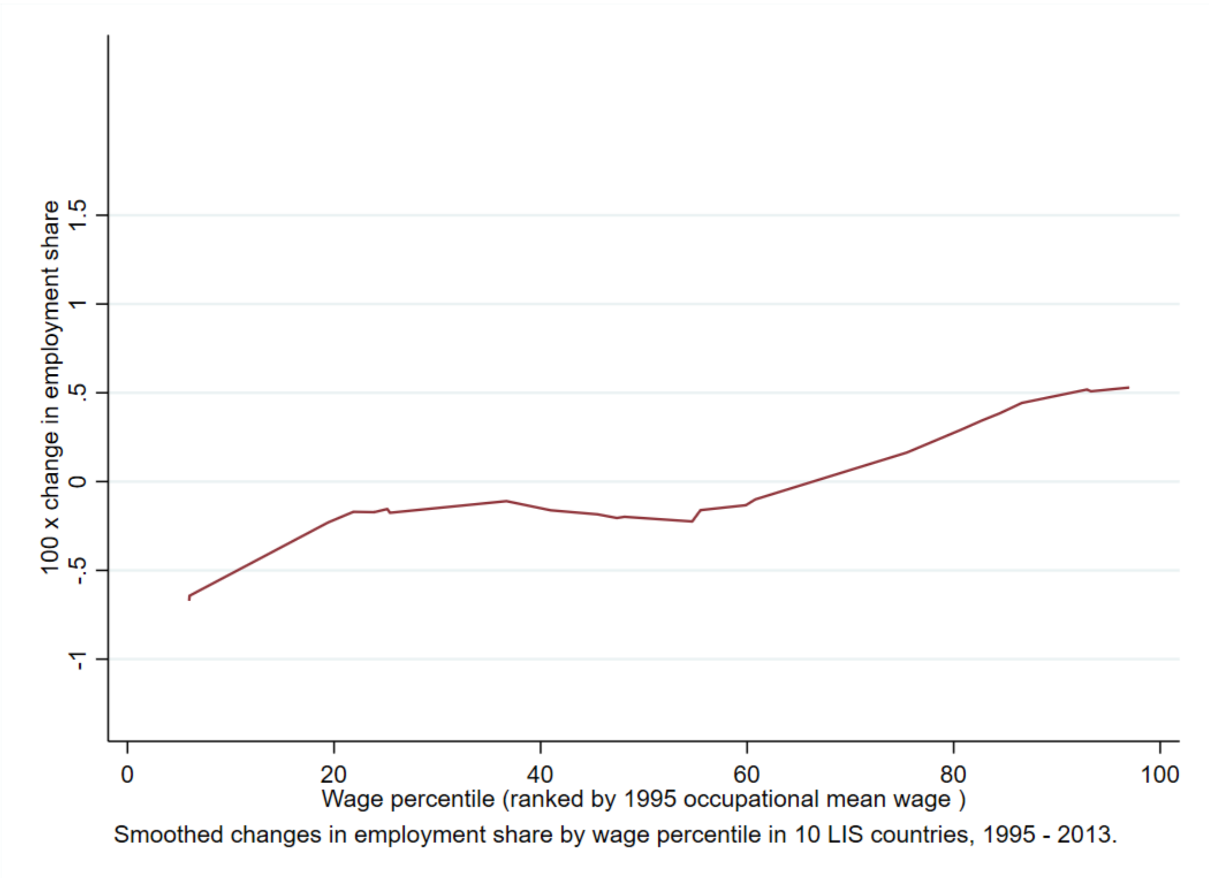


Figure A 6: This figure shows average changes in the occupational employment share by average 1995 occupational wage percentile, based on a locally weighted regression with bandwidth = 0.75.

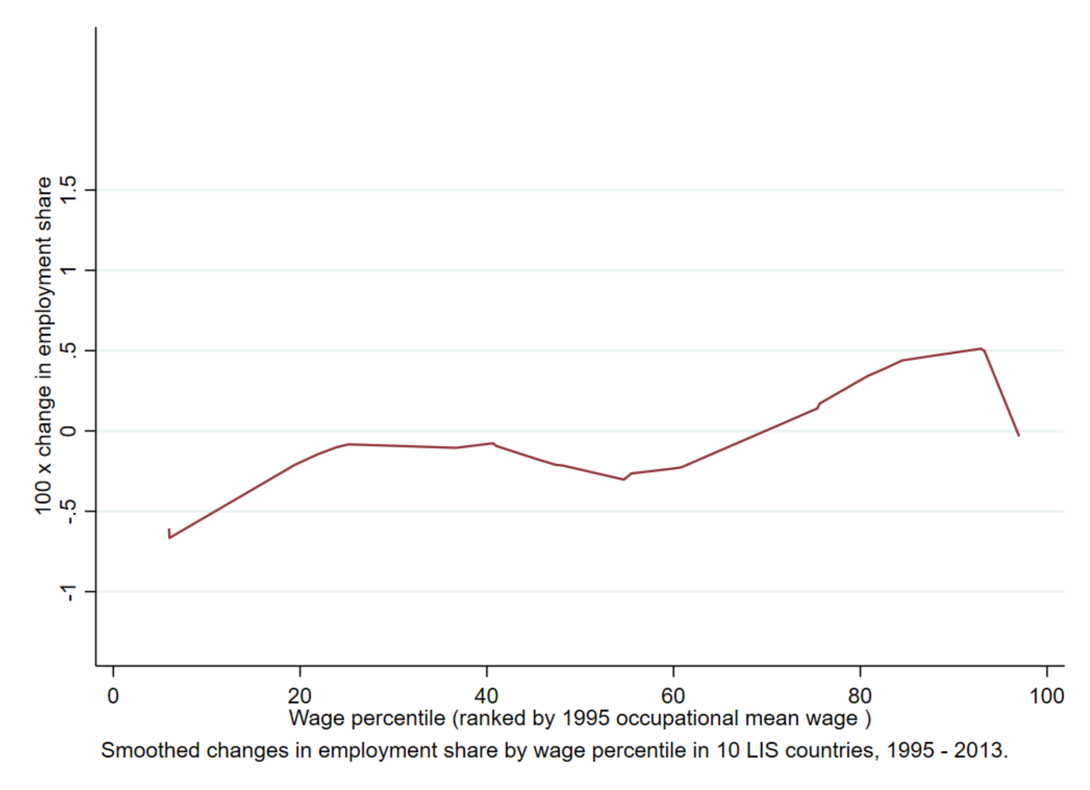


Figure A 7: This figure shows average changes in the occupational employment share by average 1995 occupational wage percentile, based on a locally weighted regression with bandwidth = 0.5.

Figure A 8: Smoothed employment changes in individual countries, 1995 - 2010. Employment changes are estimated using a locally smoothed regression with bandwidth = 0.75.

Figure A 9: Smoothed employment changes in individual countries, 1995 - 2013. Employment changes are estimated using a locally smoothed regression with bandwidth = 0.75.

