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# De-routinization of Jobs and the Distribution of Earnings – Evidence from 35 Countries*

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**Abstract:** Routine-Biased Technological Change hypothesis (RBTC) by Acemoglu and Autor [2011] suggests that automation processes have substituted workers operating middle-skilled routine tasks. Consequently, the relative demand of complementary non-routine occupations, i.e., low-skilled service and high-skilled abstract jobs, has increased. These changes in the composition of the labor force imply a polarization of jobs along skills distribution. An aspect of high socio-economical and political relevance is its distributional implications. Here we quantify polarization of jobs and its implication for earnings distributions using a novel dataset of 35 countries around the globe. We find strong evidence for job polarization in most countries but no clear-cut distributional consequences. We show that this weak link stems from variation *within*, rather than *between*, occupational classes, and from heterogeneous de-routinization effects along the earnings distribution.

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

**JEL classification**: D3, J3, J8

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## 1 Introduction

Dynamics of occupational changes in the labor force is a central topic of economic research. In particular, technological change is historically identified as a key explanation for major shifts in the workforce, through the creation and disruption of jobs.[1] Autor et al. [2003] proposed the Routine-Biased Technological Change (henceforth, RBTC) hypothesis, which relates improvements in information and communications technologies (henceforth, ICT) with de-routinization of the workforce. According to the RBTC hypothesis, the decreasing prices of technology over the last decades have exogenously driven the substitution of workers operating routine tasks by computer algorithms or machines.[2] Simultaneously, the relative demand for workers who perform complementary non-routine tasks has increased. Typical non-routine tasks include problem-solving, creativity, situational adaptability, and in-person interactions. Recent empirical literature supports the RBTC hypothesis [Acemoglu and Autor, 2011, Goos et al., 2014, De La Rica and Gortazar, 2016], finding that the increasing adaption of ICT as labor input has contributed to the de-routinization of jobs globally over the last decades.

Acemoglu and Autor [2011] empirically investigate how job de-routinization alters the distribution of skills. Because routine jobs are typically middle-skilled jobs while non-routine jobs mostly concentrate at the tails of the skill distribution, de-routinization results in job polarization: increasing employment shares of high and low skilled jobs relative to middle skilled.

The link between job de-routinization and job polarization opened the field to empirical investigation of its consequences for the wage distribution. Acemoglu and Autor [2011] and Autor and Dorn [2013] provide evidence that the RBTC framework explains overall wage polarization experienced in the US since the 1960s. The authors define wage polarization as u-shaped earnings growth along the wage distribution, which results in a reduction of bottom-half -, and an increase in top-half inequality. Following their definition, overall distributional consequences depend on which of the two margins dominate.[3]

Moreover, Autor and Dorn [2013] conclude form their empirical analyses that “labor specialization [...] play[s] a critical role as a driver of rising employment and wage polarization in the US and, potentially, in other countries” (p. 1591). However, this generalization is contested [Dustmann et al., 2009, Massari et al., 2014, Green and Sand, 2015, De La Rica and Gortazar, 2016, Hunt and Nunn, 2019, Taber and Roys, 2019, Böhm, 2020]. This is because occupations are not systematically sorted along the wage distribution.

We recognize three major reasons for the debated nexus between job polarization and wage inequality. First, the global phenomena of de-routinization of jobs potentially has diverse distributional consequences as the number of routine and non-routine workers differs across countries.

[1] See [Vivarelli, 2014] for a detailed survey of the literature.

[2] Routine intense occupations include, for example, clerical work, repetitive production, and monitoring jobs.

[3] In RBTC literature, polarization does not rely on the traditionally applied concepts of identification and alienation [Esteban and Ray, 1994], rather it simply refers to differentiated u-shaped growth patterns along the wage distribution. In this sense, the wage polarization notion used in RBTC literature is strictly bi-polar, looking at the dispersion of the distribution from the middle position, and does not contemplate the possibility of multi-polar polarization, defined as the bunching of the population into any number of income subgroups clustered around local means of the income distribution [Chakravarty et al., 2015].

Hence, an extensive cross-country comparison can shed more light on the link between job polarization and inequality. Second, several studies focus on comparisons of average wages by occupations [Acemoglu and Autor, 2011, Autor and Dorn, 2013]. Focusing on averages disregards that job polarization may also alter occupational class specific wage inequalities [Hunt and Nunn, 2019, Taber and Roys, 2019]. As this paper shows, class-specific wage and earnings inequalities respond to the changing demands for different occupational classes of workers. Hence, the quantification of the nexus between job polarization and wage inequality requires a comprehensive assessment of both wage inequalities within and between occupations. Third, embedding variation within-occupations acknowledges that workers in routine and non-routine occupational classes can overlap along the wage distribution [Böhm et al., 2019, Böhm, 2020]. In this sense, de-routinization of jobs does not just displace workers in middle-, but also at the bottom and at the top of the wage distribution. Consequently, one needs to account for different occupational composition and return effects along the quantiles of the wage distribution over time to understand the overall distributional effects of job de-routinization.

This paper contributes to the literature by providing a comprehensive international assessment of job de-routinization processes and their relevance for changes in hourly wages and annual labor earnings[4] inequalities within and between occupations. A novel and harmonized dataset for 35 countries, provided by the Luxembourg Income Study (LIS) and the Economic Research Forum (ERF), the so-called LIS-ERF dataset, provides the empirical base for our analysis. The LIS is the largest available income database of harmonized micro data from countries around the world. Technically, we estimate the Re-centered Influence Functions (RIF) decomposition method [Firpo et al., 2009, 2011, 2018] to measure ceteris paribus effects of job de-routinization for percentiles of the country specific earnings distributions, accounting for both within and between occupational variation. Further, we characterize the RIF decomposition results in the light of changes in occupational composition and returns. Finally, we are the first to quantify the relative importance of changes in earnings inequalities within and between occupations induced by job polarization around the globe. The distinction of inequalities within and between occupations is motivated by the findings for the US by Hunt and Nunn [2019], Taber and Roys [2019], and Böhm [2020], who show that the overall distributional effect is unclear if occupational groups are scattered and job displacements effects are not homogeneous along the wage distribution.

We show that job polarization occurs in 30 out of the 35 countries under investigation with different time frames ranging from the 1990s to the 2010s. Our results support the RBTC hypothesis as suited for explaining the observed shifts of employment shares in the workforce. In a cross-country perspective, we show that de-routinization is ambiguously linked with inequality within and between occupational groups. Moreover, variation in overall inequality mostly stems from variation within occupational groups. Applying the RIF decomposition method, country-specific earnings distributions have developed heterogeneously. In 14 (eleven) countries earnings growth rates are monotonically increasing (decreasing) over the quantile distribution, resulting in increasing (decreasing) overall inequality. Only five countries over 35 show u-shaped growth patterns along the earnings distribution following the definition of polarization adopted in Acemoglu and Autor [2011], Autor and Dorn [2013]. In five countries we find no

[4]Henceforth referred to as earnings.

substantial changes in inequality.

We show that the weak link between job polarization and earnings inequality is for the following reason: Overall earnings inequality is determined by inequalities between and within occupational classes. Changing the average pay of a particular occupational class will unambiguously change the between-class inequality component – as determined by differences in class-specific average earnings. However, because employees from a certain occupational class are not perfectly stratified but scattered along the earnings distribution, the implication for within-class inequalities and – ultimately - for overall inequality are ambiguous. Contrary to the RBTC framework [Acemoglu and Autor, 2011, Autor and Dorn, 2013], our results also do not support that job polarization contributed to reduce inequality at the bottom of the 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. Section 5 provides the results. Section 6 presents the results using hourly wages instead of yearly gross-income. Section 7 concludes.

## 2 Literature Review

This section reviews the empirical literature on job polarization and its debated implications for earnings inequality.

Job polarization and its direct link to ICT adoption is extensively studied in both advanced and emerging economies. 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. Autor [2019] updates these findings, also describing an increasing divide in wages between non-college and college workers in the US. Goos et al. [2014] show de-routinization in the workforce due to ICT adaption in 16 Western European countries between 1993 and 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, as well as 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; Hardy et al. [2018] do so for Central and Eastern Europe. Mahutga et al. [2018] describe de-routinization of jobs primarily as a phenomenon of the global north. Their analysis bases on 38 aggregated LIS countries. Even though they use the same data source, Mahutga et al. [2018] do not explore country-specific effects, a fundamental difference to our approach.

In sum, most previous research finds empirical evidence for job polarization due to ICT adaption in many countries around the world. We contribute to this strand of literature by using a harmonized dataset up to the year 2016 for 35 countries.

Several empirical studies investigate the nexus between job polarization and its distributional consequences. The evidence is mixed.

One stream of the literature finds that de-routinization due to ICT adaption implies wage polarization defined as u-shaped earnings growth along the wage distribution. In the US, Autor 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. The authors conclude that job de-routinization polarizes the returns to skills *between* occupational classes and can explain a substantial share of aggregated polarization. In Europe, evidence for wage polarization is provided for Germany [Dustmann et al., 2009] and the UK [Machin, 2010]. Mahutga et al. [2018] state that de-routinization contributes to earnings polarization in rich democracies.

Apart from the country-specific results, the findings also depend on the time span under analysis. Focusing on the US, Firpo et al. [2011] find that technological change was skill-biased[5] in the 1980s, while it was routine-biased[6] in the 1990s. In the 2000s, they only find a modest effect. Our results extent their analysis by adding an additional decade to the analysis. As this paper shows, we do not find that job de-routinization is associated with wages and earnings polarization in the 2010s. Although our results do not exclude temporary influences of ICT adaption on the earnings distribution in line with RBTC, we cannot observe a close nexus in the long run.

Several studies contest the link between de-routinization and earnings polarization. Goos and Manning [2007] do not find evidence for a relationship between de-routinization and wage inequality in the UK and raise doubts as the literature typically does not account for heterogeneous wages distributions within occupations. Green and Sand [2015] find similar results for Canada. Böhm et al. [2019], Hunt and Nunn [2019], and Taber and Roys [2019] suggest that the RBTC hypothesis is generally 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 US 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. Massari et al. [2014] do not find wage polarization in Europe and find only weak polarizing effects of technological change, suggesting that deterioration of labor institutions, e.g., increasing part-time and temporary jobs, may play a more important role by hindering wage growth at the bottom. According to De La Rica and Gortazar [2016], differences in ICT adoption explain an important and significant part of wage differentials but have little explanatory power for wage inequalities in OECD countries. In a theoretical analysis, [Böhm, 2020] shows that job polarization leads to a polarization of task prices, which does not translate into wage polarization. He suggests that the overall distributional effect is unclear if

[5] Wage growth strictly increases with skills.

[6] Wage growth was lower in the middle than at the tails of the skill distribution

occupational groups are scattered and job displacements effects are not homogeneous along the wage distribution.

Our analysis of a large set of countries captures these heterogeneous findings and sets them analytically into perspective compared to the results of Goos and Manning [2007], Böhm et al. [2019], Hunt and Nunn [2019], and Böhm [2020].

## 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. Compared to the standard LIS dataset, LIS-ERF includes additional data for seven countries: Egypt, Iraq, Jordan, Palestine, Somalia, Sudan, and Tunisia. The LIS cross-national data center acquires, harmonizes, and documents microdata from different national statistical institutions.[7] 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 based on two criteria:

1. 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.

2. Availability of focal variables: labor income and job information are necessary to define quantiles and occupational classes used in the analysis.

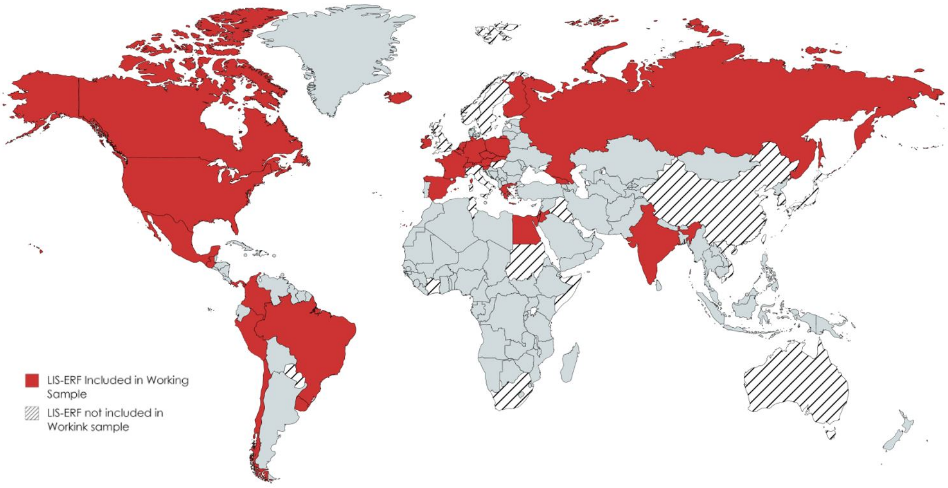
Our working sample focuses on prime-age employed individuals aged 25-55. Missing values are imputed in all LIS and ERF countries. The imputation is conducted by the individual survey institute in each country. Most countries follow a simple random sampling or a two-stage area sampling procedure. Although the imputation procedures are not completely standardized, we acknowledge a high comparability across waves and countries, as 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 2.

For most of the 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 opt for the longest available time span, which fulfills our availability criteria of the focal variables.[8]

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

[8] We also run our analysis for shorter time spans if they are available. In this paper, we provide the results for the US. The estimates for the other countries are available in supplementary materials.




*Notes.* Selected countries included in the working sample are 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, and Uruguay.

Figure 1: Countries in Working Sample

### 3.1 Focal Variable - Earnings

We rely on individual yearly gross and net labor incomes, which are defined for all LIS countries as the total income from the main job. This includes cash payments as well as the values of goods and services received from dependent employment, plus the profits/losses and values of goods from self-employment. ERF countries provide information on labor income at the household level. Therefore, for these countries, we proxy the individual income by dividing the household income[9] by the number of members in the household who receive a salary. LIS waves that do not provide individual labor income information[10] are excluded from the analysis.

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 hourly wages as dependent variable in order to provide closer comparability with the previous literature. Compatible hourly wage information is available for 21 countries. Our hourly wage variable is calculated dividing

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

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

the personal labor income by the number of actual working hours usually worked during the week multiplied by 4.33.

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

- Net earnings countries: Belgium, Chile, Egypt, Georgia, India, Mexico, Russia, Slovenia, and Uruguay.
- 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.[11]
- Greece, Spain, Estonia, Ireland, and Luxembourg do not have harmonized earnings information across the available time span. Thus, we separate gross from net earnings waves.[12]

We adjust the income variables for inflation using yearly Consumer Price Index data provided by the LIS and trimmed the distribution at 1st and 99th percentiles.[13]

### 3.2 Focal Variable – Occupation

The literature on job 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 Autor 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" (Autor and Dorn [2013], p. 1570). 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)[14] 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 occupational schemes to the two-digits ISCO-88 scheme.

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

[12] 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.

[13] 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.

[14] 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.

In our view, the use of RTI-based classifications has several drawbacks. First, RTI lacks a unique metric. Since numerous potential task scales exist, there is no obvious measure that represents a given group of tasks 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 highly developed countries, it is difficult to justify it for a set of heterogeneous countries.

For these reasons, we cluster specific occupations into three main job classes, i.e., service, routine, and abstract job classes. With this classification, we follow Acemoglu and Autor [2011]. Table 1 provides a detailed overview about the definition of the occupational classes in our analysis, the original formulation by Acemoglu and Autor [2011]. Moreover, we provide the corresponding ISCO-88 (2-digits) codes and their respective RTI value, as applied by Mahutga et al. [2018].

The Acemoglu and Autor [2011] classification is particularly convenient since it is 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.[15]

Our classification deviates in two ways from Acemoglu and Autor [2011]. We merge the "routine abstract" and the "routine manual" into one "routine" occupational class as done by Massari et al. [2014] and Böhm [2020]. Furthermore, we do not drop agricultural occupations entirely from our working sample. Even though we focus on service, routine and abstract occupations, we still control for agricultural occupations in the decomposition analysis. We argue that several countries in our working sample rely considerably on the agriculture sector, hence, it would be inappropriate to exclude them.

The main limitation of the 4-classes classification adopted in Acemoglu and Autor [2011] is that it neglects the routine-intensity gradient between different occupations: RTI scores in Table 1 ranges from 0.17 for models, salespersons, and demonstrators, 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 automation processes. In this sense, RTI scores can be interpreted as a measure of risk 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 not on the *potential* risk of layoffs. Thus, we argue that, for our analysis, the aggregated occupational classes adequately characterize the composition of the workforce.

For the assignment of employees to the aforementioned occupational classes, LIS-ESR's

[15] 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 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.

Table 1: Occupational classes based on 2-digts ISCO

| **Occupational Class** | | **ISCO-88 Label** | **ISCO-88 Code** | **RTI** |
|---|---|---|---|---|
| **Longmiur, Schroeder, Targa** | **Acemoglu and Autor** | | | |
| **Abstract Occupations** | **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 Occupations** | **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 |
| | | Drivers and mobile plant operators | 83 | -1.42 |
| | | Labourers in mining, construction, manufacturing and transport | 93 | 0.57 |
| **Service Occupations** | **Non Routine** | Personal and protective services workers | 51 | -0.50 |
| | | Sales and services elementary occupations | 91 | 0.14 |
| **Agricultural** | — | Skilled agricultural and fishery workers | 61 | 0.14 |

*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.

harmonized 1-digit occupational variable (9 clusters), *occb1*, is not appropriate since routine and non-routine occupations are mixed together within the same class.[16] 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 1.

Several major changes in the ISCO coding schemes occurred following the year 2010 (ISCO 08). Since a solid harmonization of ISCO 88 and ISCO 08 occupational schemes is not possible at the 2-digit level, we do not include these survey years in our working sample.

Table 2 provides a full overview over all countries and waves used in our working sample given the criteria described in this section. The full set of country-specific waves is included in the investigation of job de-routinization over time. The waves used for our decomposition analysis are bold.

[16]This is the case for ISCO category 5 "services and sales workers," comprising both "personal and protective services workers" (ISCO 51) and "models, salespersons and demonstrators" (ISCO 52). According to the existent literature, the former should be classified as manual non-routine (RTI index=-.60) and the latter 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=n/a) and routinized "laborers in mining, construction, manufacturing and transport" (93) with RTI=+0.53.

Table 2: 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 the decomposition analysis are bold. LIS-ERF waves in which the occupational coding scheme is updated to ISCO 08 are marked in blue and have been excluded in the decomposition exercise. We use the remaining set of waves for the analysis of the evolution of employment shares over time. Countries marked with an asterisk changed gross/net classification of earnings 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.

# 4 Methodology

In the following section, we present our main methodological framework. In Section 4.1, we introduce the descriptive approach for the analysis of job de-routinization. In the following Section 4.2, we present the methods to investigate correlations between job polarization and overall inequality patterns across countries. Section 4.3 presents the unconditional RIF decomposition technique proposed by Firpo et al. [2009] and Firpo et al. [2018], then applied in Firpo et al. [2011], which constitutes our empirical framework of the distributional consequences of job de-routinization within each country under analysis. Section 4.4 provides the procedure to analyze effects from occupational class-specific composition and returns.[17]

## 4.1 Assessing De-routinization of Jobs

We start our analysis by scrutinizing country specific changes in the composition of the workforce over time. Falling employment shares characterize job de-routinization. Accordingly, we define employment shares as

$$ES_t^{Occ} = \frac{N_t^{Occ}}{N_t^{Serivce} + N_t^{Routine} + N_t^{Abstract}}, \tag{1}$$

where *Occ* refers to service, routine, and abstract occupations, $N_t^{Occ}$ is the total number of workers in each occupational class in each period $t$, as defined in Table 2.

RBTC hypothesis suggests that occupational classes follow a strict hierarchy in earnings, with abstract workers earning, on average, more than routine workers, who earn on average more than service. To provide descriptive evidence of it, we provide the mean earnings of occupational classes over time.

## 4.2 Analysis of De-routinization and Inequality

We then describe how changes in the employment structure correlate with overall inequality within and between occupational groups across countries. The aim is to provide suggestive evidence of the importance of both within- and between occupational class dynamics for distributional analysis. Specifically, since there exists a hierarchy in the average returns of the service, routine, and abstract classes, job de-routinization should decrease (increase) inequality *between* service (abstract) and routine occupations by composition effects. As a consequence of job polarization, inequality *between* service (abstract) and routine occupations should decrease (increase). Hence, the evolution of inequality of the *overall* population is ambiguous as it depends on which of these two effects dominate. For this reason, we study correlations between de-routinization and inequality for the lower (service + routine) and upper (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 Figure A1 in Appendix.

[17] Formulas provided in this section are all country-specific. For the sake of clarity, we do not include a country index.

We consider the relative country-specific drop of the employment shares in routine occupations as the measure of job de-routinization, formally:

$$\Delta ES^{Routine} = \frac{ES_0^{Routine} - ES_1^{Routine}}{ES_0^{Routine}} \tag{2}$$

The higher $\Delta ES^{Routine}$, the stronger is the de-routinization process in that country between period $t = 0$ and $t = 1$.[18] Countries that did (not) experience job de-routinization exhibit negative (positive) $\Delta ES^{Routine}$ growth rates.

We use the variation of the Theil index in the Routine-Service population as measure of earnings inequality since it complies with the decomposition principle [Bourguignon, 1979] and to distinguish inequality within and between occupational classes:

$$\Delta T = \frac{(T_1 - T_0)}{T_0} = \frac{T_1^b + T_1^w}{T_0} - \frac{T_0^b + T_0^w}{T_0} = \frac{T_1^b - T_0^b}{T_0} + \frac{T_1^w - T_0^w}{T_0} = \Delta T^b + \Delta T^w \tag{3}$$

where $T$ is the overall Theil in the routine-service population, $T^b$ is the between component, and $T^w$ the one within.

Exploiting the heterogeneity across countries in our sample, we study correlations between job de-routinization ($\Delta ES^{Routine}$) and changes in between ($\Delta T^b$), within ($\Delta T^b$), and overall ($\Delta T$) inequality for the Service and Routine sub-population. These components enable us to unravel the nexus of de-routinization on inequality by focusing on occupational classes. We see this cross-country evidence as a contribution to the literature, as this link, to the best of our knowledge, has not yet been analyzed in this way.

### 4.3 RIF-Regression Methods

Firpo et al. [2009, 2018] introduced RIF regressions as a generalization of the traditional Oaxaca-Blinder decomposition method. This technique allows for the estimation of a broad set of distributional parameters (e.g. quantiles, Gini index, or variance) and, following Firpo et al. [2011] and Massari et al. [2014], builds a central element in our empirical analysis. We provide a detailed explanation of the methodology in Appendix A.

We apply two different decompositions, i.e., the unconditional quantile decomposition for estimating changes along the entire distribution and the P-shares decomposition for four main earnings bins. 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 providing comprehensive numeric estimates of the distributional effects.

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 u-shaped patterns in the growth curves of quantiles as evidence of overall earnings polarization.

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

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 four main segments: the lower (below the 10th percentile), the lower-middle (between the 10th and 25th), the middle (between 25th and 75th), the upper earnings segment (above the and 75th). 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 25th and the 75th percentiles of the cumulative population distribution. A decreasing middle segment share and simultaneously rising shares of upper- and lower-earnings segments indicate earnings polarization (u-shaped pattern).

The decomposition for quantiles takes the following form:

$$\begin{aligned}\Delta^p = q_1^p - q_0^p &= E[RIF(y, q_t^p, F)|T=1] - E[RIF(y, q_t^p, F)|T=0] \\ &= \textstyle\sum_i [\overline{Occ_{i1}}(\widehat{\gamma}_{1,i}^p - \widehat{\gamma}_{0,i}^p) + (\overline{Occ_{i1}} - \overline{Occ_{i0}})\widehat{\gamma}_{0,i}^p] \\ &+ \bar{X}_1(\widehat{\beta}_1^p - \widehat{\beta}_0^p) + (\bar{X}_1 - \bar{X}_0)\widehat{\beta}_0^p\end{aligned} \tag{4}$$

where $q_t^p$ represents the $p$-quantile at time $t$, $Occ_i$ is a set of occupational class dummies[19] 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).[20] Time indexes $t = 1$ and $t = 0$ are defined over the longest time span available as explained in Section 3.

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.

There are several reasons why we apply the RIF decomposition 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 $\Delta^p$;[21] the *composition effect* shows how much changes in $\Delta^p$ can be explained by over-time differences in the level of covariates.[22] Second, the methodology is designed for regression analysis on distributional statistics over the detailed list of covariates

[19] In the model, we include a dummy variable for each category where *i*: service, routine, abstract, agriculture.

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

[21] In our 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.

[22] In our framework, composition effects account for over time differences in the employment shares between routine and non-routine occupations. Specifically, we can estimate the effect on $\Delta^p$ of the pure re-allocation of jobs away from routine toward non-routine abstract and service occupations.

$X$. This means that, for each LIS-ERF country, it is possible to estimate how much of the variation in the statistic of interest can be explained by de-routinization, which is captured by composition and coefficient effects of the class dummies. Simultaneously, we are able to control for 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 once re-weighted as the counterfactual [Firpo et al., 2018].

It is important to stress two main limitations of the RIF decomposition exercises. First, decomposition methods are accounting exercises that lack of a formal identification strategy so that the estimates should not be interpreted in a strict causal sense [Fortin et al., 2011]. Nevertheless, decomposition methods represent a well-established estimation tool to deliver elaborated, descriptive investigation of aggregated phenomena based on counterfactuals. Second, as is well known for the standard Oaxaca-Blinder decomposition, decomposition results depend on the choice of the base group. As highlighted by Fortin et al. [2011], there exists no final remedy to this problem and some arbitrariness is unavoidable, even if normalization strategies are applied [Yun, 2008].[23]

For the sake of clarity, we do not provide confidence intervals for our RIF estimates in our main results section. Nevertheless, we provide the confidence intervals for the estimates of the composition and the coefficient effects in the US in Figure A2 in Appendix B. We provide robust, instead of bootstrapped standard errors, which should be interpreted as a lower-bound.[24]

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

## 4.4 Analysis of Occupational Composition and Return Effects

RIF decomposition measures the joint effect of occupational changes on earnings growth. As our interest is also a description of how each of the three main occupational classes (service, routine, and abstract occupations) contribute to shape the overall *Occupational Effects*. Therefore, we first study how the quartile-specific earnings share of each occupational class evolved over the time span considered:

$$s_{t,Q}^{Occ} = \frac{\sum_{i=1}^{N_Q^{Occ}} y_{i,t}^{Occ}}{\sum_{i=1}^{N_Q} y_{i,t}} \qquad if\ F(y_{i,t}) \leq Q \tag{5}$$

[23]In our model the baseline group is represented by male workers between 35 and 39 years old, working in routine occupations, in manufacturing, mining and quarrying industries. Results proved to be robust to different base group specifications and are available upon request.

[24]The confidence intervals are compiled using the Stata command oaxaca_rif provided by Rios-Avila [2020]. Bootstrapped standard errors are typically larger than robust standard errors (Firpo et al. [2018] and Rios-Avila [2020]). Therefore, if confidence intervals based on robust standard errors include zero values, those based on bootstrapped standard errors would as well.

$s_{t,Q}^{Occ}$ is the quartile-specific earnings share of each occupational class, i.e. service, routine, and abstract. $Q$ indicates the quartile of the earnings distribution. $N_Q$ is the total number of workers in each quartile, while $N_Q^{Occ}$ is the number of those in one of the three occupational classes. We calculate changes in the quartile-specific earnings share for each occupational class as:

$$\Delta\, s_Q^{Occ} = s_{1,Q}^{Occ} - s_{0,Q}^{Occ} \qquad\qquad where\;\; \Delta\, s_Q^{service} + \Delta\, s_Q^{routine} + \Delta\, s_Q^{abstract} = 1 \tag{6}$$

$\Delta\, s_Q^{Occ} > 0$ indicates that that class increased their earnings share in quartile Q over the time period considered.

Additionally, we explore the dynamics in composition and returns of the three different occupational classes. To describe the changes of the composition of the workforce over time, we estimate the population share of each occupational class below each ventile $V$ of the (log) monthly earnings distribution $y$ in period t=1 and t=0:

$$ES_{t,V}^{Occ} = \frac{N_t^{Occ}}{N_t^{Serivce} + N_t^{Routine} + N_t^{Abstract}} \quad if\; y \leq v. \tag{7}$$

The changes of the composition below each ventile of the distribution is described as

$$\Delta ES_V^{Occ} = ES_{1,V}^{Occ} - ES_{0,V}^{Occ}. \tag{8}$$

Positive (negative) values of $\Delta ES_V^{Occ}$ would imply, that the concentration of workers employed in the occupational class has increased (decreased) below ventile $V$ over time. Aside from composition effects, differences in occupational returns shape the overall *Occupational Effect*. To estimate how the returns of each occupational classes evolved along the ventiles of the earnings distribution, we run the following unconditional quantile regressions $Q_{i,t}$:

$$V_{i,t} = X_{i,t}\beta_{t,V} + \gamma_{t,V}^{Service} * Service_{i,t} + \gamma_{t,V}^{Abstract} * Abstract_{i,t} + \varepsilon_{t,V}. \tag{9}$$

As $Service_{i,t}$ ($Abstract_{i,t}$) is equal to one if individual $i$ belongs to the service (abstract) class, $\gamma_{t,V}^{Occ}$ represent the return of the occupation in comparison to the routine class in period $t$, at the venitle $V$. We run the regression above for the first and the last period in our dataset. Since routine occupations are generally more clustered at the middle of the distribution, we expect negative values for $\gamma_{t,V}^{Service}$ and positive values for $\gamma_{t,V}^{Abstract}$.

## 5 Results

This section provides the results for de-routinization and its distributional consequences. First, we investigate if de-routinization of jobs is a common feature in our working sample by describing how occupational classes evolved over time in all countries under analysis. Specifically, job polarization is defined as decreasing employment and earnings shares in routine occupations over time. Second, we provide cross-country correlations between de-routinization and inequality between and within occupational groups. Third, we analyze how de-routinization affects the country-specific earnings distributions, based on decomposition methods described in Section 4.3. Fourth, we expand RIF results, scrutinizing composition and return effects of each occupational class.

We first present the country-specific results explanatory for the US before we discuss the other countries in our sample. The reason is that the RBTC hypotheses are typically studied for the US and there is not a general consensus regarding the distributional effects of de-routinization of jobs. Moreover, focusing on one country facilitates the interpretation of our results. Detailed country-specific estimations are provided in Appendix D.

