LIS
Working Paper Series

No. 796

De-routinization of Jobs and Polarization of Earnings – Evidence from 35 Countries

Maximilian Longmuir, Carsten Schröder, Matteo Targa

June 2020

Luxembourg Income Study (LIS), asbl

De-routinization of Jobs and Polarization of Earnings – Evidence from 35 Countries*

Maximilian Longmuir† Carsten Schröder‡ Matteo Targa§

June 17, 2020

Abstract: The job polarization hypothesis suggests a U-shaped pattern of employment growth along the earnings/skill distribution, which is driven by simultaneous growth in the employment of high-skill/high-earnings and low-skill/low-earnings occupations due to Routine-Biased Technological Change (RBTC) [Acemoglu and Autor, 2011]. An aspect of both high social and political relevance is the implications of job polarization and technological change for earnings distributions. In this paper, we put the RBTC trend into perspective by decomposing earnings growth into parts attributable to job polarization and other components. Using a novel harmonized dataset provided by the Luxembourg Income Study and the Economic Research Forum, we find evidence for employment polarization in 30 out of the 35 countries under analysis, in both developed and developing economies. However, the effects of this displacement in the workforce have no polarizing effect on the earnings distribution in 33 countries, once we account for between and within variation in occupational classes returns.

Keywords: job polarization, technological change, earnings and wage distribution, Luxembourg Income Study database, Economic Research Forum database.

JEL classification: D3, J3, J8

*For most helpful discussions, the authors thank Patrick Burauel, Michael Coelli, Johannes König, Nicolás Salamanca, the participants of the first LIS-ERF conference in Cairo in December 2019, participants of economics seminars at the DIW Berlin, the Freie Universität Berlin, and the Melbourne Institute. The authors further thank the LIS Team Support for most helpful support in resolving our data issues. Maximilian Longmuir gratefully acknowledges financial support from the Hans-Böckler-Foundation.

†Freie Universität Berlin. E-mail: m.longmuir@fu-berlin.de.

‡Freie Universität Berlin and Socio-Economic Panel (SOEP) at DIW Berlin. E-mail: cschroeder@diw.de.

§Socio-Economic Panel (SOEP) at DIW Berlin. E-mail: mtarga@diw.de.

1 Introduction

A large body of labor market literature focuses on the dynamics of labor demand and supply at the occupational level. It documents simultaneous growth in the employment of high-skill/high-wage occupations and low-skill/low-wage occupations, with consequent deterioration of jobs in the middle of the distribution. This phenomenon is known as "job polarization" and implies a U-shaped pattern of employment growth along the wage/skill distribution, where the shares of workforce typically located in top and bottom wage quantiles are growing faster than middle ones.

A most influential explanation is introduced by Autor et al. [2003], known as the Routine-Biased Technological Change (RBTC) hypothesis. It relates employment polarization with the rapid improvements in information and communications technologies (e.g. computers and software). According to RBTC hypothesis, decreasing prices of technology over the last decades have exogenously driven the adoption of technologies, *substituting* workers who operate routine tasks.[1] Simultaneously, the automation of routine tasks increases the relative demand for workers who perform *complementary* non-routine tasks, i.e. problem-solving, creativity, situational adaptability, and in-person interactions. This shift in the workforce comprises a polarization process as routine tasks are typically characteristic of middle-skilled jobs (production, clerical, and sales occupations) while non-routine tasks mostly concentrate at both tails of the wage/skill distribution: managerial, professional, and technical occupations at the top; personal service occupations at the bottom.

David and Dorn [2013] link the RBTC hypothesis to *employment* and *wage* polarization, suggesting that "labor specialization spurred by automation of routine task activities play a critical role as a driver of rising employment and wage polarization in the US and, potentially, in other countries" (p. 1591) in addition to factors such as changes in market institutions[2], globalization and offshoring[3].

Although numerous studies provide empirical evidence for employment polarization and its direct link technological change, there is not a general consensus in the economic literature about distributional effects of the RBTC hypothesis. As suggested by Reinhold [2016], the relation between employment and wage polarization is *a priori* not clear. De-routinization of jobs increases inequality via composition effects, because the share of high and low-paying jobs increases with respect to middle ones. However, the direction of the coefficient effect, capturing the changes of return to skills *within* and *between* occupational classes, is unknown.[4] Albeit routine and non-routine occupations are clustered, on average, in different segments of the wage/earnings distribution, their distributions overlap along the quantiles. Therefore, the

[1] Acemoglu and Autor [2011] define a *routine task* as a work activity that "can be fully specified as a series of instructions to be executed by a machine" (p. 20) such as clerical work, repetitive production, and monitoring jobs.

[2] e.g. DiNardo et al. [1996], Lemieux [2006], Dustmann et al. [2009].

[3] e.g. Blinder [2009].

[4] Acemoglu and Autor [2011] provide the underlying theoretical explanations. The effect relies on the ratio between the elasticity of substitution in production between computer capital and routine labor as well as the elasticity of substitution in consumption between goods and services.

overall effect of job polarization on inequality ultimately depends on the sum of composition and coefficient effect along the entire *unconditional* distribution. We believe that this is the main reason for contradictory empirical evidence in the literature.

The existing literature primarily investigates the distributional effects of the RBTC hypothesis on hourly wages opting for an occupation-based approach [Hunt and Nunn, 2019]. This approach establishes a hierarchy of occupations based on average occupational earnings and it defines earnings polarization as faster growth in top and bottom occupational ranks with respect to middle ones. However, approximating the distribution of workers' earnings with occupational average earnings comes has two major costs: first, it estimates distributional effects conditional on fixed ranks of occupations neglecting heterogeneity in the dispersion of occupations along the quantile distribution. Second, while it provides information on differences in earnings dynamics *between*-occupations, it neglects the heterogeneity that emerges *within*-occupational classes.

We add both dimensions to our analysis by using Re-centered Influence Functions (RIF) decomposition methods based on *unconditional* quantile regressions, a statistical tool designed for joint estimation of within- and between-group earnings determinants (see Firpo et al. [2009]). In particular, we estimate the counterfactual earnings growth by quantiles that would have occurred if only occupational composition *and* returns had changed, keeping all other covariates constant. Thus, it enables us to estimate *ceteris-paribus* effects of job de-routinization for every quantile in the country specific earnings distribution while controlling for a set of socio-demographic variables.

We use these tools to investigate two hypotheses in the RBTC framework:

- Job Polarization Hypothesis (H-JP): In the last decades, countries experienced decreasing employment shares in routine-intensive occupations and increasing shares in non-routine-intensive ones.

- Earnings Polarization Hypothesis (H-EP): Job polarization implies rising earnings shares for the lower and upper earnings class, while the earnings share of the middle class hollows out.

The investigation of these two hypothesis is particularly important for policy reasons, since de-routinization ultimately reduces demand for middle-income jobs, thus polarizing the job opportunities. In this sense, automation, along with the adoption of information and communications technology (henceforth ICT), potentially increase the risk of widening inequality between social classes.

A novel and harmonized dataset for 35 countries, provided by the Luxembourg Income Study (LIS)[5] and the Economic Research Forum (ERF), the so-called LIS-ERF dataset, provides the empirical base for our analysis. We opt for yearly labor income as the main measure of individual earnings. Thus, we include the worker's choice of hours in our earnings outcome variable.[6] We argue that labor income provides a measure for labor market outcomes that is

[5] [LIS]

[6] Working hours are treated differently in the literature. For example, DiNardo et al. [1996] and Lemieux [2006] re-calibrate sample weights with working hours, while others do not consider working hours at all; see Acemoglu and Autor [2011] for further discussions.

highly comparable across countries in our sample, overcomes several data restrictions,[7] and is commonly used in the inequality literature (see, e.g. Jenkins et al. [2012]). Nevertheless, we replicate our main analysis using hourly wages for a sub-set of 21 countries where reliable information is available. Our findings are robust to either earnings or wages, suggesting that changes in working hours contribute only marginally to the evolution of inequality in our working sample.

This paper contributes to the literature by providing a comprehensive international test of the employment and earnings polarization hypotheses as well as an assessment of their relevance for inequality dynamics. Unlike the existing literature, we investigate the unconditional distributional effects of job polarization, overcoming the limitations of an occupation-based approach accounting for both *between* and *within*-occupational classes determinants of inequality, claiming that both dimensions must be considered in distributional analysis.

First, we investigate RBTC hypothesis on the employment structures (H-JP). We find decreasing employment and earnings shares in routine occupations in 30 out of 35 analyzed countries over the time period considered consistent with the RBTC framework.[8] Therefore, we conclude that the RBTC hypothesis constitutes an important theoretical framework appropriate for studying the evolution of the composition of the employed workforce internationally (H-JP not rejected).

Second, we explore how de-routinization affects country-specific earnings structures (H-EP). Our RIF counterfactual estimates reject a close link between employment and earnings polarization in 33 out of the 35 analyzed countries, confirming the overall weak predictive power of the RBTC hypotheses for distributional analysis (H-EP rejected). Our estimates suggest that the composition effects induced by employment polarization are mitigated by changes in the returns structures. In particular, the increased (decreased) demand of non-routine service (routine) occupations does not coincide with increasing (decreasing) returns in bottom (middle) quantiles.

We find overall employment *and* earnings polarization in a restricted subset of couturiers (i.e. Belgium, Ireland, Jordan, Switzerland and the United States). However, only in Ireland and Switzerland, our analysis suggests that U-shaped effects of job de-routinization drive the polarization of the earnings distribution. In Belgium, Jordan, and the United States, job polarization implies increasing inequality, suggesting that employment de-routinization *per se* cannot explain the observed polarization and other factors drove the growth of bottom-tail earnings.[9] In almost all European countries under analysis[10] as well as in Mexico and India, we observe increasing earnings inequality. In Georgia, Jordan, Russia, and in countries in Central and South America[11], we identify decreasing inequality. Inequality patterns in Egypt, Greece, Iceland, Israel, and Luxembourg are rather stable. De-routinization effects, textitceteris-paribus, are extremely heterogeneous and, in general, do not predict overall quantiles growth patterns. Therefore, we

[7] Especially availability and reliability in terms of item-non-response rates.

[8] The exceptions are Brazil, Egypt, India, Peru, and Slovakia.

[9] Such evidence may underline that labor market institutions, including unions, minimum wage, and workers protection laws, play an important role in shaping earnings distribution over time.

[10] Austria, Czech Republic, Denmark, Estonia, Finland France, Germany, Netherlands, Poland, Slovenia, Slovakia and Spain.

[11] Brazil, Chile, Colombia, Guatemala, Panama, Peru, and Uruguay.

conclude that job de-routinization has weak predictive power for distributional analysis, corroborating Hunt and Nunn [2019]'s skepticism in approximating earnings growth through the lens of the RBTC hypothesis.

Third, we descriptively scrutinize how changes in the employment structure correlate with changes in inequality between and within occupational classes separately. Consequently, we link H-JP and H-EP results in order to understand why earnings prove to be unresponsive to changes in employment composition. Two major findings result: first, we do not find any significant reduction (increase) in inequality *between* service (abstract) and routine workers. Such results corroborate the RIF decomposition results explained above: changing returns between occupations mitigate the composition effects of job polarization and are key determinants for overall earnings growth. Second, *within* occupations dynamics seem to play the major role for the distributional analysis, although it is typically neglected in RBTC literature. We invite researchers to further investigate empirically the relationship between the RBTC hypothesis and its effects on the within-occupational earnings distribution.

The paper is organized as follows: Section 2 provides a literature review, Section 3 discusses data sources and harmonization processes. Section 4 describes the methodology and the wave selection algorithm. Section 5 provides the results. Section presents the results using hourly wages instead of yearly gross-income. Section 7 concludes.

2 Literature Review

This Section reviews the empirical literature on employment polarization and its implications for earnings inequality.

Our first hypothesis (H-JP) is extensively studied in both advanced and emerging economies, with most studies providing empirical evidence for *employment* polarization[12] and its direct link to ICT adoption. In their widely recognized work, Autor et al. [2003] find evidence of job de-routinization between the 1960s and 2000s in the US. Goos and Manning [2007], analyzing different models of labor market changes for the UK between 1975 and 1999, conclude that the RBTC-hypothesis by Autor et al. [2003] works best for explaining shifts in occupational classes. Goos et al. [2014] show de-routinization in the workforce due to ICT adaption in 16 Western European countries between 1993 - 2010. Green and Sand [2015] find similar patterns between the 1980s and 2005 in Canada and Coelli and Borland [2016] between the 1980s and 1990s in Australia. Aedo et al. [2013], analyzing eight developing countries over time, find a strong correlation between economic development and the skill intensity of non-routine cognitive, analytical, and interpersonal skills, but strong negative correlations with routine and non-routine manual skills. De La Rica and Gortazar [2016] focus on a set of OECD developed countries around the world and find evidence for job polarization due to ICT adaption, as well as Hardy et al. [2018] in Central and Eastern Europe. Mahutga et al. [2018] describe de-routinization of jobs primarily as a phenomenon of the global north in their analysis of 38 LIS countries.

In sum, most previous research supports the employment polarization hypothesis due to ICT adaption in many countries around the world. We contribute to this strand of literature by testing

[12]Employment polarization and job polarization are used as synonyms.

our (H-JP) hypothesis using a harmonized dataset up to the year 2016 for 35 countries.

Several empirical studies investigate the second hypothesis (H-EP), i.e. the potential effect of job polarization on the hourly wages and earnings distribution. The evidence is mixed.

There is support for H-EP in the United States, where Firpo et al. [2011] and David and Dorn [2013] confirm the overall *wage* polarization and the important role played by ICT adoption. In particular, David and Dorn [2013] show that the hourly wage of non-college workers employed in service occupations, with relatively high routine-task intensity, rose significantly between 1980 and 2005. They also find positive wage growth for all the others occupational categories characterized by low routine task intensity. Highly routinized employment experienced wage losses with the unique exception of clerical jobs. Thus, the authors provide evidence that job de-routinization polarizes the returns to skills *between* occupational classes and can explain a substantial share of aggregate polarization. In Europe, evidence for wage polarization is provided for Germany [Dustmann et al., 2009] and the UK [Machin, 2010]. Although, the analysis of Frey and Osborne [2017] does not link de-routinization and its effect on wages, they conclude that ICT adaption replaces jobs at the lower-end of the distribution. Mahutga et al. [2018] also state that de-routinization contributes to earnings polarization in rich democracies.

Several studies reject the earnings polarization hypothesis (H-EP). Goos and Manning [2007] question the connection between de-routinization and wage inequality, as it does not account for heterogeneous wage distributions within occupations. Therefore, they reject H-EP in the UK. Nor can Green and Sand [2015] verify H-EP in Canada. Böhm et al. [2019], Hunt and Nunn [2019], and Taber and Roys [2019] suggest that the RBTC hypothesis is not suitable for studying the evolution of wages and earnings inequality, raising similar concerns as Goos and Manning [2007]. Böhm et al. [2019] find skill selection effects between occupation entrants and leavers, as they earn lower wages than stayers, suggesting that wage effects are negative for growing occupations and positive for shrinking ones. This selection cannot be captured by focusing on between-occupational changes alone. According to Hunt and Nunn [2019], 86% of the increase in wage inequality in Germany between 1973 and 2018 stems from variation within occupations. Taber and Roys [2019] argue that labor-demand changes between occupations explain only a small part of changes of the wage distribution between 1979 and 2017 in the US concluding that skill price changes within occupation are far more important.[13]

Our analysis strongly supports the findings by Goos and Manning [2007], Böhm et al. [2019], and Hunt and Nunn [2019] providing cross-country evidence and taking into account both between- and within-occupation dynamics to explain changes in the earnings distribution. Moreover, we provide further evidence for the importance of within-occupational earnings distribution for overall inequality patterns.

[13]More studies question H-EP. Massari et al. [2014] do not find wage polarization and estimate only weak polarizing effects of technology in Europe suggesting that deterioration of labor institutions, e.g. increase in part-time and temporary jobs, may play a more important role by hindering wage growth at the bottom. De La Rica and Gortazar [2016] argue that, although differences in ICT adoption explain an important and significant part of wage differentials, they do not find a significant association between wage inequality and technology adoption for OECD countries.

3 Data

Our empirical analyses rely on the LIS-ERF joint dataset, the largest available international harmonized income micro-database based on repeated cross-sections from over fifty countries.[14] The LIS cross-national data center acquires, harmonizes, and documents microdata from different national statistical institutions.[15] In addition to detailed income information, it includes a broad set of individual and household characteristics – including occupational and socio-demographic information of household members. Our final working sample includes 35 countries, which are selected by two criteria:

- Availability of repeated cross-sections: the minimum data requirement for a country to be included in the working sample is availability of at least two waves, since the empirical testing of our hypotheses requires measures of differences in earnings and employment shares over time.
- Availability of focal variables: earnings and main job information are necessary to define quantiles and occupational classes used in the analysis.

Following previous literature, our working sample focuses on prime-age employed individuals aged 25-55. Missing values are imputed in all LIS and ERF countries. The imputation is conducted by the individual survey institute in each country. Most countries follow a simple random sampling or a two-stage area sampling procedure. Even though the imputation procedures are not standardized, we rely on the comparability across waves and countries guaranteed by LIS and ERF. Top- or bottom-coding procedures do not apply.

Figure 1 depicts a map of the countries included in LIS-ERF and our working sample. A detailed overview of the country-specific waves compatible with our selection criteria are reported in Table 1.

3.1 Wave Selection

For many countries, the LIS-ERF database provides various cross-sectional waves. To avoid an arbitrary selection of the base ($t = 0$) and ending period ($t = 1$) in the decomposition exercises, we opted for a simple algorithm that proceeds as follows:

Step 1 Elaborate the most recent wave in which country specific occupations are coded according to ISCO 88 scheme.[16] Define the wave as $t = 1$.

Step 2 Let $w = \{1,2...,W\}$ denote a one-year time-span *before* $t = 1$ and W the *earliest* wave available in the sample. The index $j = \{1,2,...7\}$ describes five different scenarios j,

[14]Compared to the standard LIS dataset, LIS-ERF includes additional data for seven countries: Egypt, Iraq, Jordan, Palestine, Somalia, Sudan, and Tunisia.

[15]Access to the harmonized dataset is available to registered users and detailed description of the variables included can be found online: https://www.lisdatacenter.org/frontend#/home.

[16]As explained in Section 3.3, ISCO-88 and ISCO-08 occupational schemes cannot be harmonized exclusively.

which defines the base year $t = 0$. For each country, set $t_j = t = 0$ as described in the following **algorithm**:

while $w \leq W$ **do**

1. if $w \geq 5$ & $w < 10$, set $t_1 = 0$
2. if $w \geq 10$ & $w < 15$, set $t_2 = 0$
3. if $w \geq 15$ & $w < 20$, set $t_3 = 0$
4. if $w \geq 20$ & $w < 25$, set $t_4 = 0$
5. if $w \geq 25$ & $w < 30$, set $t_5 = 0$
6. if $w \geq 30$, set $t_6 = 0$
7. if $W < 5$, set $t_7 = 0$

end while

Besides its simplicity, this algorithm has the advantage that it allows us to use as many waves as possible without incurring in redundant decompositions.[17] If enough country-specific waves are available and compatible with the analysis, the algorithm potentially produces seven main time spans to perform the decomposition. In our sample, this is only the case for the United States. For Chile, Finland, Germany and Mexico, the algorithm constructs five time spans; for Spain four, and for Canada, France, and Slovenia, three. Two time spans are available for Colombia, the Czech Republic, Ireland, Luxembourg, Netherlands, Russia, Slovakia, and Peru; and one for each remaining country in our working sample.

3.2 Focal Variable - Earnings

The focal variable to test H-EP would be gross hourly wages, as it is the best proxy for individual productivity. The information on hourly wages is limited in the ERF/LIS data. We rely, therefore, on on individual yearly gross and net labor earnings, which are defined for all LIS countries as the total income from labor of each household member, including cash payments and value of goods and services received from dependent employment, as well as the profits/losses and value of goods from self-employment. ERF countries do not have individual information on labor income. Therefore, we divide the household income[18] by the number of members in the household who earn a salary.[19] LIS waves that do not provide individual labor income information[20] are excluded from the analysis.

As the earnings information is not harmonized across countries, we include:

- Net earnings countries: Belgium, Chile, Egypt, Georgia, India, Mexico, Russia, Slovenia, and Uruguay.

[17] Only in three countries, the wave selection is not in line with the algorithm. For Ireland, Luxembourg, and Spain, earnings are not consistently surveyed over time (sometimes it is gross or net earnings). See the Appendix for details.

[18] ERF provides net household income for Egypt, gross for Jordan.

[19] For both LIS and ERF countries we, therefore, keep only employed individuals.

[20] Estonia in 2000, Ireland in 1987, and Poland in 1999.

- Gross earnings countries: Austria, Brazil, Colombia, Czech Republic, Denmark, Finland, Germany, Guatemala, Iceland, Israel, Jordan, Panama, Peru, Slovakia, Switzerland, and the US.
- "Mixed income information": France and Poland have a "mixed" income information.[21]
- Greece, Spain, Estonia, Ireland and Luxembourg do not have harmonized earnings information across the available time span. Thus, in the econometric analysis, we separate gross from net earnings waves.[22]

In absence of gross hourly wages, gross earnings is the second best proxy for productivity, as net earnings are adjusted by different national tax regimes. The nine countries in our analysis are based on net earnings listed above should be interpreted with caution in comparison to the other countries in our sample.

We adjust the earning variables for inflation using yearly Consumer Price Index data provided by the LIS and trimmed the distribution at 1st and 99th percentiles.[23]

Within-country differences in the earning information across waves forces us to exclude several waves from our working sample to test earnings polarization hypothesis (H-EP). Waves and countries appropriate for the later analysis are reported in Table 1.

3.2.1 Robustness Check – Wages

Although most of the literature on distributional analysis of the RBTC hypothesis focuses on hourly wages, our main variable of interest in the later analysis is yearly earnings. The reason we opt for this is twofold. First, LIS provide wages and hours information for a more restricted number of countries. Since, one of the aims of the analysis is to test RBTC theory internationally, we choose the largest harmonized sample of countries possible. Second, the earnings information in LIS is more reliable than wages that suffer of higher item non-response rates. Nevertheless, in Section 6, we replicate the analysis using as dependent variable hourly wages in order to provide closer comparability with previous literature. Compatible hourly wage information is available for 21 countries summarized in Table 5. Our hourly wage variable is calculated dividing the personal labor income by the number of actual working hours usually worked during the week multiplied by 4.33. We exclude labor incomes with negative or zero values and then we trim the distribution at the 1st and 99th percentiles, following LIS recommendations. We exclude observations with working hours top-coded at 99. Finally, we obtain real wages information adjusting with official LIS CPI country-specific indexes.

---

[21] According to the code-book: "total income does not account for full taxes and contributions.".