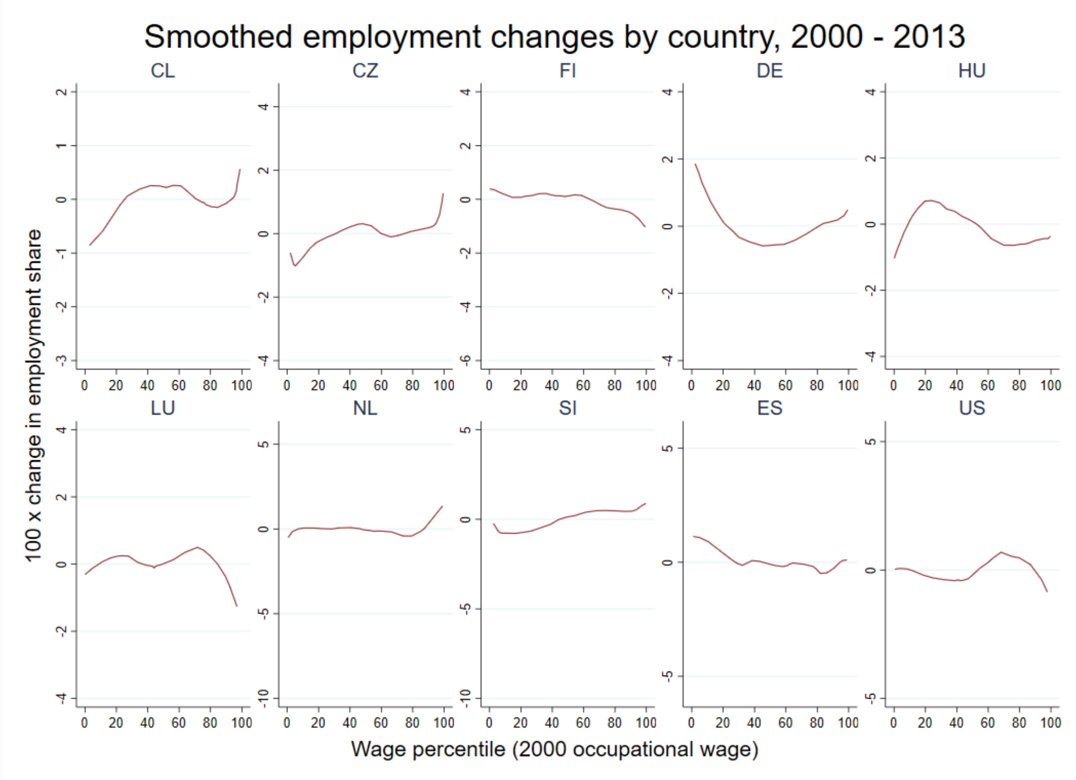


Figure A 10: Smoothed employment changes in individual countries, 2000 - 2013. Employment changes are estimated using a locally smoothed regression with bandwidth = 0.75.

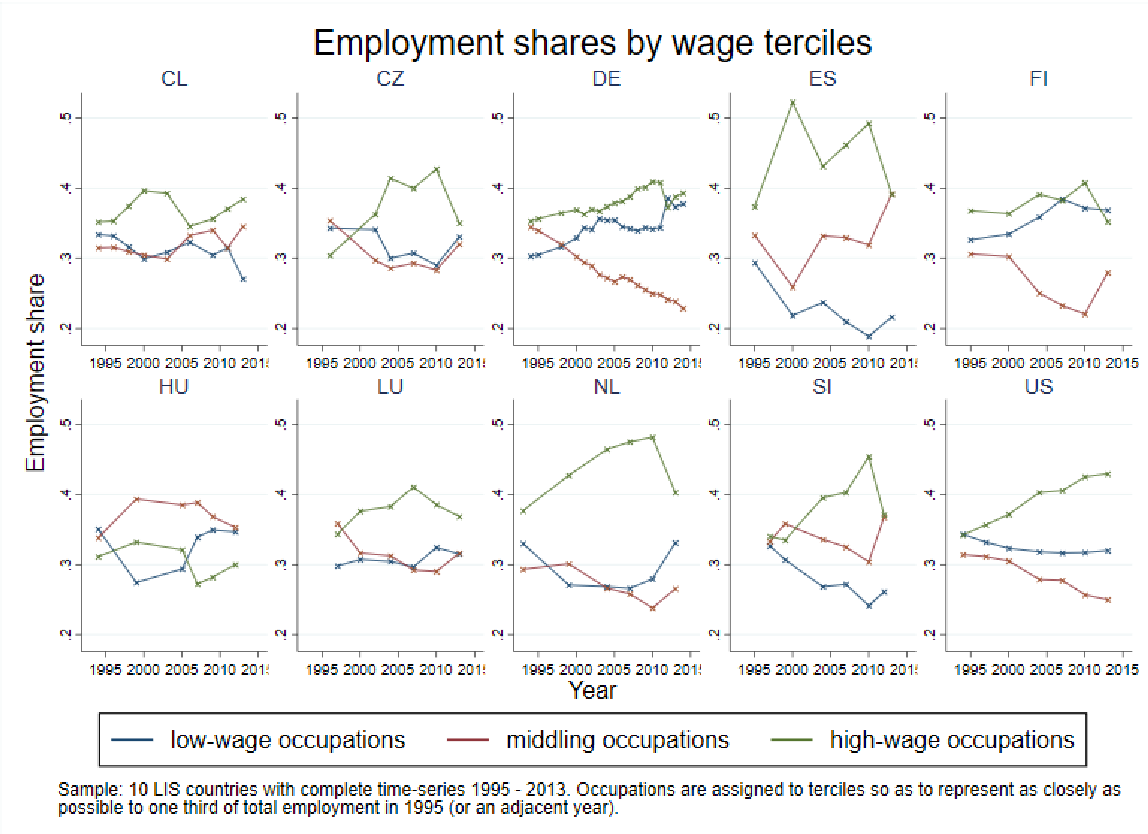
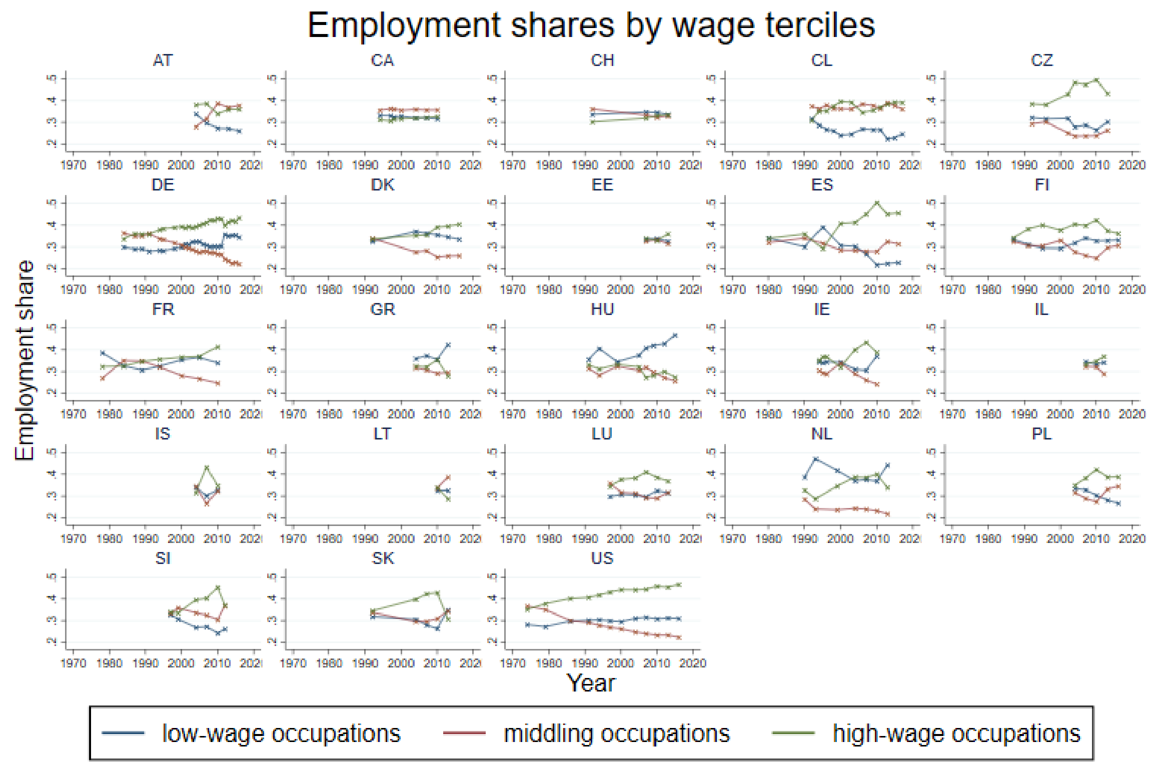