### 5.1 De-routinization of Jobs

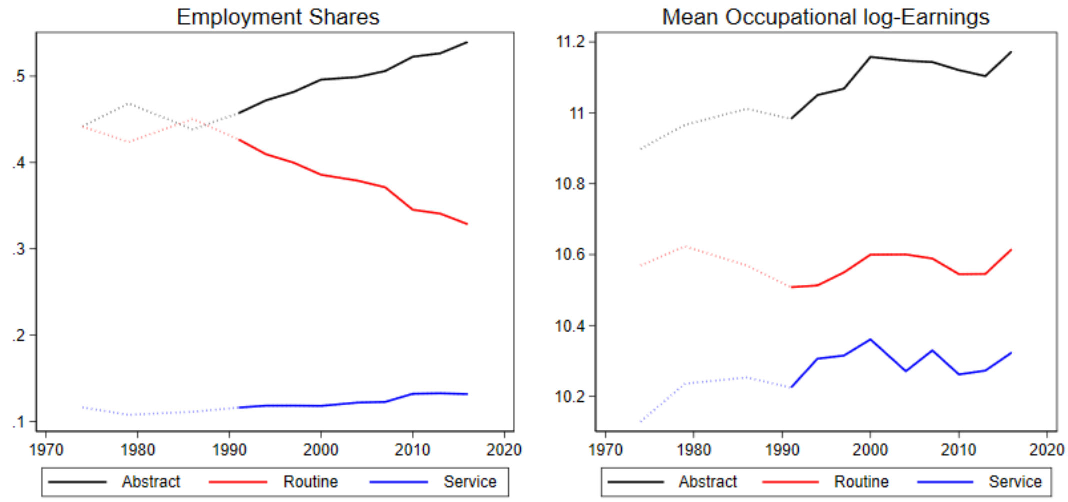
This section provides descriptive evidence for de-routinization of jobs. Figure 2 depicts class-specific inter-temporal changes in the employment (left panel) and class-specific average log-earnings (right panel) in the US. Dotted lines indicate waves incurring methodological changes in the main variable, 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.

The left panel of Figure 2 suggests that routine jobs make up a decreasing share of the work force since the 1990s, decreasing from 43% in 1991 to 33% in 2016. Service occupations, marginally increase their employment shares, from 12.2% to 13.6%, while abstract employment share grew from 45% to 53%. These findings support the results of Acemoglu and Autor [2011] regarding the secular decline of routine and abstract occupations between 1959 and 2007.

Average earnings curves in the right panel confirm a hierarchy between occupational classes consistent with the RBTC framework, where abstract occupations are, on average, located at the top, routine in the middle, and service occupations at the bottom of the earnings distribution.

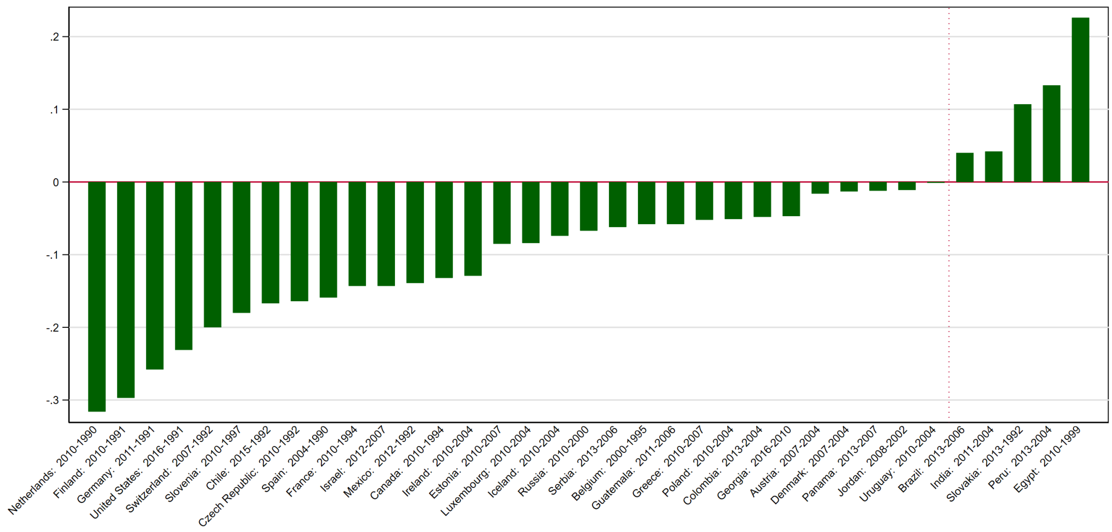
Figure 3 summarizes the relative change in the share of workers employed in routine occupations in all countries under analysis. Job polarization, as reflected by a decreasing share of employees in routine task, is present in 30 of 35 countries. These findings are in line with the aggregated analysis by Mahutga et al. [2018]. The results for countries where harmonized waves are available for long periods (e.g., Chile, Finland, Germany, and the US) suggest that de-routinization is a long-lasting phenomenon. Only five countries exhibit increasing employment shares in routine tasks, i.e., Brazil, Egypt, India, Peru, and Slovakia. These countries are economies where recent industrialization may explain increases in the production sector and, therefore, higher demand for operative jobs.

The figures with class-specific average log-earnings for each country are provided in Appendix D. The hierarchy found in the US is also confirmed for all remaining countries in our




*Notes.* Compiled by authors based on LIS data for the prime-aged, employed population. This table summarizes the results of our analysis of job-polarization for the US. The left panel shows the change of the employment share for each occupational class over time. The right panel depicts average log earnings through time. 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 earnings shares over time in the US




*Notes:* Compiled by authors based on LIS data for prime-age, employed population. This table summarizes the results of our analysis of job-polarization. Y-axis is the percentage change of the employment share in routine occupations over time. The X-axis specifies for each country the time span considered.

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

sample. Nevertheless, average earnings do not provide information on the dispersion of earnings levels within occupational classes. Consequently, they show between-class differences, but they are not informative about within-class inequalities or about the overall inequality trend.

## 5.2 De-routinization and Inequality: A Cross-Country Perspective

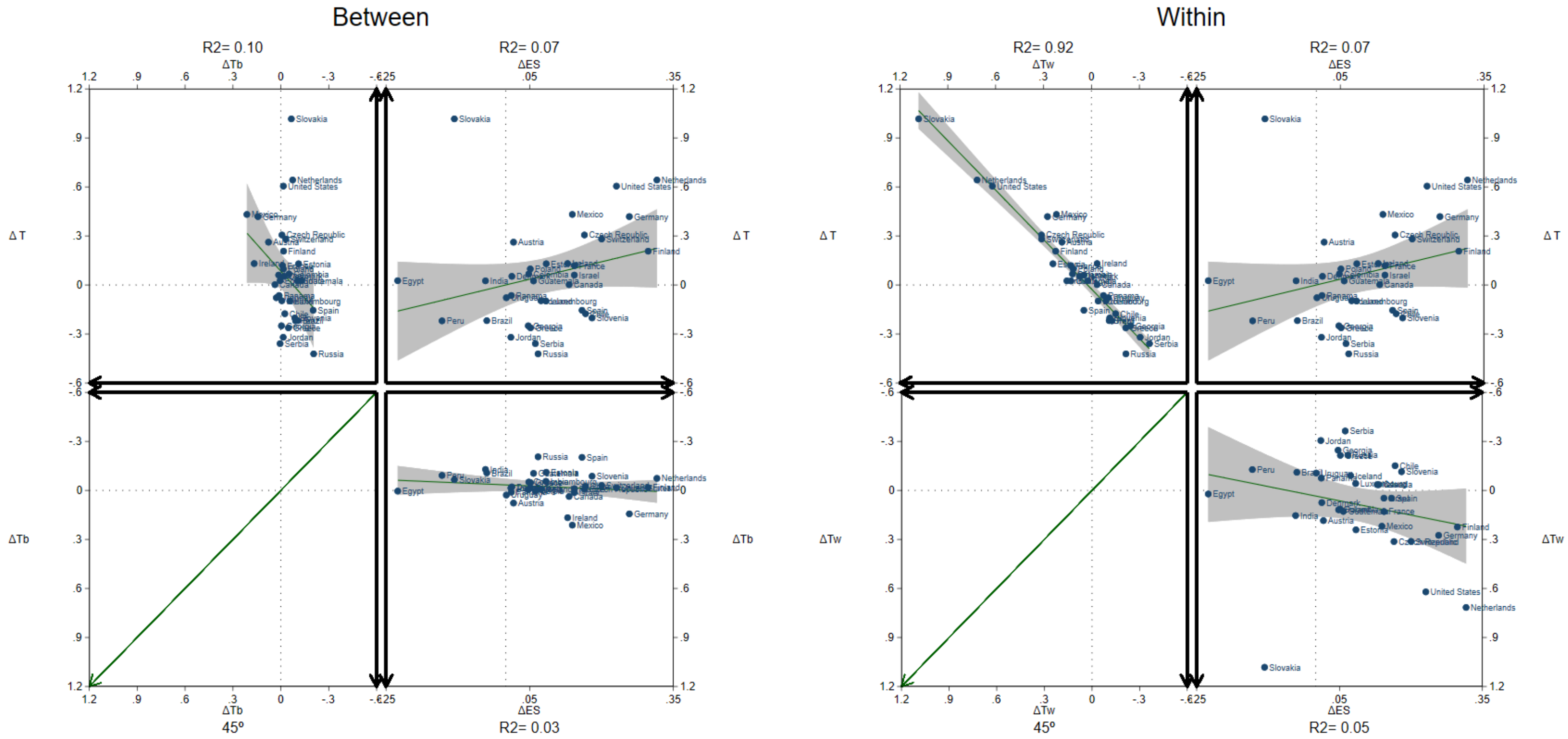
This section provides correlations between job de-routinization and earnings inequality in a cross-country perspective. As explained in Section 4.2, we focus on employees in routine and service occupations. In Figure A1 in the Appendix, we provide results for the complementary routine and abstract sub-population.

Figure 4 summarizes the results for the between- and within-class inequalities by means of two 4-quadrant diagrams. Each diagram includes three dimensions: the measure of de-routinization $\Delta ES^{Routine}$, the overall Theil of the sub-population $\Delta T$, and the Theil variation between (within) the two subgroups $\Delta T^b$ ($\Delta T^w$).

Let us first turn to the results for the between component of the Theil index (left 4-quadrant diagram). Here, the upper-right quadrant shows, for all countries in our sample, the relationship between de-routinization ($\Delta ES^{Routine}$) and changes in the Theil index for the Service-Routine sub-sample ($\Delta T$). The relationship is positive indicating that job de-routinization does not coincide with a systematic reduction in inequality at the lower end of the earnings distribution. However, the correlation is weak. $R^2$ from the binary regression including the 35 countries are low and confidence intervals bands are wide. The lower-right quadrant reenforces this result: the correlation between de-routinization ($\Delta ES^{Routine}$) and changes of the *between*-occupations margin of the Theil index ($\Delta T^b$) is close to zero. So, although the vast majority of the countries under analysis experienced job de-routinization, the *between*-occupations margin of the Theil index exhibits very small variation, which is contrary to RBTC predictions. Eventually, the upper-left quadrant shows the relationship between the Theil index for the Service-Routine sub-sample, $\Delta T$, and the *between*-occupations margin of the Theil index, $\Delta T^b$. The correlation is positive, but strongly driven by few observations. Most of the analyzed countries exhibit no, or only little, variation in the *between*-occupations Theil component. We see this as suggestive evidence that inequality *between* occupations does not sufficiently approximate changes in inequality at the lower end of the earnings distribution.

The right 4-quadrant diagram on the right in Figure 4 provides analogous estimates for the Theil variation between *within* service and routine occupations ($\Delta T^w$). The upper-right quadrant is the same as above, showing the correlation between the de-routinization measure, $\Delta ES^{Routine}$, and the Theil index for the Service-Routine sub-sample, $\Delta T$. The lower-right quadrant shows the relationship between the de-routinization measure, $\Delta ES^{Routine}$, and the Theil variation between *within* service and routine occupation $\Delta T^w$. Differently from the *between* perspective, the lower-right quadrant shows slightly positive gradient, which mirrors the relationship between job de-routinization and the change in the overall Theil in the upper-right quadrant. Eventually, the upper-left quadrant confirms that the changes in earnings inequality at the lower end of the earnings distribution ($\Delta T$) correlates almost strongly with the variation of *within*-occupations earnings inequality ($\Delta T^w$).

Figure A1 in the Appendix provides the 4-quadrant graphs for employees in routine-and ab-




*Notes.* Compiled by authors based on LIS data for prime-aged employed population. The construction of the figure is described in detail in Section 4.2 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 4: Linking H-JP and H-EP: service and routine sub-population

stract occupations. In sum, they confirm the previous findings. Job de-routinization and changes in the inequality at the upper end of the earnings distribution are slightly positively correlated. Again, changes of inequality at the upper end of the distribution emerge from variation *within*, rather than *between* routine and abstract occupations.

Disentangling the effect of de-routinization of jobs on both *between*- and *within*-class inequality on the aggregated country level, we arrive at two major findings: first, there is only little evidence for a quantitatively important link between job and earnings polarization. Second, within occupations dynamics seem to play a major role for the evolution of the earnings distribution over time.

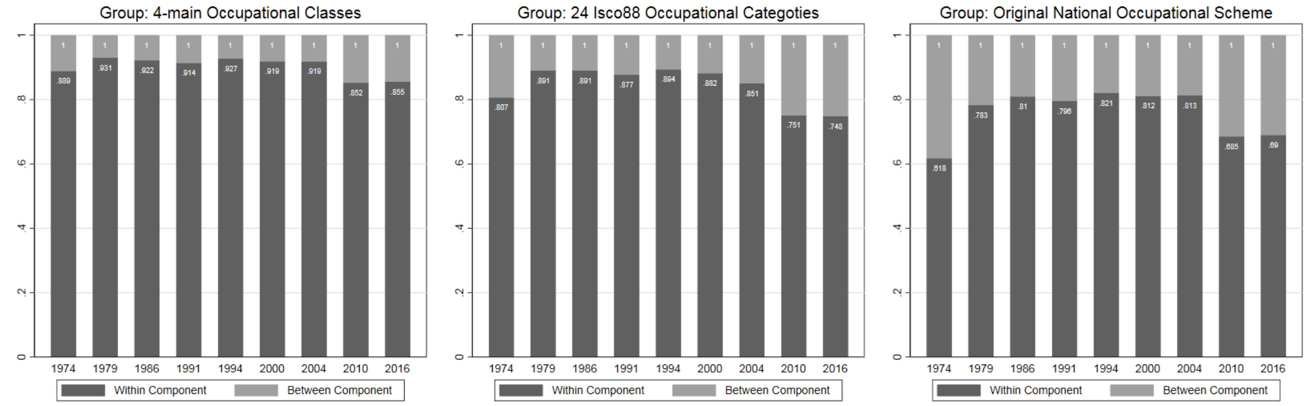
A caveat of this aggregated country perspective is that we pool gross and net earnings. This could mean that the observed variation in the Theil index originates from differences in the earnings concepts. Assuming that no substantial changes in re-distributional policies occurred, one could argue that the focus on changes over time, rather than levels, may mitigate some of the imprecision caused by this. Moreover, the nine countries with net earnings informationThese are, as discussed in the data section, Belgium, Chile, Egypt, Georgia, India, Mexico, Russia, Slovenia, and Uruguay. do not seem to represent outliers that drive the correlation to a large extent.

The importance of the within-group component for overall inequality is valid under different definitions of occupational groups. Figure 5 shows the Theil decomposition *within* and *between* occupational classes 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), overall inequality is mostly determined by inequalities *within* rather than *between* occupations. The same result holds for all countries in our working sample.[25]

### 5.3 Country-specific Distributional Consequences of De-routinization

The previous section provides static descriptions of earnings dispersion. To investigate the role of de-routinization on earnings distributions in more detail, we turn to our estimates from unconditional quantile decompositions. Figure 6 is a comprehensive summary of the results for the US. Figures 7 to 9b summarize the results for the remaining countries. The blue lines, the *Total Change*, show the unconditional quantile specific earnings growth over the respective time span. The red lines, *Occupational Effect*, 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 *Occupational Effect* and the *Total Change* provide evidence for the determinant role played by de-routinization shaping the earnings distribution. We choose this graphical representation because it enables us to analyze two important dimensions: the (dis)connection of the *Occupational Effect* and the *Total Change*, as well as the evolution of overall inequality over time. The results from the P-share decomposition are reported in Table 3. Countries are grouped according to the trend of the *Total Change*, i.e. increasing or decreasing earnings inequality, a polarizing earnings distribution, or no change over time.

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




*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 (light gray bar) and within (dark grey bar) occupations components. Different clusters of occupations are considered. The panel on the left considers 4 main occupational classes (non-routine service, routine manual, routine abstract and non-routine abstract). 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. Results of the remaining countries are provided in the Appendix.

Figure 5: Theil decomposition within and between occupational classes in US.

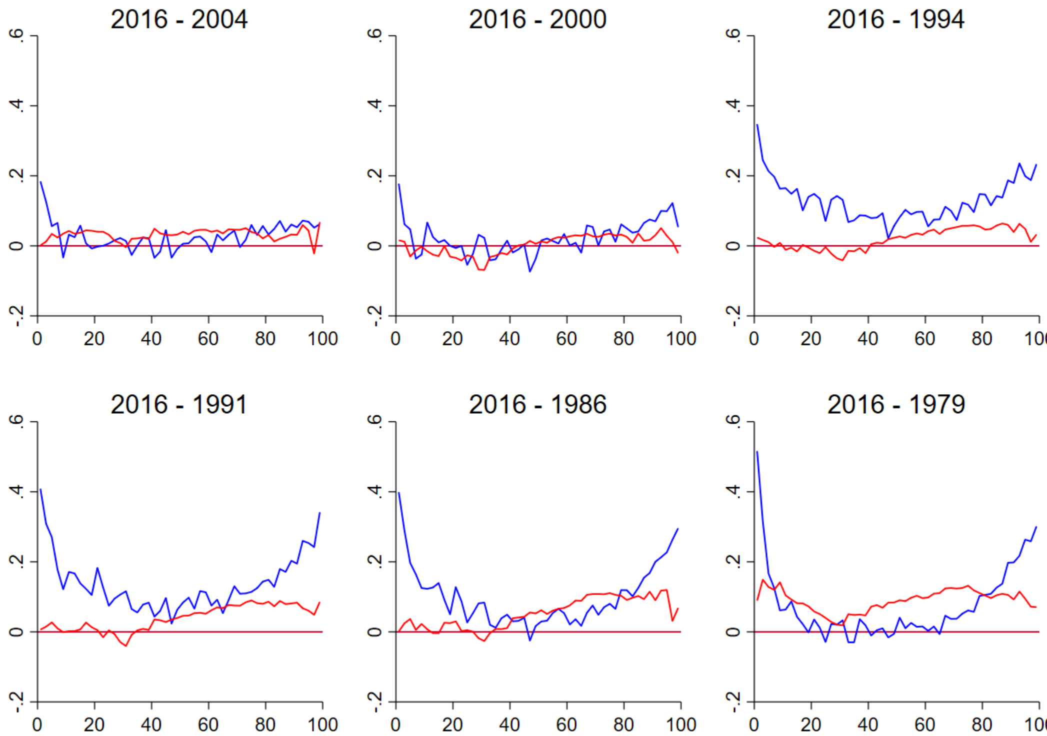
Figure 6 includes six panels, showing quantile decomposition for US over different time spans. Specifically, the x-axis reports earnings quantiles while the y-axis reports the size of the *Total Change* in blue and the *Occupational Effect* in red. The panels show that the longer the time span, the more distinct are the u-shaped polarization trends exhibited by the *Total Change*. Simultaneously, the *Occupational Effect* growth along the earnings quantiles, implying increasing inequality, and does not exhibit any polarizing pattern. This means that employment deroutinization *per se* cannot explain the observed overall polarization trend in the US.[26]

Our results are in line with those of Hunt and Nunn [2019] and Böhm et al. [2019], showing the ambiguous distributional consequences of the RBTC framework: by including within-group variation, the *Occupational Effect* does not correlate with the *Total Change*. 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, *Occupational Effects* are positive in the middle of the distribution, meaning that workers in middle quantiles experienced earnings growth driven by changes in the occupational composition. As *Occupational Effects* do not explain the *Total Change*, labor market institutions, like unions [Firpo et al., 2018] and minimum wages [DiNardo et al., 1996], might have played an important role for shaping earnings distribution over time, especially at the bottom.

Detailed P-shares decomposition in Table 3 corroborate the results: positive coefficients in the lower and upper P-shares indicate shift from the middle toward the end of the distribution.

[26]We provide the figures with confidence intervals based on robust standard errors in Appendix B. Here, the *Occupational Effect* is divided into the composition and coefficient effects. The confidence intervals are narrow and do not affect the interpretation of our results. We provide the confidence intervals for other countries upon request.

Since the 1980s, 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.




*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile earnings growth (*Total Change*, blue line) and the counterfactual earnings growth (*Occupational Effect*, red line) for the US based on RIF quantiles decomposition explained in Section 4.3. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years.

Figure 6: Quantile Decompositions Results for the United States

For the remaining countries, we find various overall distributional outcomes, but no close link between job de-routinization and changes in the earnings distribution over time. We discuss the country-specific trends with regards to changes in the overall earnings distribution, i.e., increased and decreased inequality, polarization, and no change in inequality. Specifically, we observe increasing (decreasing) inequality if the *Total Change* is monotonically increasing (decreasing) over the earnings quantiles. Moreover, we refer to polarization if the *Total Change* is u-shaped over the earnings quantiles. Finally, we characterize no change in inequality, if the *Total Change* is constantly close to zero. Our working sample 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, however, is not within the scope of this paper.

Like Figure 6, Figures 7 to 9b report RIF-quantile decomposition results for all the countries in our sample. We provide results for the longest time span available.

Figure 7 includes estimates for those countries in our working sample that experienced increased inequality: 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 in all these countries; however, our RIF decomposition results show that the *Occupational Effect* does not explain the *Total Change* along the earnings quantiles. In some countries, like Finland, Germany, Mexico, and Spain, *Occupational Effects* are positive at the bottom of the distribution. This is consistent with the RBTC framework, as bottom-tail earnings would have increased if only occupational changes had occurred. However, other mechanisms offset the impact of job de-routinization on the overall *Total Change*. In several countries, i.e., Austria, Czech Republic, Denmark, Estonia, France, Poland, Slovakia, and Slovenia, de-routinization effects are close to zero along the entire distribution. The Netherlands is the only country where we observe that the *Occupational Effects* and the *Total Change* are very similar. Nevertheless, they are both monotonically increasing along the earnings distribution, which is not in line with the RBTC framework.

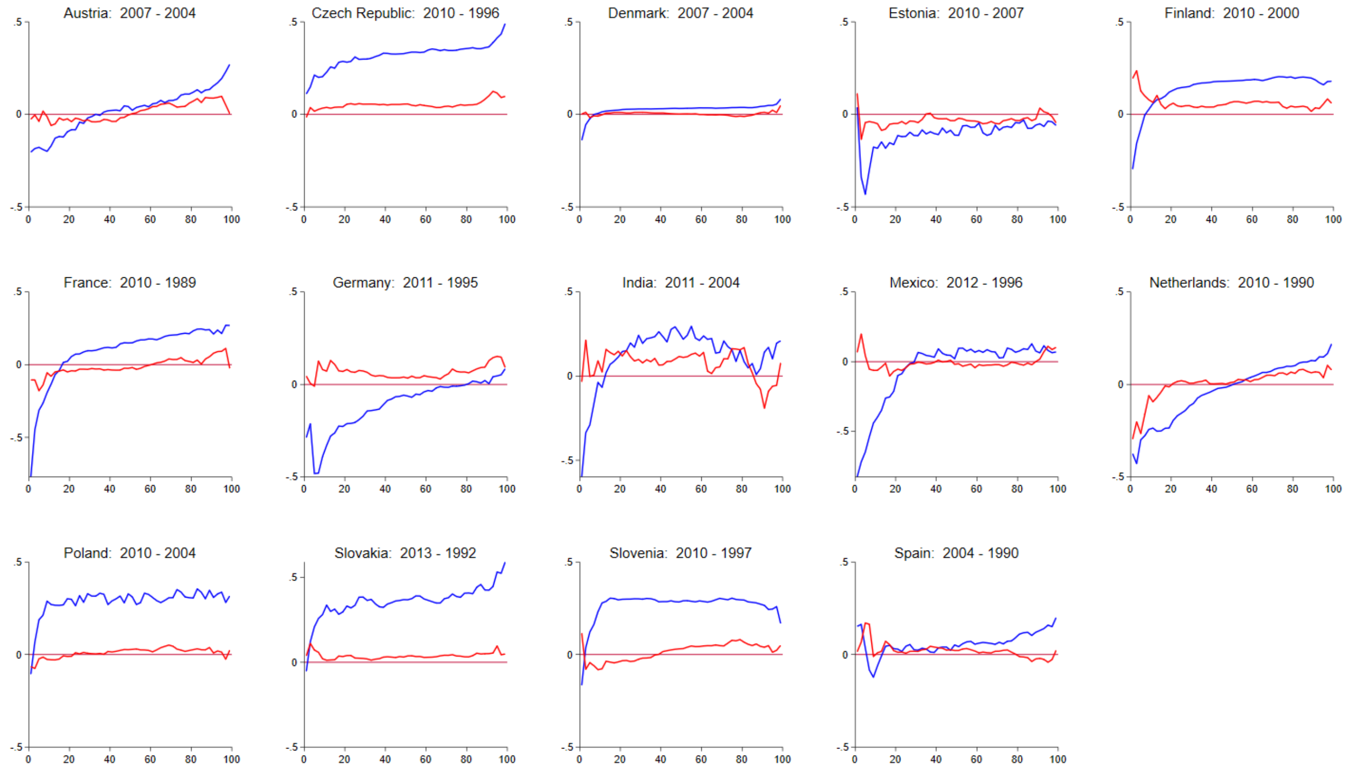
Figure 8 reports RIF decomposition results for those countries that experienced decreasing inequality. It includes Brazil, Chile, Colombia, Georgia, Guatemala, Jordan, Panama, Peru, Russia, Serbia, and Uruguay. The *Total Change* show that lower quantiles are growing at a faster rate compared to upper quantiles. Although we find evidence of job de-routinization in all these countries, except for Brazil and Peru, *Occupational Effects* are generally weak and, again, they do not explain the decreasing *Total Change*.

Figure 9a shows the results for countries that exhibit overall earnings polarization: Belgium, Canada, Ireland, Switzerland, and the United States. We find evidence of employment *and* earnings polarization in all these countries. The u-shaped *Total Change* are less extreme in comparison to the United States, suggesting that strong earnings polarization is a phenomenon limited to the latter. Ireland and Switzerland, however, seem to be the only countries in our sample where the *Total Change* at the bottom of the earnings distribution is fully explained by *Occupational Effects*, which is in line with the RBTC framework.

Figure 9b plots the results for Egypt, Greece, Iceland, Israel, and Luxembourg. These countries show rather stable inequality over the considered time horizons.

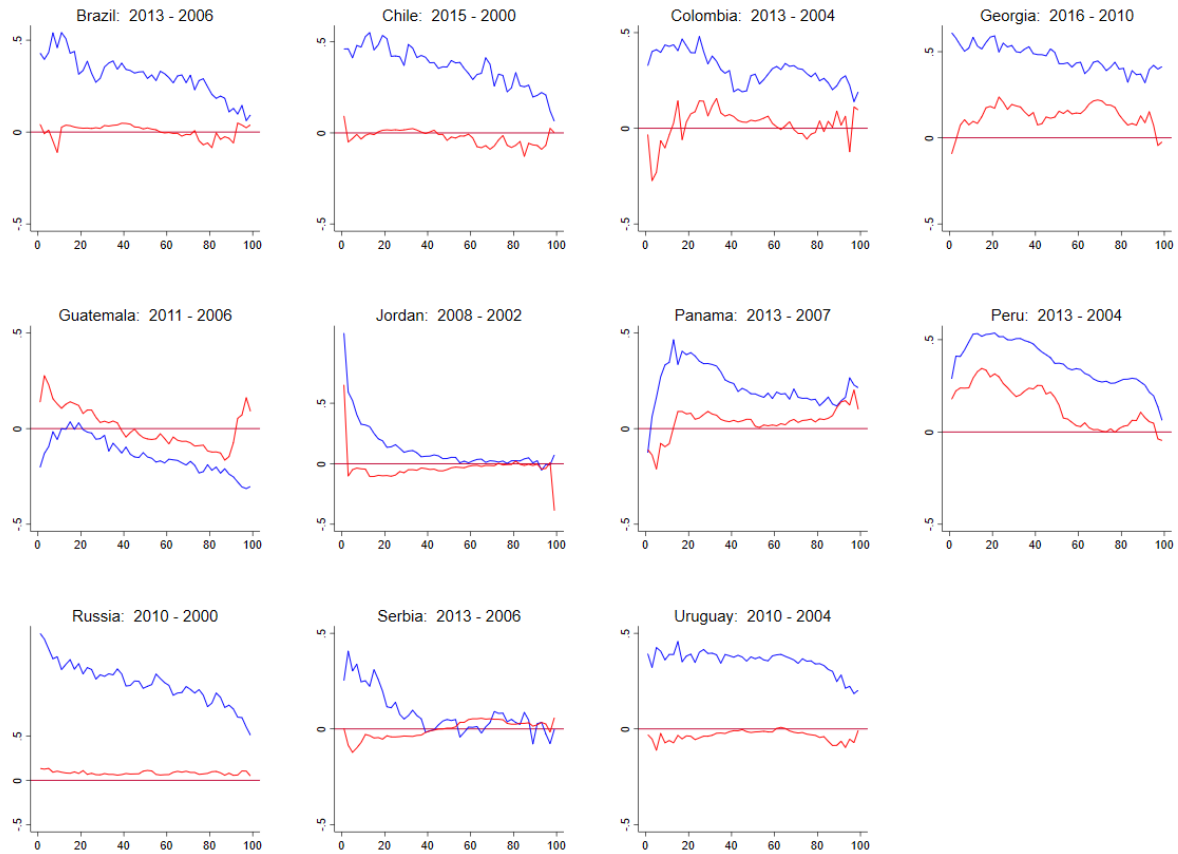
Table 3 provides a summary of the P-shares decompositions for all 35 countries. The *Total Change*, *TC*, reports the estimates of four main earnings bins: lower segment (between the 1st and 10th percentiles), lower-middle segment (between the 10th and 25th percentiles) middle segment (between the 25th and 75th percentiles), and the upper segment (between the 75th and 99th percentiles). The coefficients are multiplied by 100.[27] Table 3 confirms our graphical results by reporting heterogeneous pattern in inequality growth between the different countries under analysis and the weak distributional impact of job de-routinization. Moreover, the *Total Changes*, as well as the *Occupational Effects, OE,* vary considerably across countries, implying that a generalization of the nexus between de-routinization of jobs and the earnings distribution is not achievable. We confirm these findings for hourly wages; discussion is provided in Section 6.

[27] The complete decomposition results for each country are provided in the Appendix.



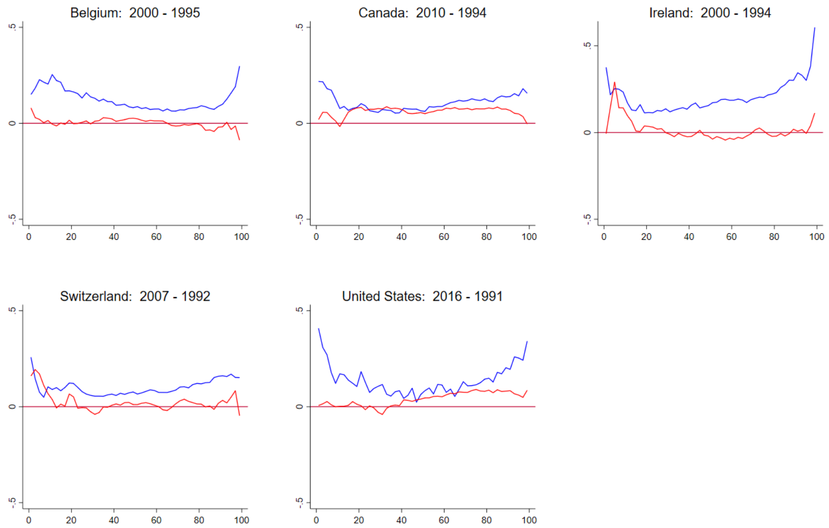

*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile earnings growth (*Total Change*, blue line) and the counterfactual earnings growth (*Occupational Effect*, red line) for countries with increasing inequality based on RIF quantiles decomposition explained in Section 4.3. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years.