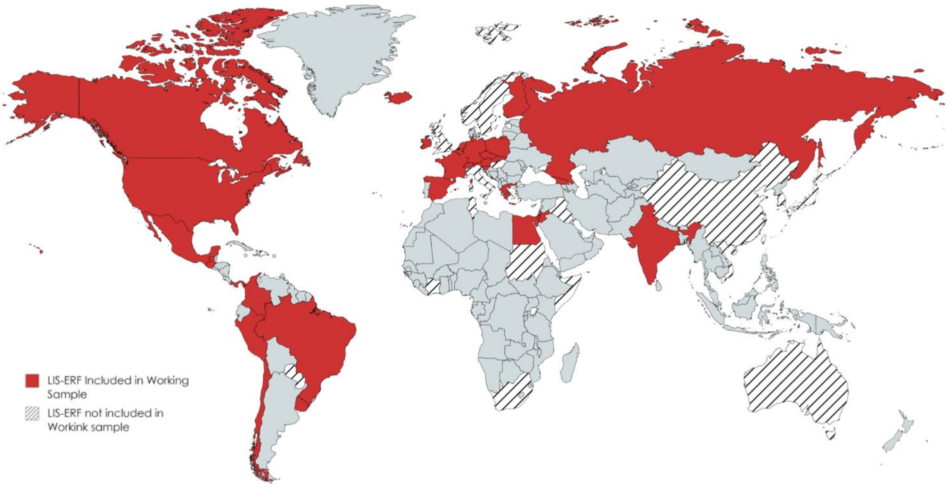
[22] Greece and Spain have gross earnings information available only from 2007 onward. Estonia, Ireland and Luxembourg switched from net to gross earnings starting in 2000.

[23] `https://www.lisdatacenter.org/data-access/web-tabulator/methods/ppp/`. CPI series for the Czech Republic and Slovakia are not complete, so we use World Bank data available at `https://data.worldbank.org/indicator/FP.CPI.TOTL`.

Table 1: Countries and waves in the working sample

Austria	2004	2007	2010	2013								
Belgium	1995	2000										
Brazil	2006	2009	2013									
Canada	1994	1997	1998	2004	2007	2010						
Chile	1992	1994	1996	1998	2000	2003	2006	2009	2011	2013	2015	
Colombia	2004	2007	2010	2013								
Czech Republic	1992	1996	2002	2004	2007	2010	2013					
Denmark	2004	2007	2010	2013								
Estonia	2000	2007	2010	2013								
Egypt	1999	2008	2010									
Finland	1987	1991	1995	2000	2004	2007	2010	2013				
France	1984	1989	1994	2000	2005	2010						
Georgia	2010	2013	2016									
Germany	1984	1987	1989	1991	1994	1995	1998	2000	2001	2002	2003	2004
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
Greece	2004	2007	2010	2013								
Guatemala	2006	2011	2014									
Iceland	2004	2007	2010									
India	2004	2011										
Ireland*	1994*	1995	1996	2000*	2004	2007	2010					
Israel	2007	2010	2012									
Jordan	2002	2006	2008	2010	2013							
Luxembourg*	1997	2000	2004	2007	2010	2013						
Mexico	1984	1989	1992	1994	1996	1998	2000	2004	2008	2010	2012	
Netherlands	1990	1993	2004	2007	2010	2013						
Panama	2007	2010	2013									
Peru	2004	2007	2010	2013								
Poland	2004	2007	2010	2013	2016							
Russia	2000	2004	2007	2010								
Serbia	2006	2010	2013	2016								
Slovakia	1992	2004	2007	2010	2013							
Slovenia	1997	1999	2004	2007	2010	2012						
Spain*	1980	1990	2000*	2004	2007	2010	2013	2016				
Switzerland	1992	2007	2010	2013								
US	1974	1979	1986	1991	1994	1997	2000	2004	2007	2010	2013	2016
Uruguay	2004	2007	2010	2013	2016							

Notes. The table shows the countries used in our analysis and provides the waves available in the LIS-ERF data. The waves used for our decomposition analysis are marked in green, isco08 waves in blue have been excluded in the decomposition exercise. Luxembourg, Ireland and Spain changed gross/net classification of earnings during the available time span and represent exceptions for the wave selection algorithm as explained in Section 4.1.3. Estonia's and Greece's first waves have been dropped because not consistent with earnings information in later waves.



Notes. Selected countries included in the working sample in red: Austria, Belgium, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Georgia , Germany, Greece, Guatemala, Iceland, India, Ireland, Israel, Jordan, Luxembourg, Mexico, Netherlands, Panama, Peru, Poland, Russia, Serbia, Slovakia, Slovenia, Spain, Switzerland US, Uruguay.

Figure 1: Countries in Working Sample

3.3 Focal Variable – Occupation

The literature on employment polarization proposes two main approaches to characterize job de-routinization and occupation definition according to task requirements. The most frequently used approach relies on the so-called Routine-Task-Index (RTI). Developed for the US by Autor et al. [2003] and later refined in David and Dorn [2013], the index "merges job tasks requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT 1977) to their corresponding (US) Census occupation classification to measure routine, abstract, and manual task content by occupation"[24]. The index is typically normalized around 0: high positive RTI values indicate jobs that are highly routinized and, consequently, more prone to the risk of being displaced according to RBTC hypothesis. Negative RTI values characterize non-routine occupations. Goos et al. [2014] mapped the RTI index from US-specific occupational classification to ISCO-88 (2-digitis)[25] in order to allow for international cross county comparison. According to their metrics, RTI is highest for office clerks and lowest for managers of small enterprises. Mahutga et al. [2018] generalized the RTI index metrics adopted in Goos et al. [2014] for 38 LIS countries, providing correspondence tables to harmonize national

[24] David and Dorn [2013], p. 1570.

[25] The International Standard Classification of Occupations (ISCO) is an International Labor Organization (ILO) classification structure for organizing information on labor and jobs. The current version, known as ISCO-08, was published in 2008 and is the fourth iteration, following ISCO-58, ISCO-68 and ISCO-88.

occupational schemes to the two-digits ISCO-88 scheme.

Despite its popularity, the use of RTI-based classifications has several weaknesses. First, RTI lacks a unique natural metric. Since numerous potential task scales exist, there is no obvious measure that represents a given task construct efficiently (Acemoglu and Autor [2011]). This also makes it difficult to interpret the regression coefficient for the RTI in econometric assessments. Second, in a cross-country perspective, RTI values rely on the assumption that tasks content and exposure to automation is the same for all jobs in all countries of interest. While this assumption might hold for a homogeneous group of, say, highly developed countries, it is difficult to justify for heterogeneous set of countries such as ours.

For these reasons, we follow Acemoglu and Autor [2011] and cluster specific occupations into four main job classes defined as follows:

- Abstract non-routine: managerial, professional, and technical occupations;
- Abstract routine: sales, clerical, and administrative support occupations;
- Manual routine: production, craft, repair, and operative occupations; and
- Manual non-routine: service occupations.

Table 2 summarizes the two approaches, reporting for each ISCO-88 (2-digits) occupation the respective RTI value and the main occupational class it belongs to. The table shows that the classification of the four occupational classes are consistent with RTI scores: positive RTI are characteristics of routine occupations, while negative RTI values denote non-routine manual and abstract jobs.

The Acemoglu and Autor [2011] classification is particularly convenient in our frameworks since more flexible for cross-countries comparison: it does not rely on US-centered metrics and it is easily implementable in those countries where ISCO classification is not available and harmonization processes must be applied.[26]

The main limitation of the 4-classes classification adopted in Acemoglu and Autor [2011] is that it neglects the routine-intercity gradient between different occupations: RTI scores in Table 2 ranges from 0.17 for models, salespersons and demonstrator, to 2.41 for office clerks within the routine abstract occupational class. This heterogeneity in the routine-intensity scale suggests important difference in the nature of the tasks performed by workers and, therefore, potential heterogeneity in the exposure to technological change and to the risk of being subject to automatization processes. In this sense, RTI can be interpreted as a potential risk-measurement and, therefore, they are particularly suitable in sensitivity analysis seeking to detect the differences in the degree of exposure to the risk of displacements effects between regional and local labor markets. Since we are interested in the distributional effects of *realized* job de-routinization and

[26] In some cases complete harmonization from national to ISCO scheme is not possible. Un-matched occupations from the national occupational scheme can, however, still be easily assigned to the appropriate routine/non-routine, manual/abstract class based on Acemoglu and Autor [2011] classification. Such manual imputations typically involve around 1-5% of the employed workforce in the wave-specific country and are available upon request.

not on the *potential* risk of layoffs, we argue that the four main occupational classes are enough to fully characterize the workforce between routine and non-routine workers.

For the assignment of employees to the aforementioned occupational classes, LIS-ESR's harmonized 1-digit occupational variable (9 clusters), *occb1*, is not appropriate since routine and non-routine occupations are mixed together within the same class.[27] For this reason, we classify workers using the country-specific, non-harmonized occupational variable, $occ1\_c$. In many countries this variable is directly available and coded in the ISCO-88 two or more digits format. For those countries that rely on national occupational coding schemes, we use the conversion tables provided by Mahutga et al. [2018]. This is necessary for Brazil, Canada, Colombia, Finland, France, India, Ireland (87), Israel, Mexico, Panama, and the US. Once the harmonization process is completed, we assign each ISCO-88 occupation to the respective class according to Table 2.

Several major changes in the ISCO coding schemes occurred following 2010 (ISCO 08). LIS-ERF waves in which the occupational coding scheme is updated to ISCO 08 are marked in blue in Table 1. Since a solid harmonization of ISCO 88 and ISCO 08 occupational schemes is not possible at the 2-digits level, we do not include these survey years in our working sample.

4 Methodology

In this section we present the methodology following Firpo et al. [2009, 2018]. The concept is a generalized version of the traditional Oaxaca-Blinder decomposition, which we provide in the Appendix.

4.1 RIF-Regression Methods

Assume a generic wage structure function, that depends on some observed components X_i, some unobserved components ε_i and time $t = 0, 1$:

$$Y_{it} = g_t(X_i, \varepsilon_i) \tag{1}$$

From observed data on (Y, T, X) we can identify the distributions of $Y_t | T = t \overset{d}{\sim} F_t$ for $t = 0, 1$. The framework proposed by Firpo et al. [2009, 2018] is a generalization of Oaxaca-Blinder that allows the estimation of a broad set of distributional parameters $\nu_t = \nu(F_t)$ including quantiles, the variance, or the Gini Index under very general assumptions on the earnings setting equation

[27] This is the case for ISCO category 5 "services and sales workers" that consists of both "personal and protective services workers" (ISCO 51), which, according to the existing literature, should be classified as manual non-routine (RTI index=-.60), and "models, salespersons and demonstrators" (ISCO 52), which should be classified as abstract routine (RTI=+.05). Similar problems exist for ISCO class 8. We need to distinguish between "machine operators and assemblers" (82) who are highly routinized (RTI=0.49) from "drivers and mobile plant operators" (83) who are highly non-routinized (RTI=-1.50). Then in class 9, we need to distinguish between "sales and services elementary occupations" (91), which are non-routinized (RTI=0.03), from agricultural jobs (92 and RTI=.) and routinized "laborers in mining, construction, manufacturing and transport" (93) with RTI=+0.53.

Table 2: Occupational classes based on 2-digts ISCO

Occupational Class	**ISCO-88 Label**	**ISCO-88 Code**	**RTI**
Non Routine Abstract	Legislators and senior officials	11	-0.57
	Corporate managers	12	-0.65
	Managers of small enterprises	13	-1.45
	Physical, mathematical and engineering professionals	21	-0.73
	Life science and health professionals	22	-0.91
	Teaching professionals	23	-1.47
	Other professionals	24	-0.64
	Physical and engineering science associate professionals	31	-0.29
	Life science and health associate professionals	32	-0.23
	Teaching associate professionals	33	-1.37
	Other associate professionals	34	-0.34
Routine Abstract	Office clerks	41	2.41
	Customer services clerks	42	1.56
	Models, salespersons and demonstrators	52	0.17
Routine Manual	Extraction and building trades workers	71	-0.08
	Metal, machinery and related trades workers	72	0.58
	Precision, handicraft, craft, printing and related trades workers	73	1.74
	Other craft and related trades workers	74	1.38
	Stationary plant and related operators	81	0.45
	Machine operators and assemblers	82	0.62
	Labourers in mining, construction, manufacturing and transport	93	0.57
Non Routine Manual	Personal and protective services workers	51	-0.50
	*Drivers and mobile plant operators	83	-1.42
	Sales and services elementary occupations	91	0.14
Agricultural	Skilled agricultural and fishery workers	61	0.14
	Agricultural, fishery and related labourers	92	0.38

Notes. The table shows the correspondence between ISCO-88 2 digits codes and the main occupational classes as proposed in Acemoglu and Restrepo [2017]. Last column on the right provides RTI vales before weighting provided in Mahutga et al. [2018]. Drivers and mobile plant operators (83) and Extraction and building trades workers (71), in the decomposition analysis have been separated with a specific class dummy. The two categories have negative RTI indexes in Goos et al. [2014], pointing non-routine characteristics, and both categories have wage and hours profile is typically different from the average non routine manual worker.

1. The central innovation is the use of Recentered Influence Functions (RIF). RIFs give the influence that each observation has on the calculation of $v(F_t)$ and have the property of integrating up to the parameter of interest $v(F_t)$. Therefore, it is possible to express group/time specific functions, v_1 and v_0, as conditional expectations:

$$v(F_t) = E[RIF(y_t, v_t, F_t)|X, T = t] \tag{2}$$

Firpo et al. [2009, 2018] prove that using the estimated $\widehat{RIF_{it}}$ as a dependent variable in a linear model, it is possible to estimate coefficients via standard OLS:

$$E[RIF(y_t, v_t, F_t)|X, T = t] = X_t \widehat{\gamma}_t^v \tag{3}$$

$$\widehat{\gamma}_t^v = E[XX'|T = t]^{-1} E[RIF(y_t, v_t, F_t)|X, T = t] \tag{4}$$

X_t is a vector of covariates that entails dummies for the occupational class, as described in the sections above, and socio-demographic controls. γ_t^v represents the marginal effect of X on $v(F_t)$. Finally, it is possible to decompose the difference of earnings v in the Oaxaca-Blinder traditional manner:

$$\Delta^v = \bar{X}_1(\widehat{\gamma}_1^v - \widehat{\gamma}_0^v) + (\bar{X}_1 - \bar{X}_0)\widehat{\gamma}_1^v \tag{5}$$

There are several reasons why we follow this methodology. First, as in the Oaxaca-Blinder, the RIF decomposition allows for disentangling two distinct channels through which job polarization may affect earnings: first, the *coefficient effect* accounts for the change in covariates returns on v;[28] the *composition effect* shows how much changes in v can be explained by over-time differences in the level of covariates.[29] Second, the methodology is designed for regression analysis on distributional statistics over the detailed list of covariates X. This means that, for each LIS-ERF country, it is possible to estimate how much the change in the statistic of interest can be explained by de-routinization (captured by composition and coefficient effects of the class dummies) while conditioning on other control variables X that might have distributional effects, such as female participation, education, aging, etc. Third, these decomposition methods are robust to non-linearity in the wage setting equation 12 once re-weighted the counterfactual as explained in Firpo et al. [2018].

We apply two different decompositions, i.e. the unconditional quantile decomposition for estimating changes along the entire distribution and the P-shares decomposition as proxies for

[28]In our analytical framework, a reason for this may be that returns of non-routine occupations grow at a faster pace than routine ones inflicted by changes in relative labor demand.

[29]In our analytical framework, composition effects account for over time differences in the employment shares between routine and non-routine occupations. Specifically, we are able to estimate the effect on v of the pure reallocation of jobs away from routine toward non-routine abstract and service occupations.

polarization measures. The unconditional quantile decomposition allows us to present the results intuitively in graphs, while the P-shares decomposition provides a formal proof of our findings.

RIF-unconditional quantile decomposition allows the comparison of observed quantile growth with the counterfactual growth that each quantile of the earnings distribution would have experienced driven by *ceteris paribus* de-routinization effects. We interpret potential U-shaped patterns in the growth curves of quantiles as evidence of overall earnings polarization.

P-shares are points on the Lorenz curve that represent the share of total earnings going to a pre-defined segment of the earnings distribution. In our analysis, we focus on five main segments: the lower (below the 15th percentile), the lower-middle (between the 15th and 40th), the middle (between 40th and 60th), the upper-middle (between 60th and 85th), and the upper income segment (above the 85th percentile). More specifically, P-shares are calculated as differences of Lorenz ordinates, such that the middle segment earnings share is the difference between the Lorenz ordinate at the 40th and the 60th percentiles of the cumulative population distribution. A decreasing middle segment share and simultaneously rising shares of upper- and lower-income segments indicate earnings polarization (U-shaped pattern).

In the specific case of quantiles, RIF is defined as:[30]

$$RIF(t;q_t^p) = q_t^p + \frac{p - I[y \leq q_t^p]}{f_Y(q_t^p)} \tag{6}$$

$$E[RIF(y_t,q_t,F_t)|T=1] = \frac{1}{f_Y(q_t^p)} Pr[Y > q_t^p|X=x] + (q_t^p - \frac{1-p}{f_Y(q_t^p)}) \tag{7}$$

$$= c_{1,p} Pr[Y > q_t^p|X=x] + c_{2,p} \tag{8}$$

In the above equations, q_t^p is the value of the p-quantiles of Y and $f_Y(q_t^p)$ is the estimated kernel density evaluated in q_t^p. Thus, RIF can be seen more intuitively as the estimation of a conditional probability model of being below or above the quantile q_t^p, re-scaled by a factor $c_{1,p}$, to reflect the relative importance of the quantile to the distribution, and re-centered by a constant $c_{2,p}$. Detailed discussion about RIF for P-shares can be found in Davies et al. [2017].

Once $RIF(y_t,q_t,F_t)$ values are obtained from Probit or Logit models, it is possible to estimate unconditional quantile regressions as in equation 3. Finally, similar to equation 5, the decomposition for quantiles takes the following form:

$$\begin{aligned}\Delta^p = q_1^p - q_0^p &= E[RIF(y,q_t^p,F)|T=1] - E[RIF(y,q_t^p,F)|T=0] \\ &= \textstyle\sum_i [\overline{Occ_{i1}}(\widehat{\gamma}_{1,i}^p - \widehat{\gamma}_{0,i}^p) + (\overline{Occ_{i1}} - \overline{Occ_{i0}})\widehat{\gamma}_{0,i}^p] \\ &+ \bar{X}_1(\widehat{\beta}_1^p - \widehat{\beta}_0^p) + (\bar{X}_1 - \bar{X}_0)\widehat{\beta}_0^p\end{aligned} \tag{9}$$

[30] See Firpo et al. [2018] for more detailed information about RIF estimation of quantiles.

where q_t^p represents the p-quantile at time t, Occ_i is a set of occupational class dummies[31] and X indicates the list of further controls included in the model. We opt for a list of covariates that are fully comparable across time and countries. Specifically, we control for gender, age (six 5-years classes), education (3 classes), and industry affiliation (9 industry classes).[32] Time indexes $t = 1$ and $t = 0$ are defined according to the algorithm explained in Section 3.1.

In the case of P-shares, $\Delta^v = L(q_t^p)^1 - L(q_r)^0$, where $L(q_t^p)^t$ is the Lorenz curve ordinate at the population p-quantile in time t. The same controls and time spans definition apply for both quantiles and P-shares decomposition.

In the following sections and in the results tables, we use the term *Total Change* for defining the overall difference in the dependent variables, Δ^p. For RIF-quantiles, it is calculated as the difference in (log)-quantiles between two reference years. Moreover, we refer to *Class Effect* for indicating the *sum* of the composition and coefficient effect due to changes in occupational classes composition and returns.[33] Such effects jointly account for within- and between-occupation determinants on earnings [Firpo et al., 2009].

4.2 Linking Job and Earnings Polarization

Our working sample allows us to conduct a cross-country analysis to further assess the link between job (H-JP) and earnings polarization (H-EP), exploring in greater detail the relationship between employment de-routinization and earnings inequality between and within occupational classes. These occupational classes cluster in specific quantiles along the earnings distribution. Therefore, inequality reduces (increases) *between* service (abstract) and routine occupations as consequence of the employment polarization. Eventually, since service (abstract) occupations are typically located in lower (higher) quantiles than routine ones, overall bottom (top) inequality should reduce (increase). Hence, it is not possible to describe inequality evolution *a priori* of the *overall* population (Non-routine Service + Routine + Non-routine Abstract) as it depends on which of these two effects prevail. For this reason, we test correlations between employment and earnings polarization for the lower (Non-routine Service + Routine) and upper (Non-routine Abstract + Routine) pole separately. We focus on workers employed in routine and service occupations. Complementary analysis for the routine and abstract sub-population is provided in the Appendix.

We consider the relative drop of the employment shares in both routine abstract and manual occupations as measure of job polarization, formally:

$$D_{EsRi} = \frac{EmpShare_{i0}^{Routine} - EmpShare_{i1}^{Routine}}{EmpShare_{i0}^{Routine}} \tag{10}$$

[31] In the model, we include a dummy variable for each category. Occ_i represents the decomposition as shown in equations (5) and (6). i: service, routine manual, routine abstract, non-routine abstract, agriculture, drivers (83), and extraction workers (71).

[32] For Canada, Mexico, and Russia, we opt for a three classes industry categorization (variable *inda*1) since more detailed classifications (variable *indb*1) suffer of considerable missing observations. Serbia and Switzerland are the unique exceptions since early waves do not have any industry information.

[33] In the Appendix, we provide detailed results distinguishing the two effects.

The higher D_{EsRi}, the stronger is the de-routinization process in country i between period $t = 0$ and $t = 1$.[34] Countries where H-JP is (not) rejected, exhibit negative (positive) D_{EsRi} growth rates.

We use the variation of the Theil index in the Routine-Service population as measure of earnings polarization. The Theil index is commonly used in the inequality literature and it complies with the decomposition principle [Bourguignon, 1979]. Hence, we distinguish inequality within and between occupational classes:

$$D_{To} = \frac{(To_1 - To_0)}{To_0} = \frac{Tb_1 + Tw_1}{To_0} - \frac{Tb_0 + Tw_0}{To_0} = \frac{Tb_1 - Tb_0}{To_0} + \frac{Tw_1 - Tw_0}{To_0} = D_{Tb} + D_{Tw} \quad (11)$$

where To is the overall Theil in the routine-service population, Tb is the between component, and Tw the one within.

We investigate whether de-routinization correlates with earnings inequality stemming from changes *between* or *within* occupational classes. It is *a priori* unclear if overtime changes in the returns structures *between* and *within* occupational classes mitigate or amplify the composition effect D_{EsR} induced by job-polarization. This specification provides suggestive evidence of these relationships, which could not be disentangled in the country-specific RIF decomposition.

Exploiting the heterogeneity across countries in our sample, we study correlations between job polarization (D_{EsRi}) and changes in between (D_{Tb}) (within (D_{Tw})) and overall (D_{To}) inequality for the Service and Routine sub-population. We choose these parameters, because it provides suggestive and comprehensive cross-country evidence for the link between the RBTC hypthesis (H-JP) and earnings polarization (H-EP). Furthermore, it enables us to unravel the effect of de-routinization on inequality by focusing on occupational classes. We see this cross-country evidence as another contribution to the literature, as this link, to the best of our knowledge, is not previously analyzed in this way.