Figure A 11: Employment change in the core sample between 1995 and 2013. Compared to figure 5, in some cases occupations are assigned to different wage terciles based on the different initial period. Hence, in some cases the conclusions may differ compared to the main text.



Sample: 23 LIS countries with employment and wage data in multiple waves. Occupations are assigned to terciles so as to represent as closely as possible to one third of total employment in the first period for which data are available.

Figure A 12: Employment shares by wage tercile in all countries with data for multiple waves.

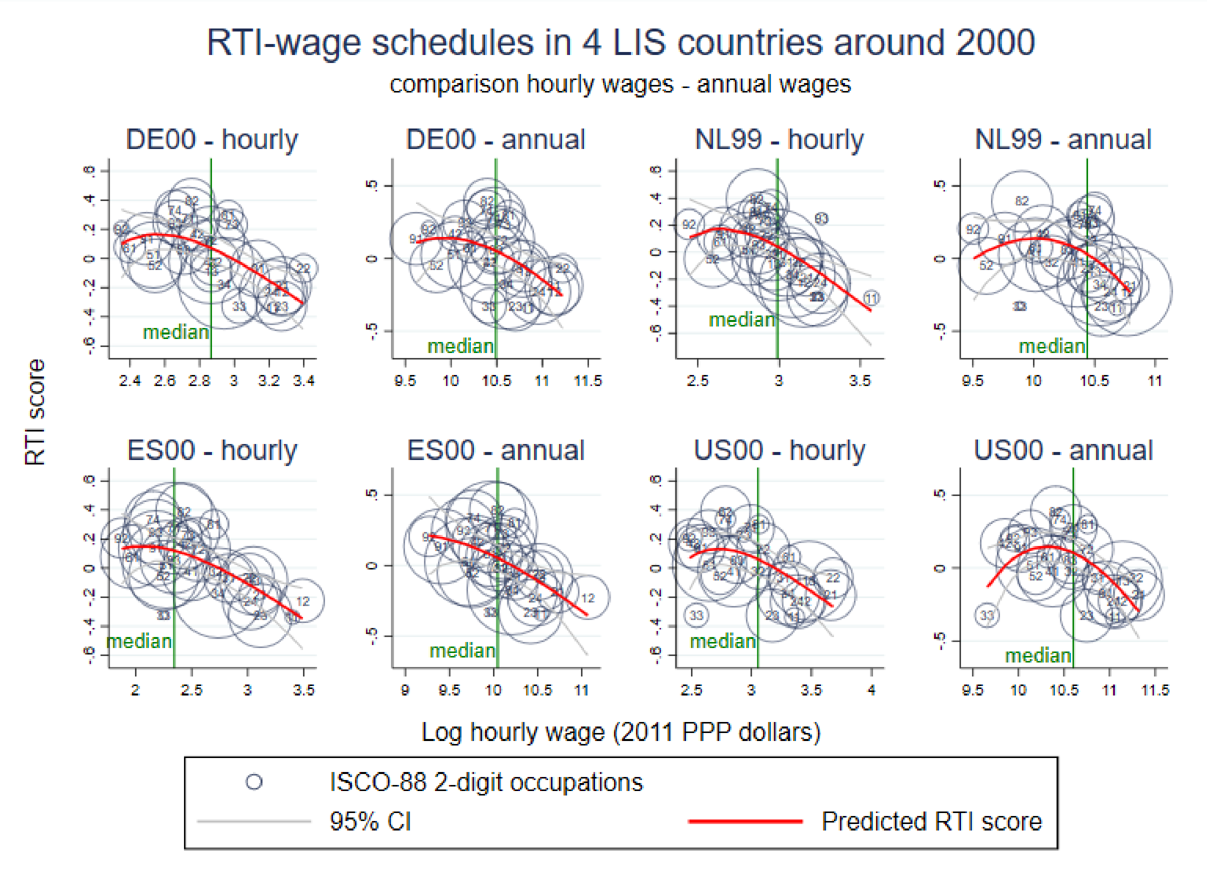


Figure A 13: Comparing RTI-wage schedules with hourly and annual wage data, all workers.