Figure 7: Increased inequality - *Total Change* and *Occupational Effect* from RIF quantiles decomposition.




*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile earnings growth (*Total Change*, blue line) and the counterfactual earnings growth (*Occupational Effect*, red line) for countries with decreasing inequality based on RIF quantiles decomposition explained in Section 4.3. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years.

Figure 8: Decreased inequality - *Total Change* and *Occupational Effect* from RIF quantiles decomposition.




(a) Polarization


(b) No change in inequality

*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile earnings growth (*Total Change*, blue line) and the counterfactual earnings growth (*Occupational Effect*, red line) for countries exhibiting (a) polarization or (b) no change in inequality, based on RIF quantiles decomposition explained in Section 4.3. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years.

Figure 9: *Total Change* and *Occupational Effect* from RIF Quantiles Decomposition.

| Country | Time Span | 1-10 | | 10-25 | | 25-75 | | 75-99 | |
|---|---|---|---|---|---|---|---|---|---|
| | | TC | OE | TC | OE | TC | OE | TC | OE |
| | | | | ***Increasing Inequality*** | | | | | |
| **Austria** | 2007 - 2004 | -0.56 | 0.00 | -1.29 | -0.33 | -1.95 | -1.14 | 3.80 | 1.47 |
| **Czech Rep.** | 2010 - 1996 | -0.58 | -0.09 | -0.65 | -0.07 | -0.71 | -0.74 | 1.93 | 0.90 |
| **Denmark** | 2007 - 2004 | -0.25 | -0.02 | -0.13 | 0.03 | -0.11 | -0.10 | 0.49 | 0.09 |
| **Estonia** | 2010 - 2007 | -0.47 | -0.03 | -0.49 | -0.11 | -0.31 | -0.63 | 1.27 | 0.76 |
| **Finland** | 2010 - 2000 | -0.76 | 0.43 | -0.56 | 0.07 | 0.52 | -0.06 | 0.79 | -0.44 |
| **France** | 2010 - 1989 | -1.58 | -0.21 | -1.41 | -0.47 | -0.40 | -0.89 | 3.39 | 1.57 |
| **Germany** | 2011 - 1995 | -0.73 | 0.01 | -1.45 | 0.05 | -1.08 | -1.58 | 3.25 | 1.52 |
| **India** | 2011 - 2004 | -0.34 | 0.09 | -0.18 | 0.25 | 1.92 | 2.00 | -1.40 | -2.33 |
| **Mexico** | 2012 - 1996 | -0.58 | 0.12 | -1.05 | -0.12 | 0.18 | -1.55 | 1.44 | 1.55 |
| **Netherlands** | 2010 - 1990 | -0.84 | -0.41 | -2.12 | -0.36 | -1.37 | -0.42 | 4.33 | 1.19 |
| **Poland** | 2010 - 2004 | -0.57 | -0.18 | -0.22 | -0.17 | 0.09 | 0.22 | 0.70 | 0.13 |
| **Slovakia** | 2013 - 1992 | -0.72 | 0.11 | -0.81 | -0.09 | -1.40 | -0.38 | 2.93 | 0.36 |
| **Slovenia** | 2010 - 1997 | -0.63 | -0.33 | 0.21 | -0.67 | 0.89 | 0.07 | -0.47 | 0.93 |
| **Spain** | 2004 - 1990 | -0.20 | 0.22 | -0.46 | 0.08 | -1.47 | 0.38 | 2.13 | -0.67 |
| | | | | ***Decreasing Inequality*** | | | | | |
| **Brazil** | 2013 - 2006 | 0.35 | -0.16 | 1.02 | -0.01 | 2.81 | 0.11 | -4.19 | 0.05 |
| **Chile** | 2015 - 2000 | 0.44 | -0.08 | 1.32 | -0.03 | 3.21 | 0.80 | -4.97 | -0.70 |
| **Colombia** | 2013 - 2004 | 0.19 | -0.26 | 0.74 | -0.07 | 0.76 | 0.60 | -1.70 | -0.27 |
| **Georgia** | 2016 - 2010 | 0.13 | -0.05 | 0.66 | 0.21 | 1.34 | 3.37 | -2.13 | -3.52 |
| **Guatemala** | 2011 - 2006 | 0.15 | 0.22 | 0.80 | 0.42 | 1.98 | -0.84 | -2.93 | 0.20 |
| **Jordan** | 2008 - 2002 | 2.50 | -0.17 | 1.48 | -0.34 | -1.54 | 0.78 | -2.44 | -0.27 |
| **Panama** | 2013 - 2007 | -0.02 | -0.17 | 0.89 | -0.32 | 0.03 | -1.35 | -0.90 | 1.84 |
| **Peru** | 2013 - 2004 | 0.11 | 0.10 | 0.85 | 0.63 | 3.20 | 1.21 | -4.16 | -1.94 |
| **Russia** | 2010 - 2000 | 1.11 | 0.02 | 1.93 | -0.11 | 5.99 | 0.33 | -9.03 | -0.25 |
| **Serbia** | 2013 - 2006 | 0.80 | -0.43 | 1.40 | -0.47 | -0.46 | 0.04 | -1.74 | 0.86 |
| **Uruguay** | 2010 - 2004 | 0.06 | -0.05 | 0.38 | -0.05 | 2.48 | 1.03 | -2.92 | -0.93 |
| | | | | ***Polarization*** | | | | | |
| **Belgium** | 2000 - 1995 | 0.36 | 0.02 | 0.67 | 0.01 | -1.43 | 0.80 | 0.40 | -0.84 |
| **Canada** | 2010 - 1994 | 0.04 | -0.11 | -0.17 | -0.02 | -1.33 | 0.49 | 1.47 | -0.35 |
| **Ireland** | 2000 - 1994 | 0.01 | 0.23 | -0.84 | 0.25 | -3.62 | -0.99 | 4.45 | 0.51 |
| **Switzerland** | 2007 - 1992 | 0.00 | 0.11 | -0.04 | -0.01 | -1.57 | -0.15 | 1.61 | 0.05 |
| **US** | 2016 - 1991 | 0.11 | -0.13 | -0.18 | -0.30 | -3.15 | -0.15 | 3.22 | 0.58 |
| | | | | ***No Change*** | | | | | |
| **Greece** | 2010 - 2007 | 0.27 | 0.00 | 1.09 | -0.00 | 1.63 | 0.79 | -2.98 | -0.79 |
| **Iceland** | 2010 - 2004 | -0.07 | -0.33 | 0.37 | -0.49 | -0.50 | -0.17 | 0.19 | 0.99 |
| **Egypt** | 2010 - 1999 | 0.12 | 0.03 | 0.55 | -0.23 | 1.66 | -1.35 | -2.32 | 1.55 |
| **Israel** | 2012 - 2007 | -0.14 | 0.08 | -0.17 | -0.05 | 0.12 | 0.29 | 0.18 | -0.31 |
| **Luxembourg** | 2010 - 2004 | 0.10 | 0.17 | 0.23 | -0.24 | 0.61 | -2.60 | -0.94 | 2.67 |

Table 3: P-shares Decomposition

*Notes.* Compiled by authors based on LIS data for prime-age, employed population. The table presents detailed result for the P-share decomposition, as explained in Section 4.3, with the estimates of four main earnings bins: lower segment (between the 1st and 10th percentiles), lower-middle segment (between the 10th and 25th percentiles) middle segment (between the 25th and 75th percentiles), and the upper segment (between the 75th and 99th percentiles). TC columns in black report estimates of *Total Change* in four wage bins considered. OE columns in light gray report estimates for *Class Effect*. Coefficents are multiplied by 100.

### 5.4 Occupational Composition and Return Effects

Our results so far show that job de-routinization does not imply generalized distributional consequences. We argue that employees from a certain occupational class are not perfectly stratified but scattered along the earnings distribution. Consequently, de-routinization does not just shift jobs from the middle toward the tails, but it replaces routine occupations along the entire earnings distribution. The weak link, therefore, arises form simultaneous movements of different occupational classes within same quantiles that can counteract and enforce each other resulting in ambiguous distributional effects. We present and discuss these arguments with the aid of three case studies - i.e., the US, Ireland, and Switzerland. We chose to focus on these countries for two reasons: first, the US case is highly debated in the literature and, with the following analysis, we contribute a novel perspective. Second, Ireland and Switzerland represent interesting study cases since *Occupational Effect* predicts well the *Total Change* at the bottom of the distribution, although, as we show it this section, the changes in occupational composition and returns are distinctively different. We provide the results for the other countries in the Appendix.

For each country in our case study, Figures 10 and 11 provide the results in three panels. The left panels provide the quartile-specific earnings share of the three occupational classes. The middle panels describe the change of the composition of employment shares along the earnings distribution. The right panels depict the returns along the earnings distribution with the routine class as base category.[28] In all panels, blue represents the service class, red the routine class, and black the abstract class. Dotted lines indicate the estimates for the initial period.

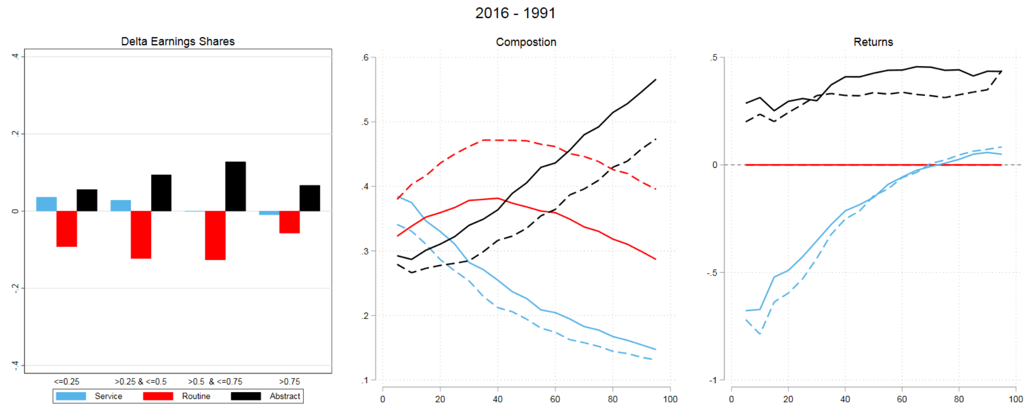
Figure 10 provides the results for the US. The left and middle panels show that the share of employees in routine occupations has reduced evenly along the earnings distribution. Hence, workers in routine jobs have been replaced equally by both workers in service occupations, with lower returns, and workers in abstract occupations, with higher returns, along the entire distribution. From the right panel, we observe that the hierarchy of returns between occupational classes has not changed over time. Thus, within each quantile, there are service (abstract) workers who replace routine workers and, therefore, reduce (increase) earnings growth. These shifts seem to neutralize each other, especially at the bottom, explaining why we find a *Occupational Effect* close to zero in lower quantiles for the US, as shown in the section above.

Although Switzerland and Ireland exhibit both similar positive *Total Change* and *Occupational Effect* at the lower end of the earnings distribution, the underlying mechanisms differ considerably. Figure 11 depicts the results for Ireland in the upper three three panels and for Switzerland in the lower three panels. In Ireland, the left panel shows that routine jobs lost their earning shares to the service and abstract classes. This is due to both a relative reduction in the composition (middle panel) and the returns (right panel). The *Total Change* at the lower end of the distribution seems to be driven by both a large increase of the composition of abstract workers and increased returns for service workers.

In Switzerland, the earning shares of routine jobs decrease especially at the top half of the distribution. For the lower 25 percent, the earnings share of abstract workers decreases, those of routine occupations remain constant, while the earnings shares of service jobs increase. Abstract workers with higher returns were clustered at the upper end of the lower part of the distribution

[28] Formulas are discussed in detail in Section 4.4.

US



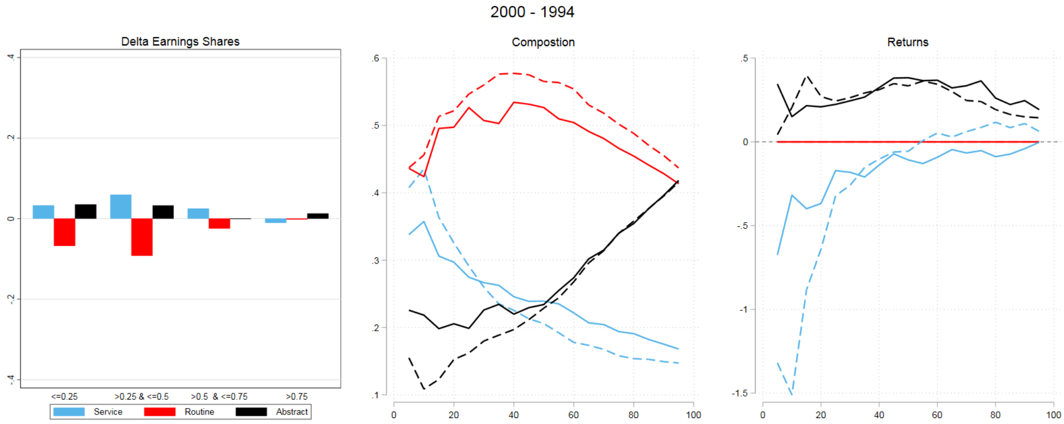

*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The left panel provides the change of earnings shares by occupational class for the quartiles of the earnings distribution over time. The central panel depicts the changes in occupational composition along the population ranked by the earnings distribution. The right panel shows the changes of occupational returns using the routine occupation as baseline category. Dashed lines indicate the estimates in the base year.

Figure 10: Occupational Composition and Return Effects

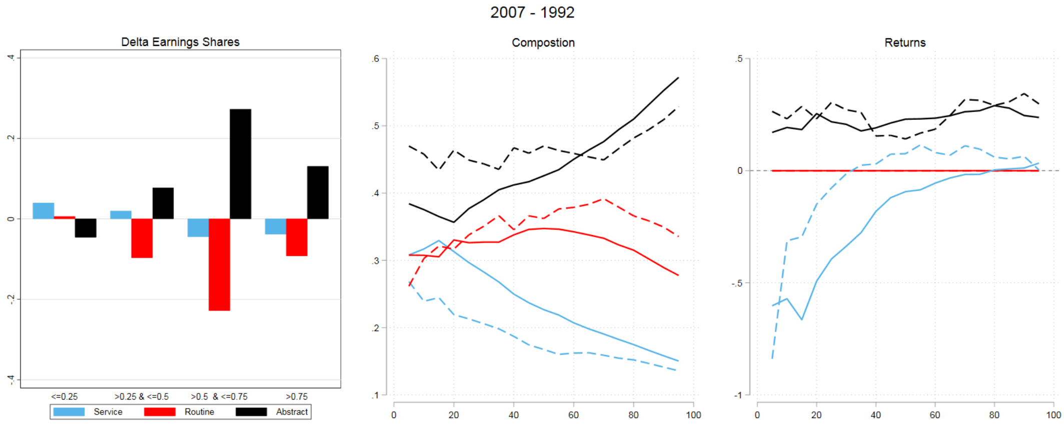
in 1992 and left it over time while service jobs increased their share. As the *Total Change* at the lower end of the distribution is positive, the returns of all classes have increased, despite the fact that abstract workers are moving up the earnings distribution.

These results suggest large differences in the composition of the workforce between and within countries. Ireland's composition comes close to patterns described by RBTC hypothesis, with service jobs at the bottom and more abstract occupations at the top. However, routine jobs still dominate in all parts of the distribution. In Switzerland, abstract occupations dominate along the whole earnings distribution. Considerable shares of abstract workers at the lower end of the distribution can be also found in Austria, Belgium, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Georgia, Germany, Greece, Israel, Netherlands, Russia, Slovakia, Slovenia.

These results suggest several insights on the link of job de-routinization and the overall earnings distribution. We find evidence for a persistent hierarchy of returns, i.e. abstract workers gaining the highest returns, routine workers in the middle, and service workers at the bottom, which is consistent with the RBTC framework. Nevertheless, occupational classes are scattered along the whole distribution and, therefore, job de-routinization is not necessarily displacing workers only in the middle of the earnings distribution. Additionally, we find that job de-routinization does not displace routine workers evenly along the earnings quantiles. As shown for Ireland and Switzerland, routine occupations have been displaced only in middle and higher quantiles, keeping their employment shares relatively unchanged at the bottom of the distribution. Similarly, increasing demand of abstract and service occupations is not necessarily concentrated only at the top and bottom of the earnings distribution, respectively. Dynamics within the abstract workers' share is potentially critical for understanding the evolution of earn-




(a) Ireland




(b) Switzerland

*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The left panel provides the change of earnings shares by occupational class for the quartiles of the earnings distribution over time. The central panel depicts the changes in occupational composition along the population ranked by the earnings distribution. The right panel shows the changes of occupational returns using the routine occupation as baseline category. Dashed lines indicate the estimates in the base year.

Figure 11: Occupational Composition and Return Effects

ings at the bottom of the distribution. A point that is commonly disregarded in the literature.

## 6 Robustness Checks - Wages instead of Yearly Gross-Income

In this section, we replicate the analysis explained in Section 5.3 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, we can reproduce the analysis on hourly wages for only 21 countries. Finally, we discuss differences between gross- and net-wage by comparing the respective decompositions in the case of Germany.

We plot tables and figures of the wage analysis in Appendix C. Figure A3 and Figure A4 provide detailed unconditional quantiles decomposition results for the United States and for eight selected countries. Table A2 reports P-shares decomposition results using wages as dependent variable.

The results for wages confirm our main findings for earnings and we do not observe critical differences. In Figure A3, the wage decomposition for the US shows very similar patterns as in Figure 6 for earnings: u-shaped *Total Change* curves indicating overall polarization of wages, which are not driven by *Occupational Effects*. Similar parallelism can be observed in Figure A4 for wage and in Figures 7, 8, 9a, and 9b for earnings. This suggests that working hours did not affect the estimation results and they contributed only marginally to the evolution of inequality in our working sample. Studying the long-run relationship of de-routinization and working hours is outside the scope of this paper, but we invite future research to provide more evidence on this matter.

There are two interesting exceptions that are important to discuss. In Ireland, our results show that *Occupational Effects* on the hourly wage distribution are negative at the bottom of the distribution, despite u-shaped patterns in *Total Change*. Once hourly wages are taken as dependent variable, *Occupational Effects* at the bottom of the earnings distribution are close to zero. Such results might be explained by the strong replacement of service with abstract jobs at the bottom of the distribution experienced in Ireland, as seen in Section 5.4 and in Figure 11. Workers in abstract occupations work, on average, more hours than individuals in the service sector, achieving higher earnings for similar hourly wage levels. Once working hours are ruled out, the *Occupational Effect* turns to zero. Overall, these findings suggest that the *earnings* growth experienced in Ireland at the bottom of the distribution results from compositions effects, i.e., the substitution of service jobs with abstract jobs, characterized by more working hours, rather than relevant wage increases.[29]

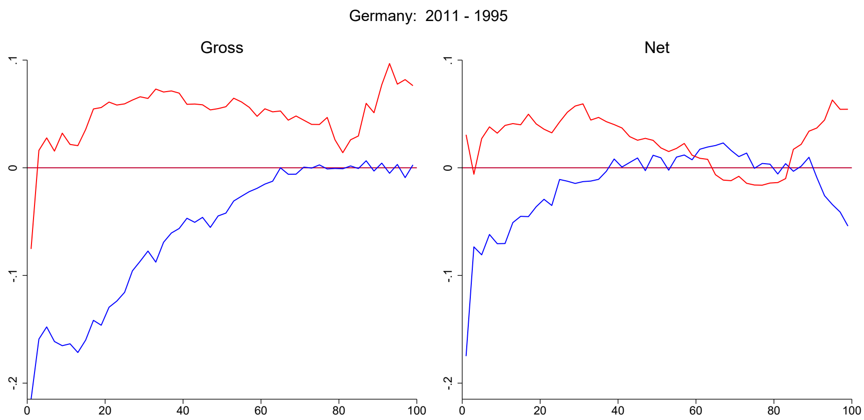
The second notable exception between earnings and wage analysis is Greece: Table A4 suggest strong wage increases at the bottom and strong wage drops at the top of the wage distribution, which should result in decreased inequality. Such results are, however, compensated by changes in the structure of working hours, so that in Table 3, we observe limited changes in overall earnings inequality.

Another concern is that we rely on mixed information of net and gross labor earnings in our sample. In the worst-case scenario, the heterogeneous results found in our analysis stem from these differences. Our results, however, do not suggest sorting conditioned on gross or net earnings information, as both concepts reveal increasing and decreasing inequality, polarization or no change. The question that remains is whether the estimates for gross and net wage would differ substantially within the same country. Consequently, we run the decomposition analysis for both earnings concepts to see if the outcomes differ substantially. Our working sample does not allow for an extensive analysis of this matter because only very few countries provide both gross and net earnings information.

Figure 12 provides the quantile decomposition for gross (net) wage in the left (right) panel

[29] Specific figures on the composition of occupational classes along the wage distribution, in spirit of Figure 11, can be provided upon request.

in Germany.The other countries, with both earnings concepts available, are Austria, Greece, Luxembourg, Panama, and Peru. The results are similar and available upon request. As above, the x-axis depicts the wage quantiles and the y-axis provides the quantile growth between 1995 and 2011. The different earnings concepts show similar patterns for the *Total Change* and the *Occupational Effect*. The *Total Change* is less distinct for net wage with a smaller decrease for lower quantiles. This might be due to re-distributional tax policies, which mitigate market outcome inequalities. The *Occupational Effect* for net wages remains different to the *Total Change* and reveals similar patterns to gross wages. This makes us confident that the different earnings concepts are not the source of the weak link between job de-routinization and overall inequality.




*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile growth (*Total Change*, blue line) and the counterfactual earnings growth (*Occupational Effect*, red line) for gross and net hourly wages in Germany, based on RIF quantiles decomposition explained in Section 4.3. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years.

Figure 12: *Total Change* and *Occupational Effect* from RIF Quantiles Decomposition - Gross vs. Net Hourly Wage

## 7 Conclusion

In this paper, we analyze whether de-routinization of the workforce can be observed internationally and if this is explains changes in earnings inequalities within and between occupations. Our analysis focuses on 35 LIS-ERF countries characterized by different economic and political systems. We confirm shifts from routine-intense jobs toward non-routine occupations in 30 countries, but we do not find a close link between de-routinization of jobs and changes in the earnings distribution.

We provide two major reasons for our findings: first, we find that, on an aggregated country level, the intensity of de-routinization does not correlate with changes in inequality between and within occupational classes. Factors *within* - rather than *between* - occupational groups determine overall inequality trends, indicating that differences in returns between occupational classes do not changes to the earnings distribution. Second, our case studies show that, although we confirm a hierarchy in their average returns, service, routine, and abstract jobs are jointly distributed along the earnings distribution. Therefore, de-routinization not only affects jobs at the middle, it also displaces workers in all earnings quantiles. We argue that such shifts in occupational shares within each quantile ultimately defines the *Occupational Effect* on overall earnings.

Our results highlight that de-routinization induced by ICT adoption is a process most countries face. Given the heterogeneous composition and returns of occupational classes within and between countries, policy makers need to take these multifaceted patterns into account. We see a further investigation of the channels through which within-occupational variation affect the earnings distribution, as a relevant field for further research to understand the effect of job de-routinization on inequality of labor market outcomes.

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## Appendix A Technical Appendix - RIF-Regression Methods

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

$$Y_{it} = g_t(X_i, \varepsilon_i) \tag{10}$$

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 $v_t = v(F_t)$ including quantiles, the variance, or the Gini Index under very general assumptions on the earnings setting equation 10. 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:

$$v(F_t) = E[RIF(y_t, v_t, F_t)|X, T = t] \tag{11}$$

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:

$$E[RIF(y_t, v_t, F_t)|X, T = t] = X_t\widehat{\gamma}_t^v \tag{12}$$

$$\widehat{\gamma}_t^v = E[XX'|T = t]^{-1}E[RIF(y_t, v_t, F_t)|X, T = t] \tag{13}$$

$X_t$ is a vector of covariates that entails dummies for the occupational class, as described in the sections above, and socio-demographic controls. $\gamma_t^v$ 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:

$$\Delta^v = \bar{X}_1(\widehat{\gamma}_1^v - \widehat{\gamma}_0^v) + (\bar{X}_1 - \bar{X}_0)\widehat{\gamma}_1^v \tag{14}$$

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

$$RIF(t; q_t^p) = q_t^p + \frac{p - I[y \leq q_t^p]}{f_Y(q_t^p)} \tag{15}$$

$$E[RIF(y_t, q_t, F_t)|T = 1] = \frac{1}{f_Y(q_t^p)}Pr[Y > q_t^p|X = x] + (q_t^p - \frac{1-p}{f_Y(q_t^p)}) \tag{16}$$

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

$$= c_{1,p} Pr[Y > q_t^p | X = x] + c_{2,p} \quad (17)$$

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 $c_{2,p}$. A detailed discussion about RIF for P-shares can be found in Davies et al. [2017].

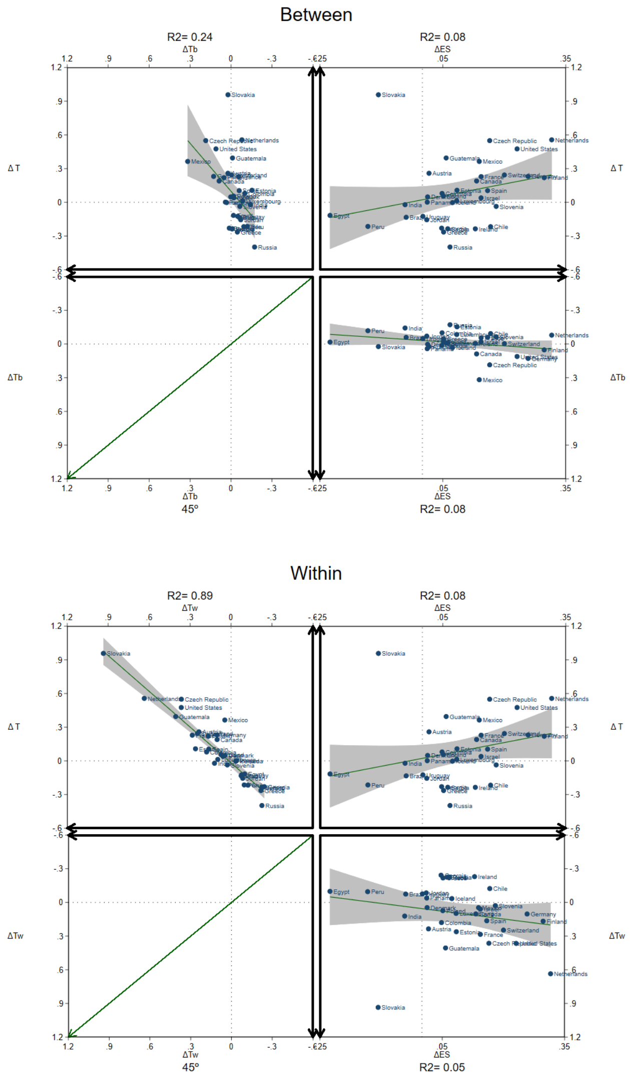
## Appendix B - Auxiliary Tables and Figures

Table A1 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 $-\Delta ES^{Routine}$ explained in Section 4.2.

Table A1: Summary Results for De-routinzation of Jobs

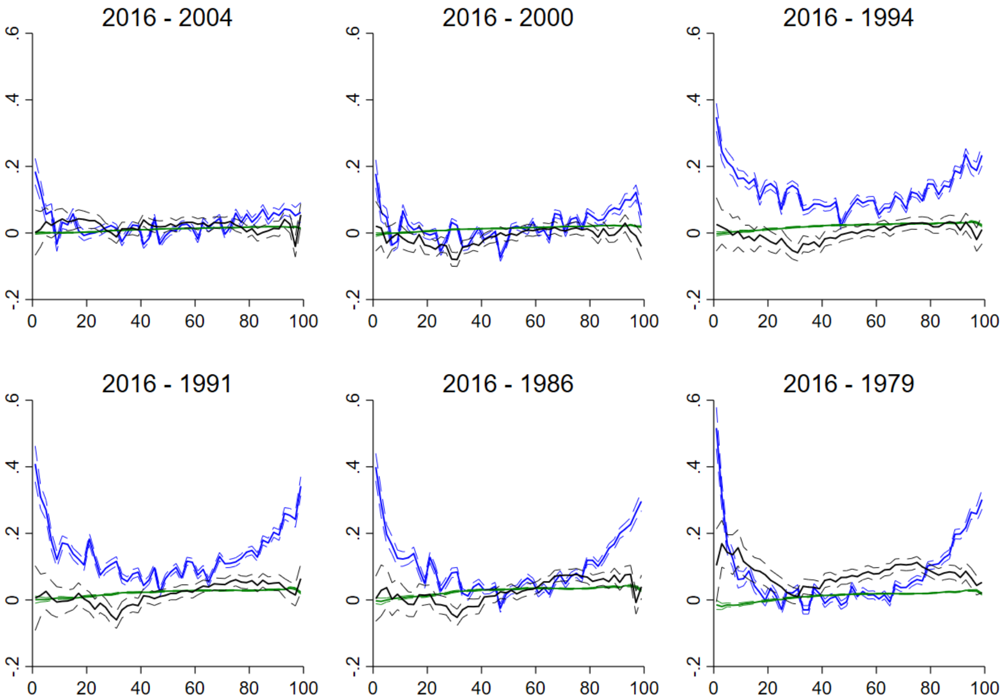
| *Country* | *Time Span* | | *Δ Employment Share in Routine Class (%)* |
|---|---|---|---|
| | ***De-routinization*** | | |
| **Austria** | *2007* | *2004* | -1,6% |
| **Belgium** | *2000* | *1995* | -5,8% |
| **Canada** | *2010* | *1994* | -13,2% |
| **Chile** | *2015* | *1992* | -16,7% |
| **Colombia** | *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% |

Here we present 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 A1: Linking H-JP and H-EP: Abstract and Routine Sub-population




*Notes:* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile earnings growth (*Total Change*, blue line) and the *Occupational Effect* has been decomposed in *Composition* (in green) and *Coefficient Effects* (in black) for the US based on RIF quantiles decomposition explained in Section 4.3. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years. Confidence intervals are provided at the 95% significance level.