5 Results

This Section provides the results for the job (H-JP) and earnings (H-EP) polarization hypotheses. First, we investigate if job de-routinization is a common feature in our working sample by describing how occupational classes evolved over time in all countries under analysis. Specifically, we confirm H-JP if we observe decreasing employment and earnings shares in routine occupations. Second, we analyze how de-routinization affects the country-specific earnings structure (H-EP). All the results are based on decomposition methods described in Section 4.1. Robustness checks for hourly wages are provided in the Section 6.

We introduce the presentation of the results firstly for the US and then for the other countries in our sample. The reason is that the RBTC hypotheses are typically studied for the US and because no general consensus has been reached on the distributional effects of job de-routinization. Moreover, focusing on one country facilitates the presentation and the interpretation of the results of the other countries. Summary Figures 5, 6 , 8 and 7 and Table 4 show stylized results

[34] Time periods are defined using the first and the last available harmonized waves.

for all 35 countries under analysis. Detailed country-specific estimations are provided in the Appendix.

Table 3 provides a first summary of our results. In our working sample, we reject H-JP for five countries, whereas H-EP is rejected for all but two. Given that H-EP is conditioned on H-JP, we do not observe countries for which we rejected H-JP and do not reject H-EP. The following subsections present the underlying analysis for the results in Table 3. The section concludes with a further examination of the link between job (H-JP) and earnings polarization hypotheses (H-EP) through an investigation of within- and between-occupational classes effects.

Table 3: Summary results

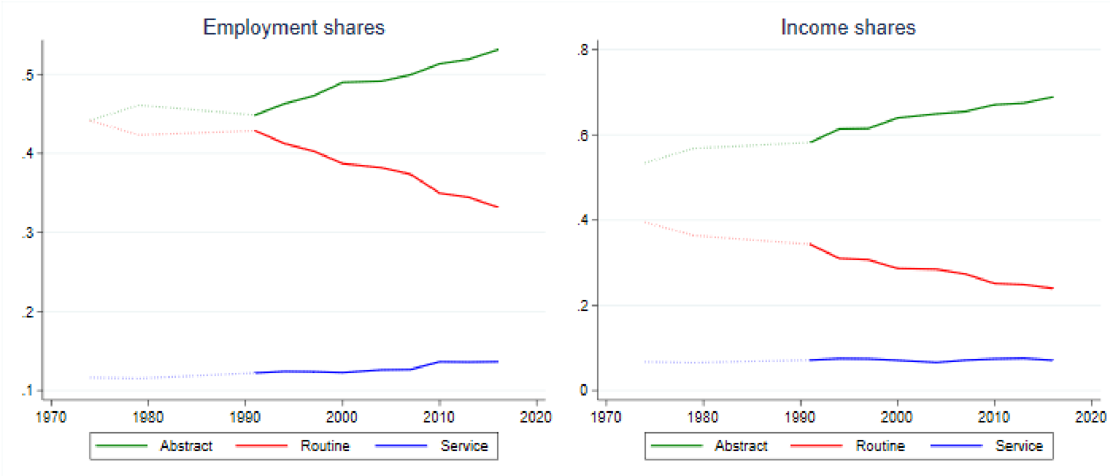
		H-EP	
		Not Rejected	*Rejected*
H-JP	*Not Rejected*	Ireland, Switzerland	Austria, Chile, Czech Republic, Colombia, Denmark, Estonia, Finland, Frnace, Germany, Guatemala, Isreael Luxembourg, Mexico, Netherlands, Panama, Poland, Russia, Serbia Slovenia, Uruguay
	Rejected	n/a	Brazil, Egypt, India, Peu, Slovakia

Notes. This table summarizes the results of our analysis considering the job- and earnings polarization hypothesis. Further description can be found in the main text.

5.1 Job Polarization Hypothesis (H-JP)

Figure 2 depicts class-specific inter-temporal changes in the employment (left panel) and earnings shares (right panel) in the US. Employment (earnings) shares by occupational classes are defined as the ratio between the total number of workers (earnings) in a given occupational class over the overall employed population (total earnings) in each year. To facilitate the description, in the graph and table below we merge routine-manual and routine-abstract jobs into one single occupational class.

Dotted lines indicate waves incurring methodological changes in the main variable, e.g. major changes in the occupational coding scheme, that may decrease their degree of comparability over time. Solid lines, however, are fully harmonized over the entire period. In the Appendix, we provide the same graphs for all countries.

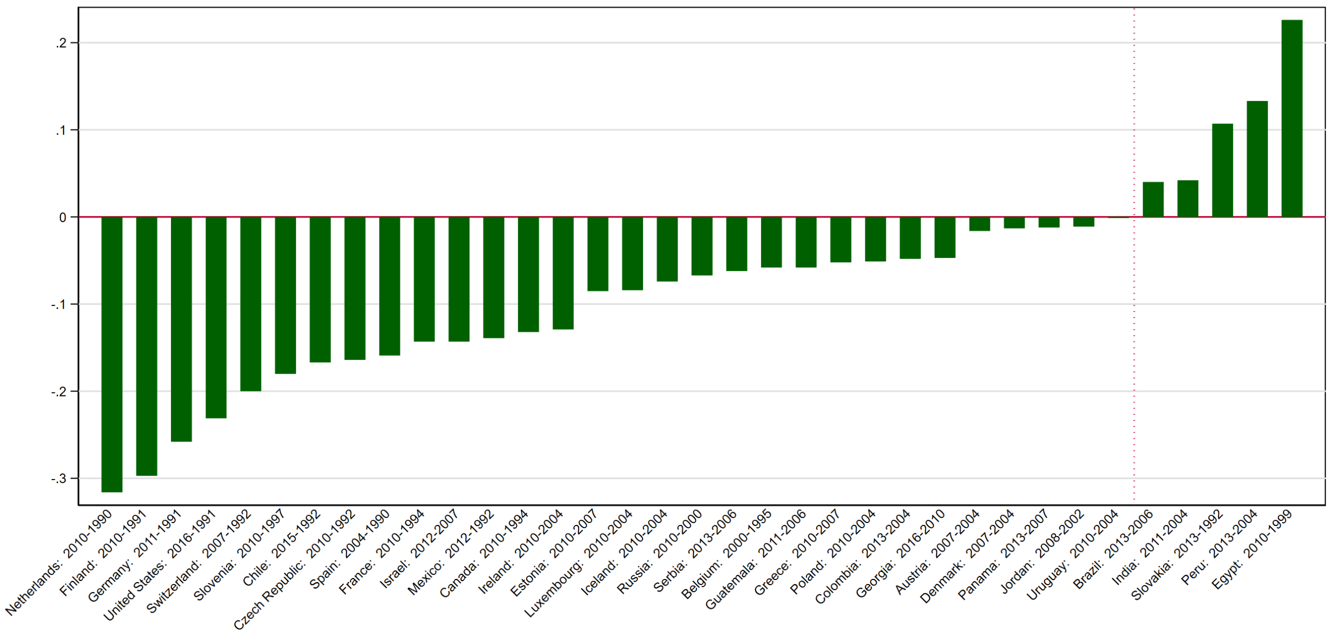


Notes. The left panels show the change of the employment share given for each occupational class over time in every country. The right panels show the change of the income given for each occupational class, respectively. Routine abstract and manual occupations are merged togheter. Dotted lines indicate waves that incur methodological changes in the main variables. Results of the other countries are provided in the Appendix.

Figure 2: Employment and income share growth by classes over time in the US

Figure 2 exhibits linear decreasing trends in routine employment and earning shares that affected almost 10% of the workforce since 1980s. This finding is consistent with the results of Acemoglu and Autor [2011] regarding the secular decline of routine-manual and abstract occupations between 1959 and 2007. Earnings growth differs across the occupational classes. This confirms a hierarchy between occupational classes consistent with RBTC framework, where non-routine abstract occupations are, on average, located at the top, routine in the middle, and service occupations at the bottom of the earnings distribution. Nevertheless, these graphs do not provide any information on the dispersion of earnings level within occupational classes; therefore, these are informative about between-class differences but not about within-class inequalities and the overall inequality trend.

Figure 3 summarizes the results for the other countries in our working sample. It reports the relative change in the share of workers employed in routine occupations in all countries in our datatset. We find supporting evidence for H-JP in 30 of 35 countries. Interestingly, in those countries where harmonized waves are available for longer time (e.g. Chile, Finland, Germany, and the US), de-routinization trends are consistent over the whole period, suggesting the long-lasting nature of the phenomenon. Only five countries exhibit increasing shares of routine tasks over the observed periods: Brazil, Egypt, India, Peru, and Slovakia. These countries are developing economies where recent industrialization may explain increases in production and operative jobs, thus explaining deviations from RBTC hypotheses. Such findings for Brazil, India, and Peru are in line with Mahutga et al. [2018].



Notes: Compiled by authors based on LIS data for prime-age, employed population. This table summarizes the results of our analysis considering the job-polarization hypothesis. The bars report the value of $-DEsR$ for each country, as explained in Section 4.2. Table 6 in the Appendix provides detailed estimation of $DEsR$.

Figure 3: Changes in the employment shares of routine manual and abstract classes.

5.2 Earnings Polarization Hypothesis (H-EP)

The results of the unconditional quantile decomposition are reported in Figure 4 for the US and in Figures 5, 6 , 8 and 7 for the remaining countries. Countries are grouped according to the main inequality trends we observe in the sample. The graphs show the percentile-specific earnings growth rates over the different time spans selected according to the algorithm explained in Section 3.1. The blue lines, the *Total Effect*, show the unconditional quantile specific growth in earnings over the respective time span. The red lines depicts the *Class Effect*, i.e. the percentile-specific growth that can be attributed to changes in the class-specific occupation shares and returns. Earnings polarization is reflected by u-shaped pattern of the percentile-specific growths curves. The results from the P-share decomposition are reported in Table 4.

We choose this graphical representation, because it enables us to analyze two important dimensions: the (dis)connection of the *Class Effect* and the *Total Effect*, as well as the evolution of inequality over time. Naturally, our working samples consists of countries that are differently embedded in the world economy, which are observed over various time spans. Interpreting the magnitude and the sources for heterogeneous earnings percentiles growth for every single country consecutively, however, would exceed the scope of this paper. Therefore, we focus on the aforementioned dimensions.[35]

Results for the US are plotted in Figure 4. It provides strong evidence for the long-lasting polarization of the US earnings structure. *Total Effects* exhibit U-shaped patterns in all periods under analysis with increasing polarization over time. Detailed P-shares decomposition in Table 4 corroborate the results: positive coefficients in the lower and upper P-shares are signals of increasing displacement effects from the middle towards the end of the distribution. This means that, in the US since the 80s, an increasing share of middle class labor income is redistributed toward the tails of the distribution, resulting in simultaneous reductions of inequality in the bottom-half and increases in the upper-half.

Our estimates do not suggest that de-routinization effects shape the observed overall polarization. The red lines in Figure 4 indicate growth rates in earnings quantiles that we would observe if only de-routinization of jobs had occurred and all other control variables were fixed at their levels in the baseline reference period. Parallel movements between the *Class Effect* and the *Total Change* lines provide evidence for the determinant role played by de-routinization shaping the earnings distribution. For the US, *Class Effects* in Figure 4 appear strictly inequality increasing and do not exhibit any polarizing pattern. This means that employment de-routinization *per se* cannot explain the observed polarization and other factors drive the growth of bottom-tail earnings and may underline that labor market institutions including unions, minimum wage, and workers protection laws, do play an important role for shaping earnings distribution over time. Our results are in line with those of Hunt and Nunn [2019] and Böhm et al. [2019]: by including within-group effects, the RBTC hypothesis fails to predict earnings and inequality growth. Our estimates also suggest that increased labor demand for non-routine occupations did not necessarily lead to higher returns for service workers at the bottom of the distribution. Moreover,

[35]The presented figures provide point estimates of percentile growths. Hence, it would accurate to provide confidence intervals based on bootstrap procedures. We will provide this in a future version of the paper.

Notes: Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile income growth (blue line) and the class effect (red line) for the US based on RIF quantiles decomposition explained in Section 4.1. Time spans are selected with the algorithm described in Section 3.1. The base group is represented by male workers, with a HS diploma, working in routine manual occupations in transport, storage, and communication industries, aged between 45 and 55 years old.

Figure 4: Quantile Decompositions Results for United States

Class Effects are positive in the middle of the distribution, meaning that middle-pay workers experienced earnings growth driven by job polarization, contrary to RBTC predictions.

For the remaining countries, results are rather diverse, suggesting a weak link between the RBTC hypothesis and earnings polarization. Quantiles decomposition results are reported in Figures 5, 6, 8, and 7. Table 4 provides stylized results of the P-share decompositions. Country-specific results considering the entire set of time span available are in the Appendix.

Figure 5 includes results for those countries in our working sample that experienced increased inequality and no polarization over the time span considered: Austria, Czech Republic, Denmark, Estonia, Finland, France, Germany, India, Mexico, Netherlands, Poland, Slovakia, Slovenia, and Spain. With the unique exception of India, we find evidence for overall job de-routinization (H-JP not rejected) in all these countries; however, our RIF decomposition results exclude polarization of earnings: *Total Change* curves show that lower quantiles experienced earnings losses, while upper quantiles experienced growth rates increasing along the distribution. Interestingly, de-routinization *Class Effects* in Mexico and, to a lesser degree , in Germany, exhibit U-shaped patterns, meaning that the reallocation of workers from routine occupations to non-routine occupations had polarizing effects on earnings consistent with the RBTC hypothesis. Nevertheless, these effects are weak and do not translate into overall earnings polarization. Other mechanisms drive earnings growth, offsetting the impact of job de-routinization and increasing inequality monotonically over the earnings distributing in both countries. In France de-routinization effects are not significant along the quantile distribution, while there is mixed evidence for the other countries: in some countries *Class Effects* predict increasing inequality well- e.g. Austria, Czech Republic, and the Netherlands - while in others *total* and *class* effects are completely unrelated -e.g. in Belgium, India, and Poland. Nevertheless, our estimates exclude a close link between employment and earnings polarization is these countries and, thus, H-EP is rejected.

We find decreased inequality and no polarization in Latin American countries,[36] Georgia, Russia, and Serbia. Figure 6 reports RIF decomposition results for this sub-set of countries. *Total Change* lines shows *relative* growth rates decreasing along the earnings distribution, meaning that lower quantiles are growing at a faster pace relative to upper quantiles. *Class Effects* are generally weak and unable to explain the reduction in the lower tail inequality, although we find evidence of employment polarization in all the countries analyzed in Figure 6 except Brazil and Peru. Again, our empirical evidence excludes the existence of a close link between employment and earnings polarization; thus, we reject H-EP.

Figures 7 shows the results for countries that exhibit polarized earnings patterns. The upper panel includes Belgium, Canada, Ireland, Jordan, Switzerland, and the United States.[37]. We find evidence of employment *and* earnings polarization in all these countries. U-shaped *Total Change* for these countries appear to be less extreme than in the United States, suggesting that strong earnings polarization is a phenomenon limited to the US. Ireland and Switzerland, however, seems to be the only exceptions in our sample where de-routinization effects have significant effects on the earnings distribution according to the RBTC framework. Interestingly, in these

[36]Brazil, Chile, Colombia, Guatemala, Panama, Peru, and Uruguay.

[37]Canada exhibits polarization patterns only over the longest time span available, i.e. between 1994 and 2010. Detailed results are provided in the Appendix.

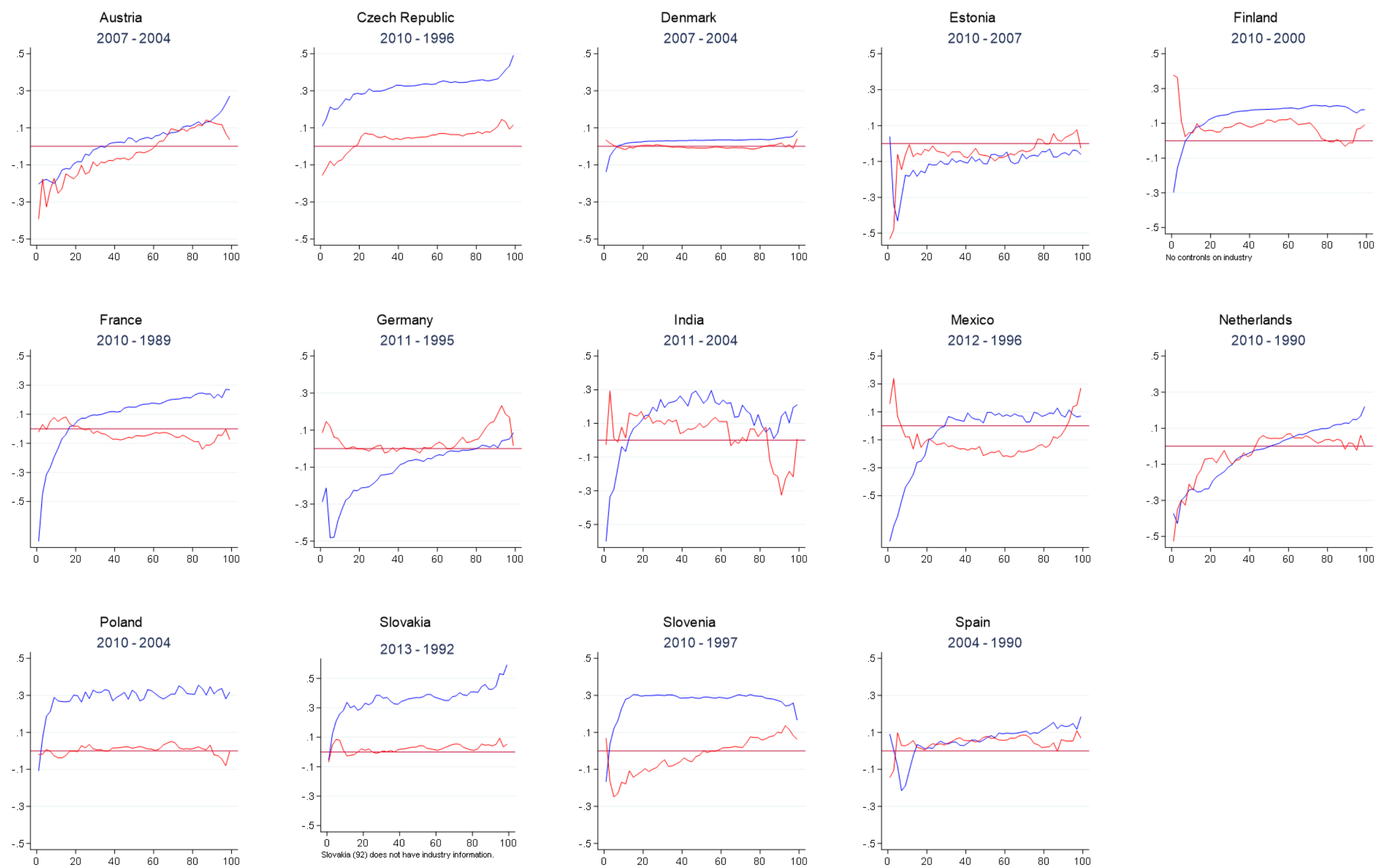
two countries, *Class Effect* curves display strong earnings growth in bottom quantiles consistent with RBTC framework. Thus, our results suggest that Ireland and Switzerland are the unique exception in our working sample, where increased labor demand for non-routine occupations (composition effect) comes with increasing returns for both service and abstract non-routine occupations. Therefore, we find evidence for H-EP only for Ireland and Switzerland.

Figure 8 plots results for Egypt, Greece, Iceland, Israel, and Luxembourg. These countries show rather stable inequality over the time horizon considered and no relevant de-routinization effects. We reject H-EP in these countries.

Table 4 provides a summary of the P-shares decompositions for all 35 analyzed countries. As explained in Section4.1,[38] we estimate the variation in the Lorenz curve ordinates at the population p-quantile in the reported time span. The *Total Change*, TE, reports the estimates of three main earnings bins: lower segment (between the 1st and 15th percentiles), middle segment (between the 15th and 85th percentiles), and the upper segment (between the 85th and 99th percentiles). The coefficients are multiplied by 100 to facilitate presentation. Table 4 confirms our previous results by reporting heterogeneous pattern in inequality growth between the different countries under analysis and the weak explanatory power of job de-routinization in predicting earnings dynamics. We also confirm these findings for hourly wages; a detailed explanation is found in Section 6.

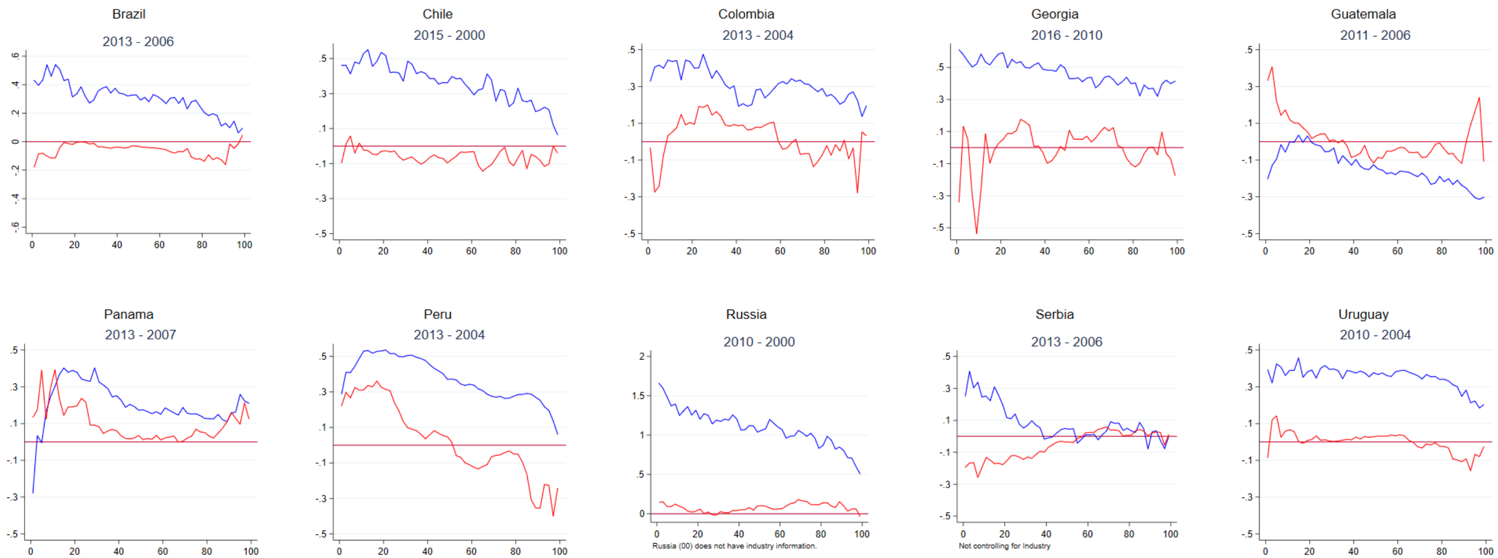
It is important to stress that the results presented above account for the *joint* estimation of *between*- and *within*-group effects. Thus, despite the fact that we find weak predictive power of RBTC hypothesis on *overall* inequality trends, our results do not exclude the possibility that employment polarization predicts the evolution of the coefficient structures *between* occupational classes well. Therefore, in the next section, we explore in greater detail this relationship, disentangling the effect of the RBTC hypothesis on both *between*- and *within*-class inequality components.