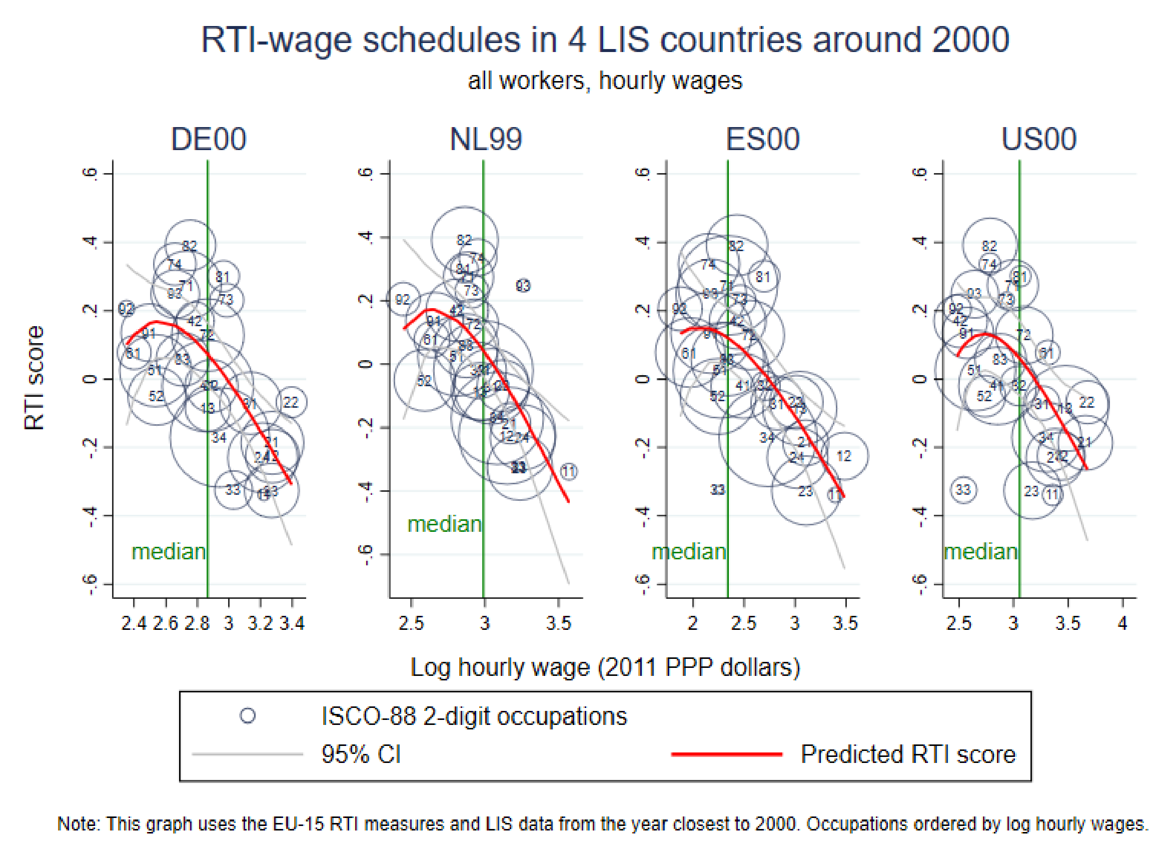


Figure A 14: RTI-wage schedules with hourly wage data, full-year full-time workers.

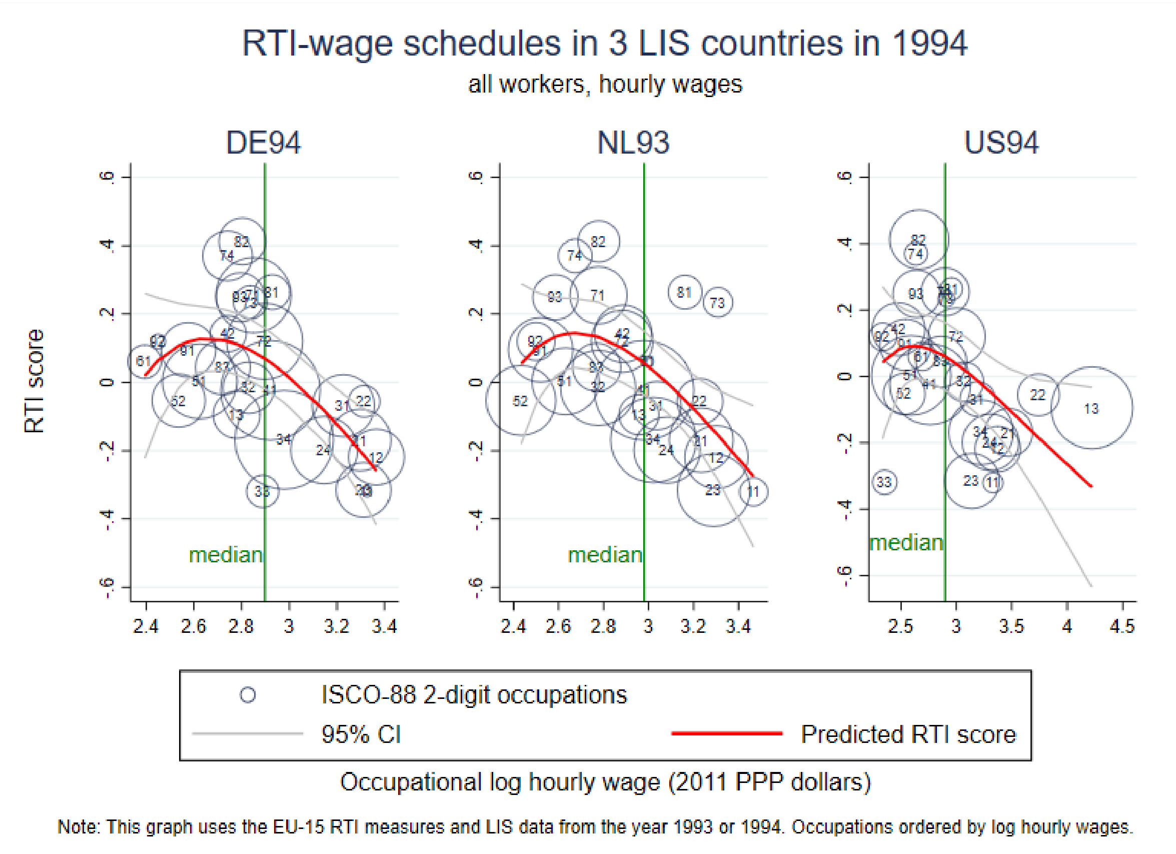


Figure A 15: RTI-wage schedules with hourly wage data, beginning of period of analysis.