Figure A2: Detailed Quantile Decompositions Results for the United States

## Appendix C - Wage Polarization

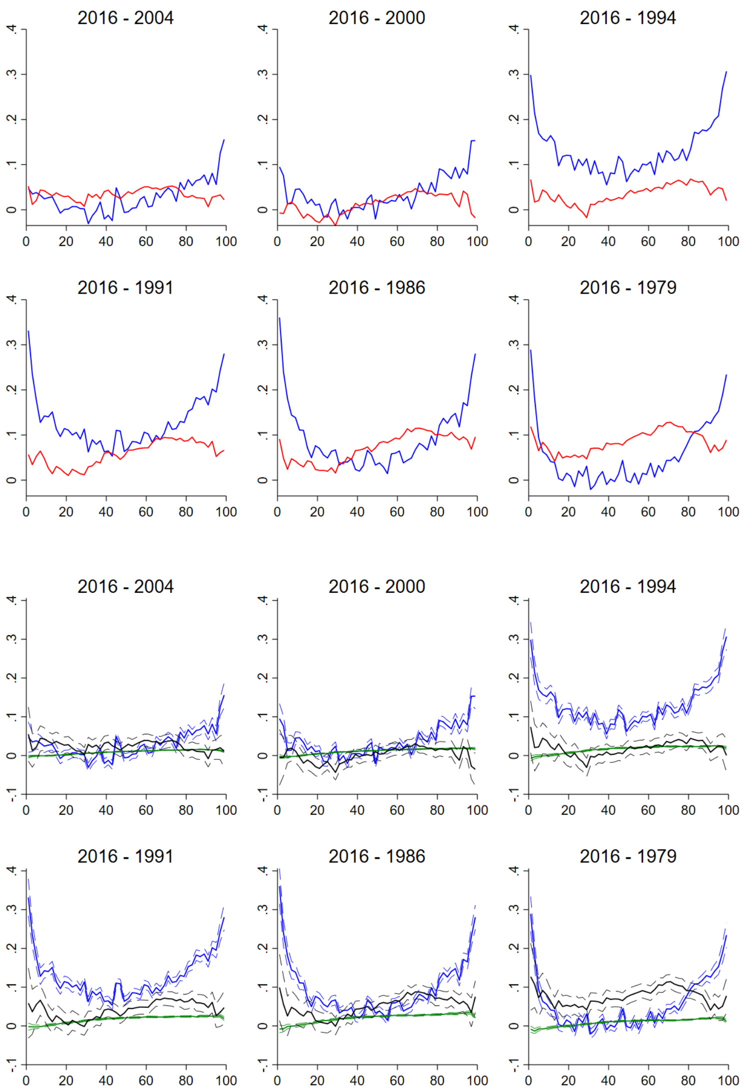



Figure A3: Quantile Decomposition Results for the United States - Wages

*Notes.* Compiled by authors based on LIS data for prime-aged, employed population. The upper panel shows the total percentile earnings growth (*Total Change*, blue line) and the *Occupational Effect* (red line) for the US based on RIF quantiles decomposition explained in Section 4.3. The lower panel, decomposes the *Occupational Effect* in *Composition* (in green) and *Coefficient Effects* (in black). Confidence intervals are provided at the 95% significance level. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years.

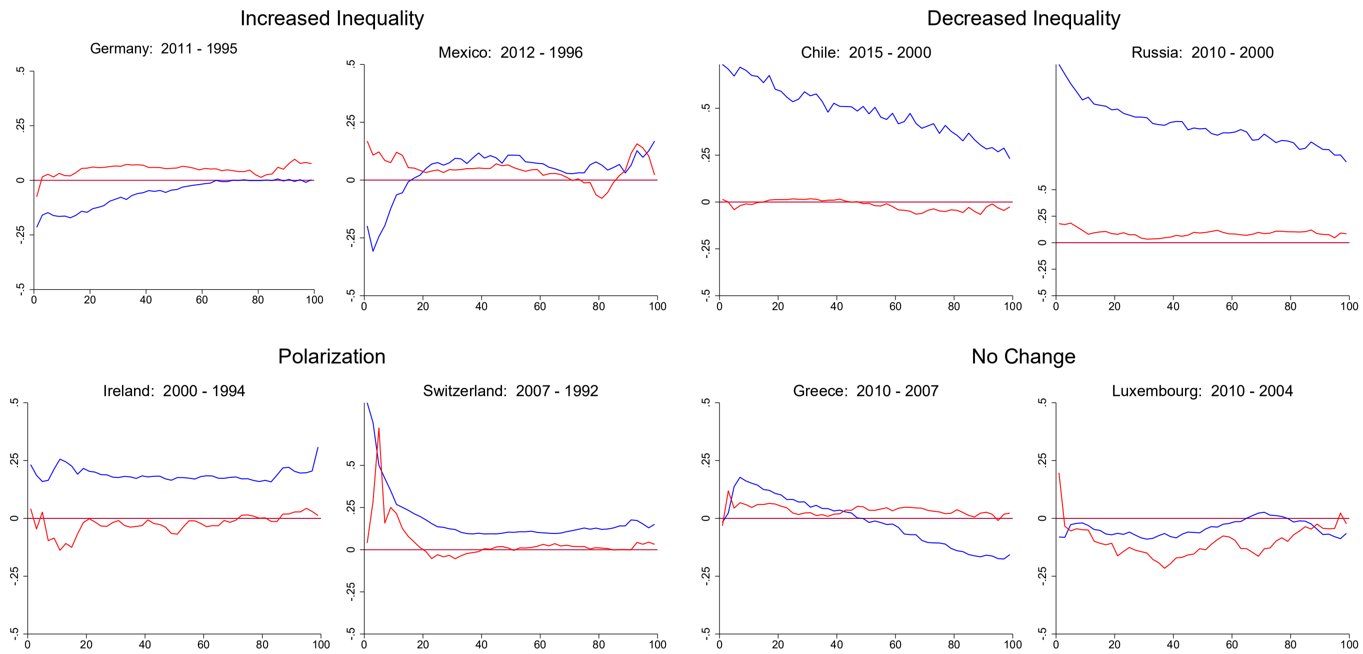



Figure A4: Percentile growth and occupational effect in selected countries - wages

*Notes.* Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile wage growth (blue line) and the Occupational Effect (red line) for selected countries based on RIF quantiles decomposition explained in Section 4. The base group is represented by male workers, with HS diploma, working in routine occupations in in manufacturing, mining, and quarrying industries, aged between 35 and 59 years old.

Table A2: P-shares decompistion - All Countries - Wages

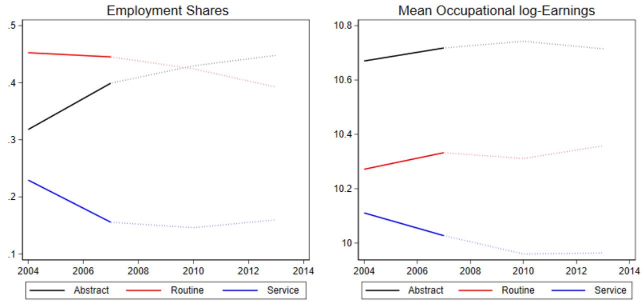
| **Country** | 1-10 | | 10-25 | | 50-75 | | 75-99 | |
|---|---|---|---|---|---|---|---|---|
| | TC | CE | TC | CE | TC | CE | TC | CE |
| | | | | ***Increased Inequality*** | | | | |
| **Austria: 2007 - 2004** | -1.251 | -.392 | -1.665 | -.736 | -1.096 | -.302 | 4.012 | 1.422 |
| **Czech Rep.: 2010 - 1996** | -.657 | -.007 | -.529 | -.148 | .092 | -.771 | 1.093 | .926 |
| **Estonia: 2010 - 2007** | -.451 | 0 | -.405 | -.128 | -.349 | -.848 | 1.205 | .968 |
| **Germany: 2011 - 1995** | -.394 | .124 | -.752 | .156 | .686 | -.292 | .46 | .011 |
| **Mexico: 2012 - 1996** | -.279 | .142 | -.274 | .079 | -.336 | -.773 | .888 | .554 |
| **Netherlands: 2010 - 1990** | -1.173 | -.403 | -1.083 | -.537 | 1.219 | -.508 | 1.037 | 1.449 |
| | | | | ***Decreased Inequality*** | | | | |
| **Brazil: 2013 - 2006** | .122 | -.038 | -.004 | .114 | -2.744 | .42 | 2.626 | -.497 |
| **Chile: 2015 - 2000** | .661 | -.143 | 1.196 | -.011 | 2.334 | .469 | -4.191 | -.313 |
| **Colombia: 2013 - 2004** | .155 | -.166 | .598 | .189 | 1.845 | -.433 | -2.598 | .409 |
| **Guatemala: 2011 - 2006** | .175 | .17 | .719 | .164 | .975 | -.68 | -1.869 | .346 |
| **Russia: 2010 - 2000** | .994 | .031 | 1.622 | -.169 | 3.253 | -.779 | -5.869 | .916 |
| **Uruguay: 2010 - 2004** | .106 | -.174 | .354 | -.071 | 1.241 | .837 | -1.7 | -.592 |
| | | | | ***Polarization*** | | | | |
| **Belgium: 2000 - 1995** | .315 | -.203 | .684 | .054 | -1.352 | 1.037 | .352 | -.888 |
| **Canada: 2010 - 1994** | -.186 | -.343 | -.359 | -.304 | -1.028 | .745 | 1.573 | -.099 |
| **Ireland: 2000 - 1994** | -.01 | -.221 | .122 | -.446 | -.877 | -.452 | .766 | 1.12 |
| **Switzerland: 2007 - 1992** | .834 | .344 | .531 | .006 | -1.779 | -.896 | .414 | .545 |
| **United States: 2016 - 1991** | .108 | -.076 | -.115 | -.279 | -1.513 | .327 | 1.52 | .03 |
| | | | | ***No Change*** | | | | |
| **Greece: 2010 - 2007** | .531 | -.194 | 1.45 | -.003 | 2.649 | .465 | -4.631 | -.268 |
| **Iceland: 2010 - 2004** | .107 | -.041 | .578 | -.407 | 1.895 | .696 | -2.581 | -.248 |
| **Israel: 2012 - 2007** | -.17 | .017 | -.058 | -.097 | -.373 | .283 | .601 | -.203 |
| **Luxembourg: 2010 - 2004** | .037 | -.009 | -.121 | -.173 | .447 | -1.926 | -.364 | 2.106 |

*Notes.* The table presents detailed result for the P-share decomposition explained in Section 4.3. TC columns in black report estimates of *Total Change* in four wage bins considered . CE columns in light gray report estimates for *Class Effect*. Coefficents are multiplied by 100.

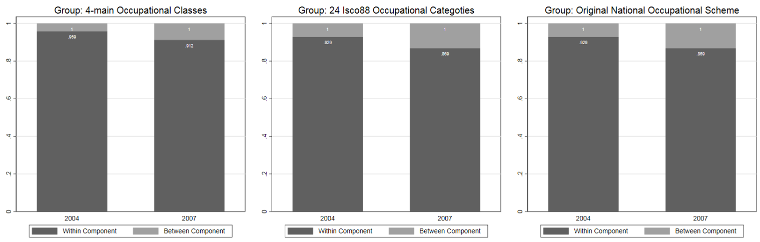
## Appendix D - Detailed country specific results

The current Appendix presents country specific results for all the main analysis. 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. Keep in mind that Serbia and Switzerland do not have industry information. Therefore, we computed RIF decompositions without controlling for industry dummies.

## Austria: 2007-2004

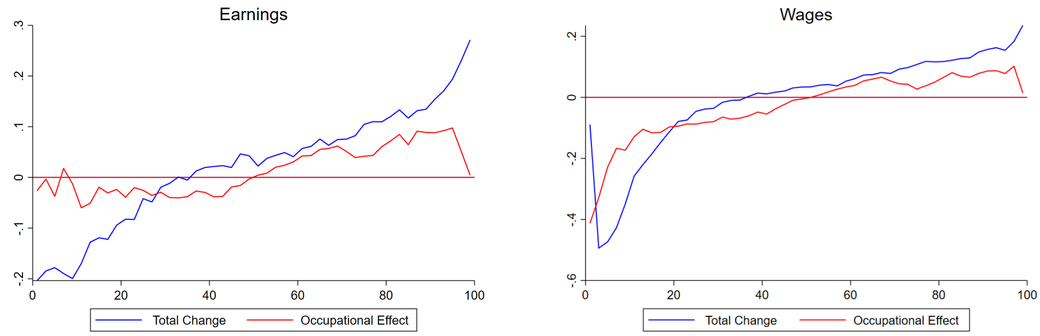



Employment and Income shares by Occupational Class

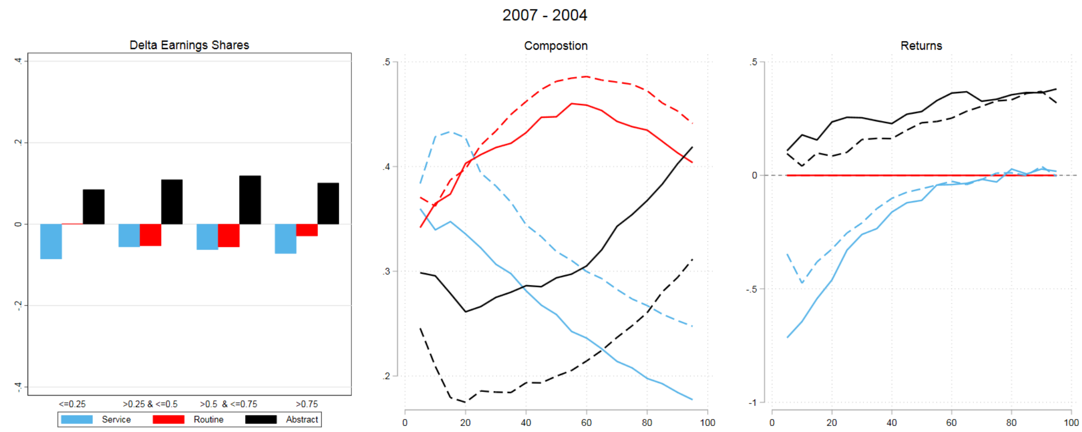



Theil Decompostion

| austria: 2007 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00289*** | 0.000570 | 0.00232*** |
| Specification Error | 3.00e-05 | 1.00e-05 | -4.00e-05 |
| Composition Effect | | | |
| Occ | 0.000130 | -0.000180 | 5.00e-05 |
| Educ | 5.00e-05 | -1.00e-05 | -0.00004* |
| Female | 3.00e-05 | 0 | -0.00003* |
| Age | 5.00e-05 | -0.00011* | 0.00006* |
| Ind | -7.00e-05 | 3.00e-05 | 4.00e-05 |
| Reweighting Error | -9.00e-05 | 1.00e-05 | 8.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000570 | -0.000310 | 0.00088* |
| Educ | 0.00100* | -0.00095* | -5.00e-05 |
| Female | -0.000960 | 0.000410 | 0.000550 |
| Age | -0.000210 | -8.00e-05 | 0.000300 |
| Ind | -0.00194 | 0.000370 | 0.00157 |
| _cons | -0.000340 | 0.00140 | -0.00105 |

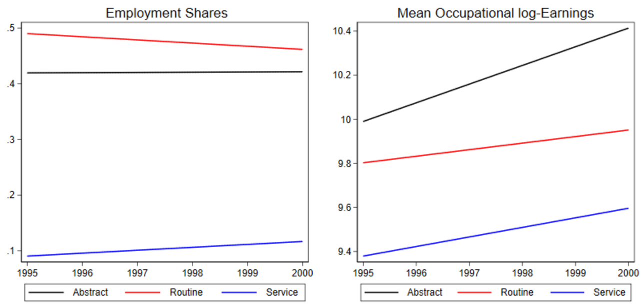



Quantile RIF Decompostion

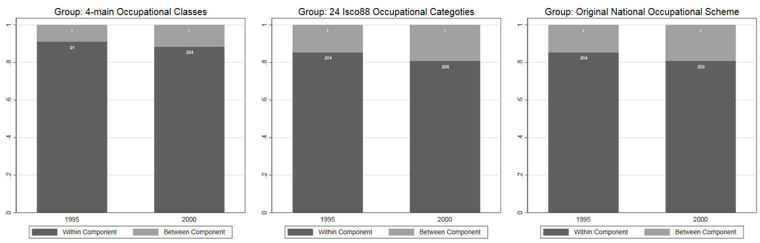



Occupational Classes Compostion and Returns

## Belgium: 2000-1995

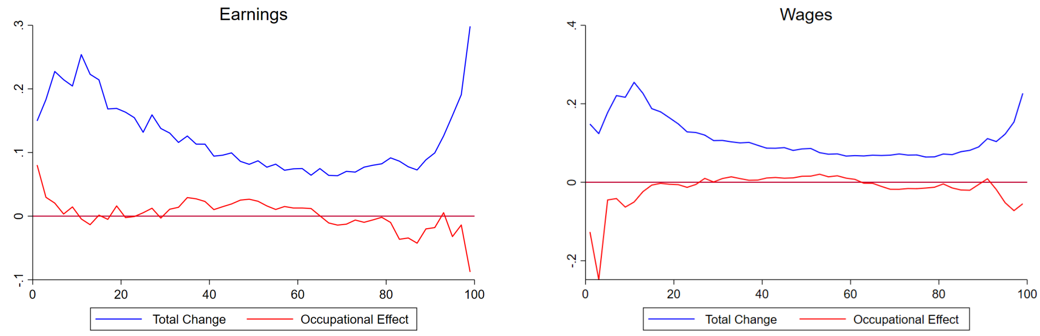



Employment and Income shares by Occupational Class

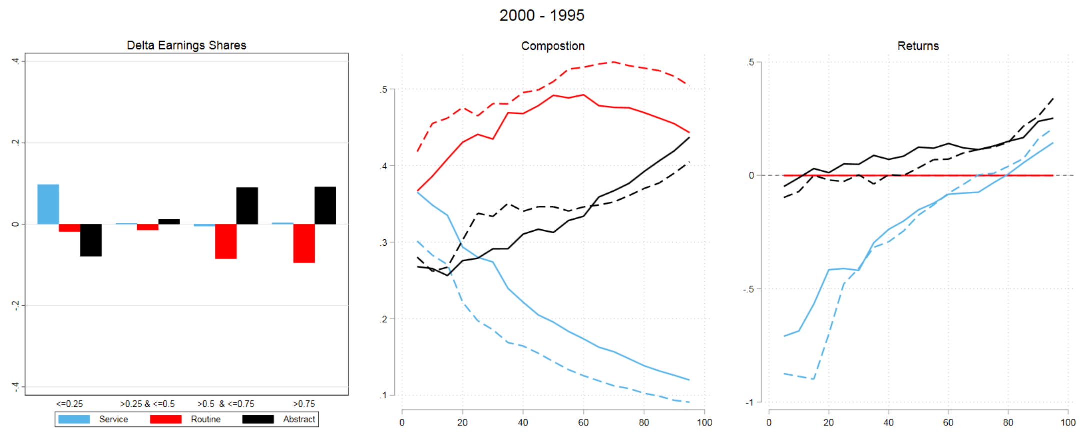



Theil Decompostion

| belgium: 2000 - 1995 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00162*** | -0.00166*** | 4.00e-05 |
| Specification Error | 0 | 0 | 0 |
| Composition Effect | | | |
| Occ | -0.00022*** | 1.00e-05 | 0.00021*** |
| Educ | 1.00e-05 | -3.00e-05 | 1.00e-05 |
| Female | -1.00e-05 | 1.00e-05 | 1.00e-05 |
| Age | 2.00e-05 | -6.00e-05 | 4.00e-05 |
| Ind | 0.00014* | -6.00e-05 | -9.00e-05 |
| Reweighting Error | -5.00e-05 | 1.00e-05 | 4.00e-05 |
| Coefficent Effect | | | |
| Occ | 0.000410 | 0.000310 | -0.000720 |
| Educ | 0.000440 | -0.000680 | 0.000250 |
| Female | 0.000180 | 0.000490 | -0.000670 |
| Age | -0.000850 | 0.000450 | 0.000400 |
| Ind | 0.00217 | 0.00281 | -0.00498 |
| _cons | -0.000620 | -0.00492 | 0.00554 |

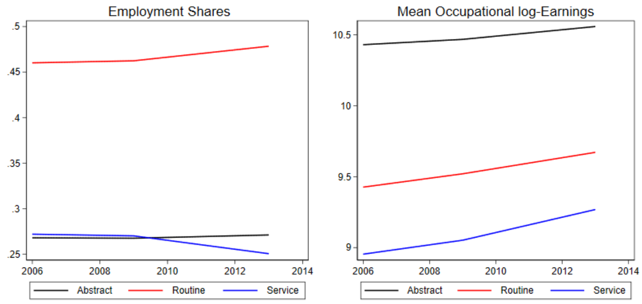



Quantile RIF Decompostion

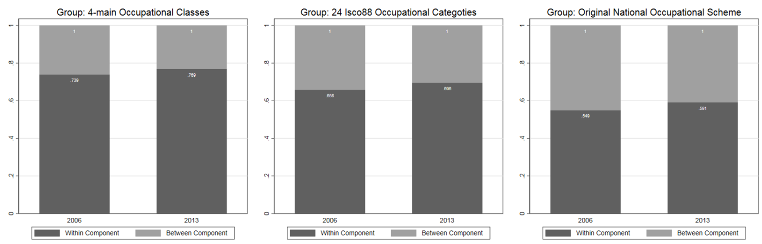



Occupational Classes Compostion and Returns

## Brazil: 2013-2006

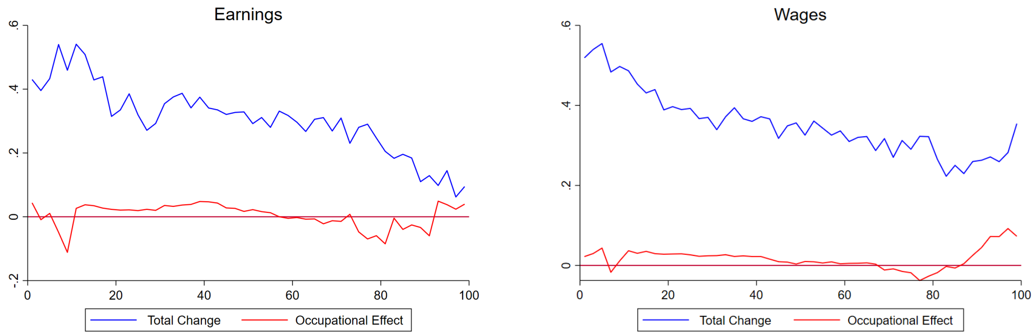



Employment and Income shares by Occupational Class

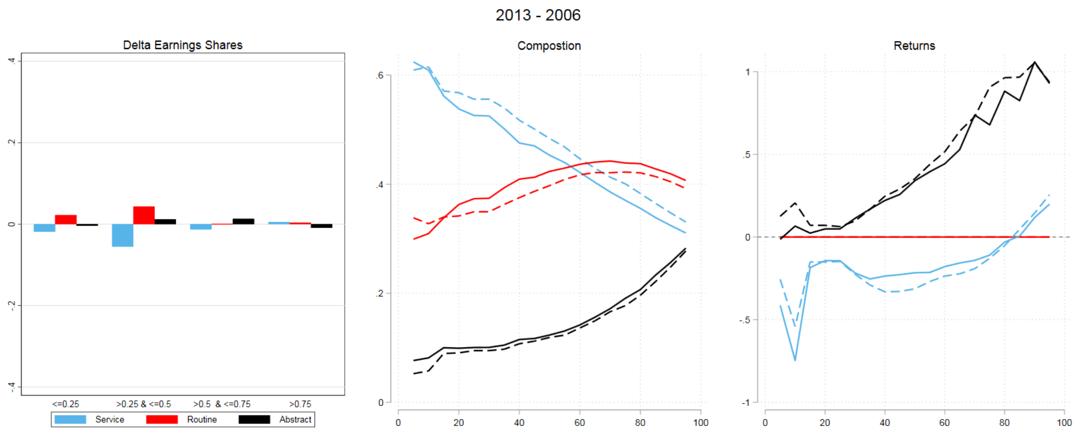



Theil Decompostion

| brazil: 2013 - 2006 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00313*** | 0.00024* | -0.00336*** |
| Specification Error | 0.00009*** | 0.00025*** | -0.00033*** |
| Composition Effect | | | |
| Occ | 0.00039*** | -0.00009*** | -0.00030*** |
| Educ | -0.00014*** | -0.00054*** | 0.00068*** |
| Female | -0.00003*** | 0.00002*** | 0 |
| Age | -0.00007*** | -0.00001* | 0.00008*** |
| Ind | 0.00020*** | -0.00009*** | -0.00011*** |
| Reweighting Error | -5.00e-05 | 0.00005* | -1.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000240 | 0.000160 | 8.00e-05 |
| Educ | 0.000190 | 0.00049** | -0.00068*** |
| Female | 0.00049*** | -0.00038** | -0.000110 |
| Age | 0.000240 | 0.000140 | -0.000380 |
| Ind | 3.00e-05 | 0.00812*** | -0.00815*** |
| _cons | 0.00201*** | -0.00787*** | 0.00586*** |

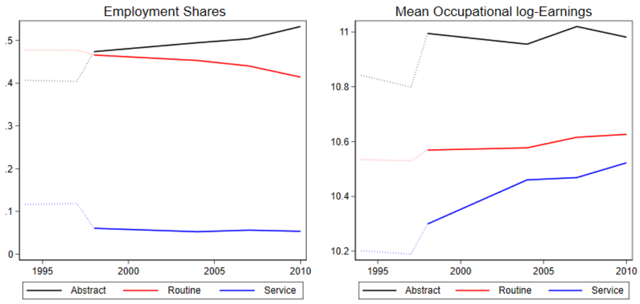



Quantile RIF Decompostion

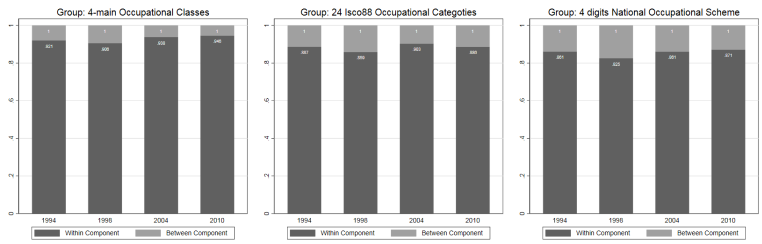



Occupational Classes Compostion and Returns

## Canada: 2010-1994

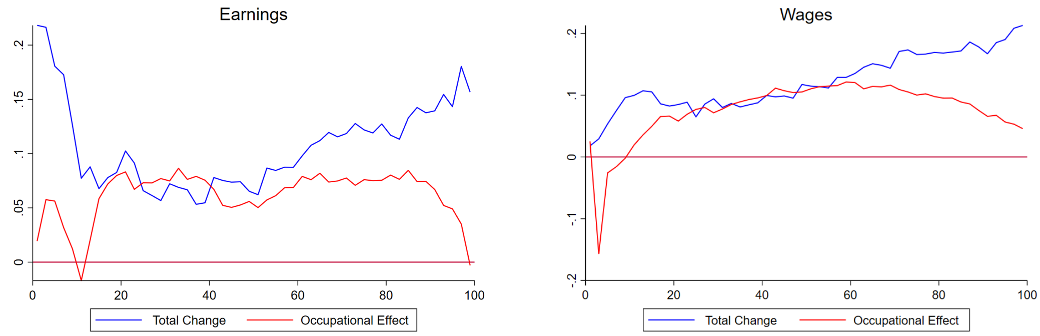



Employment and Income shares by Occupational Class

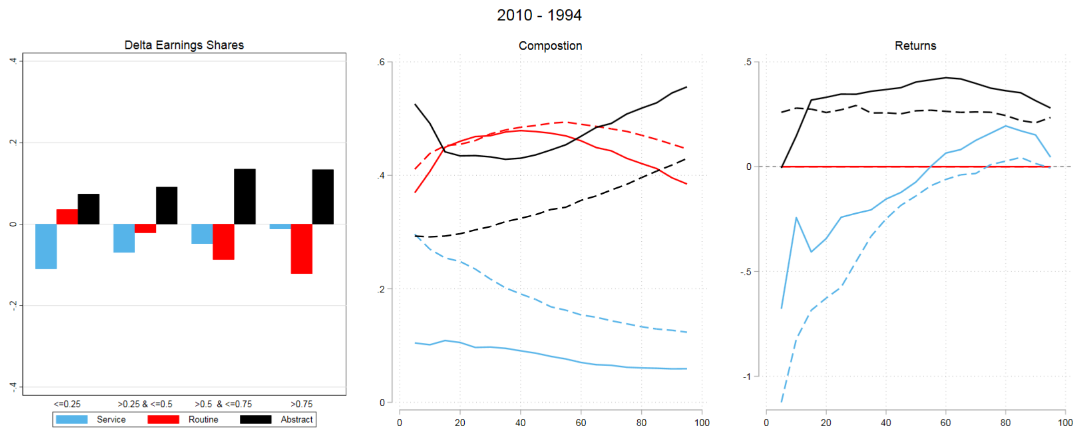



Theil Decompostion

| canada: 2010 - 1994 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000470 | -0.00112*** | 0.00066*** |
| Specification Error | 8.00e-05 | 0 | -0.00007*** |
| Composition Effect | | | |
| Occ | 0.00032*** | -4.00e-05 | -0.00027*** |
| Educ | -3.00e-05 | 0.00018*** | -0.00015*** |
| Female | -0.00001** | -0.00001* | 0.00002** |
| Age | 0 | 2.00e-05 | -2.00e-05 |
| Ind | -2.00e-05 | -1.00e-05 | 0.00003** |
| Reweighting Error | -1.00e-05 | -1.00e-05 | 3.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.00102 | 0.00105* | -3.00e-05 |
| Educ | 0.00115 | -0.000820 | -0.000330 |
| Female | 0.00110* | -0.000470 | -0.00064** |
| Age | 0.00236 | -0.00181 | -0.000540 |
| Ind | -0.000900 | 0 | 0.00090* |
| _cons | -0.00254 | 0.000800 | 0.00174* |