[38] Standard errors are reported in the Appendix.



Notes. Compiled by authors based on LIS data for prime-aged, employed population. The figure shows the total percentile income growth (blue line) and the *Class Effect* (red line) for selected countries based on RIF quantiles decomposition explained in Section 4. Time spans are selected with the algorithm described in Section 3.1. The base group is represented by male workers, with a HS diploma, working in routine manual occupations in transport, storage, and communication industries, aged between 45 and 55 years old.

Figure 5: Increased inequality - *Total Change* and *Class Effect* from RIF quantiles decomposition.



Notes. Compiled by authors based on LIS data for prime-aged, employed population. The figure shows the total percentile income growth (blue line) and the *Class Effect* (red line) for selected countries based on RIF quantiles decomposition explained in Section 4. Time spans are selected with the algorithm described in Section 3.1. The base group is represented by male workers, with a HS diploma, working in routine manual occupations in transport, storage, and communication industries, aged between 45 and 55 years old.

Figure 6: Decreased inequality - *Total Change* and *Class Effect* from RIF quantiles decomposition.

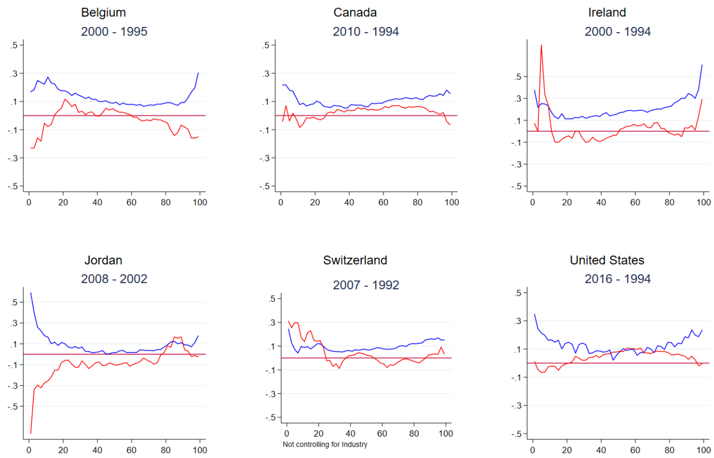


Figure 7: Polarization - *Total Change* and *Class Effect* from RIF quantiles decomposition.

Notes. Compiled by authors based on LIS data for prime-aged, employed population. The figure shows the total percentile income growth (blue line) and the *Class Effect* (red line) for selected countries based on RIF quantiles decomposition explained in Section 4. Time spans are selected with the algorithm described in Section 3.1. The base group is represented by male workers, with a HS diploma, working in routine manual occupations in transport, storage, and communication industries, aged between 45 and 55 years old.

Figure 8: No change in inequality - *Total Change* and *Class Effect* from RIF quantiles decomposition.

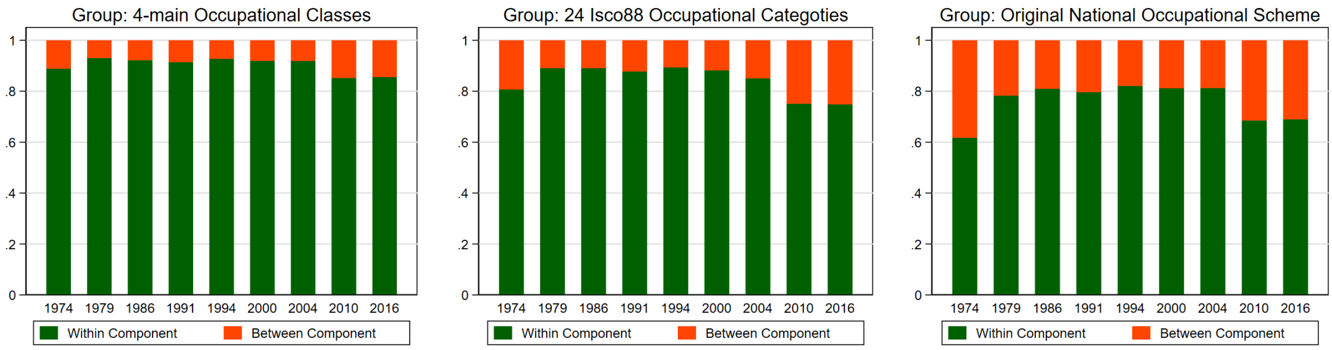
Table 4: P-shares decomposition - All Countries

Country	Time Span	1-15		15-85		85-99	
		TE	CE	TE	CE	TE	CE
				Increased Inequality			
Austria	*2007 2004*	-0.29	-0.25	0.06	0.02	0.23	0.23
Cz. Rep.	*2010 1996*	-0.12	-0.16	0.05	0.09	0.08	0.07
Denmark	*2007 2004*	-0.06	0.01	0.03	-0.01	0.03	-0.00
Estonia	*2010 2007*	-0.23	-0.14	0.13	0.04	0.11	0.10
Finland	*2010 2000*	-0.25	0.04	0.21	0.04	0.05	-0.08
France	*2010 1989*	-0.59	0.14	0.37	-0.04	0.22	-0.10
Germany	*2011 1995*	-0.39	0.08	0.16	-0.19	0.23	0.11
India	*2011 2004*	-0.43	-0.11	0.46	0.22	-0.03	-0.10
Mexico	*2012 1996*	-0.70	0.17	0.51	-0.39	0.19	0.22
Netherlands	*2010 1990*	-0.37	-0.23	0.11	0.22	0.26	0.02
Poland	*2010 2004*	-0.15	-0.06	0.13	0.04	0.02	0.01
Slovakia	*2013 1992*	-0.18	-0.01	0.01	-0.02	0.17	0.03
Slovenia	*2010 1997*	-0.17	-0.31	0.22	0.10	-0.05	0.21
Spain	*2004 1990*	-0.16	-0.09	0.05	-0.01	0.11	0.09
				Reduced inequality			
Brazil	*2013 2006*	0.31	-0.14	0.02	0.16	-0.34	-0.02
Chile	*2015 2000*	0.16	0.04	0.06	-0.05	-0.22	0.01
Colombia	*2013 2004*	0.10	-0.10	-0.00	0.15	-0.10	-0.05
Georgia	*2016 2010*	0.34	-0.21	-0.03	0.38	-0.31	-0.17
Guatemala	*2011 2006*	0.08	0.11	0.08	-0.20	-0.16	0.09
Panama	*2013 2007*	0.02	0.19	0.12	-0.25	0.10	-0.05
Peru	*2013 2004*	0.26	0.48	0.11	-0.09	-0.38	-0.58
Russia	*2010 2000*	0.61	0.07	0.01	-0.03	-0.62	-0.04
Serbia	*2013 2006*	0.26	-0.19	-0.14	0.11	-0.12	0.08
Uruguay	*2010 2004*	0.06	0.09	0.13	0.06	-0.19	-0.14
				Polarization			
Belgium	*2000 1995*	0.16	-0.20	-0.17	0.32	0.00	-0.12
Canada	*2010 1994*	0.08	-0.02	-0.12	0.08	0.04	-0.06
Ireland	*2000 1994*	0.07	0.20	-0.28	-0.23	0.22	0.03
Jordan	*2008 2002*	0.62	-0.85	-0.41	0.56	-0.21	0.29
Switzerland	*2007 1992*	0.04	0.26	-0.11	-0.25	0.07	-0.01
US	*2016 1991*	0.13	-0.10	-0.26	0.15	0.13	-0.05
				No changes in inequality			
Egypt	*2010 1999*	-0.03	0.04	0.10	-0.12	-0.07	0.08
Greece	*2010 2007*	0.10	0.15	0.05	-0.12	-0.15	-0.03
Iceland	*2010 2004*	-0.01	-0.30	-0.01	0.23	0.02	0.07
Israel	*2012 2007*	-0.08	-0.10	0.06	0.14	0.02	-0.04
Luxembourg	*2010 2004*	0.05	0.07	0.02	-0.20	-0.07	0.13

Notes. The table presents detailed result for the P-share decomposition explained in Section 4.1. TE columns in black report estimates of *Total Effect* in three wage bins considered: lower class (between the 1st and 15th percentiles), middle class (between the 15th and 85th percentiles) and for the upper class (between the 85th and 99th percentiles). CE columns in light gray report estimates for *Class Effect*. Effects size is multiplied by 100 for the sake of clarity. Detailed decompositions for all the countries and all the waves are in Appendix.

5.3 Linking H-JP and H-EP

We start by looking at the relative composition of Theil indexes, once decomposed its between (red bar) and within (green bar) occupations components for each wave included in our working sample. Figure 9 shows results for the US. The three panels consider different classifications of occupational classes, from the most aggregated (4 main clusters of workers) on the left to the least aggregated (4-digits classification) on the right. Even with dis-aggregated occupational information (right panel), the majority of inequality lies *within* rather then *between* occupations. The same result holds for all countries in our working sample.[39]



Notes. Compiled by authors based on LIS data for prime-aged employed population. The figure shows the relative composition of Theil index once decomposed in its between (red bar) and within (green bar) occupations components. Different clusters of occupations are considered. The panel on the left considers 4 main occupational classes as explained in Section 3.1.2. The panel in the middle decomposed the Theil index in the 24 ISCO-88 occupation categories. The panel on the right uses 4-digits occupational codes. Agriculture occupations are not included. Results of all the countries are provided in the Appendix

Figure 9: Theil decomposition within and between occupational classes in US.

Figure 9 shows that inequality *within* occupational classes is a key determinant of overall inequality, corroborating our claim that for distributional analysis both *within* and *between* margins must be considered. Nevertheless, Figure 9 provides a static description of earnings dispersion and it is not informative about inequality evolution over time. Thus, we complement our analysis with Figure **??**. As explained in the methodological Section, we focus on employees in routine and service occupations[40] while providing the results in a 4-quadrant diagram.

Our results are summarized in Figure **??** with two panels, one focusing on between and one on within occupational class inequality. Each panel includes three dimensions: we plot the results in a two coordinates system, determining the polarization measure D_{EsRi} at the positive area of the x-axis, variation of the overall Theil of the sub-population D_{To} at the positive area of the y-axis, and the Theil variation between (within) the two subgroups D_{Tb} (D_{Tw}) at the negative area of the x-, and y-axis.

Starting with the upper-right graph of the first four panels, we observe the relationship between job de-routinization (D_{EsRi}) and changes in the *overall* Theil index in the Service-Routine

[39]Country-specific results are presented in the Appendix.

[40]In the Appendix, we provide results for the complementary Routine and Abstract sub-population.

sub-sample (D_{To}). We can observe a positive, but not statistically significant, relationship between the two dimensions, which contradicts the earnings polarization hypothesis. In particular, countries experiencing higher de-routinization processes i.e. the Netherlands and the US, demonstrate the highest increases in inequality between the routine and service workers. Consistent with our previous analysis, employment polarization does not predict a reduction in *overall* inequality in the lower tail of the earnings distribution, where routine and service occupations are heavily distributed. The lower-right graph of the first four panels enforces these results, as there is no correlation between de-routinization and changes of the *between*-occupations margin of Theil. Although the countries under analysis experienced job de-routinization, D_{Tb_i} exhibits very small variation, contrary to the RBTC predictions. Again, the composition effects, D_{Esr}, are mitigated by the evolution of the returns structures *between* occupational classes, breaking the link between employment and earnings polarization.

The 4-quadrants graph in the lower panel of Figure **??** replicate the analysis for D_{Tw}. Again, we cannot confirm a significant correlation between de-routinization and *within* occupational inequality. Moreover, the upper-left graph of the second four-panels confirms, on a cross-country level, the findings for the US in Figure that changes within occupational classes explain almost all the observed variation in inequality.

Overall, our descriptive analysis results suggest that the evolution of the returns of different occupational classes are not sensitive to employment polarization, meaning that increased labor demand in service occupations does not translate in higher earnings growth rates relative to routine jobs.

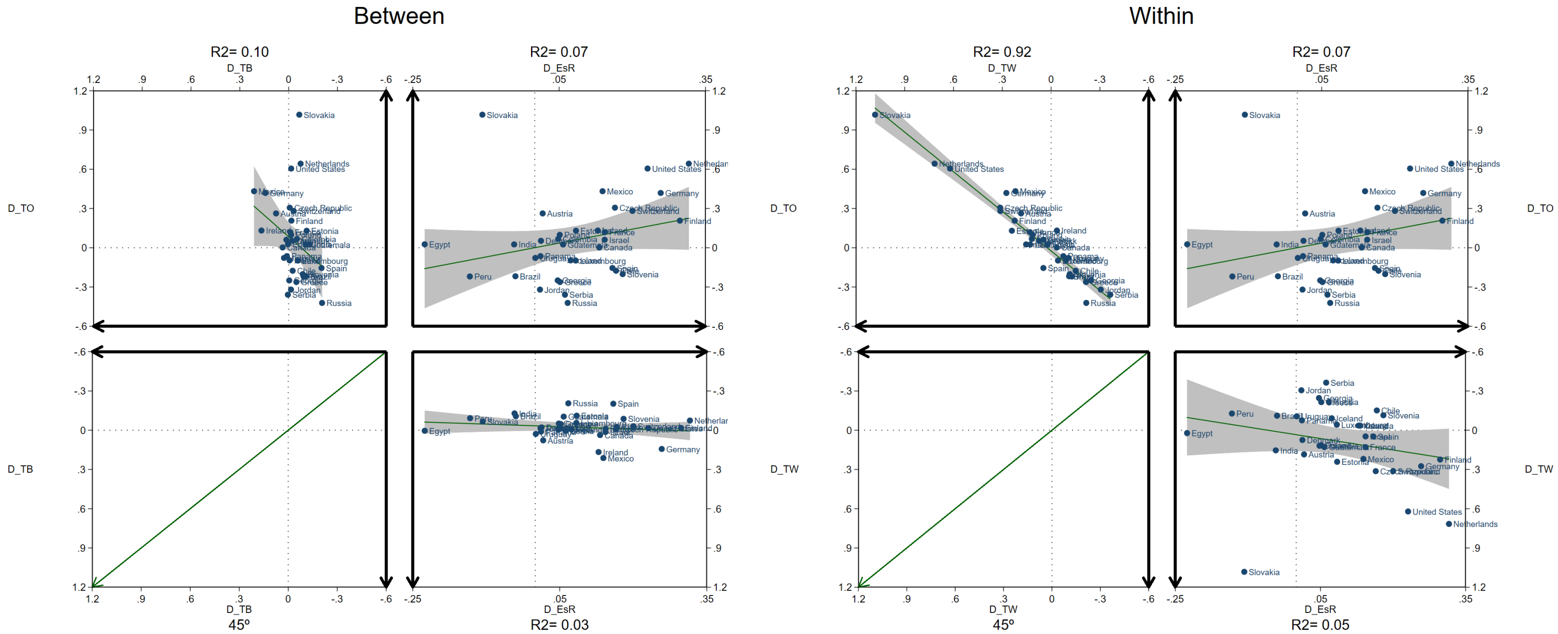
Thus, we arrive at two major findings: first, there is only little evidence for a quantitatively important link between employment and earnings polarization. Second within occupations dynamics seem to play a major role for the evolution of the earnings distribution over time.

6 Robustness Checks - Wages instead of Yearly Gross-Income

In this section, we replicate the analysis explained in Section 5.2 using hourly wages as the dependent variable in order to provide closer comparability with the existing literature. Due to data constraints explained in Section 3.2.1, we are able to reproduce the analysis on wages only for 21 countries. Table 5 reports P-shares decomposition results using wages as dependent variable. Figure 11 and Figure 12 provide detailed unconditional quantiles decomposition results for the United States and for eight selected countries.[41]

Results for wages confirm our main findings for earnings and we do not observe strong differences in wages and earnings evolution. In Figure 11, the wage decomposition for the US shows very similar patterns as in Figure 4 for earnings: U-shaped *Total Effects* curves indicating overall polarization of wages, which are not driven by de-routinization *Class Effects*. Similar parallelism can be observed in Figure 12 for wage and in Figures 5, 6, 8, and 7 for earnings. This seems to suggest that working hours did not change much during the time span considered and do not affect the estimation results. In particular, we can observe very similar trends in both Table 5 for wages and in Table 4 for earnings in those countries with both information available.

[41] In the Appendix all the country-specific results.



Notes. Compiled by authors based on LIS data for prime-aged employed population. The construction of the figure is described in detail in Section4.2, and relates changes of the employment share of workers employed in routine occupations with changes in the overall Theil index and in its between-(within-)occupations component. Occupational classes are defined using the LIS variable $occ1_c$, which is the most detailed occupation information available in LIS. Confidence intervals are reported at the 95% confidence level. R^2 are calculated regressing the y-variable on the x-variable in each graph.

Figure 10: Linking H-JP and H-EP: service and routine sub-population

The results suggest that changes in working hours contribute only marginally to the evolution of inequality in our working sample. The unique notable exception seems to be Greece: Table 12 suggest strong wage increases at the bottom and strong wage drops at the top of the wage distribution, which should result in decreased inequality. Such results are, however, compensated by changes in the structure of hours worked, so that in Table 4, we observe limited changes in overall earnings inequality.[42] Nevertheless, studying the joint dynamics of wages and hours on earnings distribution is outside the scope of this paper and we invite future research to analyze these dynamics under the lens of the RBTC framework.

7 Conclusions

In our analysis we contribute novel evidence for two highly debated questions in the literature, i.e., whether job polarization is a local or global phenomenon and if it implies distributional effects. Our analysis focuses on 35 LIS-ERF countries characterized by different economic and political systems. Although we confirm important shifts in employment from routine-intense toward non-routine occupations (H-JP confirmed), we find little evidence for a close link between employment and earnings polarization (H-JP rejected). In line with Hunt and Nunn [2019], we argue that the RBTC hypothesis fails to explain developments in overall earnings growth and inequality once both *between* and *within*-occupation dynamics are considered. We provide evidence that inequality is mostly generated *within* rather than *between*-occupations in all countries under analysis and both components must be considered in order to investigate the evolution of inequality. These results may corroborate the hypothesis that labor market institutions, like unions, minimum wage, and contracts conditions, do play an important role for earnings. We invite future research to deepen the understanding behind the interrelation between exogenous de-routinization forces and (endogenous) political control on labor market policies.

[42] Also see the quantile decomposition graph in the Appendix.

Table 5: P-shares decompistion - All Countries - Wages

Country	Time Span	1-15		15-85		85-99	
		TE	CE	TE	CE	TE	CE
				Increased Inequality			
Austria	2007 2004	-0.93	-0.62	0.42	0.06	0.51	0.57
Czechrep	2010 1996	-0.21	-0.17	0.16	0.09	0.06	0.08
Estonia	2010 2007	-0.83	0.05	0.46	-0.27	0.37	0.22
Germany	2011 1995	-0.41	0.09	0.17	-0.18	0.24	0.09
Mexico	2012 1996	-0.64	0.21	0.53	-0.84	0.11	0.63
Netherlands	2010 1990	-0.78	-0.10	0.40	0.25	0.37	-0.15
				Reduced inequality			
Brazil	2013 2006	0.90	-0.00	-0.02	0.05	-0.87	-0.05
Chile	2015 2000	0.40	0.04	-0.00	-0.02	-0.39	-0.02
Colombia	2013 2004	0.14	0.17	0.07	-0.13	-0.22	-0.04
Guatemala	2011 2006	0.15	0.12	-0.01	-0.45	-0.14	0.33
Russia	2010 2000	1.34	0.18	-0.24	-0.05	-1.11	-0.13
Uruguay	2010 2004	0.22	-0.04	0.11	0.24	-0.33	-0.20
				Polarization			
Belgium	2000 1995	0.30	-0.34	-0.29	0.44	-0.01	-0.10
Canada	2010 1994	0.00	-0.07	-0.10	0.11	0.10	-0.04
Ireland	2000 1994	0.13	0.31	-0.16	-0.57	0.03	0.27
Switzerland	2007 1992	-0.06	0.50	-0.10	-0.40	0.15	-0.10
Us	2016 1991	0.13	-0.15	-0.44	0.30	0.30	-0.15
				No changes in inequality			
Greece	2010 2007	0.39	0.26	0.07	-0.42	-0.47	0.16
Iceland	2010 2004	-0.01	-0.03	0.02	-0.05	-0.01	0.08
Israel	2012 2007	-0.06	-0.14	0.01	0.24	0.05	-0.10
Luxembourg	2010 2004	0.00	0.03	0.03	-0.31	-0.03	0.28

Notes. The table presents detailed result for the P-share decomposition explained in Section 4.1. TE columns in black report estimates of *Total Effect* in three wage bins considered: lower class (between the 1st and 15th percentiles), middle class (between the 15th and 85th percentiles) and for the upper class (between the 85th and 99th percentiles). CE columns in light gray report estimates for *Class Effect*. Effects size is multiplied by 100 for the sake of clarity. Detailed decompositions for all the countries and all the waves are in Appendix.