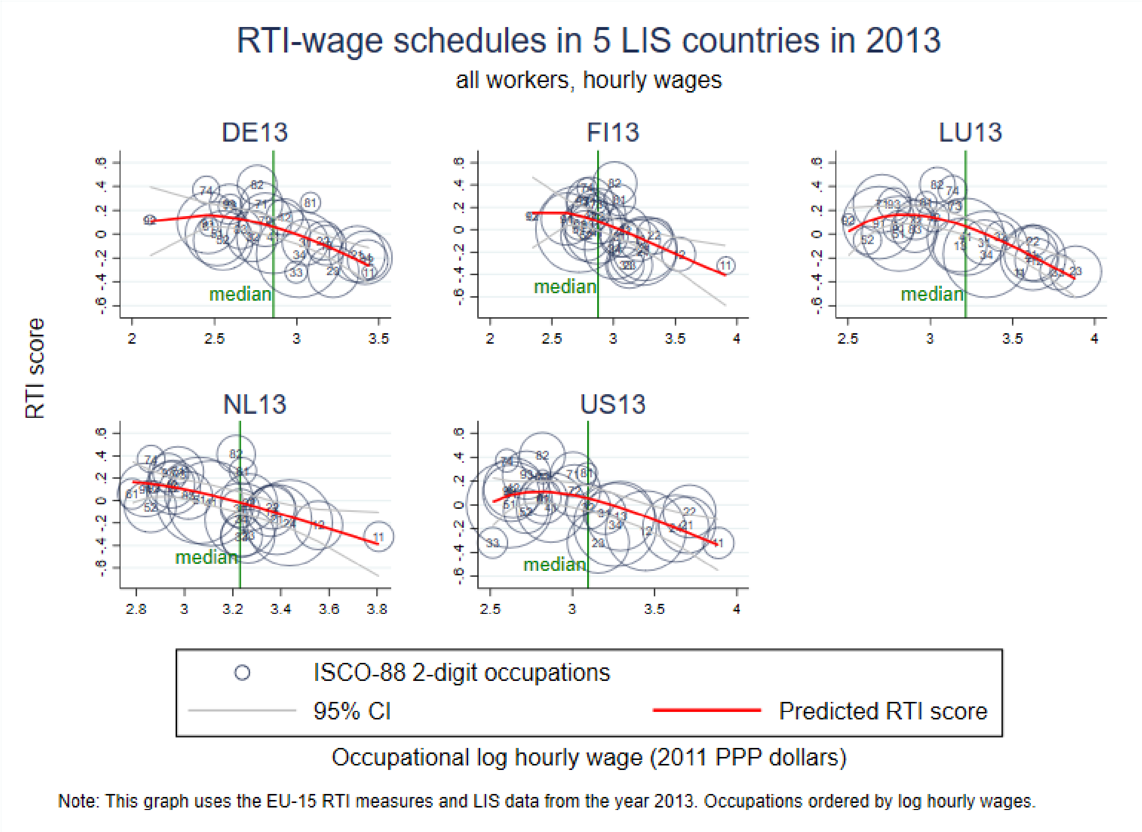


Figure A 16: RTI-wage schedules with hourly wage data, end of period of analysis.

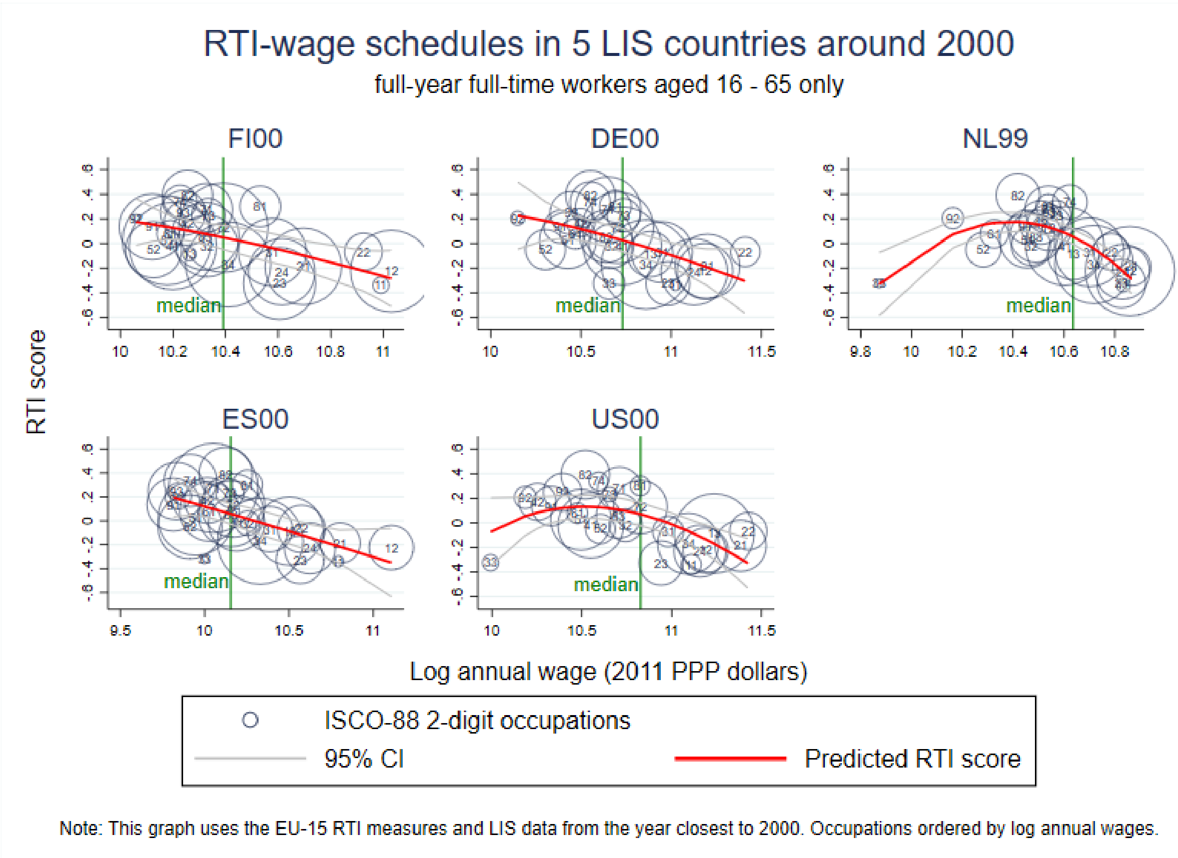


Figure A 17: RTI-wage schedule using annual wages for FYFT workers in countries with information on worker status in 2000.