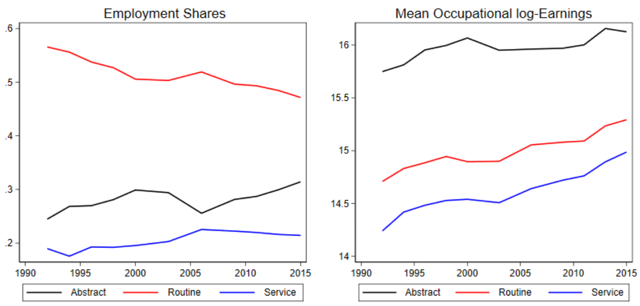



Quantile RIF Decompostion

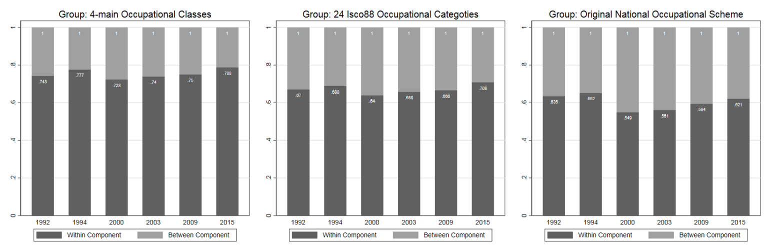



Occupational Classes Compostion and Returns

# Chile: 2015-1992

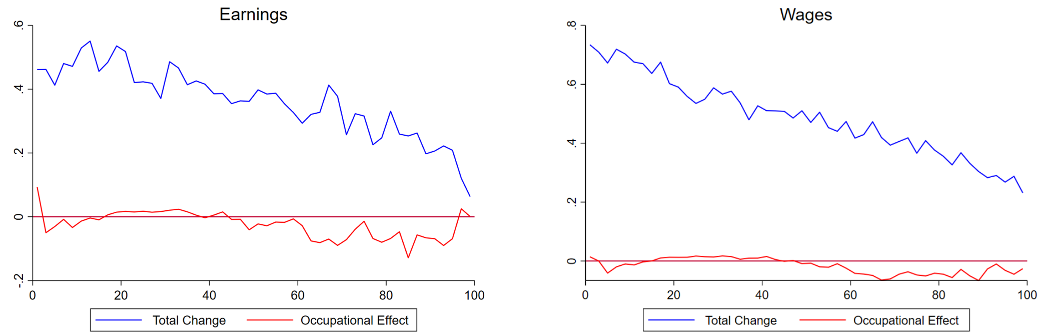



Employment and Income shares by Occupational Class

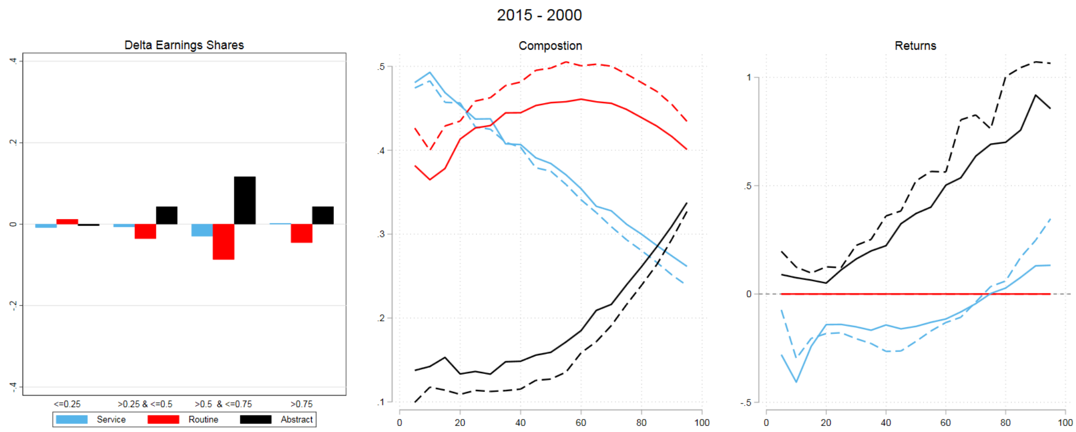



Theil Decompostion

| chile: 2015 - 2000 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00162*** | 0.00056*** | -0.00219*** |
| Specification Error | 0.00004* | 6.00e-05 | -0.00011** |
| Composition Effect | | | |
| Occ | -0.00007*** | -3.00e-05 | 0.00010*** |
| Educ | -0.00014*** | 2.00e-05 | 0.00012** |
| Female | -0.00002*** | 0.00004*** | -0.00002** |
| Age | -0.00011*** | 3.00e-05 | 0.00007** |
| Ind | 0.00023*** | 0 | -0.00022*** |
| Reweighting Error | -4.00e-05 | 0.00010*** | -6.00e-05 |
| Coefficent Effect | | | |
| Occ | 0.000240 | 0.000100 | -0.000330 |
| Educ | 0.000220 | -3.00e-05 | -0.000180 |
| Female | -0.00046*** | -0.000120 | 0.00058*** |
| Age | 9.00e-05 | 0.000620 | -0.000700 |
| Ind | -0.00120** | 0.00235** | -0.00115 |
| _cons | 0.00286*** | -0.00256* | -0.000300 |

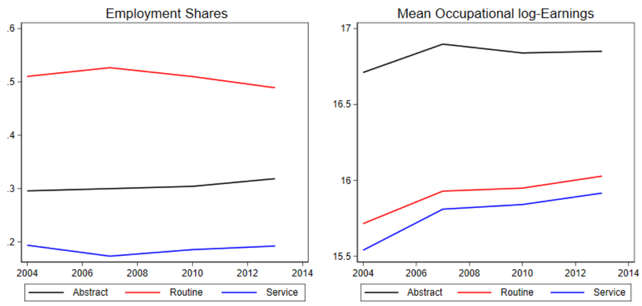



Quantile RIF Decompostion

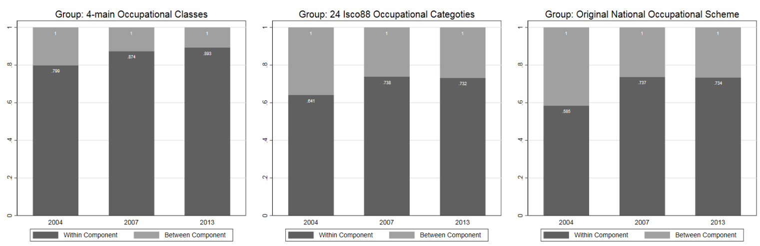



Occupational Classes Compostion and Returns

# Colombia: 2013-2004

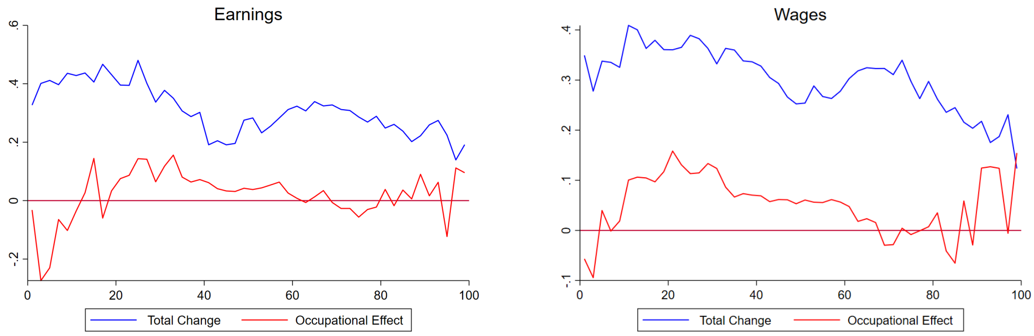



Employment and Income shares by Occupational Class

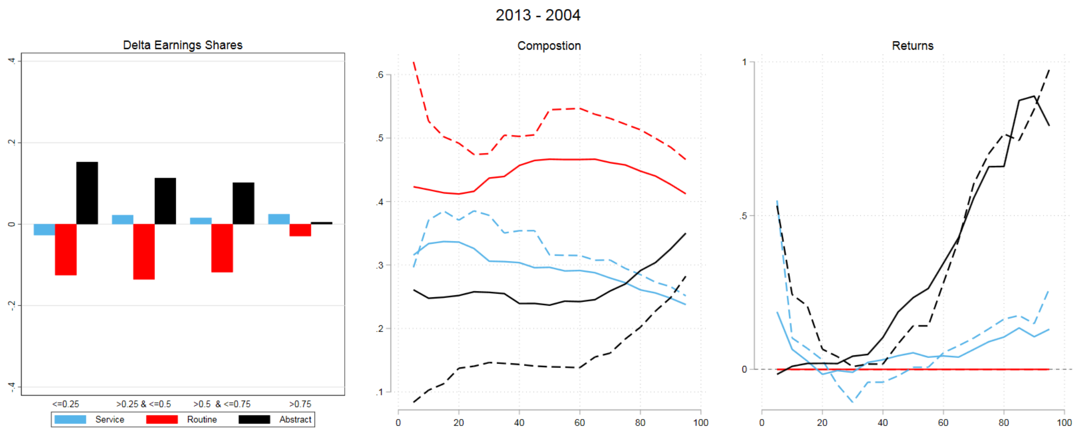



Theil Decompostion

| colombia: 2013 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00100 | -3.00e-05 | -0.000970 |
| Specification Error | 1.00e-05 | 0.00031* | -0.00032** |
| Composition Effect | | | |
| Occ | -0.000100 | 4.00e-05 | 7.00e-05 |
| Educ | -0.00020*** | -0.000100 | 0.00030*** |
| Female | 1.00e-05 | -1.00e-05 | 0 |
| Age | -0.00008* | 2.00e-05 | 0.00005* |
| Ind | 0.00026* | -0.00028** | 2.00e-05 |
| Reweighting Error | 5.00e-05 | -4.00e-05 | -2.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000650 | 0.000570 | 8.00e-05 |
| Educ | 0.000260 | -0.000230 | -3.00e-05 |
| Female | -1.00e-05 | -0.000510 | 0.000510 |
| Age | -0.000180 | -0.000300 | 0.000480 |
| Ind | 0.00212 | -0.00163 | -0.000490 |
| _cons | -0.000500 | 0.00212 | -0.00162 |

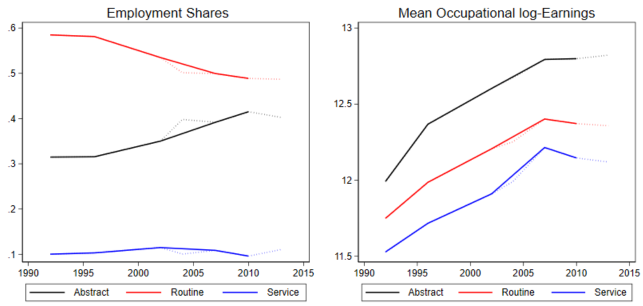



Quantile RIF Decompostion

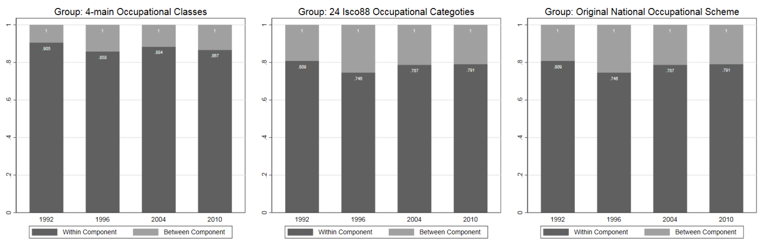



Occupational Classes Compostion and Returns

## Czeck Republic: 2010-1996

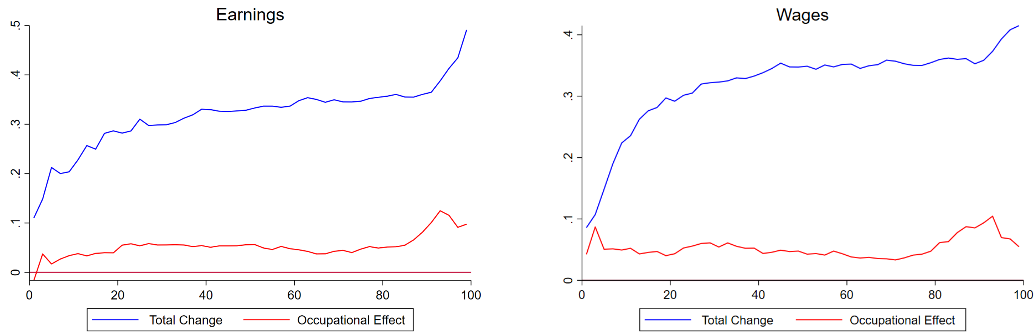



Employment and Income shares by Occupational Class

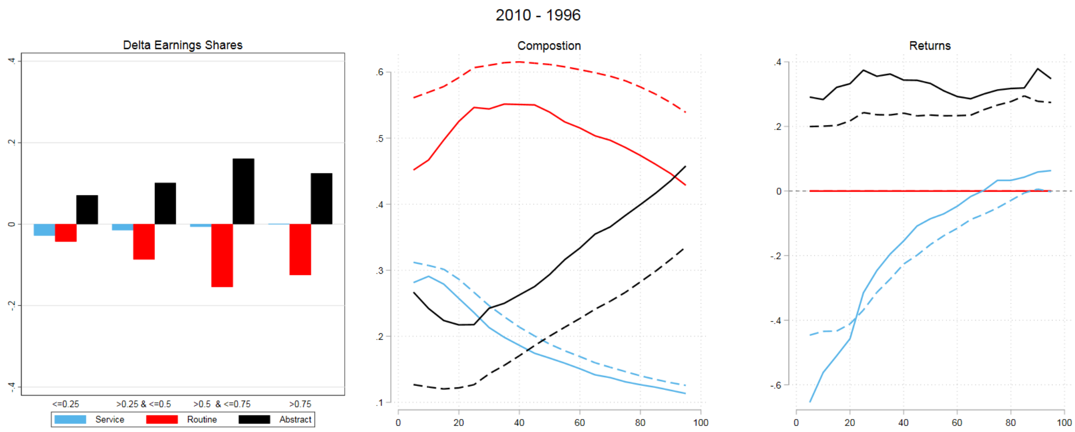



Theil Decompostion

| czechrep: 2010 - 1996 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00125** | 0.000490 | 0.00076* |
| Specification Error | 0.00006** | 0.00008** | -0.00014*** |
| Composition Effect | | | |
| Occ | -0.00004* | -1.00e-05 | 0.00005** |
| Educ | -0.00006* | -0.00014*** | 0.00020*** |
| Female | 0 | 0.00002*** | -0.00002*** |
| Age | -0.00005*** | 2.00e-05 | 0.00003** |
| Ind | -0.00014*** | -4.00e-05 | 0.00017*** |
| Reweighting Error | 1.00e-05 | 1.00e-05 | -2.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000240 | -0.000200 | 0.000440 |
| Educ | 9.00e-05 | -0.000210 | 0.000120 |
| Female | 0.000120 | 0.000210 | -0.000330 |
| Age | -0.000110 | -0.000130 | 0.000240 |
| Ind | -0.00346 | 0.00193 | 0.00153 |
| _cons | 0.00257 | -0.00105 | -0.00152 |

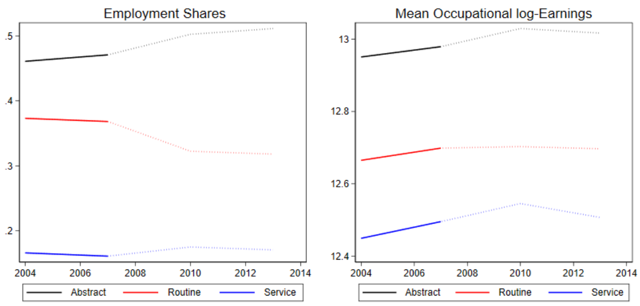



Quantile RIF Decompostion

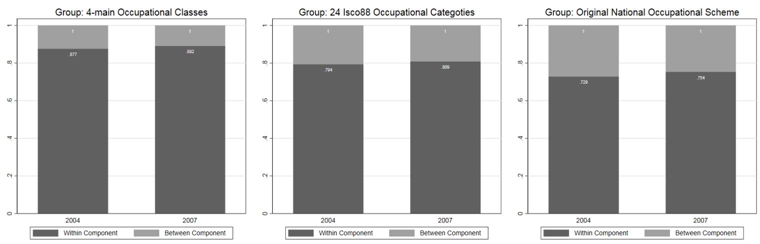



Occupational Classes Compostion and Returns

## Denmark: 2007-2004



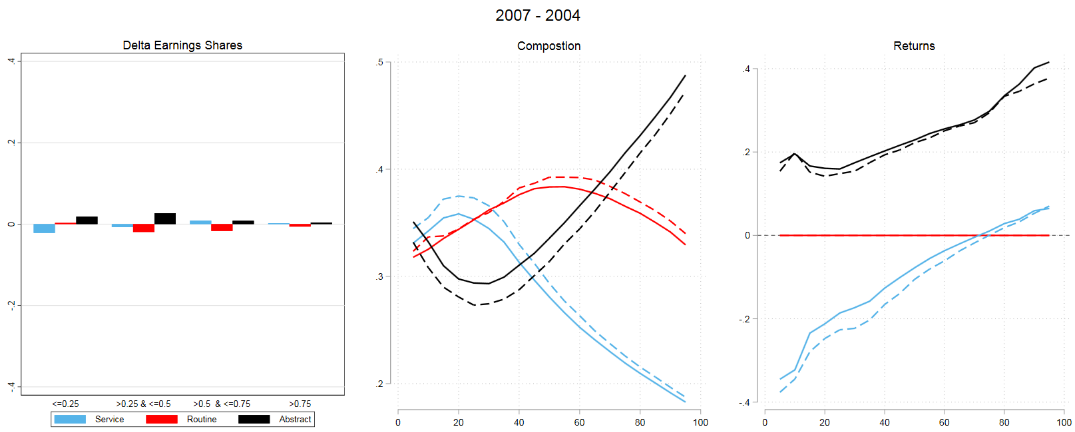

Employment and Income shares by Occupational Class




Theil Decompostion

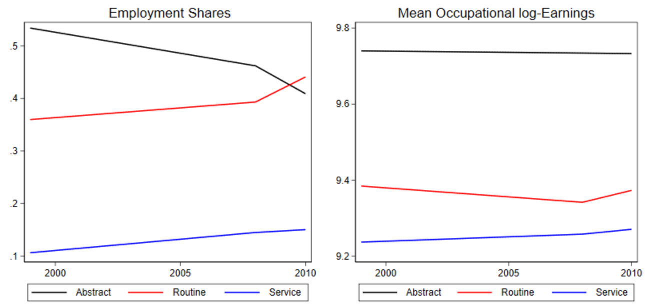
| denmark: 2007 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00057*** | 0.00030*** | 0.00027*** |
| Specification Error | 0 | 1.00e-05 | 0 |
| Composition Effect | | | |
| Occ | 0 | 0 | -0.00000* |
| Educ | -0.00002*** | 0.00000* | 0.00001*** |
| Female | 0 | 0 | 0.00001*** |
| Age | 0.00007*** | -0.00005*** | -0.00001*** |
| Ind | -0.00004*** | -0.00002** | 0.00006*** |
| Reweighting Error | 0 | 0 | 0 |
| Coefficent Effect | | | |
| Occ | -7.00e-05 | -6.00e-05 | 0.000130 |
| Educ | -1.00e-05 | 5.00e-05 | -4.00e-05 |
| Female | -5.00e-05 | 9.00e-05 | -4.00e-05 |
| Age | 0.000250 | -0.00036** | 0.000110 |
| Ind | 0.00530*** | -0.00368*** | -0.00162** |
| _cons | -0.00599*** | 0.00433*** | 0.00167** |


Quantile RIF Decompostion

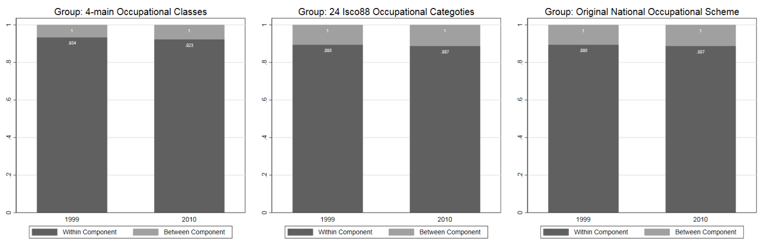



Occupational Classes Compostion and Returns

# Egypt: 2010-1999



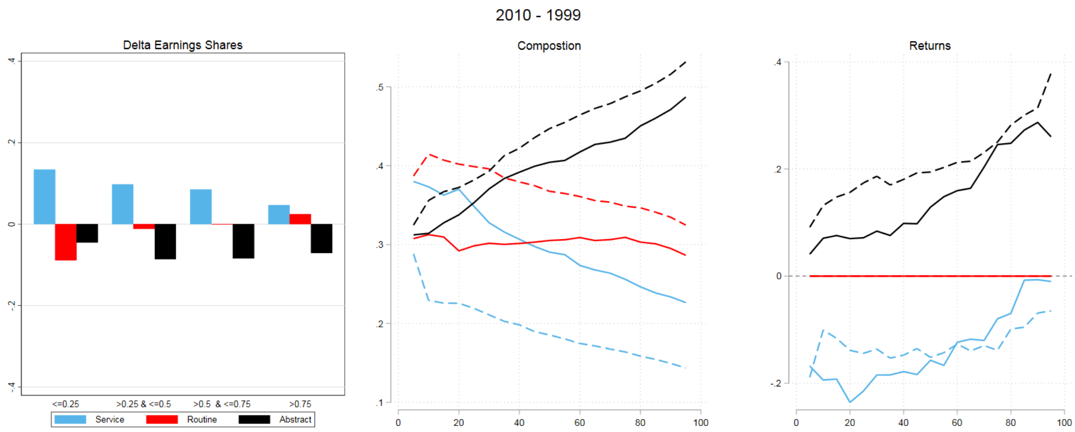

Employment and Income shares by Occupational Class




Theil Decompostion

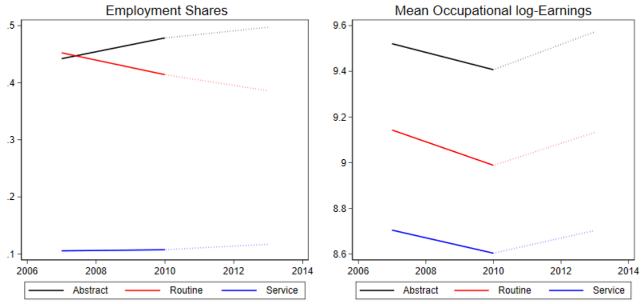
| egypt: 2010 - 1999 | | | |
|---|---|---|---|
| | <15 | >85 | 15-85 |
| Δ | 0.000200 | -0.0012* | 0.00100 |
| Specification Error | 0 | 0 | 0 |
| Composition Effect | | | |
| Occ | 0.0003*** | -0.0003*** | -0.000100 |
| Educ | 0.0001** | -0.0001** | 0 |
| Female | 0.0003*** | -0.0001*** | -0.0002*** |
| Age | -0.0001*** | 0.0000* | 0.0001* |
| Ind | -0.0001* | 0.0001*** | 0 |
| Reweighting Error | -0.000200 | 0.000100 | 0.000100 |
| Coefficent Effect | | | |
| Occ | -0.000100 | 0.000900 | -0.000800 |
| Educ | 0.000400 | 0.000100 | -0.000500 |
| Female | -0.000200 | 0 | 0.000200 |
| Age | 0.00170 | -0.000500 | -0.00110 |
| Ind | -0.000700 | -0.00100 | 0.00180 |
| _cons | -0.00120 | -0.000400 | 0.00150 |


Quantile RIF Decompostion

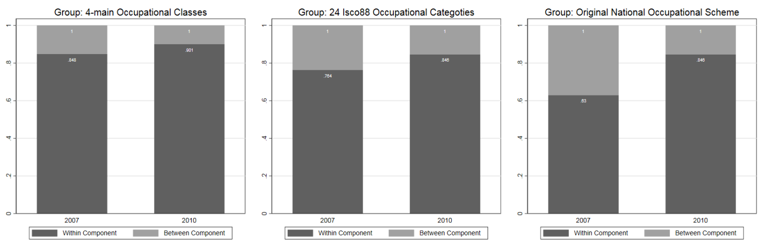



Occupational Classes Compostion and Returns

## Estonia: 2010-2007

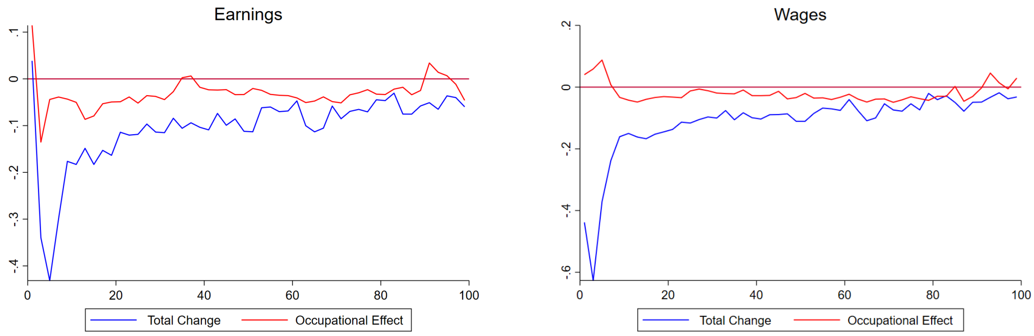



Employment and Income shares by Occupational Class

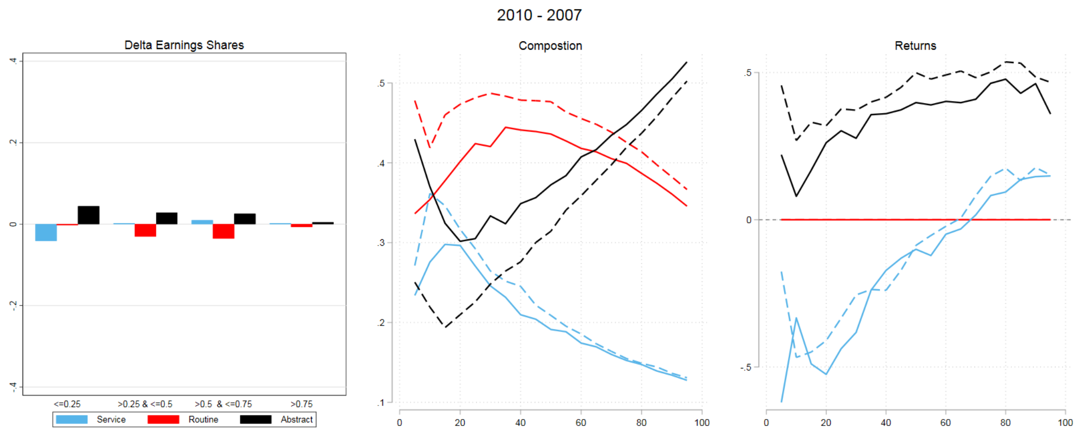



Theil Decompostion

| estonia: 2010 - 2007 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00234** | 0.00127* | 0.00107* |
| Specification Error | 2.00e-05 | -4.00e-05 | 1.00e-05 |
| Composition Effect | | | |
| Occ | 0 | 2.00e-05 | -2.00e-05 |
| Educ | -0.00014* | 0.00022** | -7.00e-05 |
| Female | 0.00004* | -0.00006** | 0.00002* |
| Age | -1.00e-05 | 2.00e-05 | -2.00e-05 |
| Ind | 0.000110 | -6.00e-05 | -5.00e-05 |
| Reweighting Error | -2.00e-05 | 8.00e-05 | -5.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000490 | -0.000280 | 0.000780 |
| Educ | 0 | -0.000790 | 0.000800 |
| Female | -0.00130 | 0.00105 | 0.000240 |
| Age | -8.00e-05 | -0.000560 | 0.000630 |
| Ind | -0.00128 | -0.000600 | 0.00188 |
| _cons | 0.000820 | 0.00226 | -0.00307 |

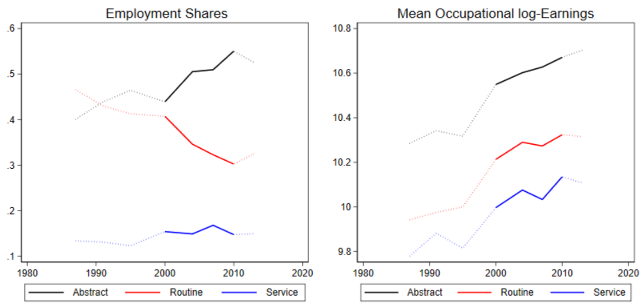



Quantile RIF Decompostion

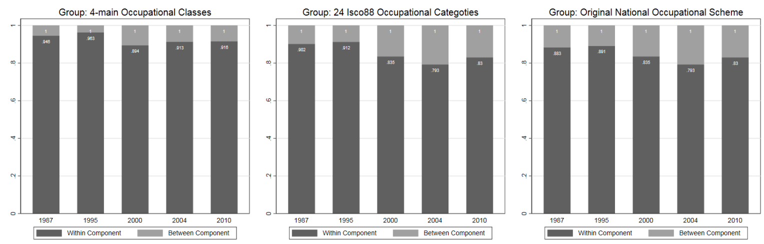



Occupational Classes Compostion and Returns

## Finland: 2010-1991



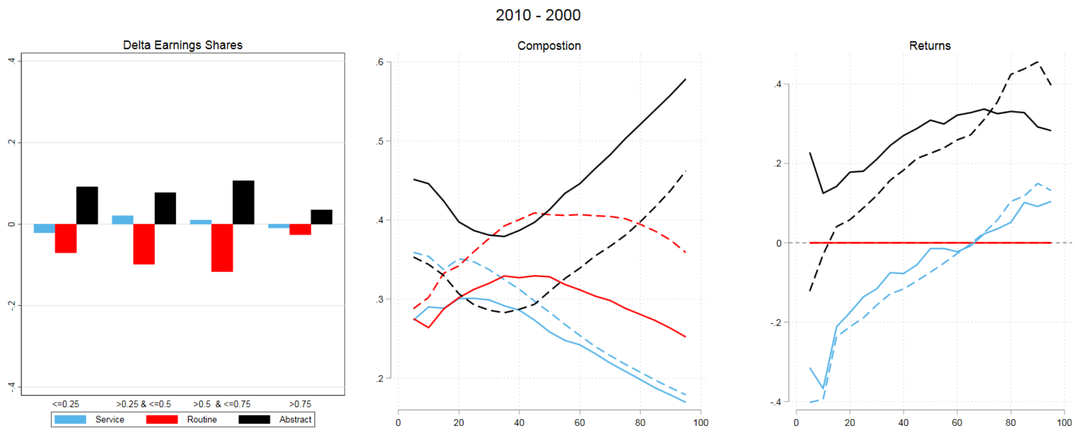

Employment and Income shares by Occupational Class




Theil Decompostion

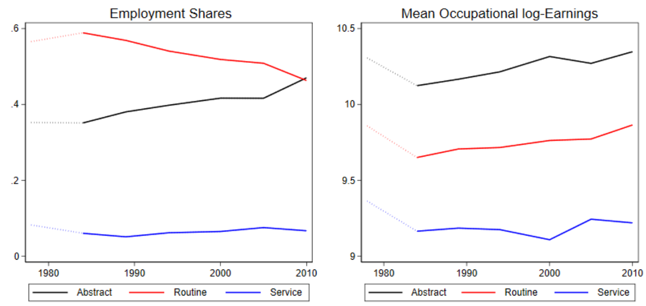
| finland: 2010 - 2000 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00250*** | 0.00205*** | 0.00045* |
| Specification Error | 4.00e-05 | 3.00e-05 | -0.00007* |
| Composition Effect | | | |
| Occ | -0.00025*** | 7.00e-05 | 0.00018*** |
| Educ | 0.00018* | -0.00019** | 2.00e-05 |
| Female | 2.00e-05 | -1.00e-05 | -1.00e-05 |
| Age | 2.00e-05 | 1.00e-05 | -0.00003* |
| Ind | 0.00011* | -0.00010** | -1.00e-05 |
| Reweighting Error | -1.00e-05 | 0 | 1.00e-05 |
| Coefficent Effect | | | |
| Occ | 0.00138 | -0.000780 | -0.000600 |
| Educ | -0.000640 | 0.000290 | 0.000360 |
| Female | -0.000180 | -1.00e-05 | 0.000200 |
| Age | 0.00108 | -0.00113 | 5.00e-05 |
| Ind | -0.000100 | 0.00173 | -0.00163 |
| _cons | -0.00414 | 0.00216 | 0.00197 |