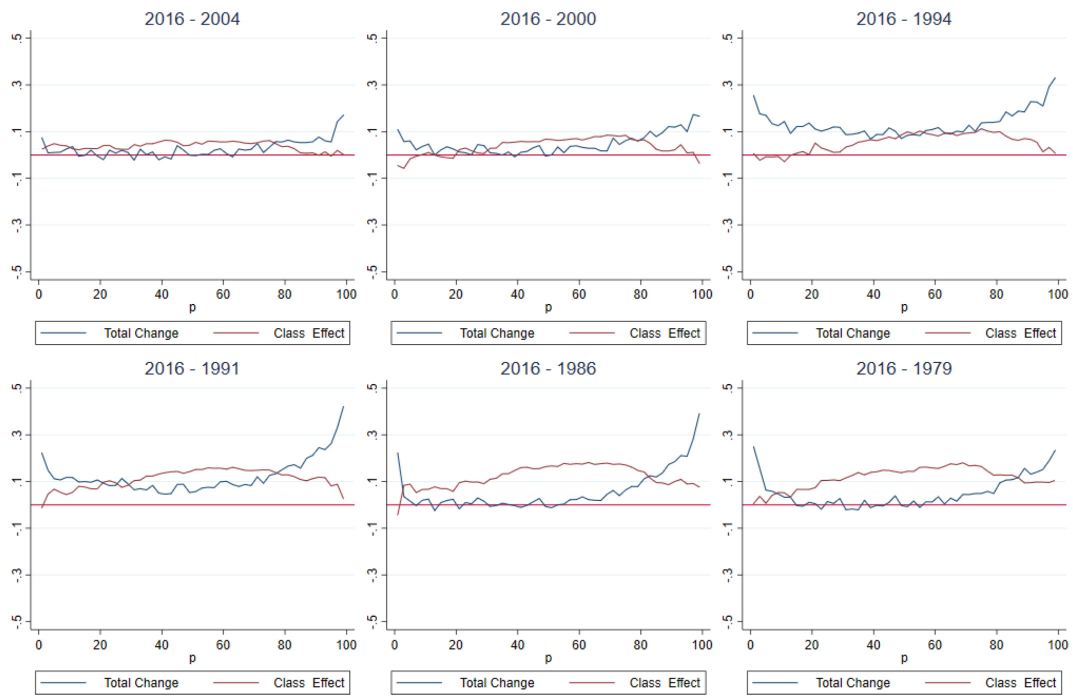


Figure 11: Percentile growth and class effect in US - wages

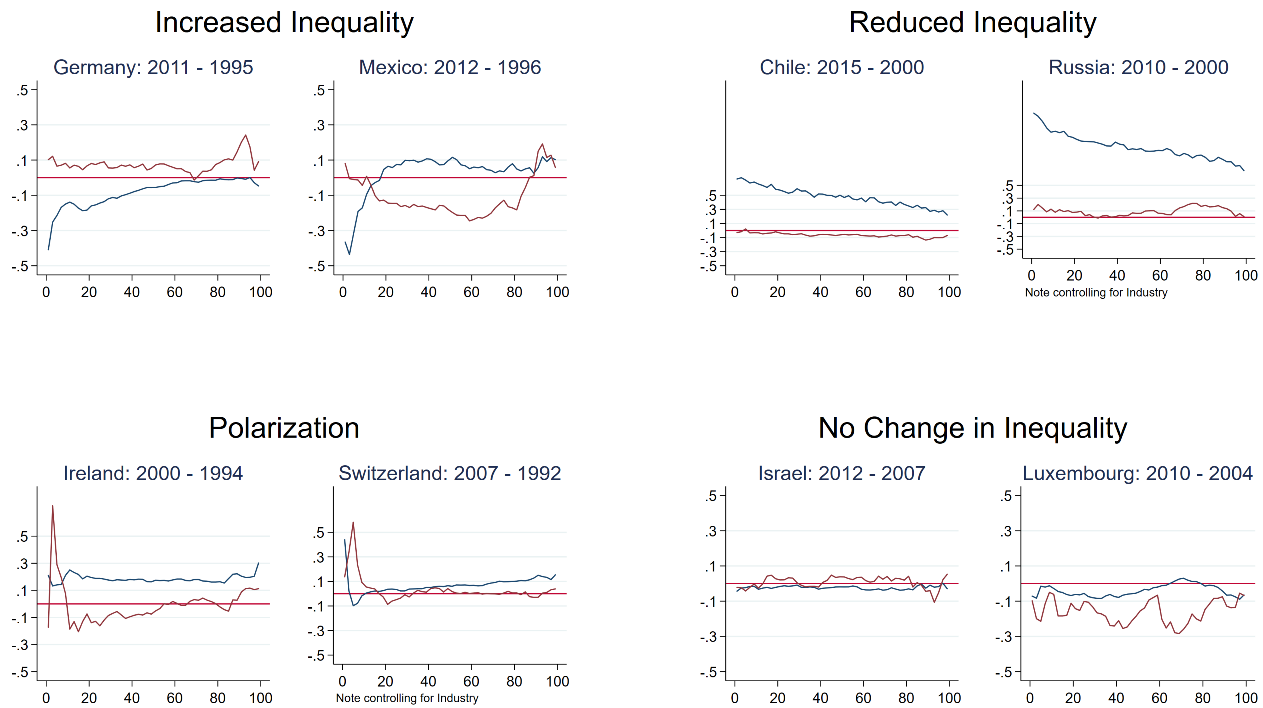


Figure 12: Percentile growth and class effect in selected countries - wages

References

Luxembourg Income Study (LIS) Database, `http://www.lisdatacenter.org` (multiple countries; August 2019 - May 2020). Luxembourg: LIS.

Daron Acemoglu and David Autor. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier, 2011.

Daron Acemoglu and Pascual Restrepo. Robots and jobs: Evidence from US labor markets. *NBER Working Paper*, (w23285), 2017.

Cristian Aedo, Jesko Hentschel, Javier Luque, and Martin Moreno. From occupations to embedded skills: A cross-country comparison. *World Bank Policy Research Working Paper.*, 2013.

David H Autor, Frank Levy, and Richard J Murnane. The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333, 2003.

Alan S Blinder. Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources*, pages 436–455, 1973.

Alan S Blinder. Offshoring: Big deal, or business as usual? *Offshoring of American Jobs: what Response from US Economic Policy*, pages 19–60, 2009.

Michael J Böhm, Hans-Martin von Gaudecker, and Felix Schran. Occupation, growth, skill prices, and wage inequality. 2019.

Francois Bourguignon. Decomposable income inequality measures. *Econometrica*, pages 901–920, 1979.

Michael Coelli and Jeff Borland. Job polarisation and earnings inequality in Australia. *Economic Record*, 92(296):1–27, 2016.

H David and David Dorn. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5):1553–97, 2013.

James B Davies, Nicole M Fortin, and Thomas Lemieux. Wealth inequality: Theory, measurement and decomposition. *Canadian Journal of Economics/Revue canadienne d'économique*, 50(5):1224–1261, 2017.

Sara De La Rica and Lucas Gortazar. Differences in job de-routinization in OECD countries: Evidence from piaac. *IZA Discussion Papers*, (9736), 2016.

John DiNardo, Nicole M Fortin, and Thomas Lemieux. Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, (64):1001–44, 1996.

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

Sergio Firpo, Nicole M Fortin, and Thomas Lemieux. Unconditional quantile regressions. *Econometrica*, 77(3):953–973, 2009.

Sergio Firpo, Nicole M Fortin, and Thomas Lemieux. Occupational tasks and changes in the wage structure. *IZA Discussion Papers*, (5542), 2011.

Sergio P Firpo, Nicole M Fortin, and Thomas Lemieux. Decomposing wage distributions using recentered influence function regressions. *Econometrics*, 6(2):28, 2018.

Carl Benedikt Frey and Michael A Osborne. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280, 2017.

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

Maarten Goos, Alan Manning, and Anna Salomons. Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–26, 2014.

David A Green and Benjamin M Sand. Has the Canadian labour market polarized? *Canadian Journal of Economics/Revue Canadienne d'Économique*, 48(2):612–646, 2015.

Wojciech Hardy, Roma Keister, and Piotr Lewandowski. Educational upgrading, structural change and the task composition of jobs in Europe. *Economics of Transition*, 26(2):201–231, 2018.

Jennifer Hunt and Ryan Nunn. Is employment polarization informative about wage inequality and is employment really polarizing? *IZA Discussion Papers*, (12472), 2019.

Stephen Jenkins, Andrea Brandolini, John Micklewright, and Brian Nolan. *The Great Recession and the Distribution of Household Income*. OUP Oxford, 2012.

Thomas Lemieux. Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *American Economic Review*, 96(3):461–498, 2006.

Stephen Machin. Changes in uk wage inequality over the last forty years. *The Labour Market in Winter: State of Working Britain*, 2010.

Matthew C Mahutga, Michaela Curran, and Anthony Roberts. 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, 2018.

Riccardo Massari, Paolo Naticchioni, and Giuseppe Ragusa. Unconditional and conditional wage polarization in Europe. *IZA Discussion Papers*, (8465), 2014.

Ronald Oaxaca. Male-female wage differentials in urban labor markets. *International Economic Review*, pages 693–709, 1973.

Mario Reinhold. On the link between job polarisation and wage inequality in Germany. 2016.

Christopher R Taber and Nicolas A Roys. Skill prices, occupations, and changes in the wage structure for low skilled men. *NBER Working Paper*, (26453), 2019.

Appendix A - Oaxaca Blinder Decompistion

Oaxaca [1973] and Blinder [1973] develop a method that helps us to decompose differences in mean earnings between two classes (or two time periods). The earnings setting model is assumed to be linear in observable and unobservable characteristics at two points in time ($t = 0, 1$):

$$Y_t = X\beta_t + \varepsilon_t \tag{12}$$

where $E[\varepsilon_t|X] = 0$. Therefore, the difference in the mean earnings gap between the two time periods is:

$$\Delta_y = E[Y_1|t=1] - E[Y_0|t=0] = E[X_1|t=1]\hat{\beta}_1 - E[X_0|t=0]\hat{\beta}_0 = \bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 \tag{13}$$

Adding and subtracting the counterfactual earnings that would have been earned on average in time 1 under the returns structure of time 0, $\widehat{Y_C} = E[X_1|t=1]\widehat{\beta_0}$, we obtain the two-fold decomposition:

$$\Delta_y = \bar{X}_1\widehat{\beta_1} - \widehat{Y_C} + \widehat{Y_C} - \bar{X}_0\widehat{\beta_0} \tag{14}$$

$$\Delta_y = \bar{X}_1(\widehat{\beta_1} - \widehat{\beta_0}) + (\bar{X}_1 - \bar{X}_0)\widehat{\beta_0} = \Delta^S + \Delta^X \tag{15}$$

Δ^S represents the *coefficients* effect and isolates how much of the difference in earnings is explained by differences in the covariates returns between the two years, keeping fixed the characteristics at their levels in year 1. Δ^X is the *composition* effect, that isolates how much of the difference between the average earnings of the two classes is explained by difference in the expected values of their characteristics. In the case of the vector of covariates X, it is possible to further decompose the two effects into the contribution of each explanatory variable, due to the additive linearity assumption:

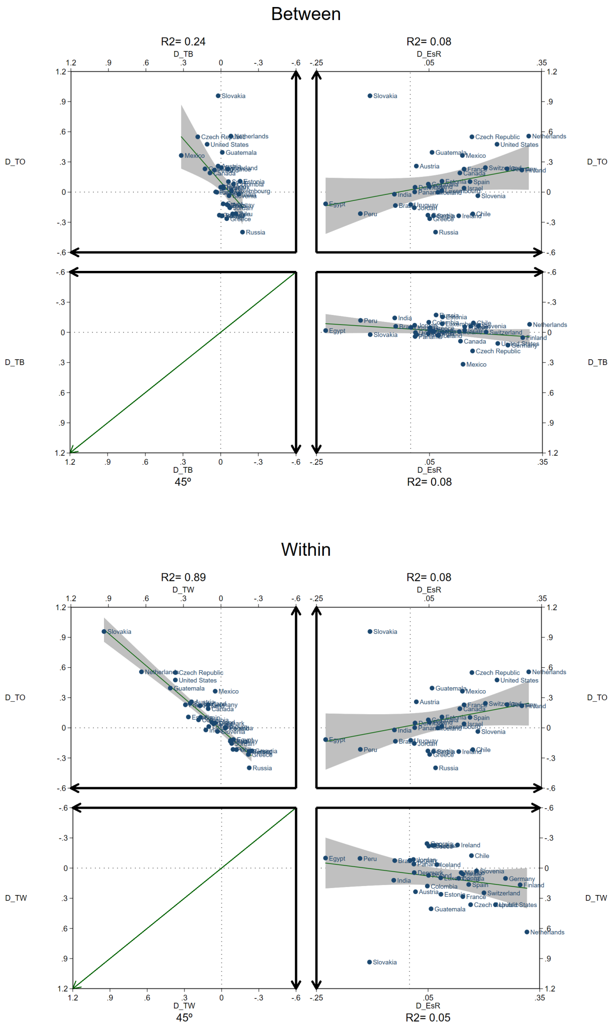
$$\Delta^S = (\hat{\beta}_{1,0} - \hat{\beta}_{0,0}) + \sum \bar{X}_{1,k}(\hat{\beta}_{1,k} - \hat{\beta}_{0,k}) \tag{16}$$

$$\Delta^X = \sum(\bar{X}_{1,k} - \bar{X}_{0,k})\hat{\beta}_{0,k} \tag{17}$$

It is straight forward to obtain the estimation of these detailed effects by plugging the sample means and the OLS estimates $\hat{\beta}_t$ in the formulas above. Certainly the validity of the results from the estimation rests on two assumptions: firstly, consistency of the estimates $\hat{\beta}_{t,k}$ requires that the linearity assumption in equation 12 holds. Secondly, focusing on average earnings gaps is not informative about changes in the overall distribution.

Appendix B - Descriptive Evidence linking H-JP and H-EP

Here results for the complementary analysis on workers employed in routine and abstract occupations.



Notes. Compiled by authors based on LIS data for prime-aged employed population. The construction of the figure is described in detailed in Section4.2, and relates changes of the employment share of workers employed in routine occupations (x-axis in the upper right and bottom right panel), with changes in the overall Theil index (y-axis in the upper right and left panels) and in its within-occupations component (y-axis in the lower right panel and x-axis in the upper left panel). Confidence intervals are reported at the 95% confidence level. R^2 are calculated regressing the y-variable on the x-variable in each graph.

Figure 13: Linking H-JP and H-EP: Abstract and Routine Sub-population

Appendix C - Auxiliary Tables and Figures

Table 6 summarizes the results of our analysis considering the job-polarization hypothesis. The last column reports value of the change in the shares of workers employed in Routine occupations between the indicated time span. Specifically these values are $-D_{EsRi}$ explained in Section 4.2.

Table 6: Summary Results for H-JP

Country	*Time Span*		*Δ Employment Share in Routine Class (%)*
	De-routinization		
Austria	*2007*	*2004*	-1,6%
Belgium	*2000*	*1995*	-5,8%
Canada	*2010*	*1994*	-13,2%
Chile	*2015*	*1992*	-16,7%
Colombia	*2013*	*2004*	-4,8%
Czech Republic	*2010*	*1992*	-16,4%
Denmark	*2007*	*2004*	-1,3%
Estonia	*2010*	*2007*	-8,5%
Finland	*2010*	*1991*	-29,7%
France	*2010*	*1994*	-14,3%
Georgia	*2016*	*2010*	-4,7%
Germany	*2011*	*1991*	-25,8%
Greece	*2010*	*2007*	-5,2%
Guatemala	*2011*	*2006*	-5,8%
Iceland	*2010*	*2004*	-7,4%
Ireland	*2010*	*2004*	-12,9%
Israel	*2012*	*2007*	-14,3%
Jordan	*2008*	*2002*	-1,1%
Luxembourg	*2010*	*2004*	-8,4%
Mexico	*2012*	*1992*	-13,9%
Netherlands	*2010*	*1990*	-31,6%
Panama	*2013*	*2007*	-1,2%
Poland	*2010*	*2004*	-5,1%
Russia	*2010*	*2000*	-6,7%
Serbia	*2013*	*2006*	-6,2%
Slovenia	*2010*	*1997*	-18,0%
Spain	*2004*	*1990*	-15,9%
Switzerland	*2007*	*1992*	-20,0%
United States	*2016*	*1991*	-23,1%
Uruguay	*2010*	*2004*	-0,1%
	No De-rotuinzation		
Brazil	*2013*	*2006*	4,0%
Egypt	*2010*	*1999*	22,6%
India	*2011*	*2004*	4,2%
Peru	*2013*	*2004*	13,3%
Slovakia	*2013*	*1992*	10,7%

Appendix D - Detailed country specific results

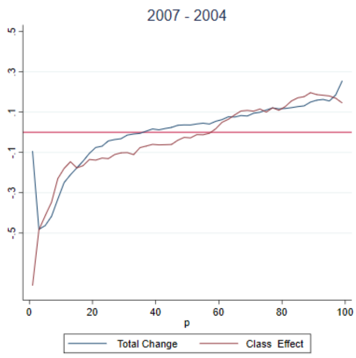
The current Appendix presents country specific results for the two hypothesis (H-EP) and (H-JP) introduced in Section 1 of the paper. Results are based on the LIS-ERF joint dataset and harmonized following to the guidelines explained in Section 3. Decomposition results for unconditional quantile regressions and P-shares are reported in country-specific tables and figures as described in Section 4 and 5. We want to report only two minor exceptions:

- Estonia, Greece, Ireland, Luxembourg and Spain do not have harmonized gross/net information on earnings. Therefore, we depart from the wave selection algorithm in order to keep consistent earnings comparison. Specifically:
  - Estonia (2000) and Greece (2004) are ignored in the decomposition.
  - In Ireland we consider two time intervals: ($t1$=2007 ; $t0$=1987), ($t1$=2000 ; $t0$=1996)
  - In Luxembourg we consider only one time interval: ($t1$=2010 ; $t0$=2004)
  - In Spain we consider 3 time intervals: ($t1$=2010 ; $t0$=2004), ($t1$=2000 ; $t0$=1990) and ($t1$=2000 ; $t0$=1980)
- Serbia and Switzerland do not have industry information. Therefore, we computed equation (14) - and relative quantile and P-shares decompositions - without controlling for industry dummies.
- France does not have industry information in 2000 and 1994, Slovakia in 1992, Russia in 2000, and Spain in 1980. We compute the P-shares and quantile decompositions without controlling for industry for those time span that include the aforementioned waves.
- In order to allow comparability between wage and earning quantile results in same time span, Finland (2010-1991) has been added.

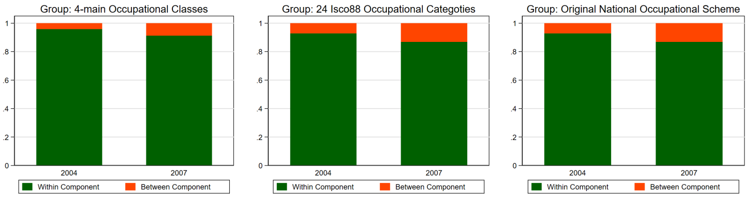
Austria

H-JP Results: Employment and Income shares by Occupational Class

H-EP Results: Quantile Decompositon - Earnings

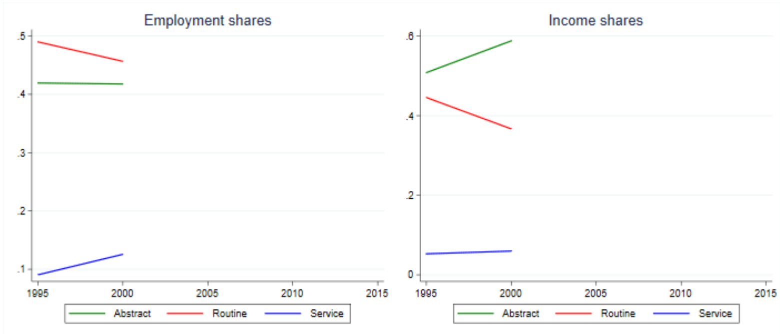


H-EP Results: Quantile Decompositon - Wages

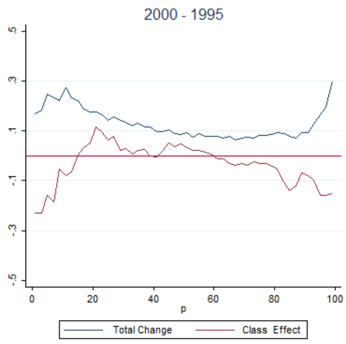


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2007 - 2004			
Δ	-0.0029***	0.000600	0.0023***
CE-X	0	-0.000100	0
CE-	-0.0033*	0.000800	0.0024***

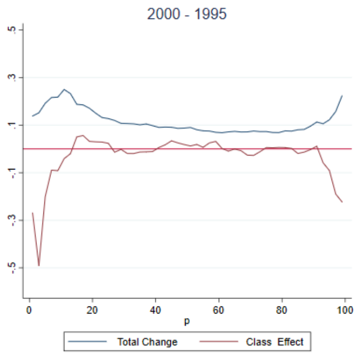
Belgium



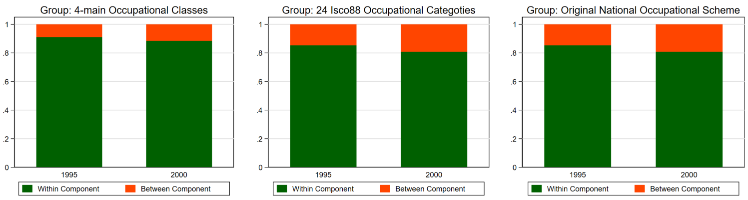
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

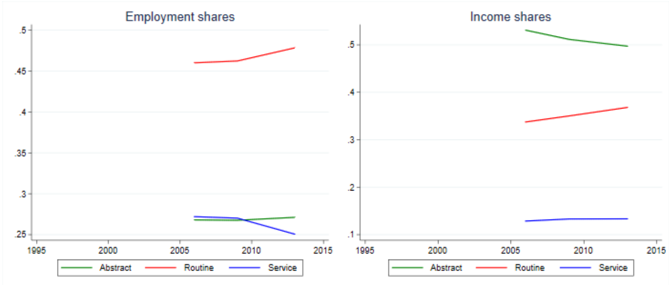


H-EP Results: Quantile Decompositon - Wages

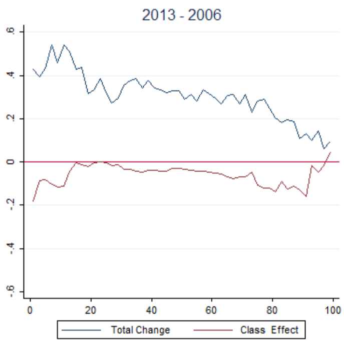


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2000 - 1995			
Δ	0.0016***	-0.0017***	0
CE-X	-0.0003***	0	0.0003***
CE-	-0.00120	0.0030**	-0.0018*

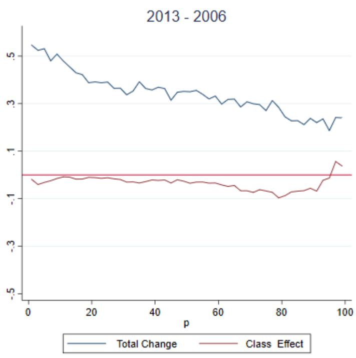
Brazil



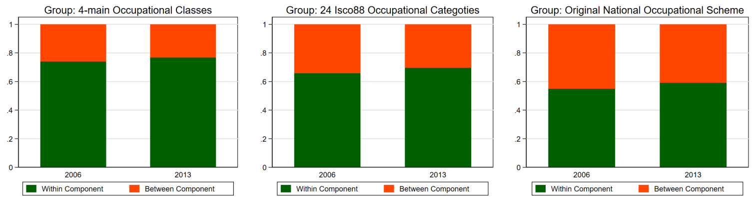
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

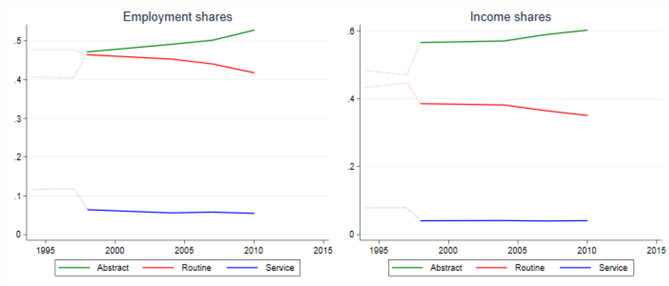


H-EP Results: Quantile Decompositon - Wages



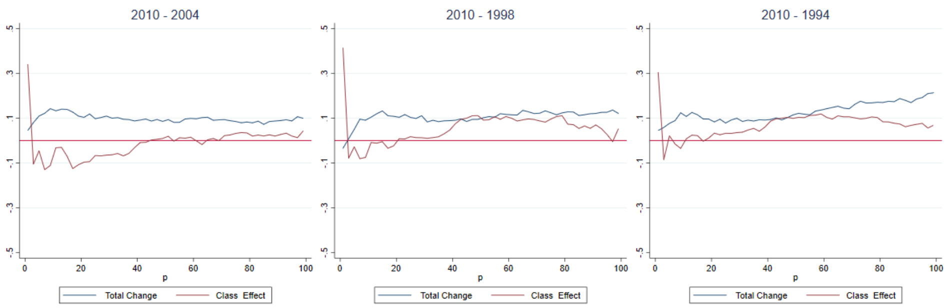
A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2013 - 2006			
Δ	0.0031***	0.0002*	-0.0034***
CE-X	0.0004***	-0.0001***	-0.0003***
CE-	-0.0016***	0.0012***	0.000400