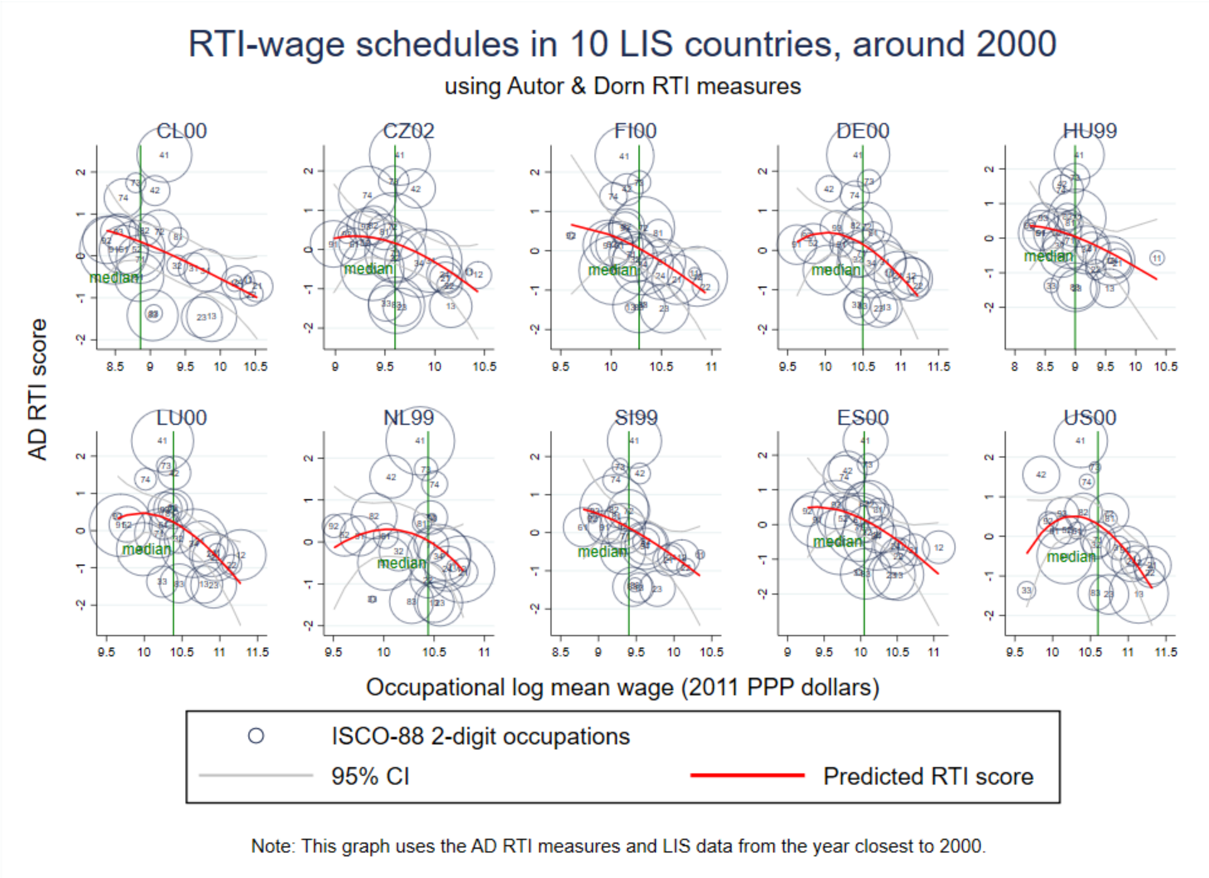
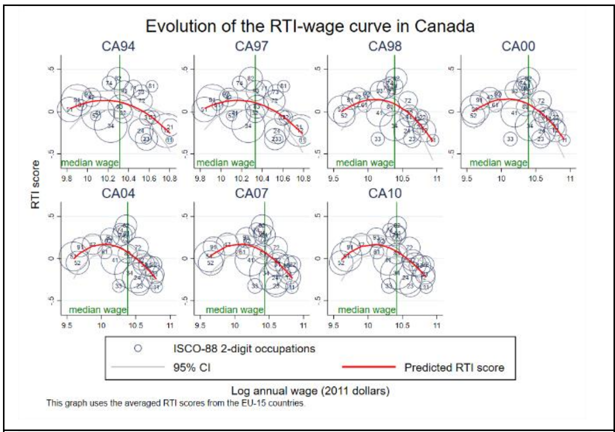
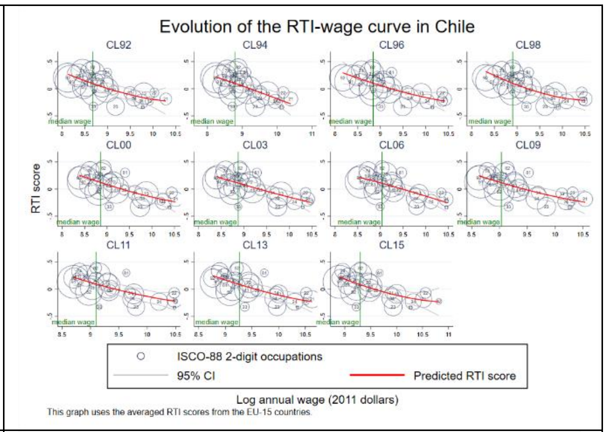
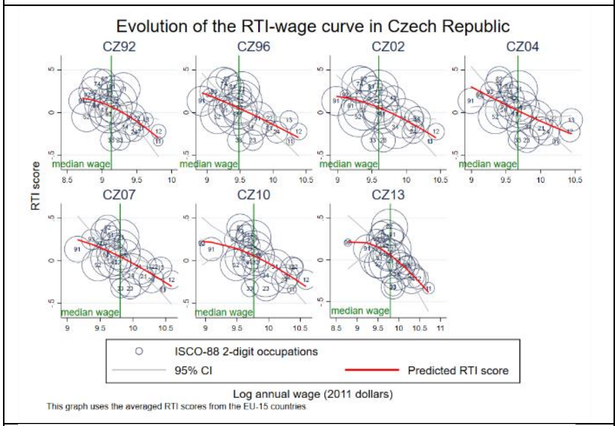


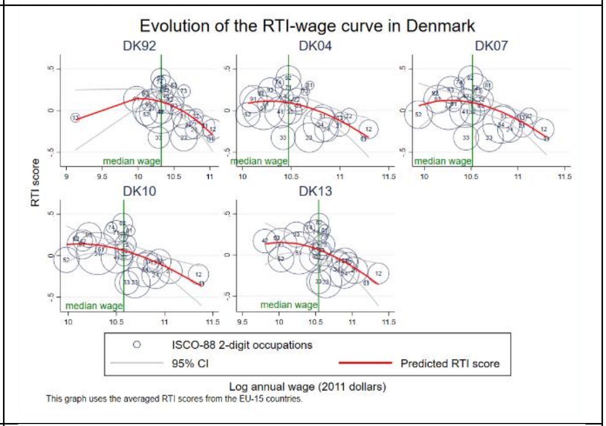
Figure A 18: This figure shows that very similar results obtain when the AD RTI measures are used.

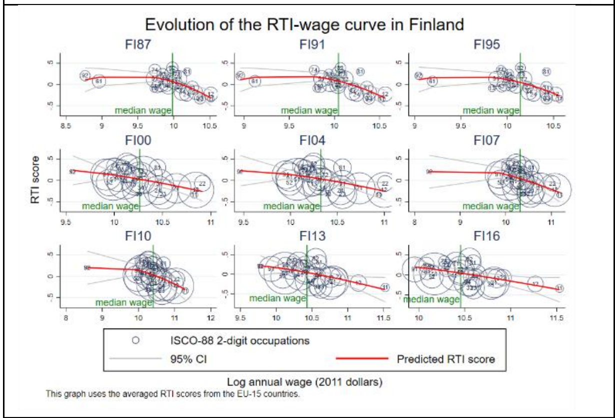
Appendix D: RTI-Wage Curves Over Time in Individual Countries