Quantile RIF Decompostion

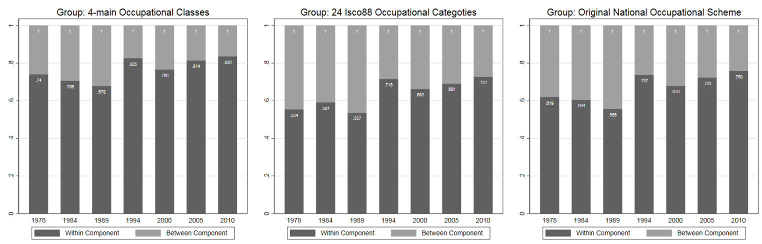



Occupational Classes Compostion and Returns

## France: 2010-1994

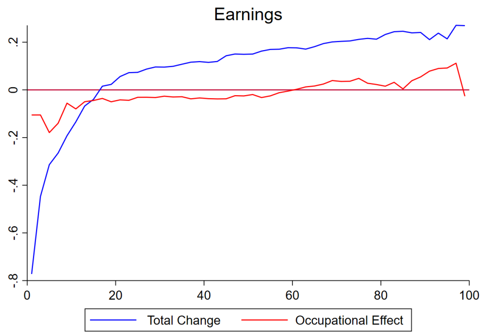



Employment and Income shares by Occupational Class

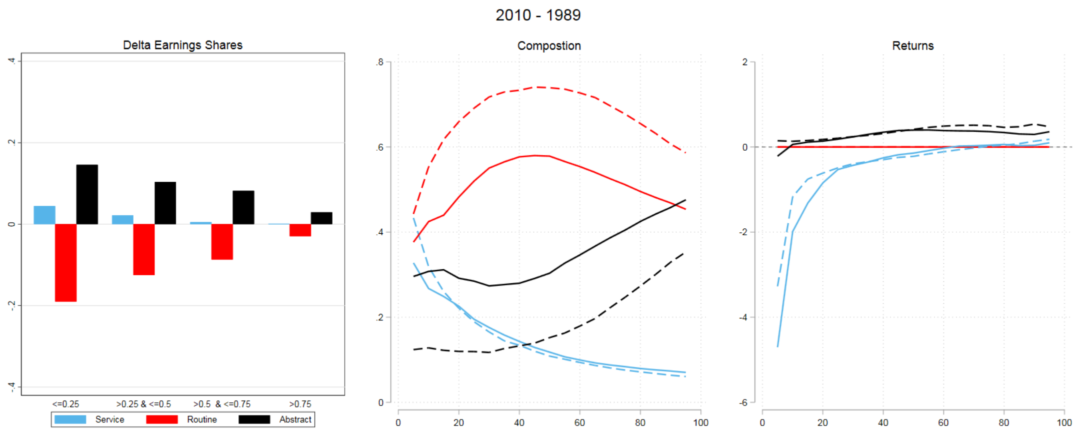



Theil Decompostion

| france: 2010 - 1989 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00589*** | 0.00368*** | 0.00220*** |
| Specification Error | 1.00e-05 | 0.00070* | -0.00071* |
| Composition Effect | | | |
| Occ | -0.00060*** | 0.00032** | 0.00028** |
| Educ | -0.000190 | -0.00108*** | 0.00127*** |
| Female | 4.00e-05 | -5.00e-05 | 0 |
| Age | -0.000140 | -0.000120 | 0.00026** |
| Ind | -0.00041* | 9.00e-05 | 0.00033** |
| Reweighting Error | 0.000130 | -0.000130 | -1.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000860 | -9.00e-05 | 0.000950 |
| Educ | 0.00201* | -0.000800 | -0.00121* |
| Female | -9.00e-05 | -0.000450 | 0.000540 |
| Age | 0.00210 | -0.00188 | -0.000220 |
| Ind | -1.00e-05 | 0.00166 | -0.00165 |
| _cons | -0.00787* | 0.00549 | 0.00237 |

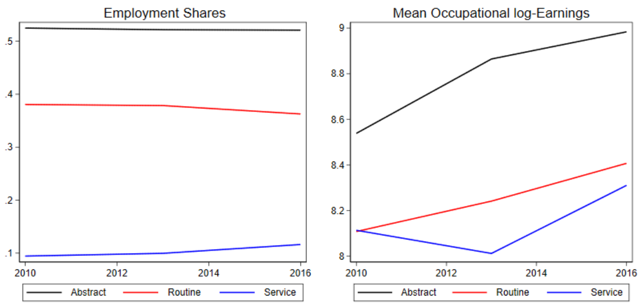



Quantile RIF Decompostion

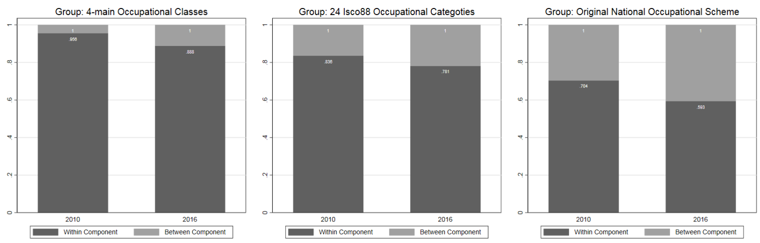



Occupational Classes Compostion and Returns

## Georgia: 2016-2010



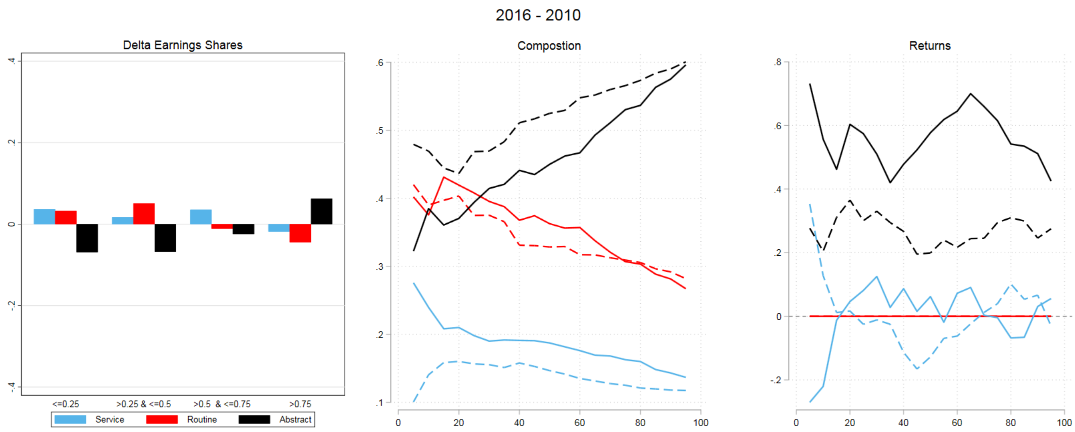

Employment and Income shares by Occupational Class




Theil Decompostion

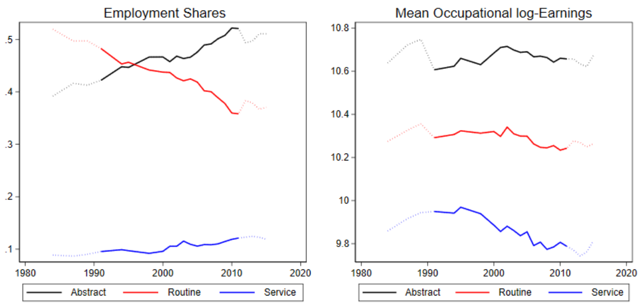
| georgia: 2016 - 2010 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00337** | -0.000250 | -0.00312*** |
| Specification Error | 5.00e-05 | 0 | -5.00e-05 |
| Composition Effect | | | |
| Occ | 0.00034** | -0.000130 | -0.00021** |
| Educ | 7.00e-05 | 5.00e-05 | -0.00012** |
| Female | -1.00e-05 | 0.00005** | -0.00004** |
| Age | 2.00e-05 | -1.00e-05 | -1.00e-05 |
| Ind | -5.00e-05 | 0.000180 | -0.000130 |
| Reweighting Error | 6.00e-05 | -3.00e-05 | -3.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000750 | 0.00248 | -0.00173 |
| Educ | -0.00247 | 0.00121 | 0.00126 |
| Female | -0.00179 | 0.000880 | 0.000910 |
| Age | -0.00117 | 0.00130 | -0.000130 |
| Ind | 0.00496 | 0.00412 | -0.00908* |
| _cons | 0.00412 | -0.01036* | 0.00624 |


Quantile RIF Decompostion

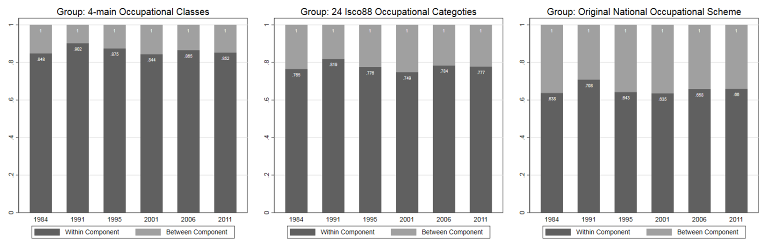



Occupational Classes Compostion and Returns

## Germany: 2011-1991

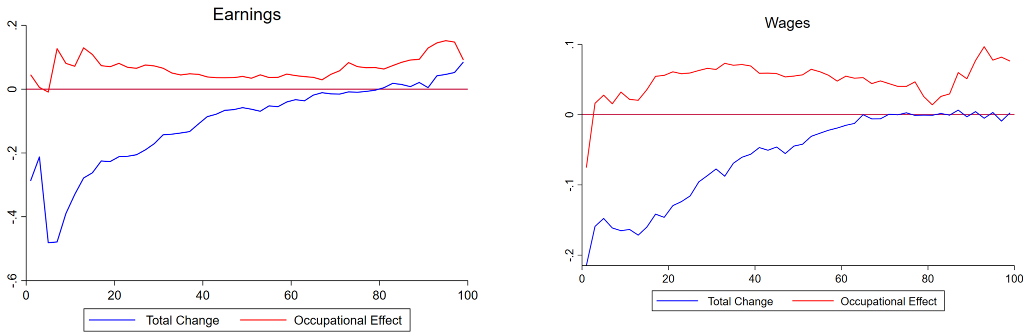



Employment and Income shares by Occupational Class

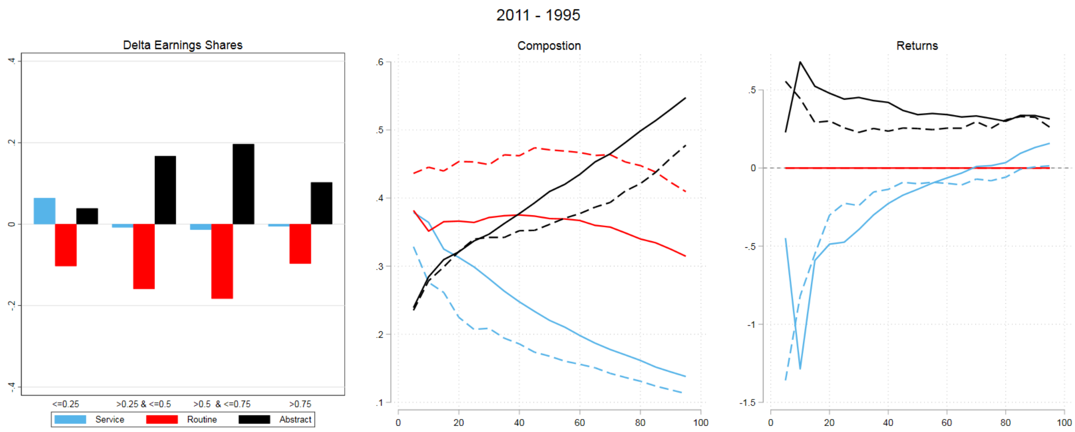



Theil Decompostion

| germany: 2011 - 1995 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| $\Delta$ | -0.00390*** | 0.00163** | 0.00227*** |
| Specification Error | 5.00e-05 | 5.00e-05 | -0.000100 |
| Composition Effect | | | |
| Occ | -0.000150 | 0 | 0.00014** |
| Educ | -2.00e-05 | -3.00e-05 | 4.00e-05 |
| Female | -6.00e-05 | 3.00e-05 | 3.00e-05 |
| Age | -0.00060*** | 0.00042** | 0.000180 |
| Ind | 2.00e-05 | 0 | -2.00e-05 |
| Reweighting Error | -0.00046** | 0.000190 | 0.00027** |
| Coefficent Effect | | | |
| Occ | 0.000270 | -0.000820 | 0.000550 |
| Educ | 0.000630 | -0.000590 | -4.00e-05 |
| Female | 0.000750 | -0.000680 | -7.00e-05 |
| Age | -2.00e-05 | -0.000560 | 0.000590 |
| Ind | -0.00482 | 0.00394 | 0.000890 |
| _cons | 0.000520 | -0.000330 | -0.000200 |

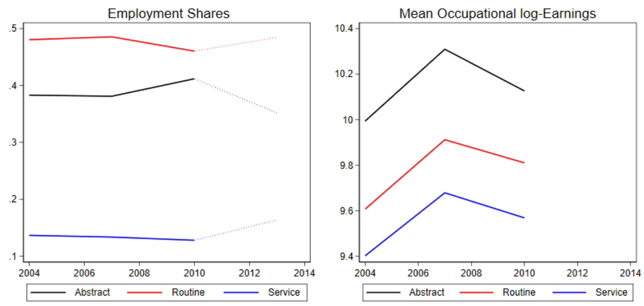



Quantile RIF Decompostion

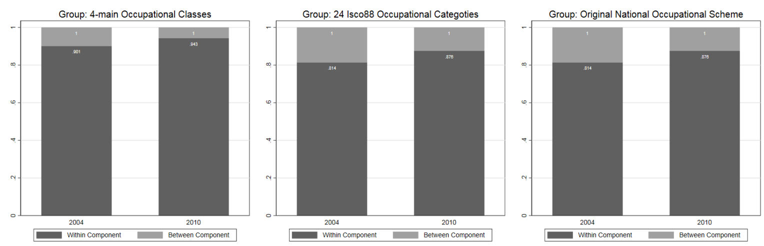



Occupational Classes Compostion and Returns

## Greece: 2010-2007

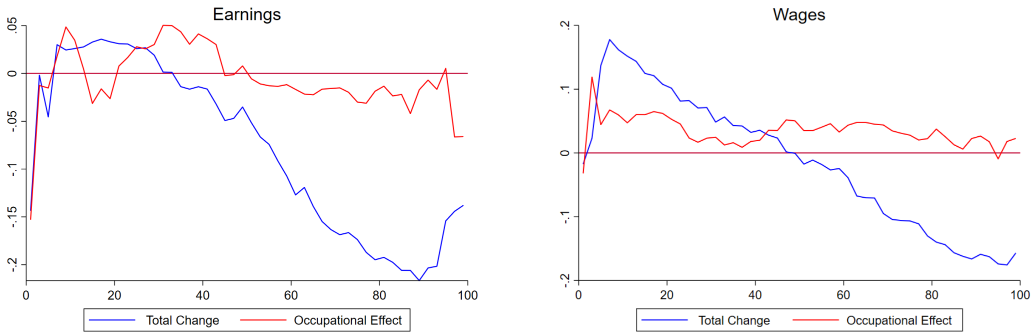



Employment and Income shares by Occupational Class

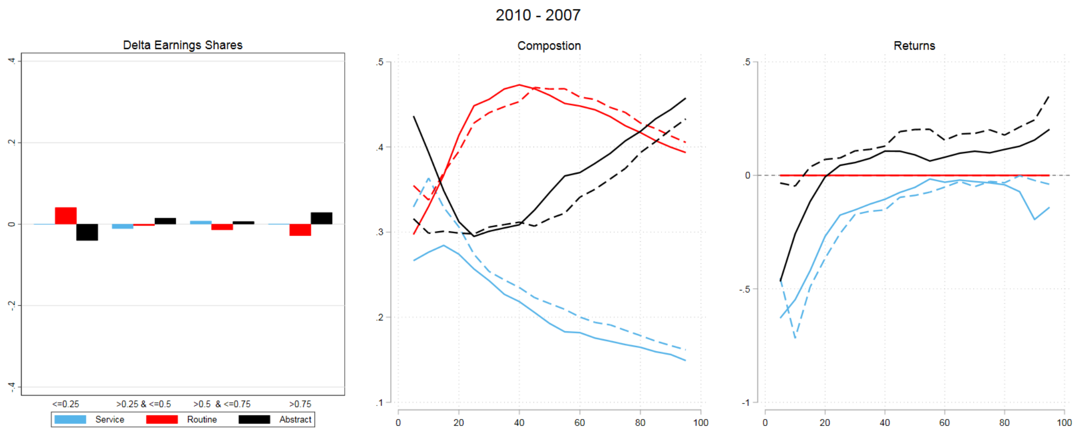



Theil Decompostion

| greece: 2010 - 2007 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000970 | 0.000550 | -0.00152*** |
| Specification Error | 2.00e-05 | 0 | -2.00e-05 |
| Composition Effect | | | |
| Occ | 5.00e-05 | -5.00e-05 | -1.00e-05 |
| Educ | 0.000130 | -7.00e-05 | -5.00e-05 |
| Female | -0.00003** | 0.00002* | 0.00001* |
| Age | -4.00e-05 | 0.00008** | -4.00e-05 |
| Ind | -0.00015* | 8.00e-05 | 7.00e-05 |
| Reweighting Error | 1.00e-05 | 1.00e-05 | -1.00e-05 |
| Coefficent Effect | | | |
| Occ | -7.00e-05 | 0.000460 | -0.000400 |
| Educ | 0.00110 | -0.000880 | -0.000220 |
| Female | -0.000200 | 0.000760 | -0.000550 |
| Age | 8.00e-05 | -0.00104 | 0.000960 |
| Ind | -0.00196 | 0.00773** | -0.00575 |
| _cons | 0.00203 | -0.00653* | 0.00449 |

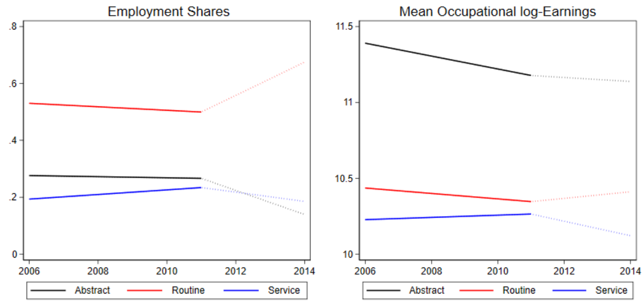



Quantile RIF Decompostion

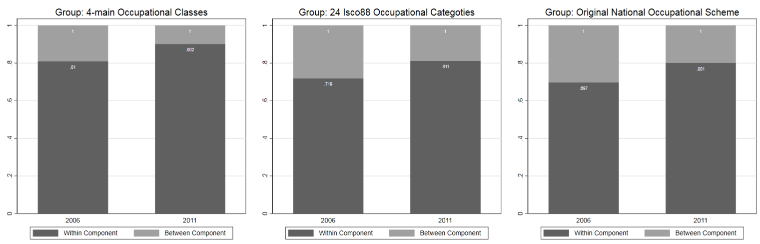



Occupational Classes Compostion and Returns

## Guatemala: 2011-2006

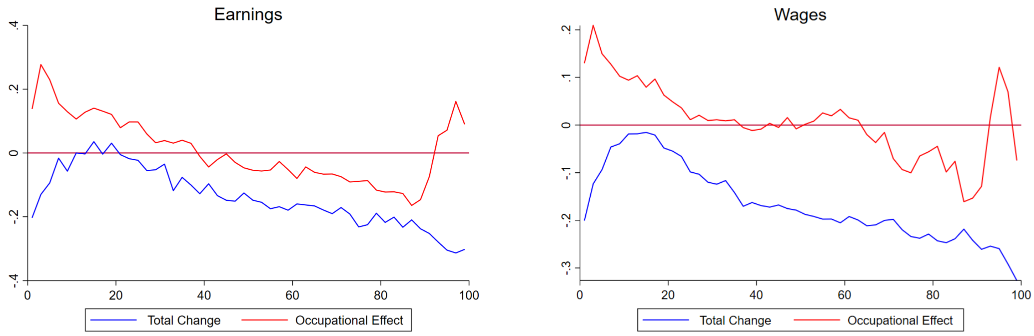



Employment and Income shares by Occupational Class

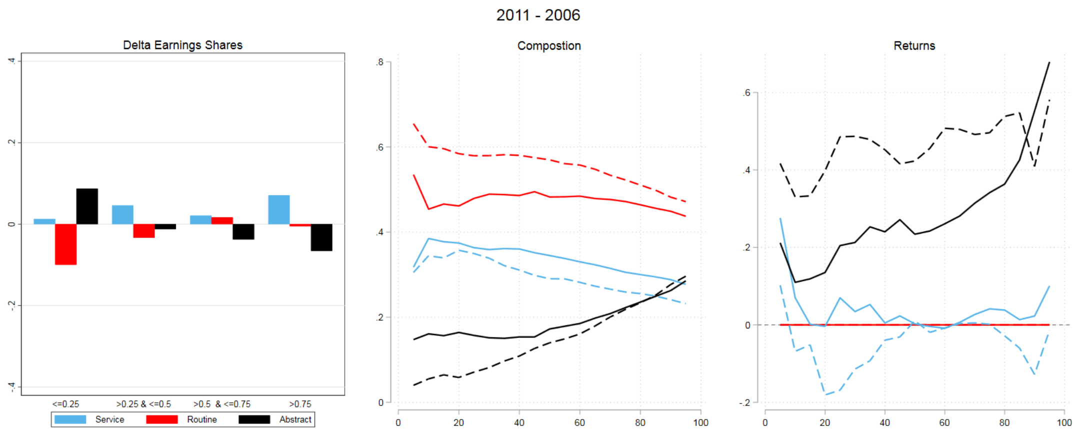



Theil Decompostion

| guatemala: 2011 - 2006 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000790 | 0.000770 | -0.00155*** |
| Specification Error | 1.00e-05 | -2.00e-05 | 1.00e-05 |
| Composition Effect | | | |
| Occ | 0 | -5.00e-05 | 4.00e-05 |
| Educ | 4.00e-05 | 0.000100 | -0.000140 |
| Female | 0.00031*** | -9.00e-05 | -0.00022*** |
| Age | 2.00e-05 | 2.00e-05 | -5.00e-05 |
| Ind | -0.00065*** | 0.000290 | 0.000360 |
| Reweighting Error | -0.00058*** | 0.000100 | 0.00049* |
| Coefficent Effect | | | |
| Occ | 0.00257 | -0.00214 | -0.000440 |
| Educ | -0.000590 | -0.000990 | 0.00158 |
| Female | -0.000730 | 0.000370 | 0.000350 |
| Age | -0.00243** | 0.000750 | 0.00169 |
| Ind | -0.000680 | -0.00342 | 0.00411 |
| _cons | 0.00350 | 0.00585 | -0.00935* |

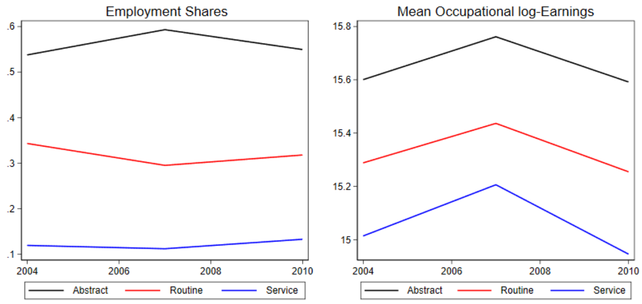



Quantile RIF Decompostion

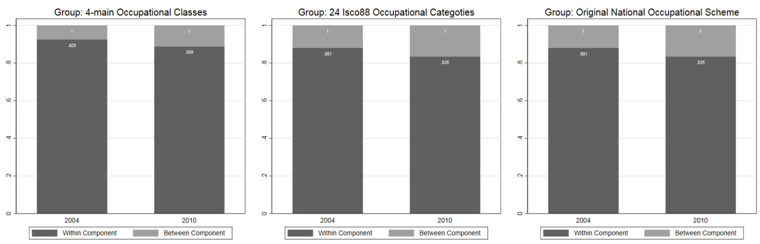



Occupational Classes Compostion and Returns

# Iceland: 2010-2004

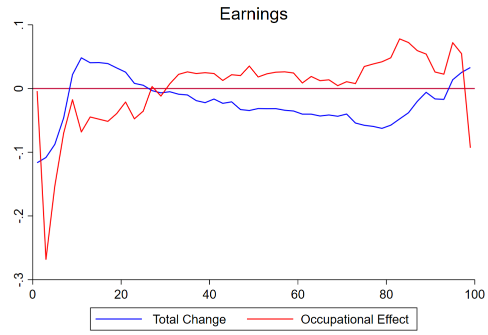



Employment and Income shares by Occupational Class



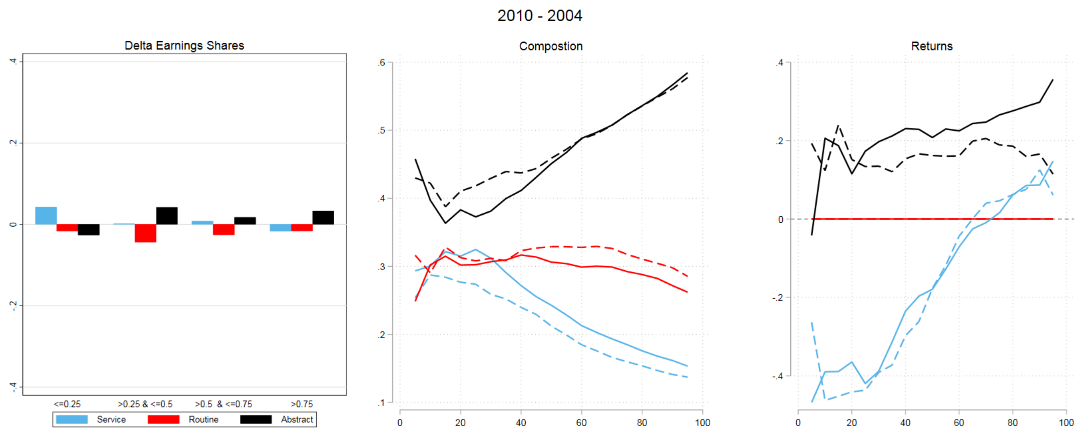

Theil Decompostion

| iceland: 2010 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -9.00e-05 | -0.000120 | 0.000210 |
| Specification Error | 2.00e-05 | 0 | -2.00e-05 |
| Composition Effect | | | |
| Occ | -5.00e-05 | -2.00e-05 | 0.00007*** |
| Educ | -7.00e-05 | 4.00e-05 | 3.00e-05 |
| Female | 0 | -1.00e-05 | 1.00e-05 |
| Age | 6.00e-05 | -2.00e-05 | -0.00004* |
| Ind | 0.000100 | -0.000110 | 1.00e-05 |
| Reweighting Error | 1.00e-05 | -1.00e-05 | 0 |
| Coefficent Effect | | | |
| Occ | -0.00113 | 0.000810 | 0.000320 |
| Educ | 0.000190 | 0.000140 | -0.000330 |
| Female | -0.000310 | 0.000250 | 6.00e-05 |
| Age | -0.00104 | -0.000310 | 0.00135* |
| Ind | 0.00453* | -0.00370 | -0.000830 |
| _cons | -0.00240 | 0.00281 | -0.000420 |



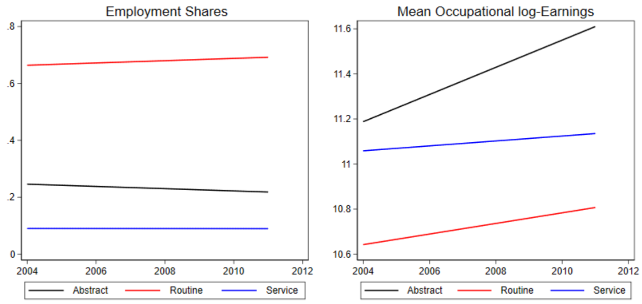

Appendix/Quantiles/Wages/iceland.png

Quantile RIF Decompostion

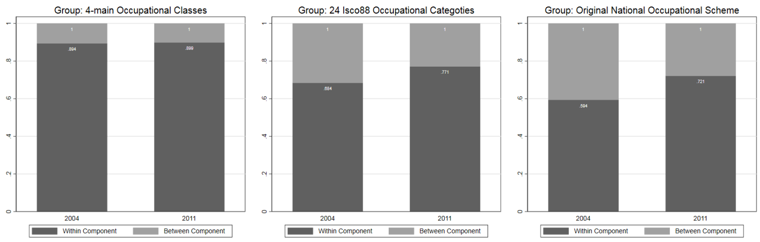



Occupational Classes Compostion and Returns

## India: 2011-2004



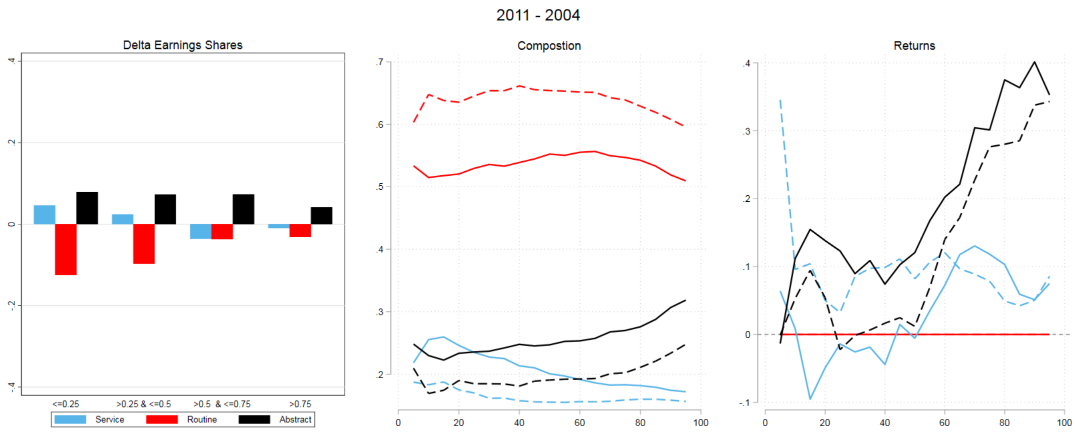

Employment and Income shares by Occupational Class




Theil Decompostion

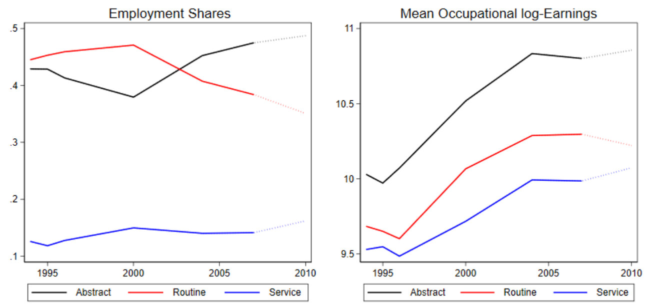
| india: 2011 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00426*** | 0.00461*** | -0.000350 |
| Specification Error | 7.00e-05 | -5.00e-05 | -2.00e-05 |
| Composition Effect | | | |
| Occ | 0 | 0.00028*** | -0.00028*** |
| Educ | -0.00011*** | 0 | 0.00011*** |
| Female | 0.00002** | 0.00011*** | -0.00012*** |
| Age | -0.00008*** | -0.00004** | 0.00012*** |
| Ind | 0.000130 | -5.00e-05 | -8.00e-05 |
| Reweighting Error | -1.00e-05 | -0.000160 | 0.000180 |
| Coefficent Effect | | | |
| Occ | 4.00e-05 | 0.00223 | -0.00227* |
| Educ | -0.000450 | 0.00355*** | -0.00310*** |
| Female | 0.000340 | 7.00e-05 | -0.00041*** |
| Age | -0.000900 | 0.000210 | 0.00069* |
| Ind | -0.00355* | 0.00460* | -0.00104 |
| _cons | 0.000260 | -0.00614** | 0.00588** |