Canada

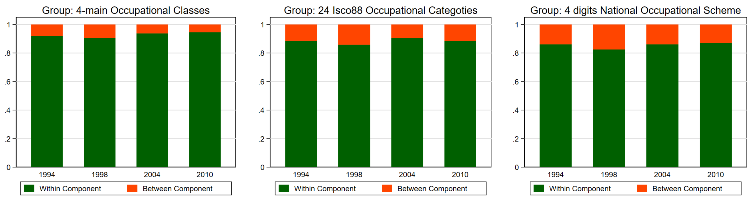


H-JP Results: Employment and Income shares by Occupational Class

H-EP Results: Quantile Decompositon - Earnings

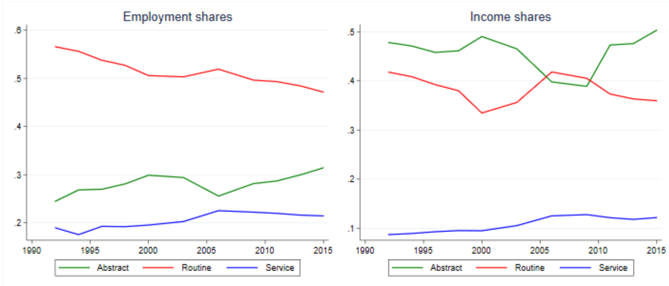


H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	0	0.000100	-0.000100
CE-X	0	0	0
CE-	-0.000700	0.000400	0.000300
2010 - 1998			
Δ	-0.000100	0.000300	-0.000300
CE-X	0.000100	-0.000100	0
CE-	-0.000900	0.00140	-0.000500
2010 - 1994			
Δ	0.0008*	-0.0012***	0.0004*
CE-X	0.0003***	-0.000100	-0.0002***
CE-	-0.000400	0.000900	-0.000500

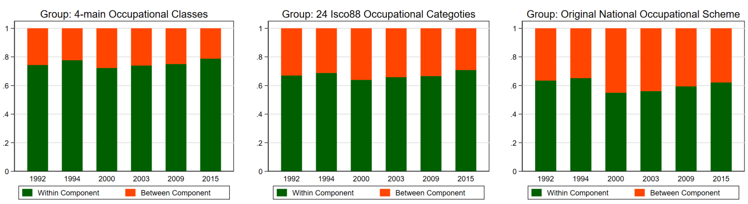
Chile



H-JP Results: Employment and Income shares by Occupational Class

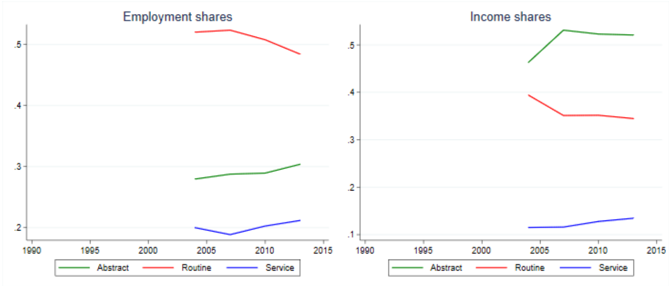
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2015 - 2009			
Δ	0.0004***	0.0003*	-0.0007***
CE-X	-0.0001***	0	0.0001***
CE-	0.000500	-0.0008*	0.000400
2015 - 2003			
Δ	0.0015***	0.000100	-0.0017***
CE-X	0	-0.0001***	0.0001***
CE-	0.000100	0	0
2015 - 2000			
Δ	0.0016***	0.0006***	-0.0022***
CE-X	-0.0001**	0	0.0001***
CE-	0.000500	-0.000300	-0.000200
2015 - 1994			
Δ	0.0018***	0.0003*	-0.0021***
CE-X	-0.0002***	-0.0002***	0.0004***
CE-	0.000400	-0.000700	0.000300
2015 - 1992			
Δ	0.0003*	0.0019***	-0.0022***
CE-X	-0.0004***	-0.0004***	0.0008***
CE-	0.000700	-0.000900	0.000300

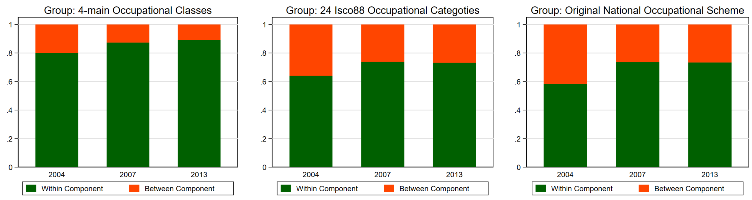
Colombia



H-JP Results: Employment and Income shares by Occupational Class

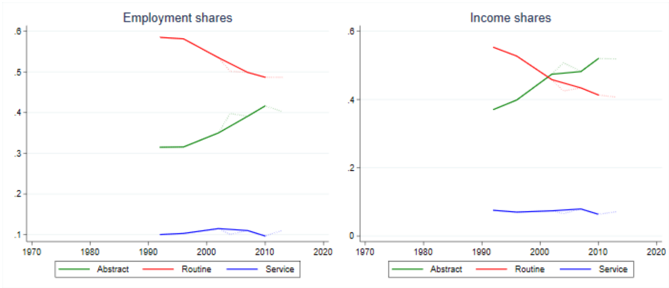
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2013 - 2007			
Δ	0.0009***	0.0002*	-0.0011***
CE-X	0	-0.0001***	0.0000***
CE-	-0.0005**	0.0006**	-0.000100
2013 - 2004			
Δ	0.00100	0	-0.00100
CE-X	-0.0002**	0.000100	0.000100
CE-	-0.000300	0.00110	-0.000800

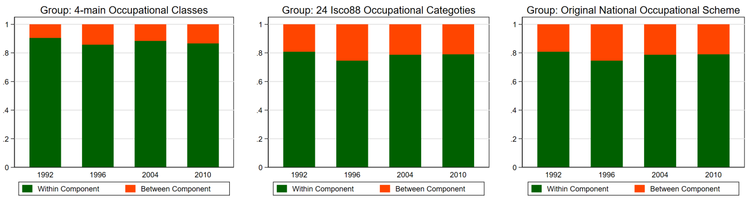
Czechrep



H-JP Results: Employment and Income shares by Occupational Class

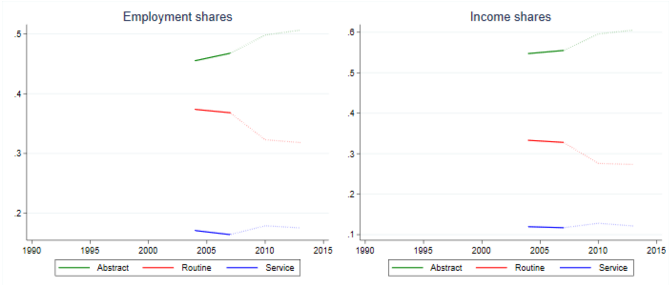
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages

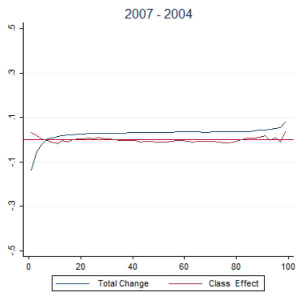


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.000500	0.000500	0
CE-X	0	0.0000*	-0.0000*
CE-	-0.000800	0.000300	0.000500
2010 - 1996			
Δ	-0.0012**	0.000500	0.0008*
CE-X	0	0	0.0000*
CE-	-0.00130	0.000600	0.000700

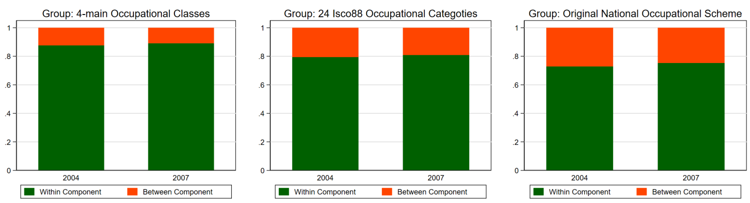
Denmark



H-JP Results: Employment and Income shares by Occupational Class

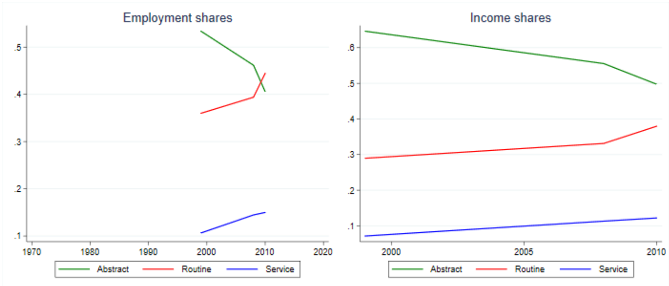


H-EP Results: Quantile Decompositon - Earnings

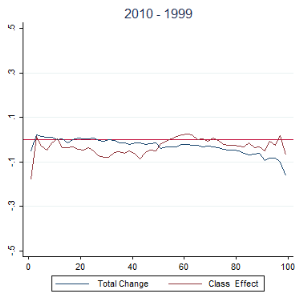


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2007 - 2004			
Δ	-0.0006***	0.0003***	0.0003***
CE-X	0.0000**	0.0000**	-0.0000***
CE-	0	-0.000200	0.000100

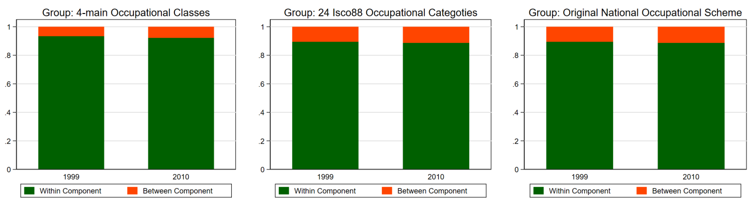
Egypt



H-JP Results: Employment and Income shares by Occupational Class

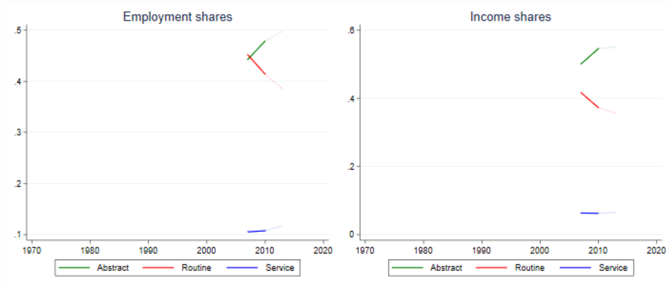


H-EP Results: Quantile Decompositon - Earnings

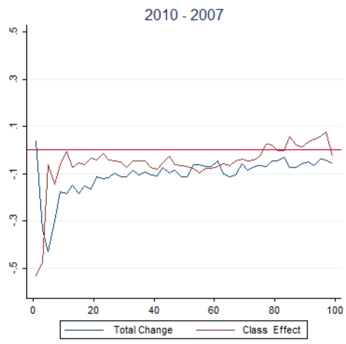


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 1999			
Δ	-0.000300	0.00100	-0.000700
CE-X	0.0002**	0.0001*	-0.0003***
CE-	0.000200	-0.00130	0.00110

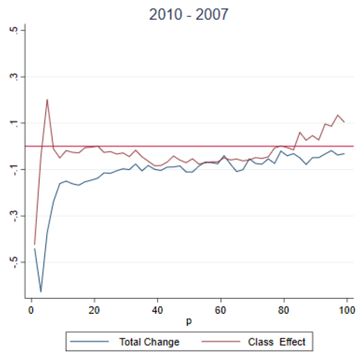
Estonia



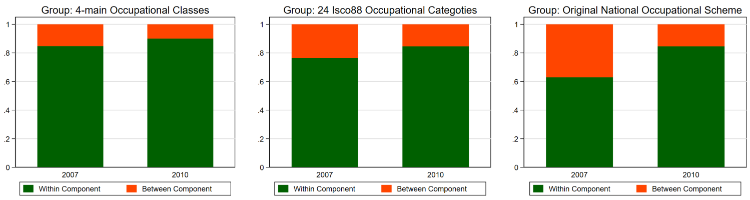
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

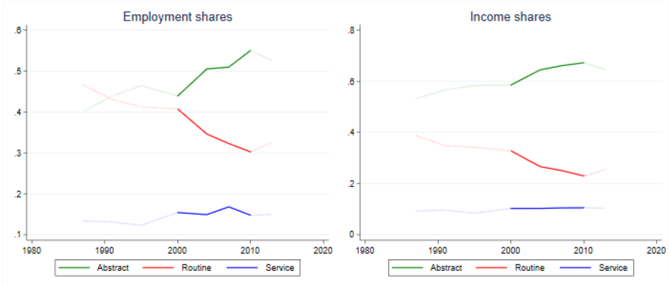


H-EP Results: Quantile Decompositon - Wages

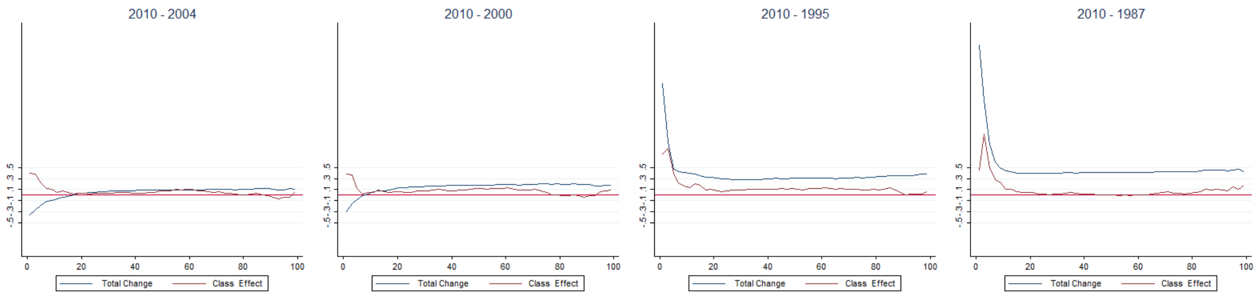


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2007			
Δ	-0.0023**	0.0013*	0.0011*
CE-X	0	-0.000100	0.000100
CE-	-0.00210	0.000400	0.00170

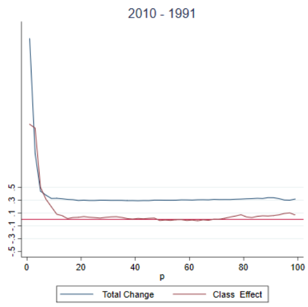
Finland



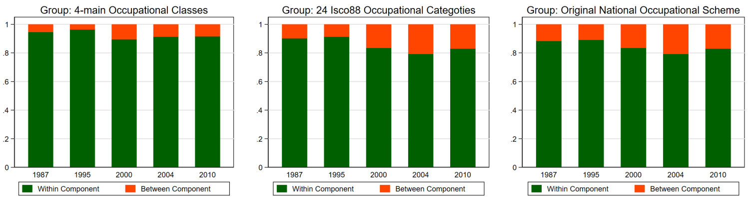
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

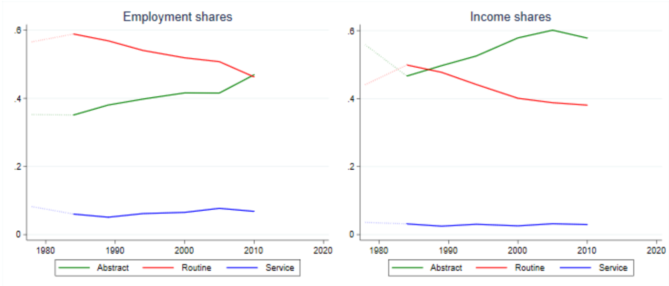


H-EP Results: Quantile Decompositon - Wages

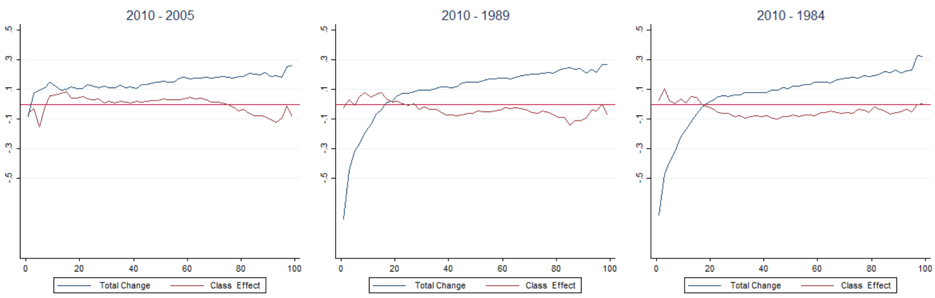


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.0029***	0.0021***	0.0008***
CE-X	-0.0001***	0	0.0001***
CE-	0.00200	-0.000700	-0.0013*
2010 - 2000			
Δ	-0.0025***	0.0021***	0.0005*
CE-X	-0.0002**	0	0.0002***
CE-	0.00120	0.000100	-0.0012*
2010 - 1995			
Δ	0.0055***	-0.0049***	-0.0006**
CE-X	-0.000100	-0.000100	0.0002***
CE-	0.0044*	-0.00250	-0.0019**
2010 - 1987			
Δ	0.0085***	-0.0071***	-0.0014***
CE-X	0.0016***	-0.0015***	-0.000100
CE-	0.00300	-0.00320	0.000200

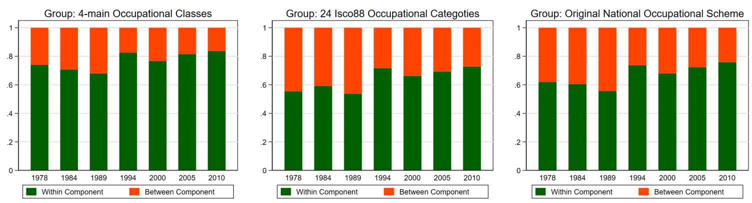
France



H-JP Results: Employment and Income shares by Occupational Class

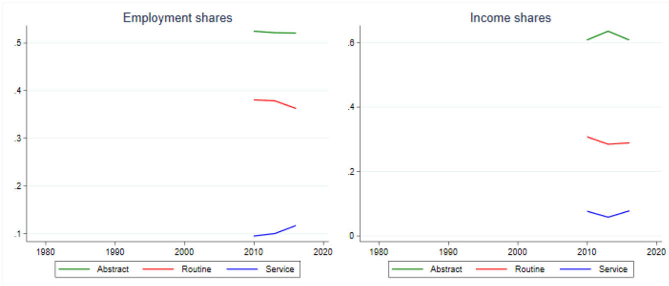


H-EP Results: Quantile Decompositon - Earnings

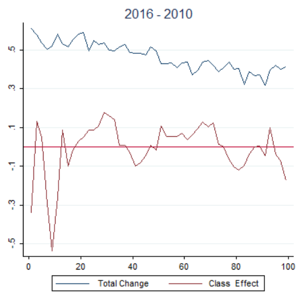


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2005			
Δ	-0.00100	0.000200	0.0008**
CE-X	0.000200	-0.000100	0
CE-	-0.000100	0.00130	-0.00120
2010 - 1989			
Δ	-0.0059***	0.0037***	0.0022***
CE-X	-0.0006***	0.0003**	0.0003**
CE-	0.00180	-0.00100	-0.000700
2010 - 1984			
Δ	-0.0060***	0.0032***	0.0027***
CE-X	-0.0005***	0.0002*	0.0003***
CE-	0.00150	-0.00140	-0.000200

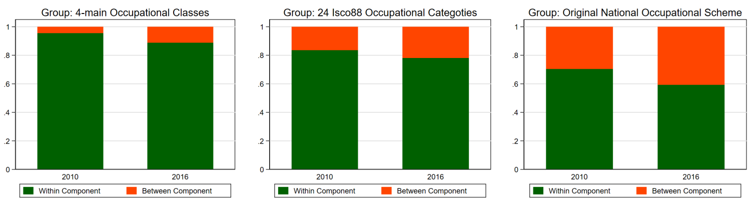
Georgia



H-JP Results: Employment and Income shares by Occupational Class

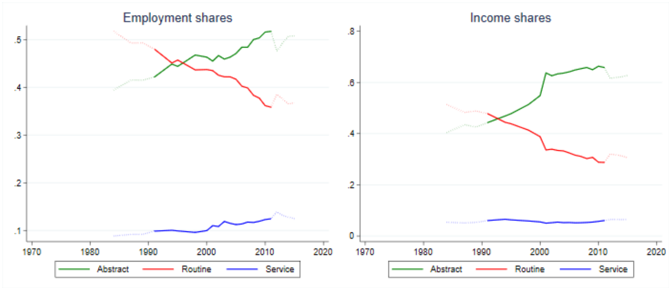


H-EP Results: Quantile Decompositon - Earnings

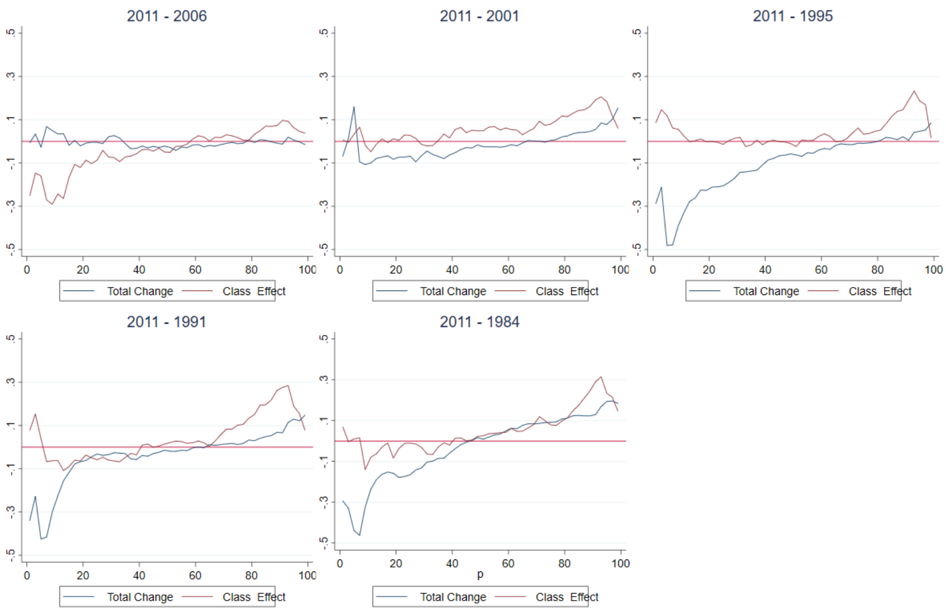


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2016 - 2010			
Δ	0.0034**	-0.000300	-0.0031***
CE-X	0.000300	-0.000100	-0.0001*
CE-	-0.00260	0.00340	-0.000800