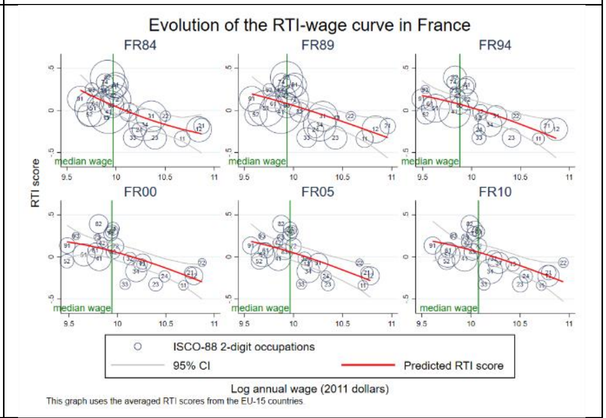


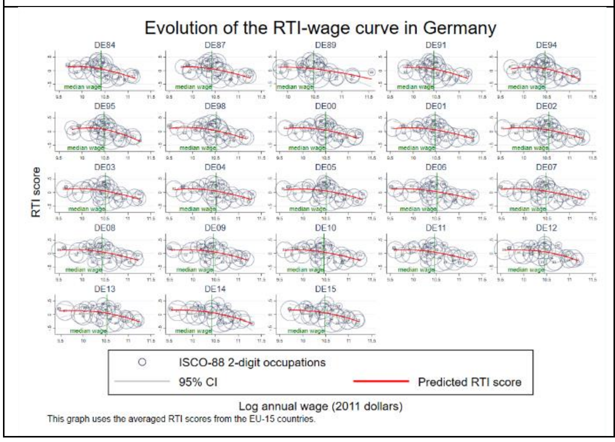


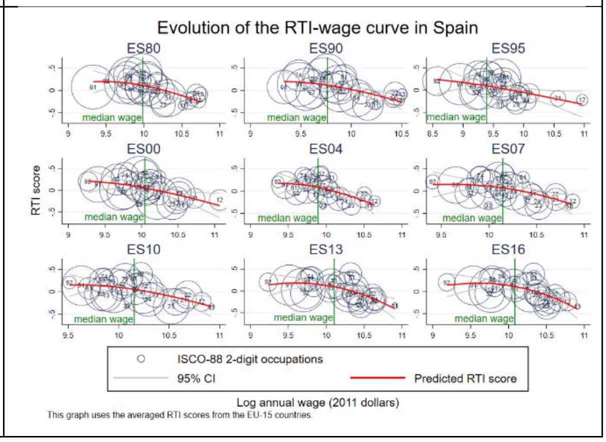


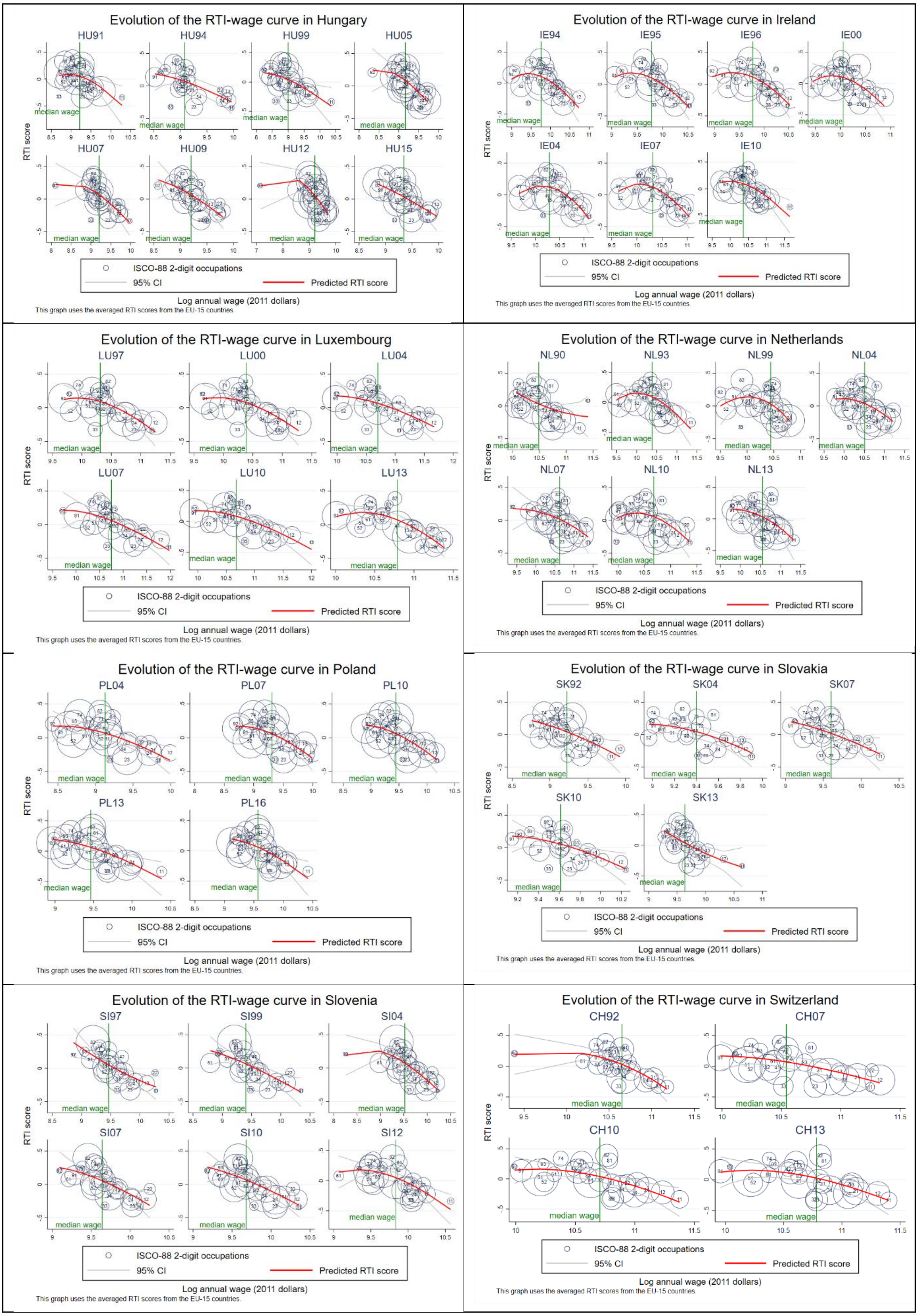












This figure shows the evolution of RTI-wage curves in individual countries which form the basis of the evaluation in column 1 of table 6. A RTI-wage curve is classified as concave if it exhibits a local maximum in the graph area. Note that where small individual occupations are extreme outliers that distort the overall pattern (such as in Finland until 2010 or in Slovenia in 2004), these occupations are discarded.

Appendix E: Methodological Notes

LIS Earnings Data

The sample includes employed individuals with non-zero earnings, excluding armed forces occupations. The variable used in the analyses is *pilabour*, which includes ‘cash payments and value of goods and services received from dependent employment, profits/losses and value of goods from self-employment, as well as the value of own consumption’. The LIS recommends deleting zero and negative values for labour income and then top- and bottom-coding the variable. Thus, following the method used for the LIS key figures, I bottom-code non-zero values at 1 percent of mean labour income in a country-year and top-code income at ten times the median income. This reduces the sensitivity to outliers which could otherwise be a problem for mean rather than median wage data. I use the PPP tables provided by the LIS to convert all occupational wages into 2011 USD.