Quantile RIF Decompostion

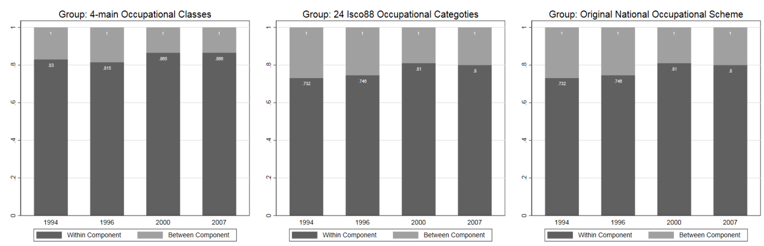



Occupational Classes Compostion and Returns

## Ireland: 2010-2004

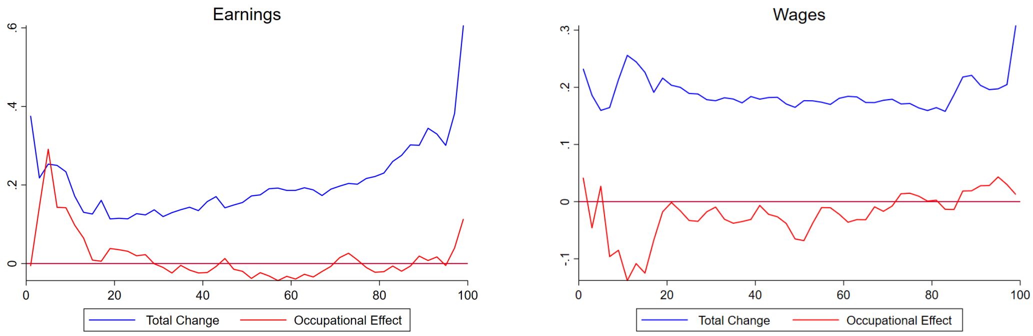



Employment and Income shares by Occupational Class

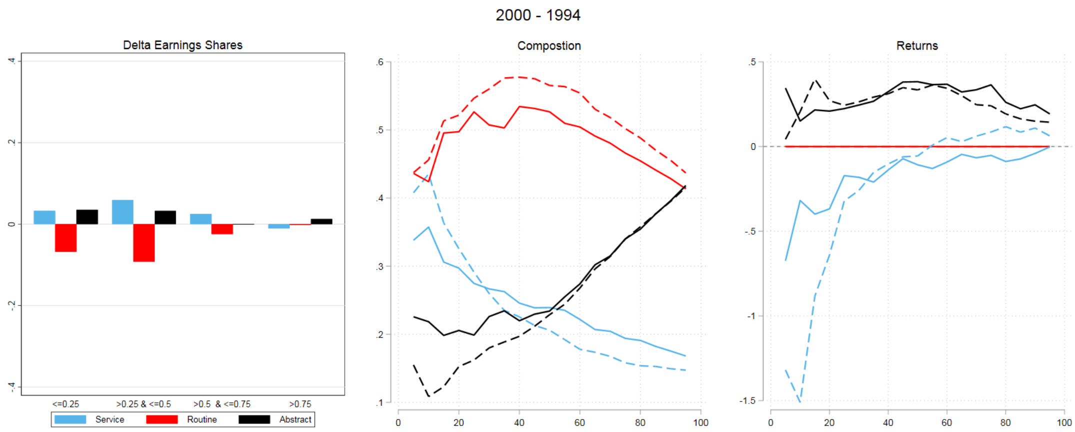



Theil Decompostion

| ireland: 2000 - 1994 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000690 | -0.00284*** | 0.00215*** |
| Specification Error | 4.00e-05 | -3.00e-05 | -1.00e-05 |
| Composition Effect | | | |
| Occ | -7.00e-05 | -6.00e-05 | 0.000130 |
| Educ | -0.000120 | 0.000120 | 0 |
| Female | 0.00030*** | -0.00014** | -0.00016*** |
| Age | -1.00e-05 | -7.00e-05 | 0.00008* |
| Ind | -0.00112** | 0.00050* | 0.00062*** |
| Reweighting Error | -0.000320 | 0.000170 | 0.000140 |
| Coefficent Effect | | | |
| Occ | 0.00144 | -0.00132 | -0.000120 |
| Educ | 0.00166 | -0.000570 | -0.00109 |
| Female | 0.00234* | -0.00183* | -0.000510 |
| Age | -0.00395 | 0.00334* | 0.000610 |
| Ind | -0.02253** | 0.0105 | 0.01202*** |
| _cons | 0.02304** | -0.01350* | -0.00956* |

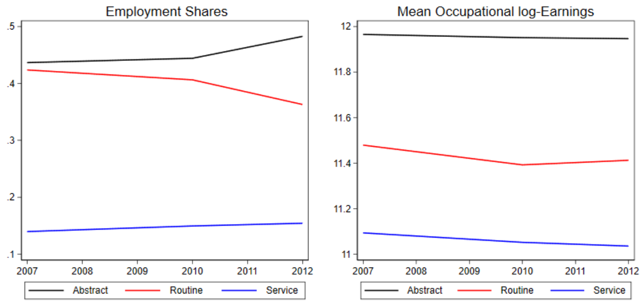



Quantile RIF Decompostion

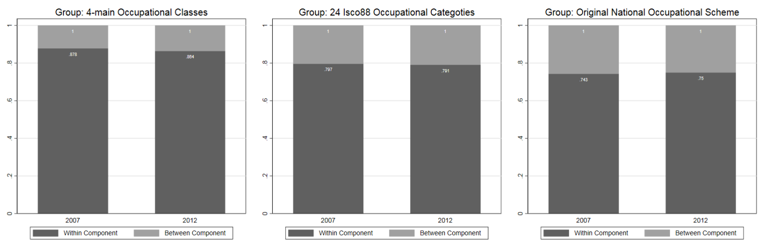



Occupational Classes Compostion and Returns

## Israel: 2012-2007

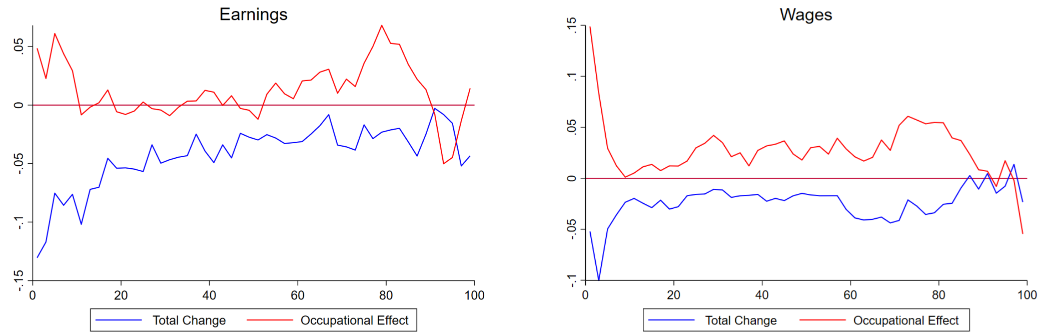



Employment and Income shares by Occupational Class

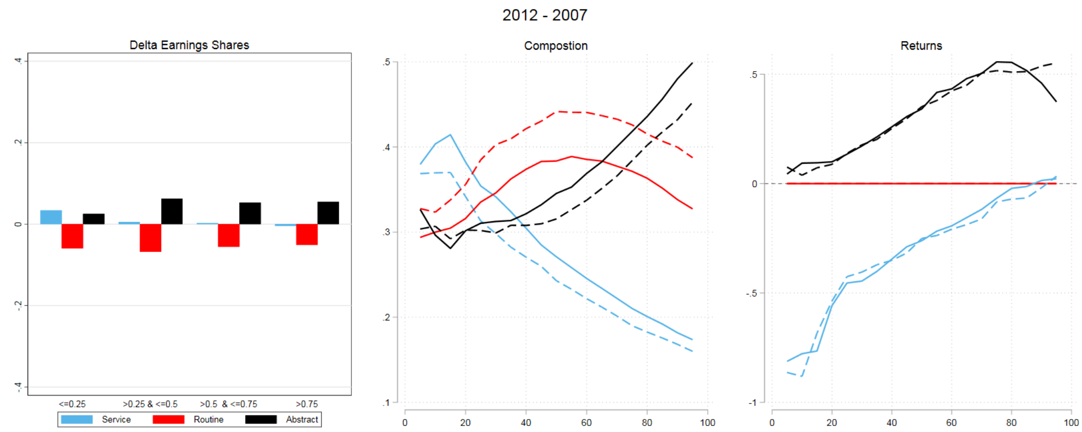



Theil Decompostion

| israel: 2012 - 2007 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00081* | 0.000590 | 0.000220 |
| Specification Error | 0 | 2.00e-05 | -2.00e-05 |
| Composition Effect | | | |
| Occ | -0.00021*** | 0.00007* | 0.00014*** |
| Educ | 4.00e-05 | 1.00e-05 | -0.00005** |
| Female | -1.00e-05 | 0 | 0 |
| Age | -2.00e-05 | 2.00e-05 | 0 |
| Ind | -4.00e-05 | 1.00e-05 | 0.00004* |
| Reweighting Error | -1.00e-05 | 0 | 0 |
| Coefficent Effect | | | |
| Occ | 0.000420 | -0.000100 | -0.000320 |
| Educ | 0.000590 | -0.000260 | -0.000340 |
| Female | 0.000120 | 0 | -0.000110 |
| Age | -0.000340 | 0.000510 | -0.000180 |
| Ind | -0.00492* | -7.00e-05 | 0.00499** |
| _cons | 0.00356 | 0.000370 | -0.00393* |

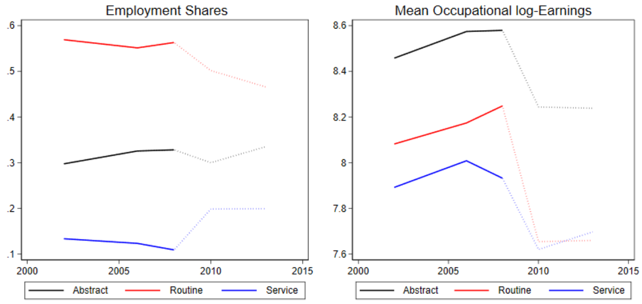



Quantile RIF Decompostion

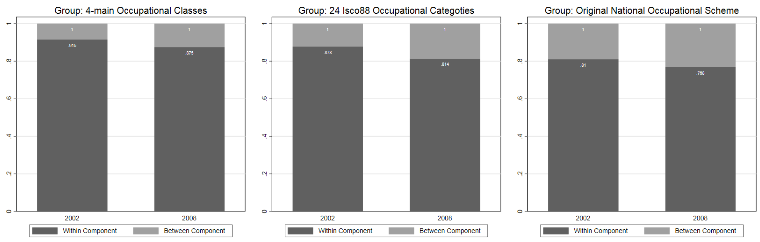



Occupational Classes Compostion and Returns

# Jordan: 2008-2002




Employment and Income shares by Occupational Class



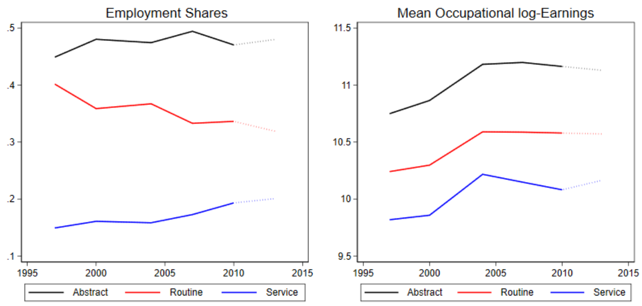

Theil Decompostion

| jordan: 2008 - 2002 | | | |
|---|---|---|---|
| | <15 | >85 | 15-85 |
| Δ | 0.0074*** | -0.0022* | -0.0052*** |
| Specification Error | -0.000100 | -0.000200 | 0.000300 |
| Composition Effect | | | |
| Occ | 0.000300 | 0 | -0.000300 |
| Educ | -0.000100 | 0.0002*** | -0.000100 |
| Female | 0 | 0 | 0 |
| Age | 0 | 0 | -0.000100 |
| Ind | -0.000300 | 0.0002* | 0.000100 |
| Reweighting Error | 0.000400 | 0 | -0.000400 |
| Coefficent Effect | | | |
| Occ | -0.000400 | -0.000300 | 0.000700 |
| Educ | 0.00120 | -0.00220 | 0.00100 |
| Female | -0.000100 | 0 | 0 |
| Age | 0.00110 | -0.00120 | 0.000100 |
| Ind | 0.000300 | -0.000400 | 0.000100 |
| _cons | 0.00510 | 0.00160 | -0.00670 |

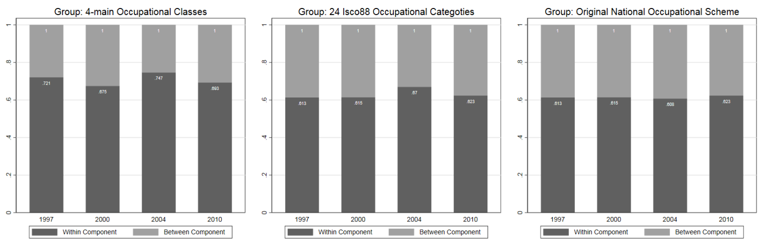

Quantile RIF Decompostion


Occupational Classes Compostion and Returns

# Luxembourg: 2010-2004

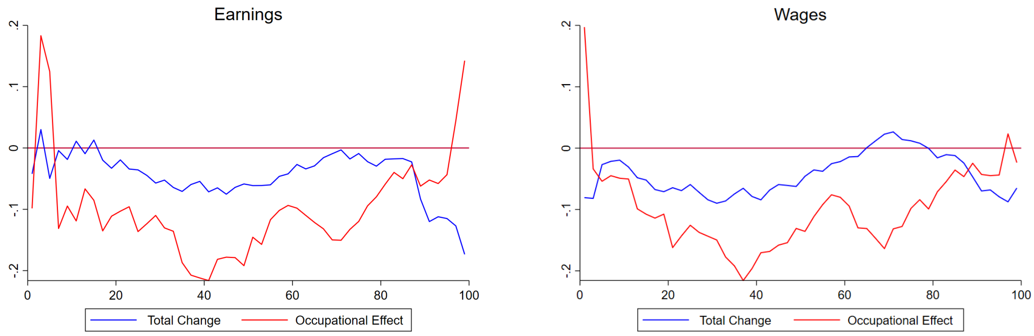



Employment and Income shares by Occupational Class

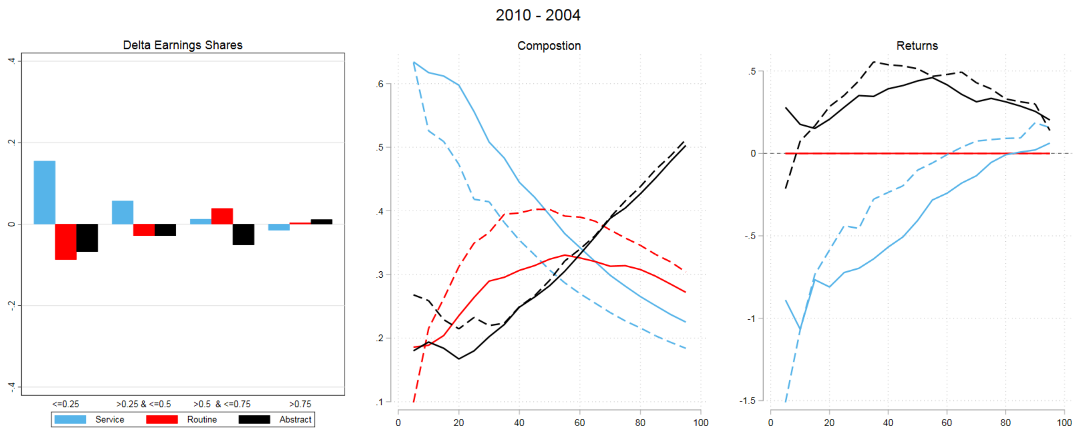



Theil Decompostion

| luxembourg: 2010 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000460 | 0.000210 | -0.000660 |
| Specification Error | 3.00e-05 | 2.00e-05 | -5.00e-05 |
| Composition Effect | | | |
| Occ | -0.00033*** | 0.00012* | 0.00021*** |
| Educ | -1.00e-05 | 6.00e-05 | -5.00e-05 |
| Female | 3.00e-05 | -2.00e-05 | -1.00e-05 |
| Age | 2.00e-05 | -2.00e-05 | 1.00e-05 |
| Ind | 0.00026* | -0.000180 | -8.00e-05 |
| Reweighting Error | -0.000290 | 0.000150 | 0.000140 |
| Coefficent Effect | | | |
| Occ | 0.00127 | -0.00215* | 0.000880 |
| Educ | -0.000170 | 0.000440 | -0.000270 |
| Female | 0.000560 | -0.000380 | -0.000180 |
| Age | -0.000570 | -0.000160 | 0.000720 |
| Ind | -2.00e-05 | -0.000500 | 0.000520 |
| _cons | -0.000310 | 0.00282 | -0.00251 |

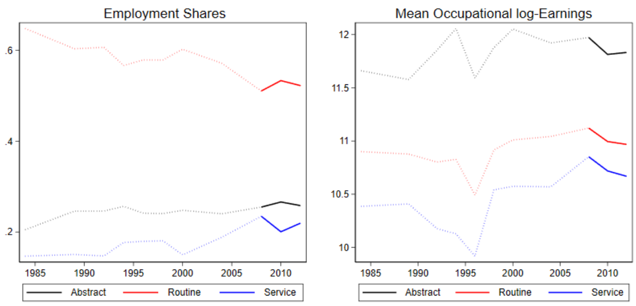



Quantile RIF Decompostion

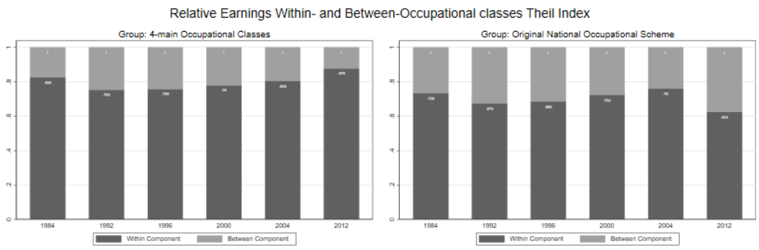



Occupational Classes Compostion and Returns

## Mexico: 2012-1992

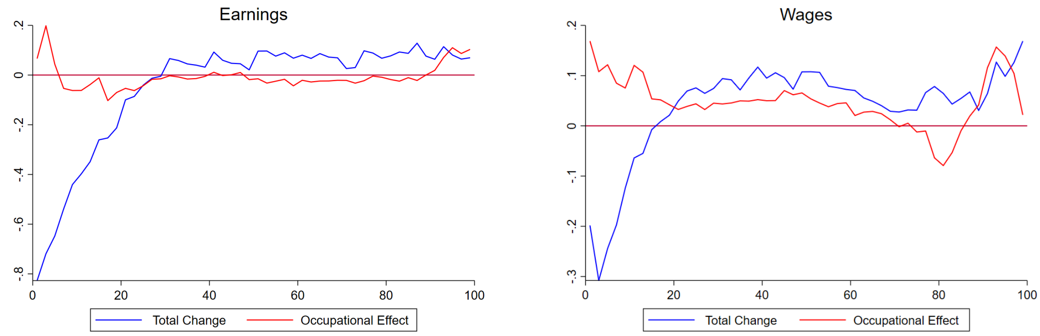



Employment and Income shares by Occupational Class

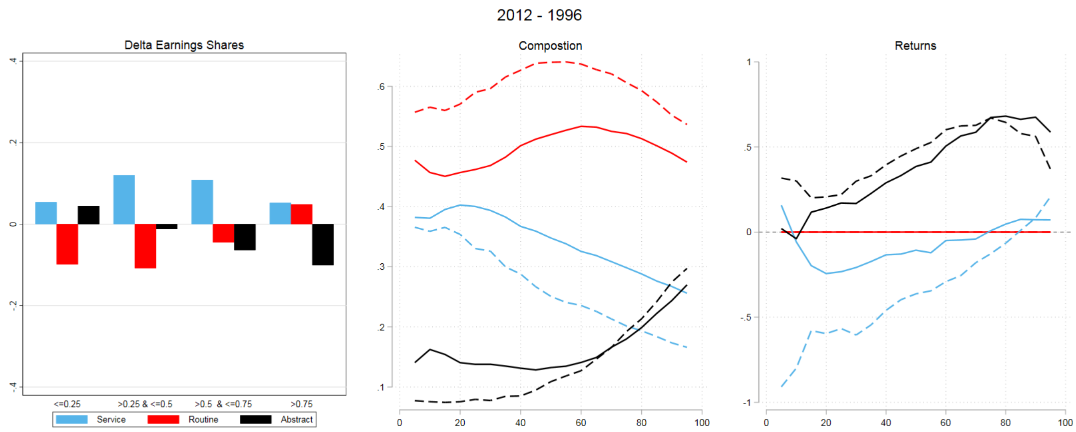



Theil Decompostion

| mexico: 2012 - 1996 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00701*** | 0.00512*** | 0.00189*** |
| Specification Error | 6.00e-05 | -5.00e-05 | 0 |
| Composition Effect | | | |
| Occ | -0.00023*** | -0.00021*** | 0.00044*** |
| Educ | -0.00024*** | -0.00021*** | 0.00045*** |
| Female | -0.00005** | 0.00004** | 1.00e-05 |
| Age | -0.00034*** | 6.00e-05 | 0.00028*** |
| Ind | 0.00011*** | 0.00010*** | -0.00020*** |
| Reweighting Error | -0.000260 | 0.00026** | 0 |
| Coefficent Effect | | | |
| Occ | 0.000450 | -0.000740 | 0.000290 |
| Educ | -0.00304*** | 0.00229* | 0.000750 |
| Female | -0.00338*** | 0.000810 | 0.00258*** |
| Age | -0.00168 | 0.00159 | 9.00e-05 |
| Ind | -0.00170 | -0.000320 | 0.00202** |
| _cons | 0.00331 | 0.00149 | -0.00481** |

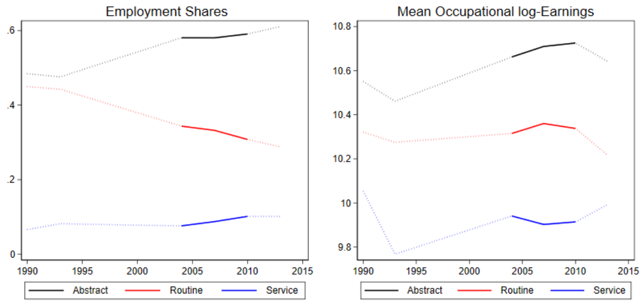



Quantile RIF Decompostion

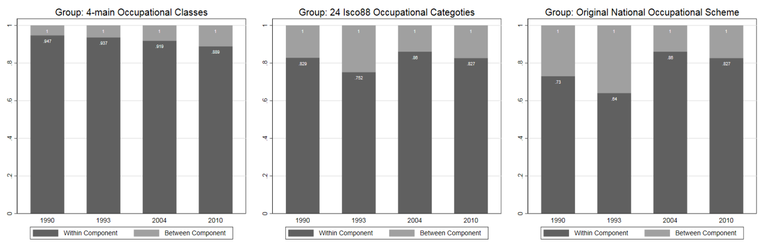



Occupational Classes Compostion and Returns

## Netherlands: 2010-1990

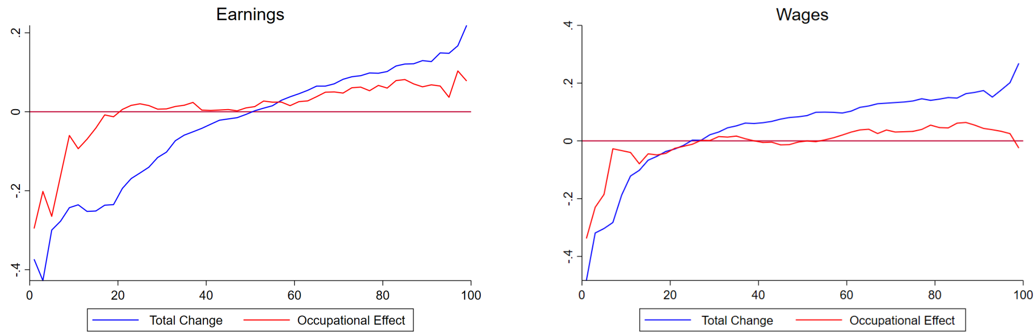



Employment and Income shares by Occupational Class

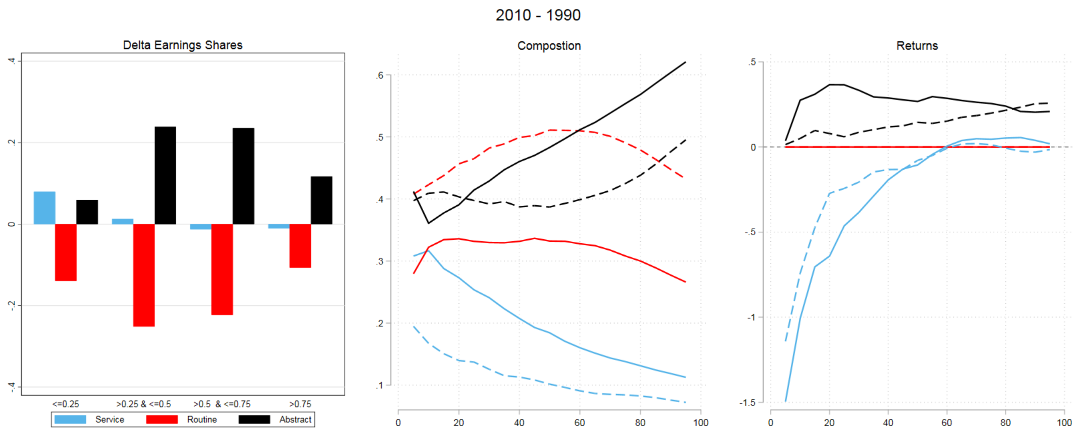



Theil Decompostion

| netherlands: 2010 - 1990 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00382*** | 0.00112 | 0.00270*** |
| Specification Error | 0.000140 | 0.000200 | -0.00035* |
| Composition Effect | | | |
| Occ | -0.000370 | 0.000140 | 0.00023* |
| Educ | 0.000170 | -0.000260 | 9.00e-05 |
| Female | 0.00019** | -0.00011* | -0.00008** |
| Age | -0.00058*** | 0.00030* | 0.00028*** |
| Ind | 0.000240 | -0.000100 | -0.000150 |
| Reweighting Error | -0.00242*** | 0.00134*** | 0.00108*** |
| Coefficent Effect | | | |
| Occ | -0.00192 | 0.00125 | 0.000670 |
| Educ | -0.00152 | 0.00137 | 0.000150 |
| Female | 0.00503*** | -0.00357*** | -0.00146*** |
| Age | -0.00197 | 0.00217 | -0.000200 |
| Ind | 0.00605 | -0.00371 | -0.00234 |
| _cons | -0.00686 | 0.00209 | 0.00477* |

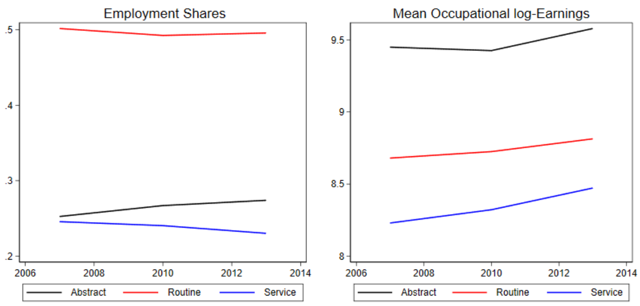



Quantile RIF Decompostion

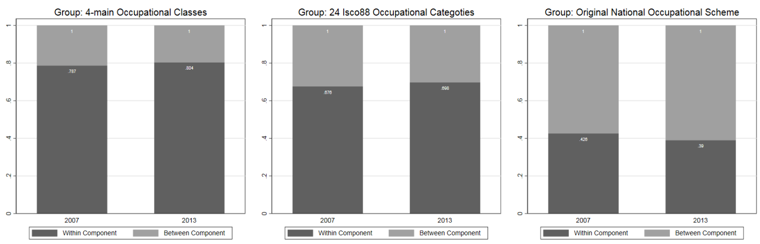



Occupational Classes Compostion and Returns

## Panama: 2013-2007



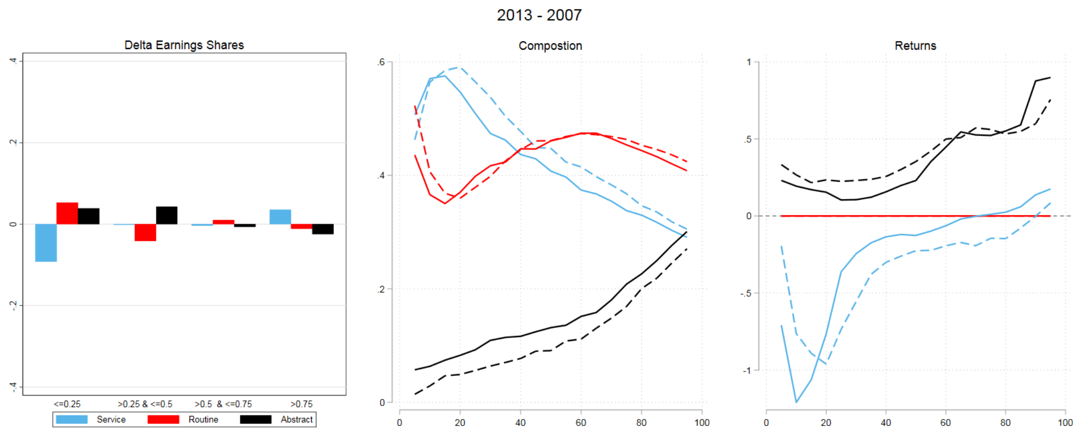

Employment and Income shares by Occupational Class




Theil Decompostion

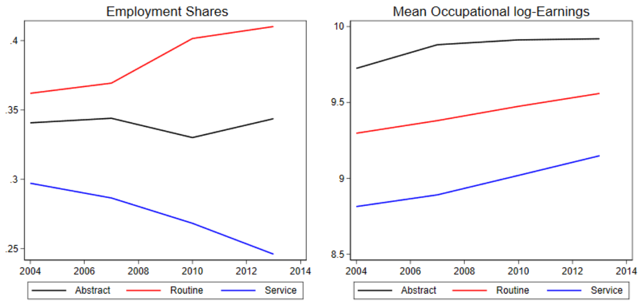
| panama: 2013 - 2007 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000780 | 0.000480 | -0.00126** |
| Specification Error | 0.00027*** | -0.000110 | -0.00016** |
| Composition Effect | | | |
| Occ | 0.00022** | 0.00013* | -0.00035*** |
| Educ | 5.00e-05 | -0.00034*** | 0.00029*** |
| Female | -0.00003** | 0.00001** | 0.00002** |
| Age | -0.00004* | -1.00e-05 | 0.00006*** |
| Ind | 0.00025** | 6.00e-05 | -0.00031*** |
| Reweighting Error | -0.000180 | 9.00e-05 | 9.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.00193** | 0.000260 | 0.00167** |
| Educ | -1.00e-05 | 0.000470 | -0.000460 |
| Female | 0.000110 | 0.000770 | -0.00089* |
| Age | 0.00100 | -0.000130 | -0.000880 |
| Ind | 0.00662 | -0.00611* | -0.000510 |
| _cons | -0.00558 | 0.00540 | 0.000180 |