Germany

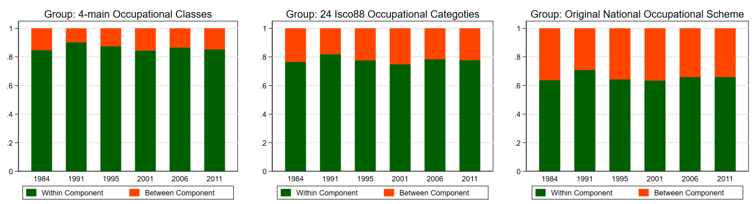


H-JP Results: Employment and Income shares by Occupational Class



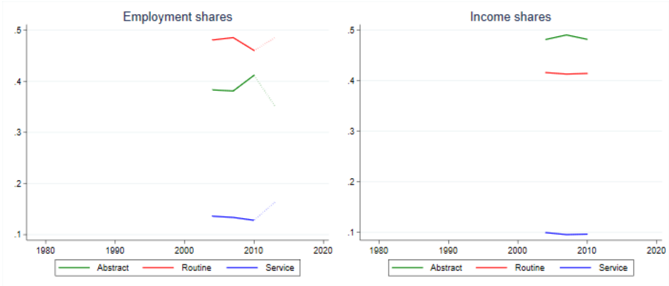
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages

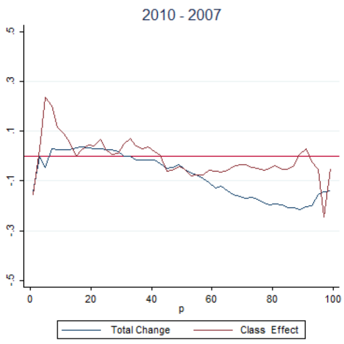


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2011 - 2006			
Δ	0.000500	-0.000500	0.000100
CE-X	-0.0001*	0	0.0001***
CE-	-0.00210	0.000600	0.00150
2011 - 2001			
Δ	-0.000700	-0.0009*	0.0015***
CE-X	-0.000100	0	0.0001*
CE-	-0.000200	-0.00100	0.00130
2011 - 1995			
Δ	-0.0039***	0.0016**	0.0023***
CE-X	-0.0002*	0	0.0002**
CE-	0.000800	-0.00220	0.00140
2011 - 1991			
Δ	-0.0038***	0.0017***	0.0021***
CE-X	-0.0004***	0.0002*	0.0002**
CE-	-0.000200	-0.00210	0.0022**
2011 - 1984			
Δ	-0.0042***	0.0013*	0.0029***
CE-X	-0.0004**	0	0.0004***
CE-	-0.000500	-0.00180	0.0024*

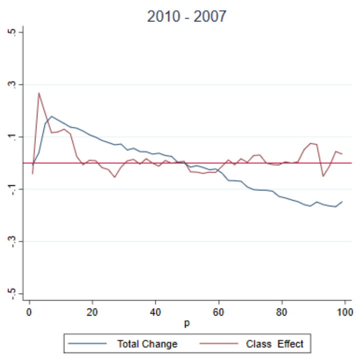
Greece



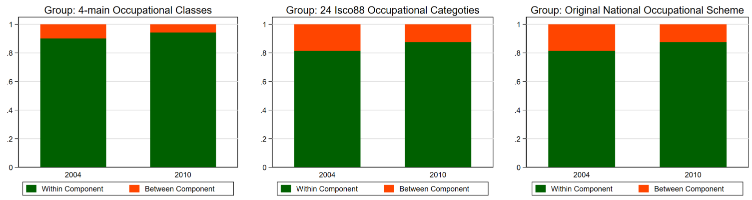
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

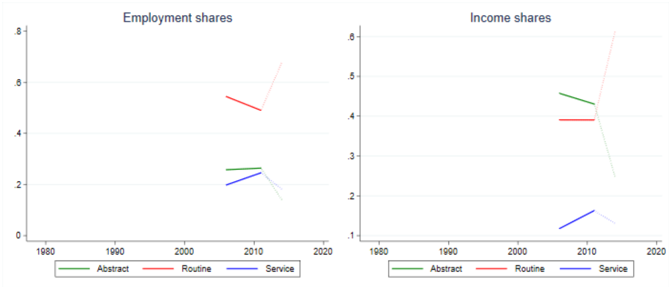


H-EP Results: Quantile Decompositon - Wages

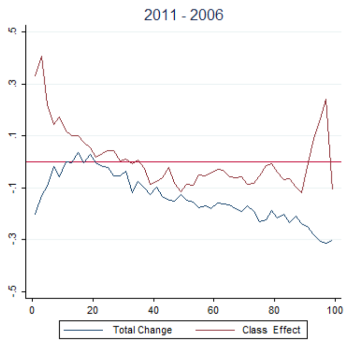


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2007			
Δ	0.00100	0.000500	-0.0015***
CE-X	0	-0.000100	0
CE-	0.00140	-0.000700	-0.000800

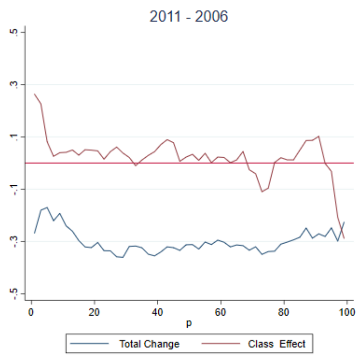
Guatemala



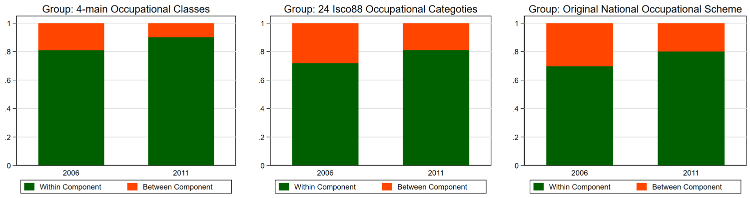
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

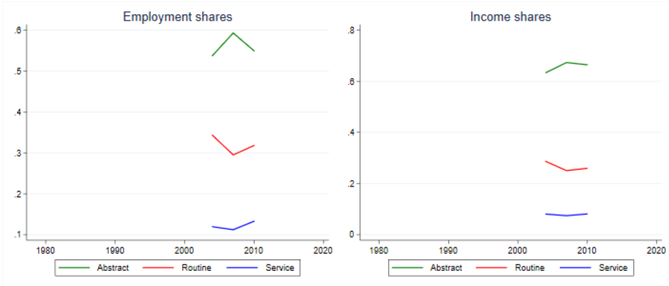


H-EP Results: Quantile Decompositon - Wages

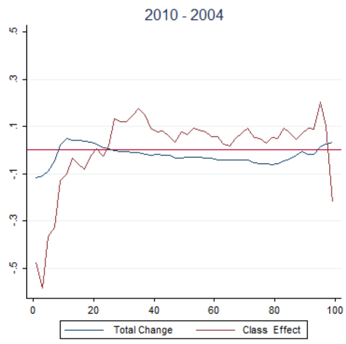


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2011 - 2006			
Δ	0.000800	0.000800	-0.0016***
CE-X	0	0.000100	-0.000200
CE-	0.00290	-0.00350	0.000500

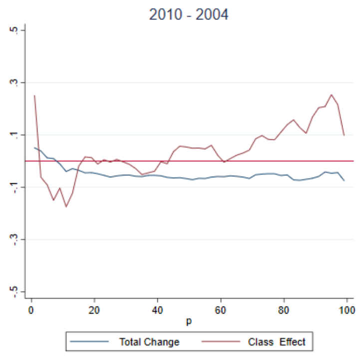
Iceland



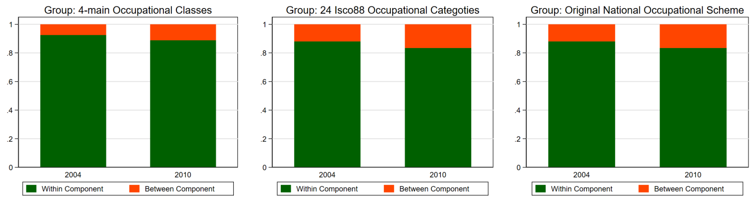
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

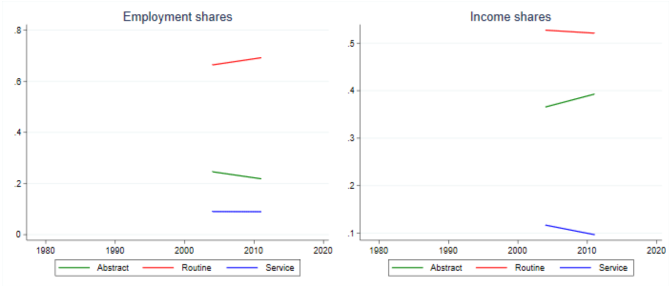


H-EP Results: Quantile Decompositon - Wages



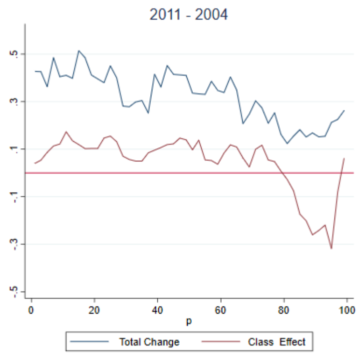
A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.000100	-0.000100	0.000200
CE-X	0	0	0.0001***
CE-	-0.0028*	0.00230	0.000500

India

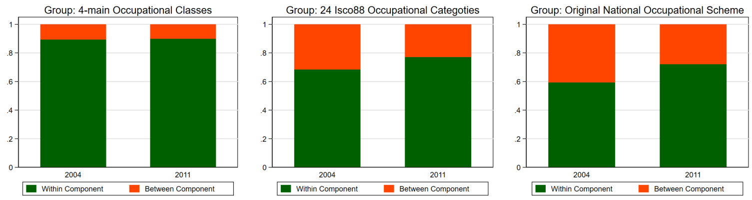


H-JP Results: Employment and Income shares by Occupational Class

H-EP Results: Quantile Decompositon - Earnings

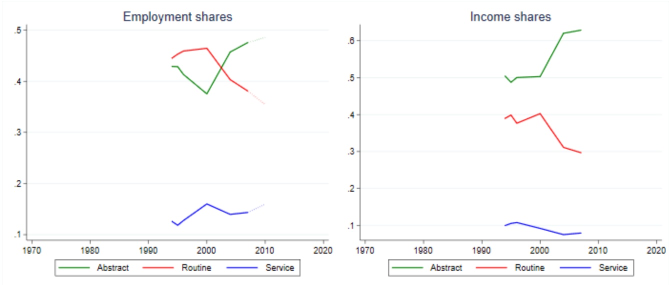


H-EP Results: Quantile Decompositon - Wages

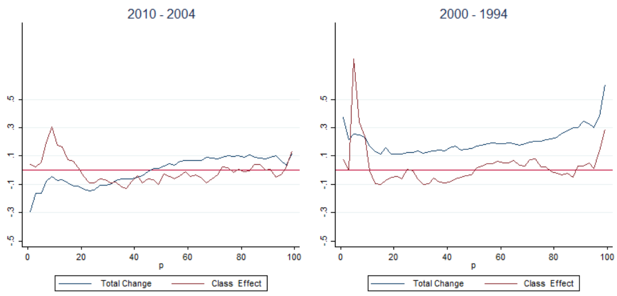


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2011 - 2004			
Δ	-0.0043***	0.0046***	-0.000300
CE-X	0.0002**	0.0002*	-0.0004***
CE-	0.000400	0.00270	-0.0032**

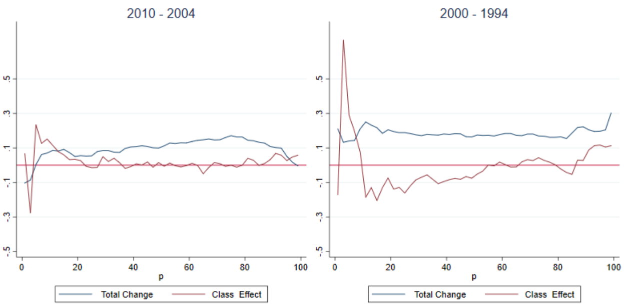
Ireland



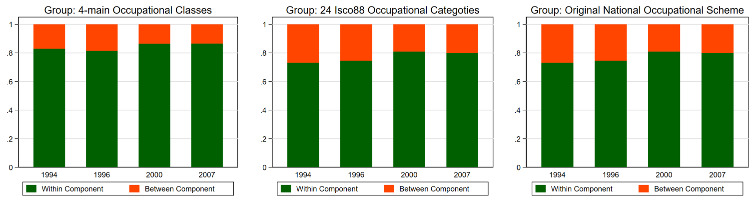
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

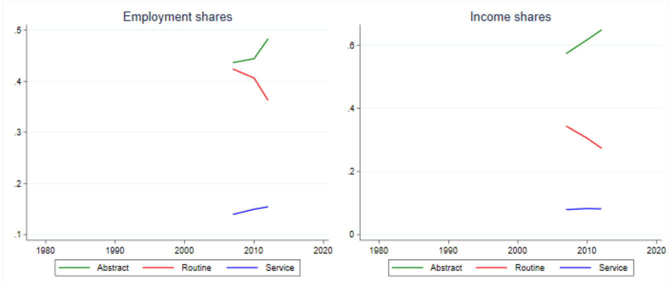


H-EP Results: Quantile Decompositon - Wages

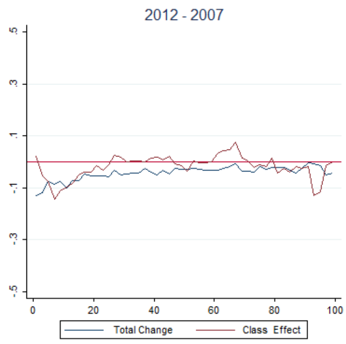


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.0018*	0.000500	0.0013**
CE-X	0.000100	-0.000100	0
CE-	0.00160	-0.00210	0.000500
2000 - 1994			
Δ	0.000700	-0.0028***	0.0022***
CE-X	0	-0.000100	0.000100
CE-	0.00200	-0.00220	0.000200

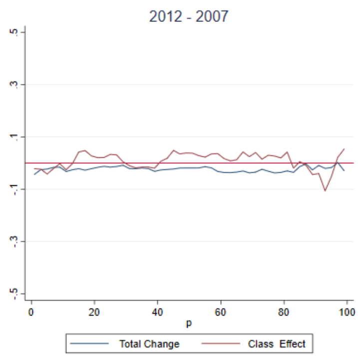
Israel



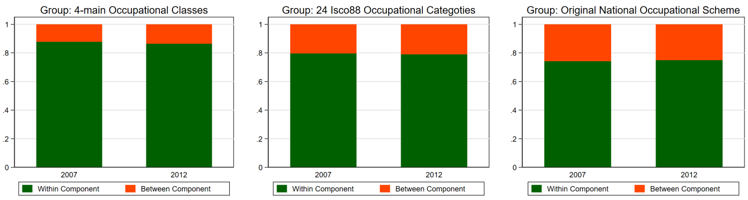
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings



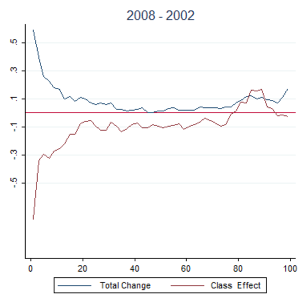
H-EP Results: Quantile Decompositon - Wages



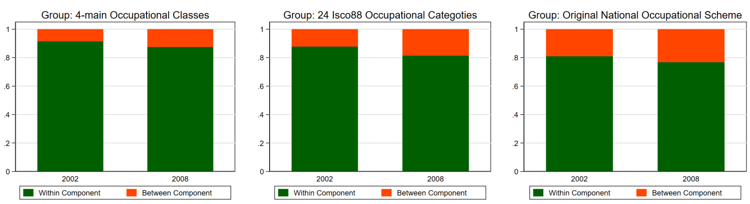
A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2012 - 2007			
Δ	-0.0008*	0.000600	0.000200
CE-X	-0.0002***	0.0001*	0.0001***
CE-	-0.000800	0.00120	-0.000300

Jordan

H-JP Results: Employment and Income shares by Occupational Class

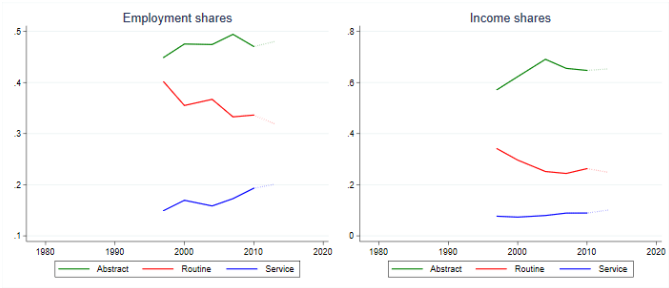


H-EP Results: Quantile Decompositon - Earnings



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2008 - 2002			
Δ	0.0062***	-0.0041***	-0.0021**
CE-X	0.000500	-0.000500	0
CE-	-0.0089*	0.0061*	0.00290

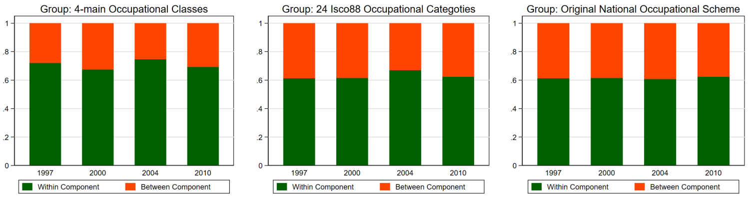
Luxembourg



H-JP Results: Employment and Income shares by Occupational Class

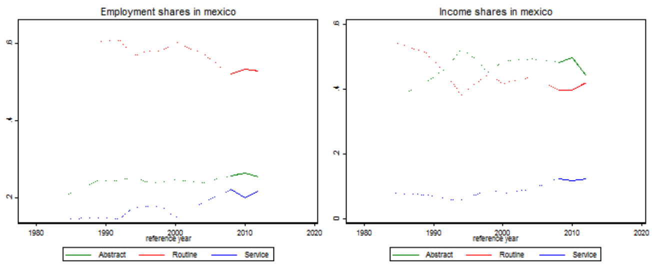
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	0.000500	0.000200	-0.000700
CE-X	-0.0003***	0.0001*	0.0002***
CE-	0.000800	-0.00160	0.000700
2000 - 1997			
Δ	-0.000100	0	0.000100
CE-X	-0.0002***	0.0002***	0
CE-	0.00110	-0.00130	0.000200

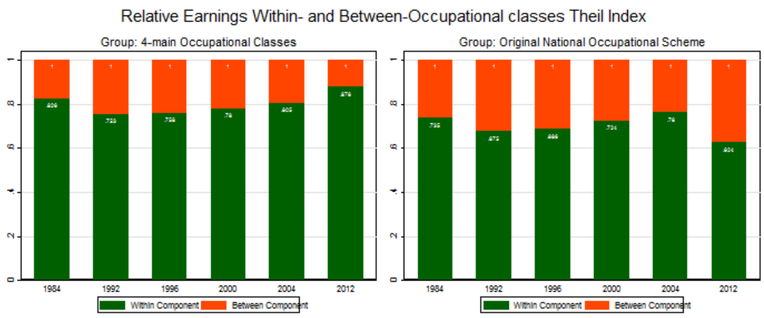
Mexico



H-JP Results: Employment and Income shares by Occupational Class

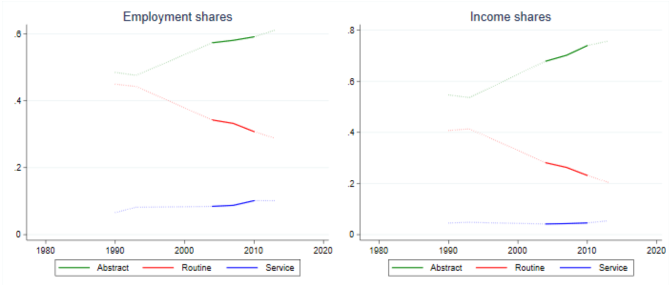
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2012 - 2004			
Δ	-0.0041***	0.0030***	0.0011*
CE-X	-0.000200	0.000100	0.000100
CE-	0.000500	-0.00190	0.00140
2012 - 2000			
Δ	-0.0028***	0.0028***	0
CE-X	0.0003*	-0.0002*	0
CE-	0.00100	-0.00140	0.000400
2012 - 1996			
Δ	-0.0070***	0.0051***	0.0019***
CE-X	-0.000200	-0.0002**	0.0004***
CE-	0.00160	-0.0040***	0.0024*
2012 - 1992			
Δ	-0.0086***	0.0058***	0.0028***
CE-X	0.000100	-0.0004***	0.0003***
CE-	0.00250	-0.00130	-0.00120
2012 - 1984			
Δ	-0.0062***	0.00100	0.0053***
CE-X	0.0011**	-0.0007*	-0.000400
CE-	-0.000400	-0.00140	0.00170

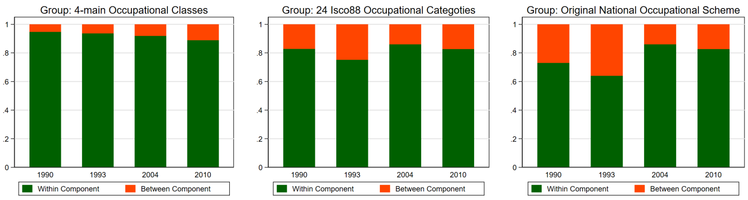
Netherlands



H-JP Results: Employment and Income shares by Occupational Class

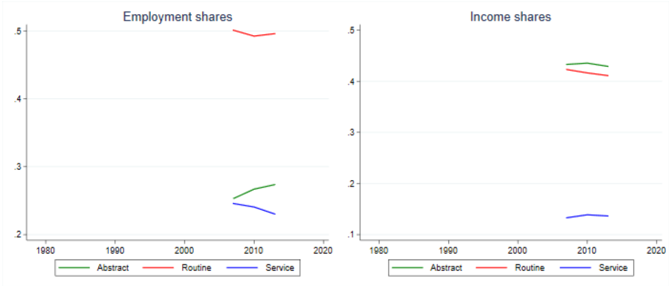
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages

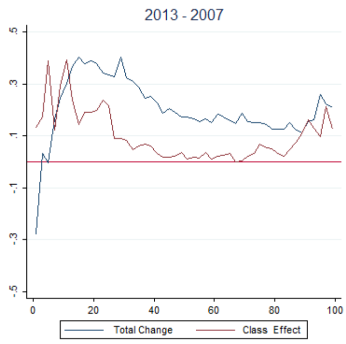


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.0029***	0.0019**	0.0010**
CE-X	-0.0002*	0	0.0002***
CE-	-0.00350	0.0045*	-0.00100
2010 - 1990			
Δ	-0.0038***	0.00110	0.0027***
CE-X	-0.000400	0.000100	0.0002**
CE-	-0.00290	0.00250	0.000400