I also perform robustness checks including only full-year full-time workers aged 16 – 65, using gross hourly wages in addition to annual labour income in the country-years where both income variables are available. The results are similar although somewhat less consistent (see the figures in appendix C). For example, excluding non-standard workers renders the German RTI-wage curve linear while the curve for the US is unaffected. Looking at working-age full-year full-time workers and log hourly wages, both Germany and the US exhibit the hump-shaped RTI-wage curve again. This indicates that the relationships described in this article may be somewhat contingent on the subset of the working population that is being analysed. The findings described in the main body of the article refer to the unrestricted full working population.

Task Intensity Data

My indices of routine intensity and task complexity are based on the following questions from the European Working Conditions Survey (EWCS).

Routine intensity index

- Does your main job involve repetitive hand or arm movements? (Scale from 1: “all of the time” to 7: “never”)
- Does your job involve short repetitive tasks of less than 1 minute? (Scale from 1: ”yes” to 2: “no”)
- Does your job involve short repetitive tasks of less than 10 minutes? (Scale from 1: ”yes” to 2: “no”)
- Does your main paid job involve monotonous tasks? (Scale from 1: ”yes” to 2: “no”)
- Does your main paid job involve meeting precise quality standards? (Scale from 1: ”yes” to 2: “no”)

Task complexity index

- Does your main paid job involve working with computers, laptops, smartphones etc.? (Scale from 1: “all of the time” to 7: “never”)

- Does your main paid job involve complex tasks? (Scale from 1: ”yes” to 2: “no”)
- Does your main paid job involve solving unforeseen problems on your own? (Scale from 1: ”yes” to 2: “no”)
- Does your main paid job involve learning new things? (Scale from 1: ”yes” to 2: “no”)

The indices are constructed by standardising the constituent variables to have a mean of 0 and a standard deviation of 1 following Acemoglu and Autor (2011) and then first averaging across individual survey respondents and subsequently across 2-digit ISCO codes. Where appropriate, I reverse code the answers. Principal component analysis, which is sometimes used in the literature, is not useful in the present case because of the low number of items that make up each index.

The main advantages of this index compared to Autor & Dorn (2013) are the nature of the data (repeated waves of survey data from a large number of countries) and the fact that the severe mismatch between the theoretical concepts and the variables used that is also criticised in Fernández-Macías & Hurley (2017) is addressed. Compared to Fernández-Macías & Hurley (2017), one advantage of this approach is the use of all suitable waves of the EWCS. Additionally, Haslberger (2021) shows that “dealing with unforeseen problems”, which Fernández-Macías & Hurley (2017) consider part of the routine intensity measure, properly belongs in the complexity index, while meeting quality standards, as opposed to enforcing them, belongs in the routine index.

A look at the correlation structure furthermore validates the claim that routine intensity and complexity are empirically distinct concepts. All components of the RTI and complexity indices are positively and significantly correlated with the other components of the index they are part of, with correlation coefficients usually in the range between 0.2 and 0.5. On the other hand, they tend to be very weakly negatively correlated with the components of the other index. The only outlier is the quality standards item which is positively correlated with all components of both indices, but for conceptual reasons is included in the routine index Haslberger (2021).

The resulting measure of routine intensity is strongly positively correlated with the measures of Autor & Dorn (2013) (r = 0.74) and Fernández-Macías & Hurley (2017) (r = 0.94). However, in my view it better captures the idea of routine intensity, which is defined by the notions of repetitiveness and codifiability. Most importantly, the variables used in Autor & Dorn (2013) (“adaptability to situations requiring the precise attainment of set limits, tolerances and standards” for cognitive routine intensity and “finger dexterity” for manual routine intensity) completely fail to capture repetitiveness even though it is at the core of the very concept of routine intensity. Additionally, as mentioned above, the use of survey data, asking a large number of people what they do in their jobs, is preferrable to experts assigning one value to an occupation. Not least, the availability of an auxiliary measure of task complexity (related but not identical to cognitive intensity) is a further advantage because it allows for the investigation of SBTC alongside RBTC. For these reasons, my task indices are a superior alternative to the widely used measure of Autor & Dorn (2013).

Wages, RTI, and Complexity

It is no surprise that occupational wages and task requirements are correlated. In all 20 countries for which we have country-specific task data (spanning the period from 2000 – 2015) from the

EWCS and data on occupational wages from the LIS, we see a positive correlation between complexity and wages, and a negative correlation between routine-intensity and wages. The well-established negative correlation between routine-intensity and task complexity is also present, taking values between -0.44 and -0.79. This reinforces the arguments made elsewhere that wages reflect skill demands. The table below shows country-specific rank-order correlations. Interestingly, in every single one of the 20 European countries in the analysis, the correlation of wages with complexity is stronger than with RTI. In some countries, the difference is furthermore substantial. While the wage – RTI correlations are mostly in the range between -0.3 and -0.4, the wage – complexity correlations typically are between 0.6 and 0.7. This is in line with what we would expect based on the classical RBTC hypothesis: of course, the correlation between wages and RTI is expected to be weaker in the cases where there is a hump-shaped relationship (such as Germany). A similar picture, with slightly stronger correlations, emerges when we correlate the average percentile ranks rather than the raw measures.

Country-specific correlations: wages are more closely related to complexity than to RTI				
Country	**Wage – RTI**	**Wage – Complexity**	**RTI – Complexity**	**N**
AT	-0.4388	0.7335	-0.6656	130
BE	-0.3403	0.4997	-0.6944	78
CH	-0.3579	0.7916	-0.4421	104
CZ	-0.3883	0.4941	-0.7880	182
DE	-0.3341	0.7043	-0.6369	598
DK	-0.5677	0.6666	-0.7832	130
EE	-0.2935	0.7121	-0.4968	78
ES	-0.3579	0.4815	-0.6851	231
FI	-0.3316	0.4333	-0.7265	234
FR	-0.5158	0.6740	-0.6366	166
GR	-0.3852	0.6480	-0.5502	103
HU	-0.3136	0.3566	-0.7415	208
IE	-0.3045	0.4957	-0.4557	182
LT	-0.4310	0.6581	-0.6137	52
LU	-0.5039	0.6326	-0.4728	156
NL	-0.5528	0.6530	-0.7420	180
PL	-0.4714	0.6684	-0.6075	130
SI	-0.3119	0.5614	-0.4680	156
SK	-0.2525	0.4386	-0.6588	130
UK	-0.4735	0.7976	-0.5029	26

Table A 6: Country-year-occupation level correlations of task and wage measures. Data source: Haslberger (2021) for task data and LIS for wages.

At first sight, this indicates that the complexity of the tasks making up an occupation seems to matter more for its employment and wage trajectories than its routine-intensity. Complex occupations command higher wages and routine occupations earn lower wages, but of the two, the wage ranking more closely tracks the complexity ranking. Further analyses show that the correlations tend to increase in later periods, indicating a better matching of workers and occupations, or simply a reduction in measurement error. I also find higher correlations in the EU-15 and in the time periods from which the EWCS data are taken. This suggests that the closer the EWCS task data and LIS wage data are temporally and geographically, the better the fit. This is not to say that technological change has not been routine-biased, but the correlation structure goes some way to explaining why SBTC remains relevant for understanding changes in the labour market.