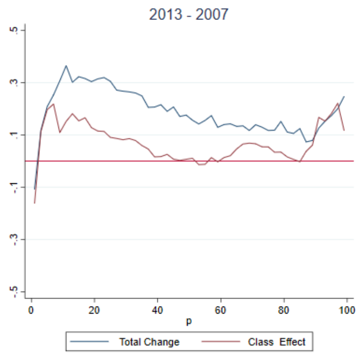
Panama



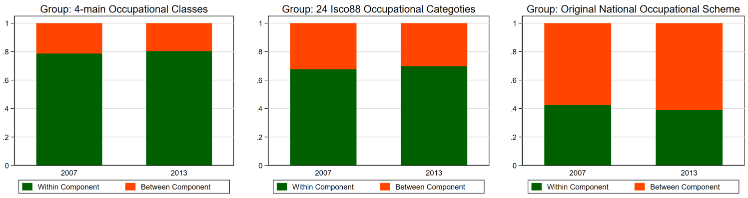
H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

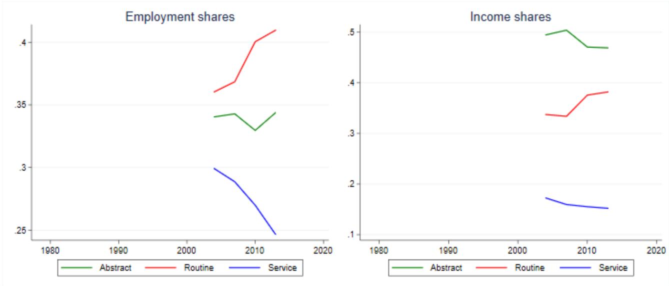


H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2013 - 2007			
Δ	-0.000200	0.0012**	-0.0010*
CE-X	0.0003***	0.000100	-0.0005***
CE-	0.00160	-0.0026*	0.00100

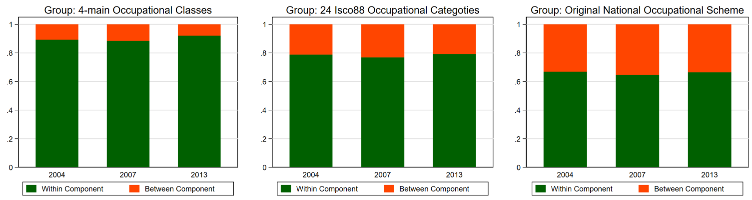
Peru



H-JP Results: Employment and Income shares by Occupational Class

H-EP Results: Quantile Decompositon - Earnings

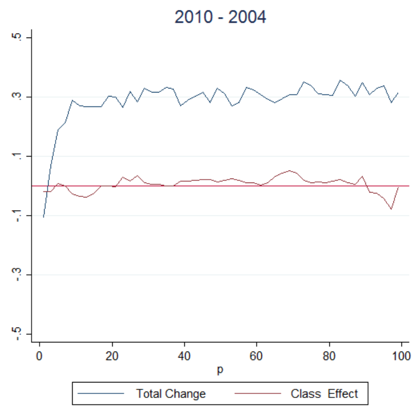
H-EP Results: Quantile Decompositon - Wages



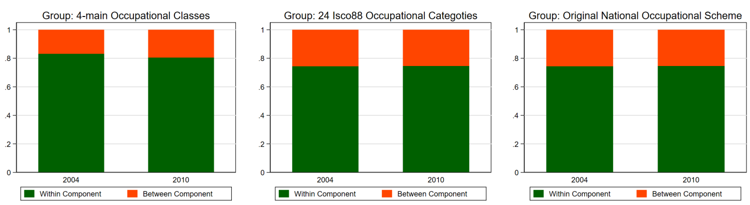
A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2013 - 2007			
Δ	0.0021***	0.0014***	-0.0035***
CE-X	0.0003***	0.0002***	-0.0005***
CE-	-0.00140	0.000800	0.000600
2013 - 2004			
Δ	0.0026***	0.0011**	-0.0038***
CE-X	0.0008***	0.000100	-0.0009***
CE-	0.0039***	0.000800	-0.0048**

Poland

H-JP Results: Employment and Income shares by Occupational Class

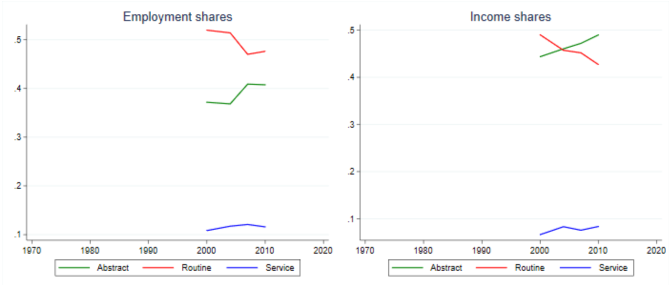


H-EP Results: Quantile Decompositon - Earnings



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.0015***	0.0013***	0.000200
CE-X	-0.0001***	0.0001***	-0.0000**
CE-	-0.000200	0.000300	-0.000200

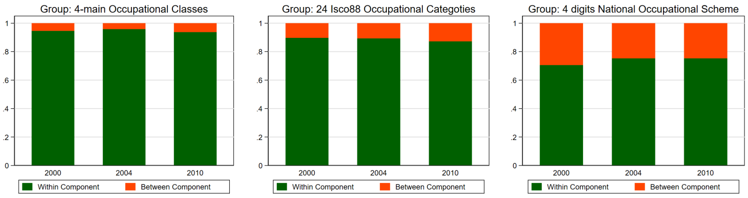
Russia



H-JP Results: Employment and Income shares by Occupational Class

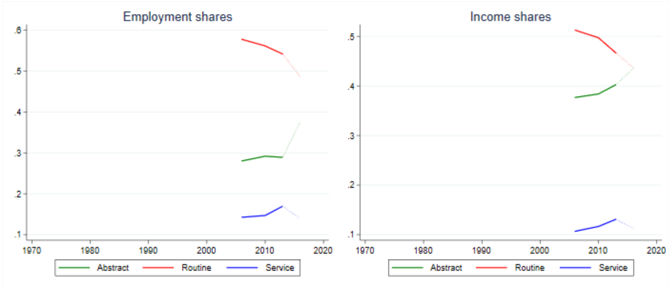
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages

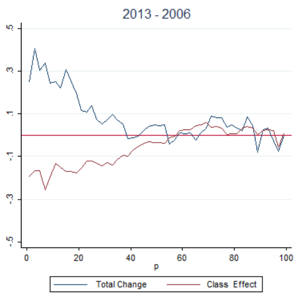


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2000			
Δ	0.0061***	0.000100	-0.0062***
CE-X	0.000100	0	-0.000100
CE-	0.000600	-0.000300	-0.000300

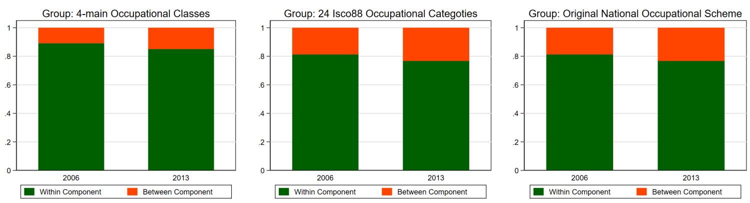
Serbia



H-JP Results: Employment and Income shares by Occupational Class

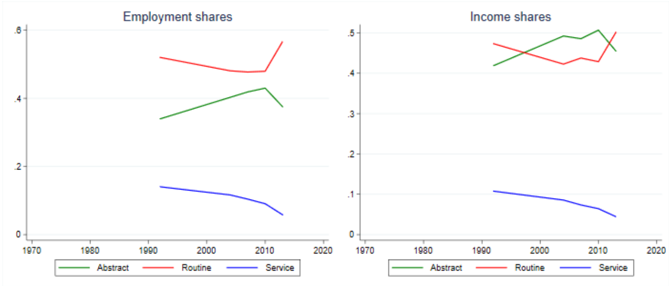


H-EP Results: Quantile Decompositon - Earnings



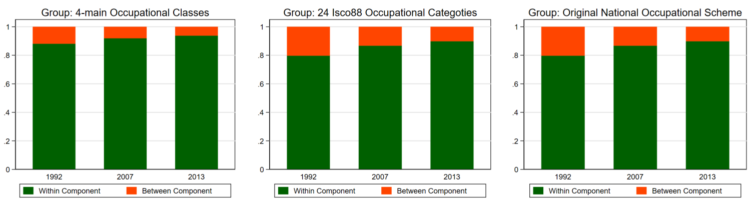
A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2013 - 2006			
Δ	0.0026***	-0.0014***	-0.0012***
CE-X	0	0	0
CE-	-0.0019*	0.00110	0.000800

Slovakia



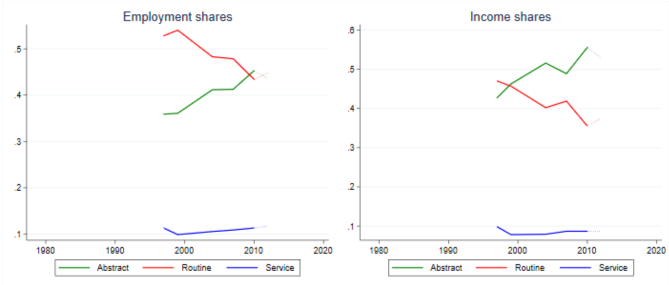
H-JP Results: Employment and Income shares by Occupational Class

H-EP Results: Quantile Decompositon - Earnings

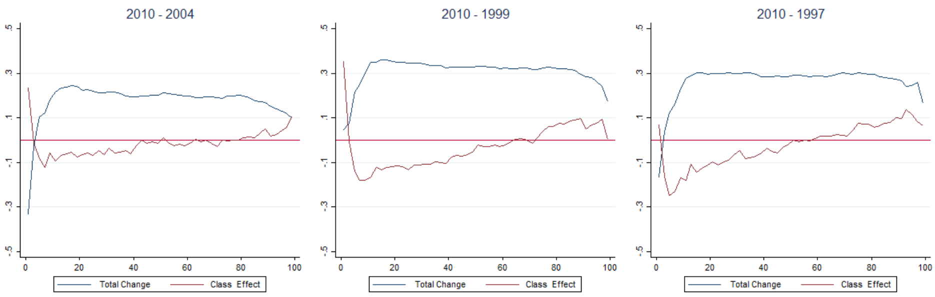


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2013 - 2007			
Δ	0.000200	-0.000100	-0.000100
CE-X	0.000200	-0.000100	-0.0001**
CE-	0.000700	-0.000300	-0.000500

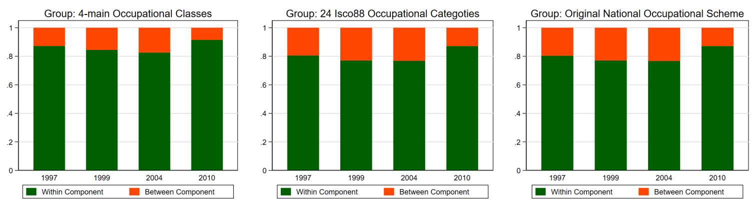
Slovenia



H-JP Results: Employment and Income shares by Occupational Class

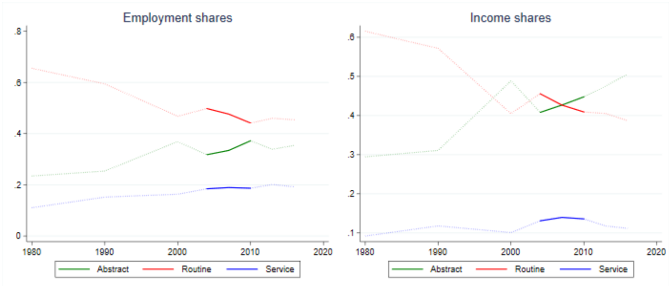


H-EP Results: Quantile Decompositon - Earnings



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	-0.0014**	0.0022***	-0.0008**
CE-X	0	0.0001*	-0.0001***
CE-	-0.000300	-0.000900	0.0012*
2010 - 1999			
Δ	-0.000900	0.0019***	-0.0010***
CE-X	0.000100	0.000100	-0.0001*
CE-	-0.000900	-0.00100	0.0019***
2010 - 1997			
Δ	-0.0017***	0.0022***	-0.000500
CE-X	-0.0003*	0.0003***	-0.000100
CE-	-0.00200	-0.000100	0.0020***

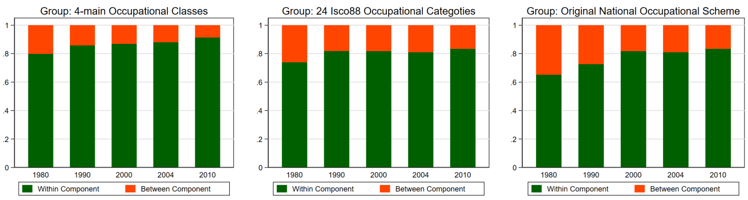
Spain



H-JP Results: Employment and Income shares by Occupational Class

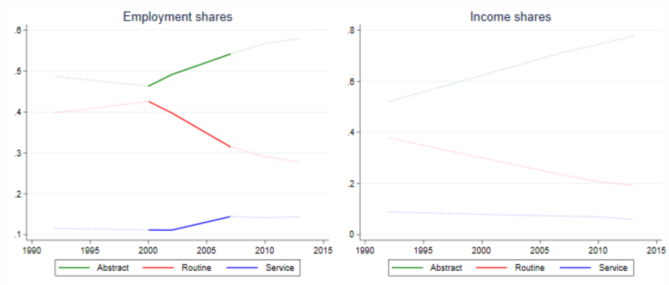
H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages



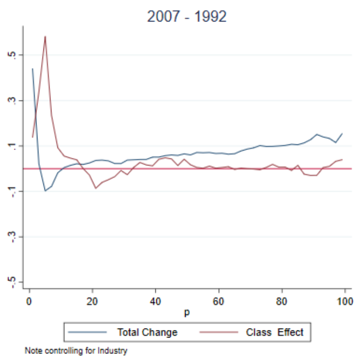
A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2007			
Δ	-0.000300	-0.000100	0.0004*
CE-X	-0.000100	0	0.0001***
CE-	-0.000800	-0.000200	0.000900
2004 - 2000			
Δ	0.0018**	-0.000500	-0.0013***
CE-X	0.000100	-0.000100	0
CE-	0.000800	-0.000500	-0.000300
2004 - 1990			
Δ	-0.0016***	0.000500	0.0011***
CE-X	-0.0001*	-0.0003***	0.0004***
CE-	-0.000700	0.000900	-0.000200

Switzerland

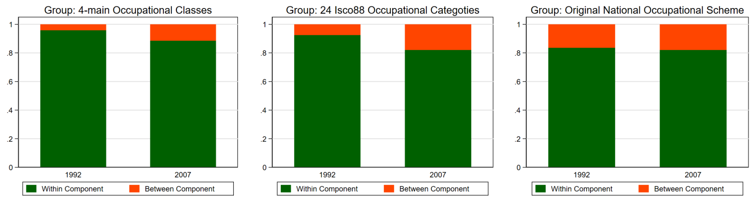


H-JP Results: Employment and Income shares by Occupational Class

H-EP Results: Quantile Decompositon - Earnings

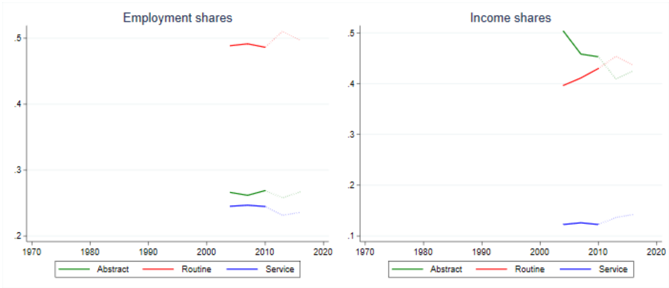


H-EP Results: Quantile Decompositon - Wages

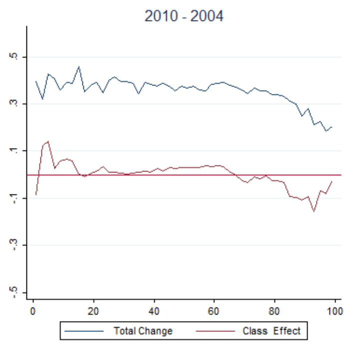


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2007 - 1992			
Δ	0.000400	-0.00110	0.000700
CE-X	-0.0008***	0.0004***	0.0004***
CE-	0.00350	-0.00290	-0.000500

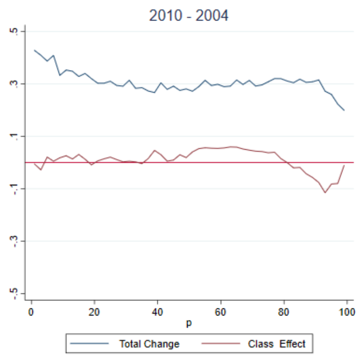
Uruguay



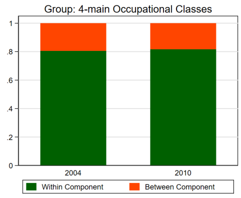
H-JP Results: Employment and Income shares by Occupational Class

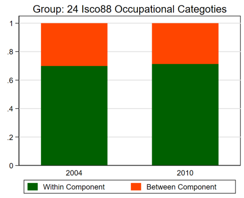


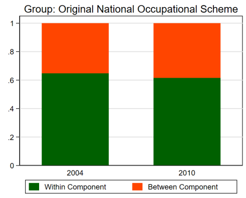
H-EP Results: Quantile Decompositon - Earnings



H-EP Results: Quantile Decompositon - Wages

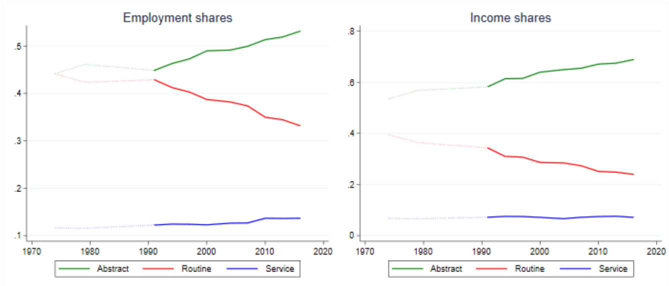




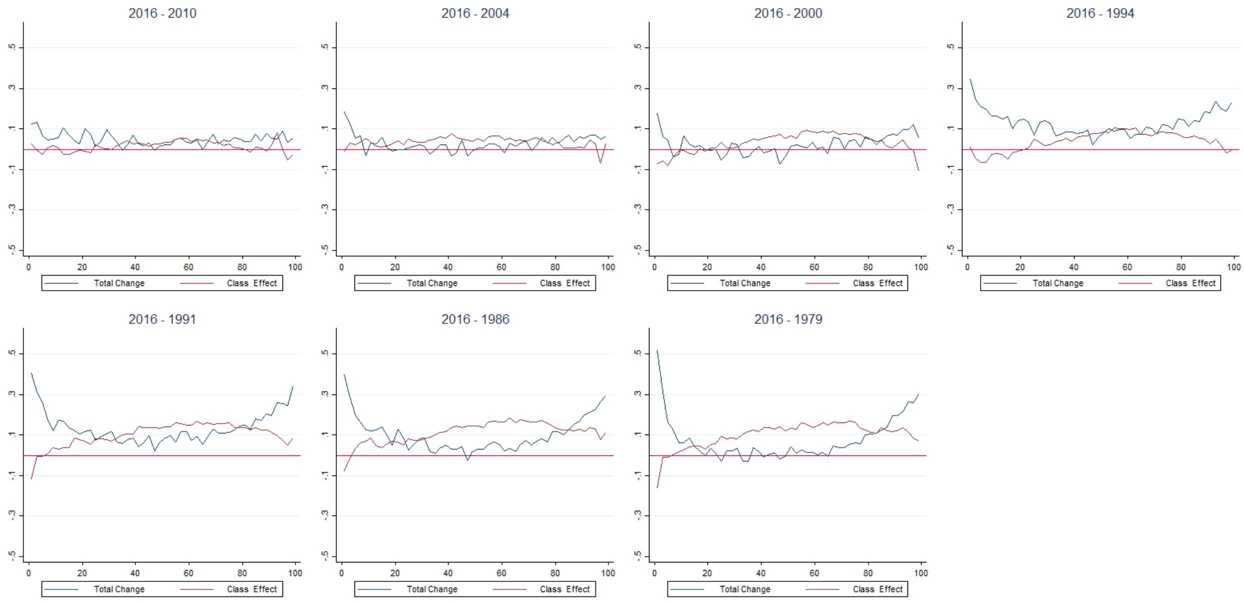


A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2010 - 2004			
Δ	0.0006*	0.0013***	-0.0019***
CE-X	-0.0001**	0	0.0001**
CE-	0.00100	0.000100	-0.00110

United States

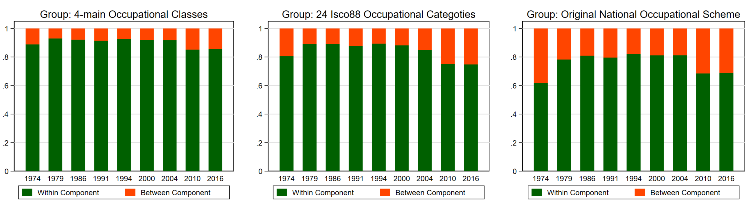


H-JP Results: Employment and Income shares by Occupational Class



H-EP Results: Quantile Decompositon - Earnings

H-EP Results: Quantile Decompositon - Wages



A	B	G	F
	Lower Class (0-15)	Middle Class (15-85)	Upper Class (85-100)
2016 - 2010			
Δ	0.0005***	-0.0006***	0.000100
CE-X	-0.0000***	0.0000***	0
CE-	-0.000200	0.0006*	-0.000400
2016 - 2004			
Δ	0.0004**	-0.0009***	0.0006***
CE-X	-0.0001***	0.0000***	0.0001***
CE-	0	0.000600	-0.0006*
2016 - 2000			
Δ	0.000200	-0.0010***	0.0008***
CE-X	-0.0002***	0	0.0002***
CE-	-0.0008*	0.0018***	-0.0010***
2016 - 1994			
Δ	0.0014***	-0.0019***	0.0006***
CE-X	-0.0002***	0.0001***	0.0001***
CE-	-0.0009*	0.0015***	-0.0006*
2016 - 1991			
Δ	0.0013***	-0.0026***	0.0013***
CE-X	-0.0002***	0.0001***	0.0001***
CE-	-0.0010*	0.0015***	-0.0005*
2016 - 1986			
Δ	0.0015***	-0.0030***	0.0015***
CE-X	-0.0003***	0.0001***	0.0002***
CE-	-0.000800	0.0014***	-0.0005*
2016 - 1974			
Δ	0.0047***	-0.0065***	0.0018***
CE-X	-0.000100	-0.000100	0.0001*
CE-	-0.00180	0.00140	0.000400