Quantile RIF Decompostion

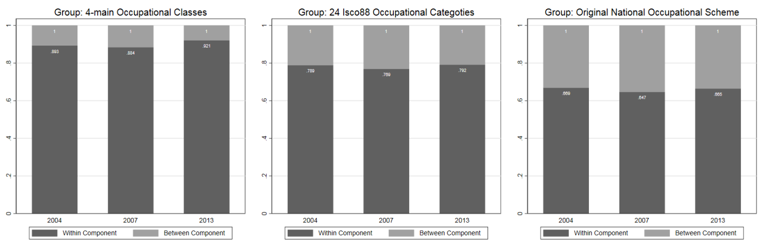



Occupational Classes Compostion and Returns

# Peru: 2013-2004

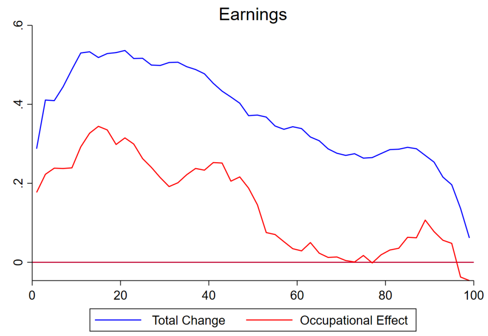



Employment and Income shares by Occupational Class

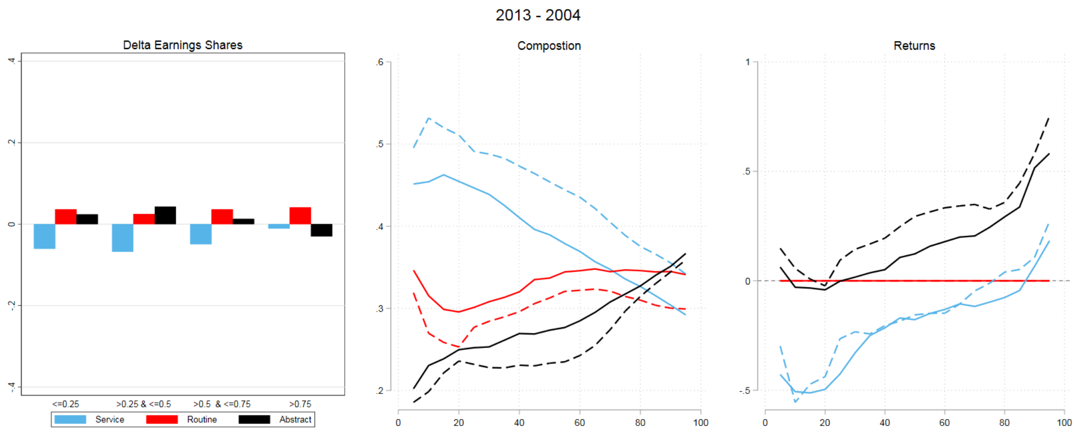



Theil Decompostion

| peru: 2013 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00260*** | 0.00115** | -0.00375*** |
| Specification Error | 0.00031** | -0.00026** | -5.00e-05 |
| Composition Effect | | | |
| Occ | 0.00084*** | 0.000240 | -0.00108*** |
| Educ | 5.00e-05 | 1.00e-05 | -6.00e-05 |
| Female | 0.00008*** | -0.00002* | -0.00006*** |
| Age | -0.00015*** | -6.00e-05 | 0.00021*** |
| Ind | 6.00e-05 | -5.00e-05 | -1.00e-05 |
| Reweighting Error | -0.00049*** | 0.00020* | 0.00029* |
| Coefficent Effect | | | |
| Occ | 0.00164* | -0.000570 | -0.00108 |
| Educ | -0.000500 | 0.000850 | -0.000340 |
| Female | -0.000360 | -6.00e-05 | 0.000420 |
| Age | 0.000630 | 0.000960 | -0.00160* |
| Ind | 0.00137 | -0.00427** | 0.00290 |
| _cons | -0.000880 | 0.00418* | -0.00329 |

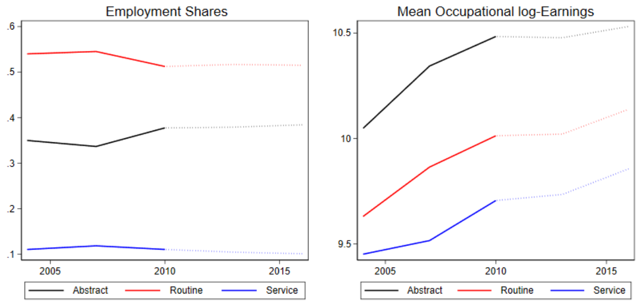



Quantile RIF Decompostion

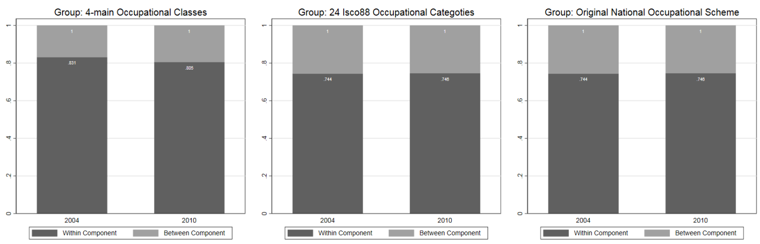



Occupational Classes Compostion and Returns

# Poland: 2010-2004



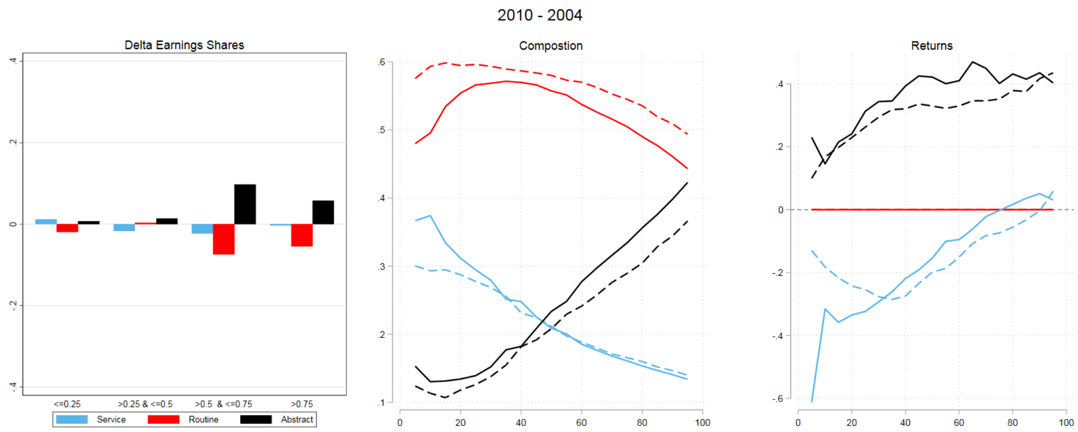

Employment and Income shares by Occupational Class




Theil Decompostion

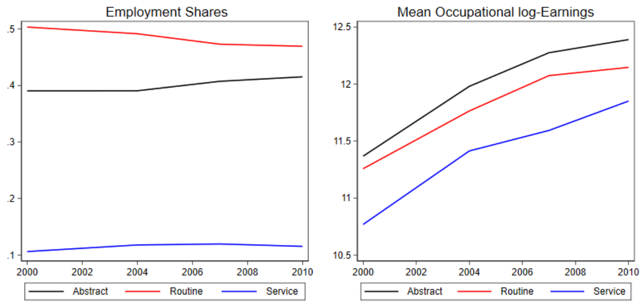
| poland: 2010 - 2004 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00148*** | 0.00130*** | 0.000180 |
| Specification Error | 0 | 5.00e-05 | -5.00e-05 |
| Composition Effect | | | |
| Occ | -0.00008*** | 0.00010*** | -0.00002** |
| Educ | -0.00020*** | -2.00e-05 | 0.00022*** |
| Female | -0.00002*** | 0.00002*** | 0 |
| Age | -0.00001* | -2.00e-05 | 0.00003*** |
| Ind | -3.00e-05 | -0.00008*** | 0.00011*** |
| Reweighting Error | -0.00016** | 1.00e-05 | 0.00014* |
| Coefficent Effect | | | |
| Occ | -0.00059*** | 0.00035* | 0.000240 |
| Educ | 0.000170 | -1.00e-05 | -0.000160 |
| Female | -8.00e-05 | 7.00e-05 | 1.00e-05 |
| Age | -0.000100 | 0.000310 | -0.000210 |
| Ind | -0.000800 | 0.00195 | -0.00115 |
| _cons | 0.000430 | -0.00145 | 0.00102 |


Quantile RIF Decompostion

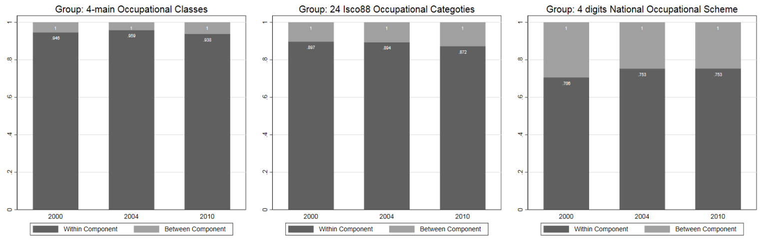



Occupational Classes Compostion and Returns

# Russia: 2010-2000

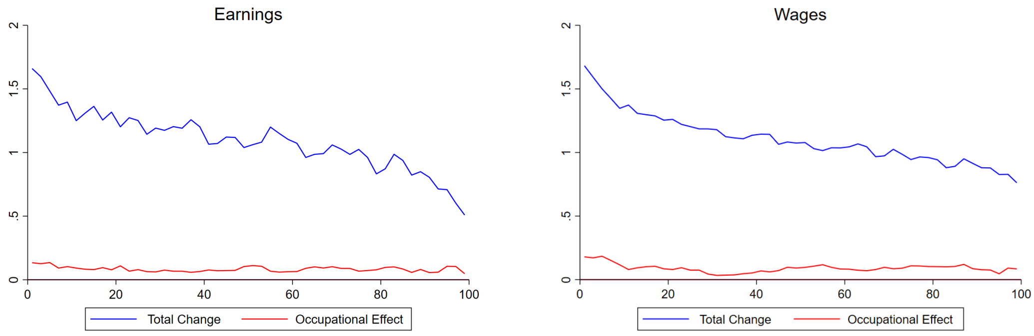



Employment and Income shares by Occupational Class

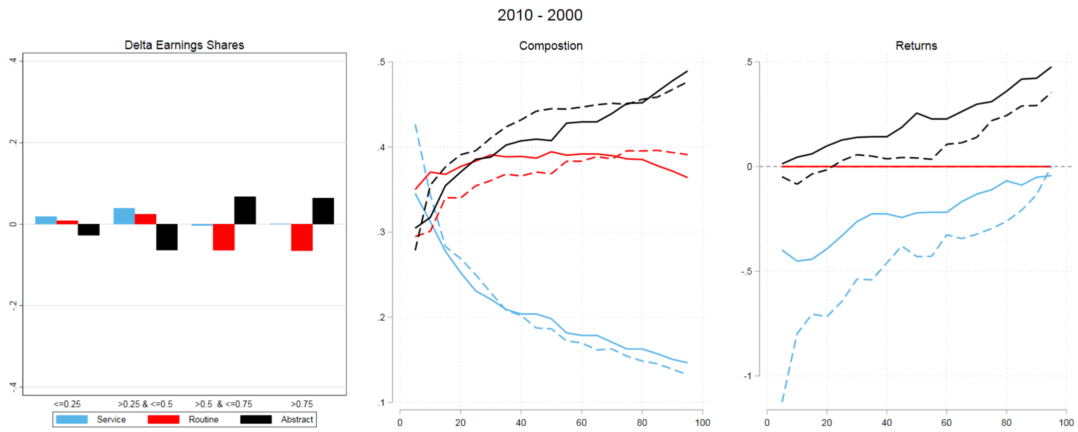



Theil Decompostion

| russia: 2010 - 2000 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00609*** | 7.00e-05 | -0.00615*** |
| Specification Error | 3.00e-05 | -1.00e-05 | -1.00e-05 |
| Composition Effect | | | |
| Occ | 9.00e-05 | -5.00e-05 | -4.00e-05 |
| Educ | 0.00012** | 6.00e-05 | -0.00017*** |
| Female | 0.00003* | -0.00004* | 1.00e-05 |
| Age | 0.000110 | -5.00e-05 | -6.00e-05 |
| Reweighting Error | 2.00e-05 | 0 | -2.00e-05 |
| Coefficent Effect | | | |
| Occ | 0.000540 | -0.000220 | -0.000330 |
| Educ | -0.000930 | 7.00e-05 | 0.000860 |
| Female | -0.000480 | 0.000600 | -0.000120 |
| Age | -0.00134 | 1.00e-05 | 0.00133 |
| _cons | 0.00789*** | -0.000300 | -0.00759*** |

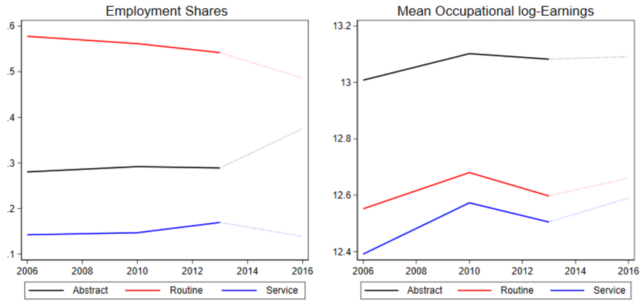



Quantile RIF Decompostion

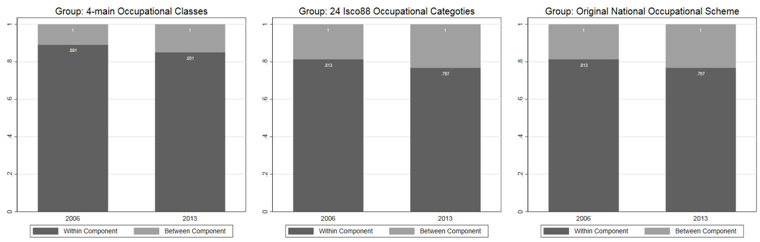



Occupational Classes Compostion and Returns

## Serbia: 2013-2006

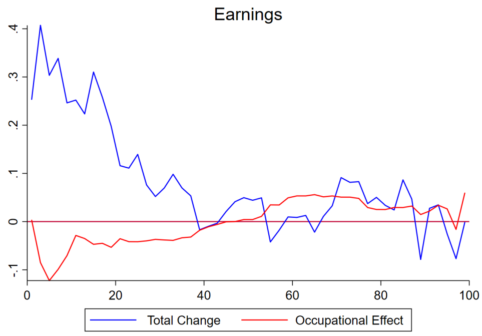



Employment and Income shares by Occupational Class

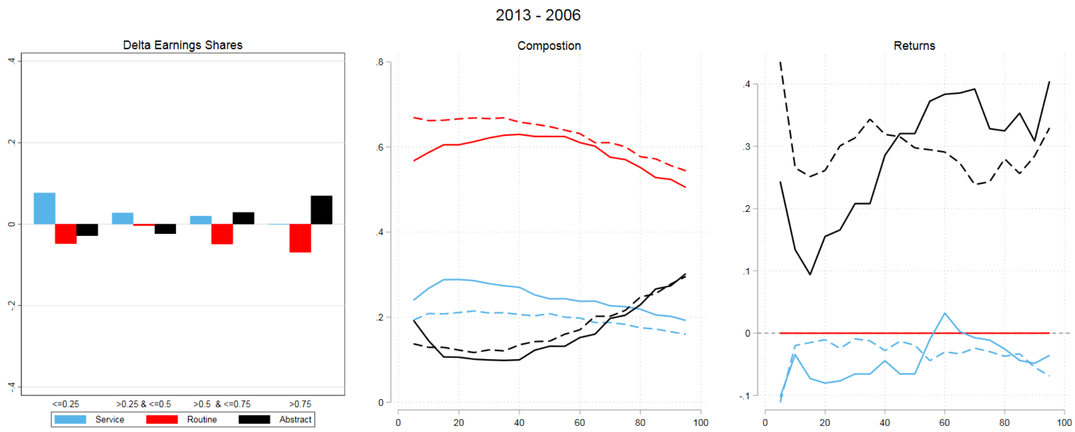



Theil Decompostion

| serbia: 2013 - 2006 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00262*** | -0.00141*** | -0.00122*** |
| Specification Error | 0 | 2.00e-05 | -1.00e-05 |
| Composition Effect | | | |
| Occ | -0.00006* | 4.00e-05 | 2.00e-05 |
| Educ | -0.00012** | 4.00e-05 | 0.00008** |
| Female | 1.00e-05 | 0 | 0 |
| Age | 3.00e-05 | -2.00e-05 | 0 |
| Reweighting Error | 1.00e-05 | -1.00e-05 | 0 |
| Coefficent Effect | | | |
| Occ | -0.00091* | 0.00068* | 0.000230 |
| Educ | 0.000290 | 0.000380 | -0.00067* |
| Female | 7.00e-05 | -0.000240 | 0.000170 |
| Age | -0.000270 | 0.000480 | -0.000210 |
| _cons | 0.00359** | -0.00277** | -0.000820 |

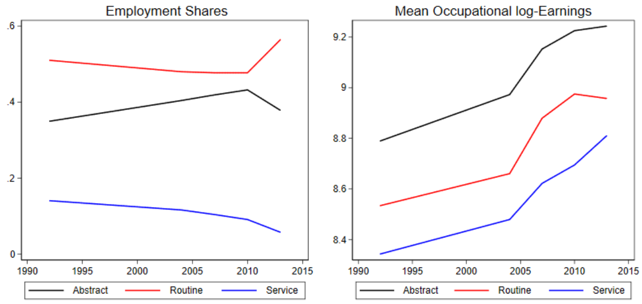



Quantile RIF Decompostion

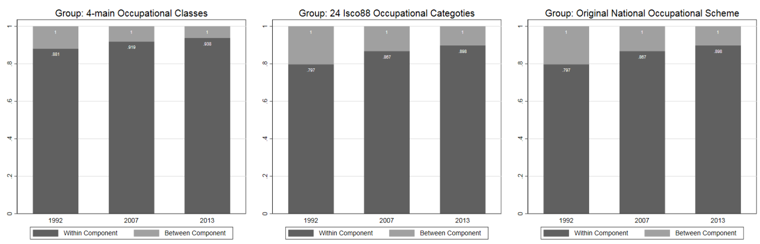



Occupational Classes Compostion and Returns

## Slovakia: 2013-1992



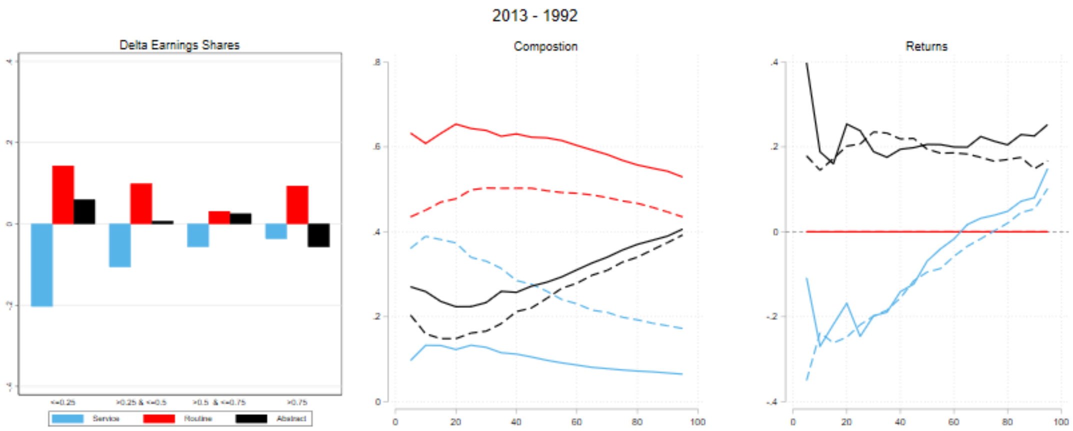

Employment and Income shares by Occupational Class




Theil Decompostion

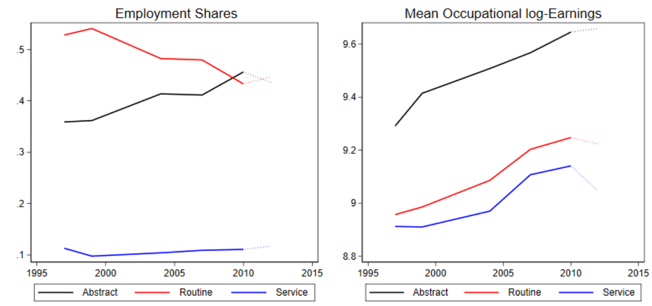
| slovakia: 2013 - 1992 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00181** | 0.000120 | 0.00169*** |
| Specification Error | 0.00025*** | 2.00e-05 | -0.00027*** |
| Composition Effect | | | |
| Occ | 0.00042*** | -5.00e-05 | -0.00036*** |
| Educ | -0.00032*** | 0 | 0.00031*** |
| Female | 1.00e-05 | 0.00005*** | -0.00006*** |
| Age | 3.00e-05 | 1.00e-05 | -0.00003* |
| Reweighting Error | -0.00012** | 1.00e-05 | 0.00011*** |
| Coefficent Effect | | | |
| Occ | -0.000260 | -0.000290 | 0.000540 |
| Educ | 0.000130 | -0.000110 | -3.00e-05 |
| Female | 0.000940 | -0.000510 | -0.000430 |
| Age | 0.000610 | -0.000260 | -0.000350 |
| _cons | -0.00349* | 0.00123 | 0.00226* |


Quantile RIF Decompostion

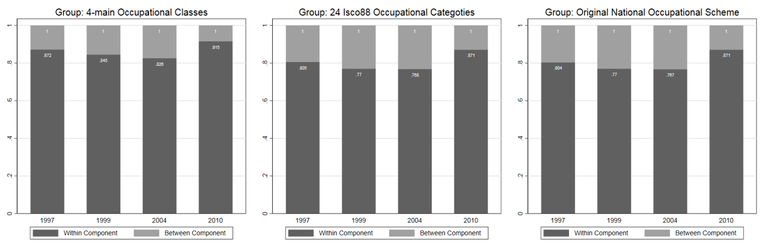



Occupational Classes Compostion and Returns

## Slovenia: 2010-1997

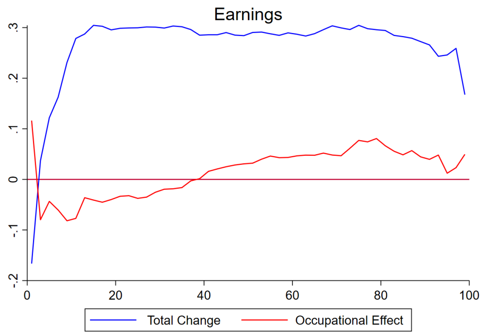



Employment and Income shares by Occupational Class

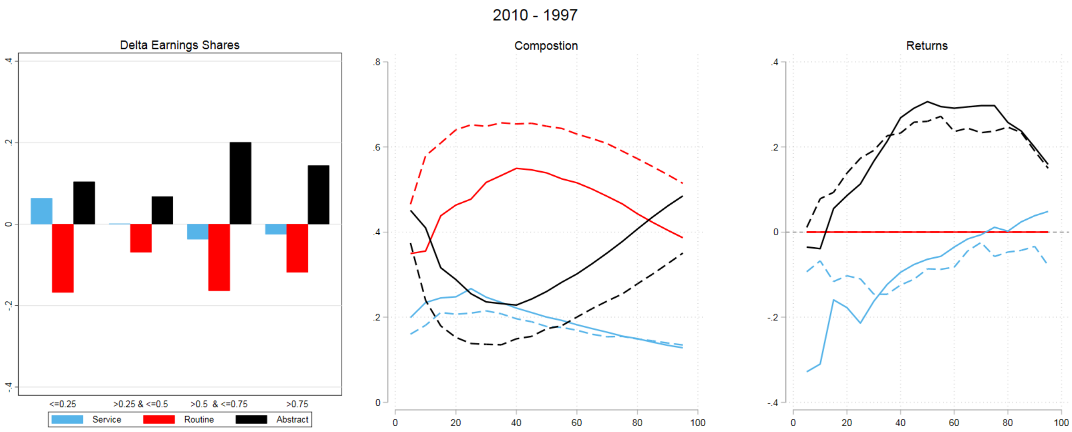



Theil Decompostion

| slovenia: 2010 - 1997 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.00171*** | 0.00222*** | -0.000510 |
| Specification Error | 0.00028* | 0.000130 | -0.00040** |
| Composition Effect | | | |
| Occ | -0.00024* | 0.00023** | 1.00e-05 |
| Educ | -0.00061*** | 9.00e-05 | 0.00051*** |
| Female | 0.00009** | -0.00005* | -0.00003* |
| Age | -9.00e-05 | -3.00e-05 | 0.000110 |
| Ind | -0.00029** | 0.00029** | 0 |
| Reweighting Error | -6.00e-05 | 5.00e-05 | 1.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000740 | 0.000360 | 0.000380 |
| Educ | 0.00118 | -0.000610 | -0.000570 |
| Female | 0.000660 | -0.000440 | -0.000220 |
| Age | 0.00121 | -0.00108 | -0.000130 |
| Ind | 0.02084* | -0.01453* | -0.00632* |
| _cons | -0.02394** | 0.01781* | 0.00614 |

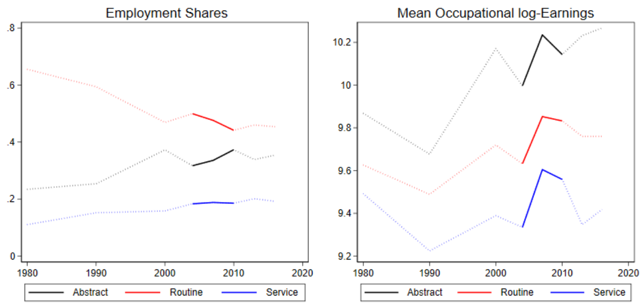



Quantile RIF Decompostion

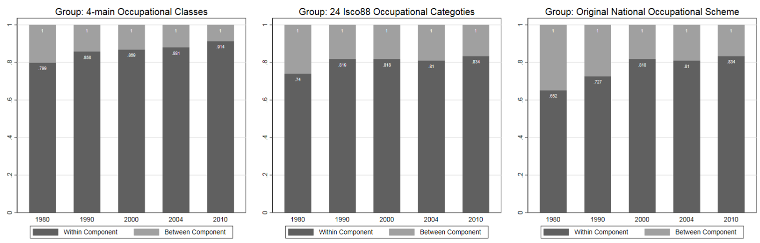



Occupational Classes Compostion and Returns

## Spain: 2004-1990



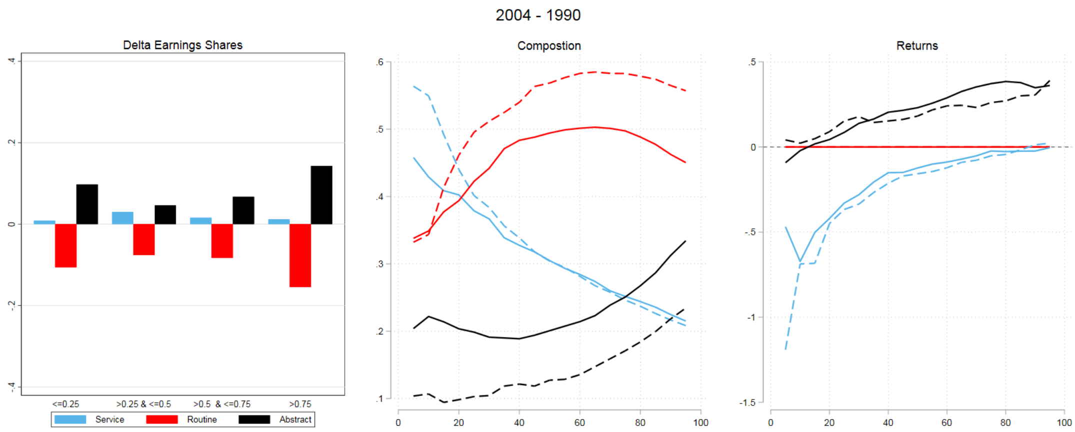

Employment and Income shares by Occupational Class




Theil Decompostion

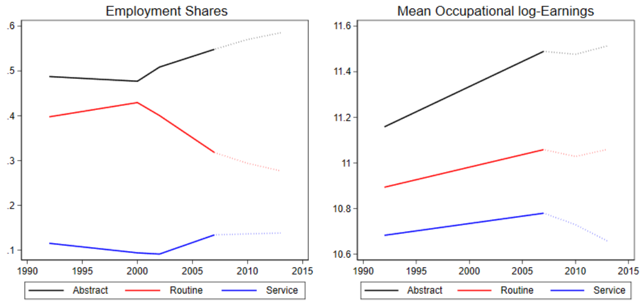
| spain: 2004 - 1990 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | -0.000450 | -0.00073* | 0.00118*** |
| Specification Error | 2.00e-05 | -4.00e-05 | 2.00e-05 |
| Composition Effect | | | |
| Occ | 0.00037*** | -0.00008*** | -0.00029*** |
| Educ | -0.00011*** | -0.00002*** | 0.00012*** |
| Female | 0.00065*** | -0.00025*** | -0.00039*** |
| Age | -1.00e-05 | 0.00004** | -0.00002** |
| Ind | 0.00016*** | -0.00096*** | 0.00080*** |
| Reweighting Error | -0.00144*** | 0.00158*** | -0.00013* |
| Coefficent Effect | | | |
| Occ | 0.00011*** | -0.00020*** | 0.00009*** |
| Educ | 0.00029*** | -0.00011*** | -0.00018*** |
| Female | 0.00135*** | -0.00068*** | -0.00068*** |
| Age | -0.00125*** | 0.00089*** | 0.00035*** |
| Ind | 0.00271*** | 0.00249*** | -0.00520*** |
| _cons | -0.00331 | -0.00339 | 0.00670 |


Quantile RIF Decompostion

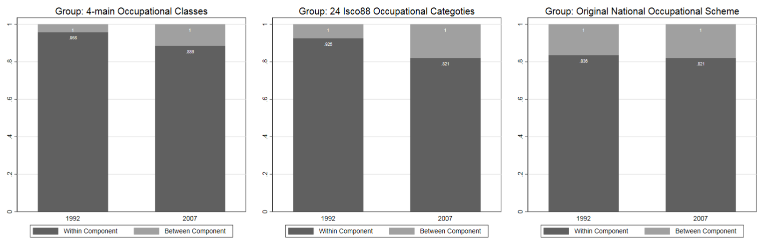



Occupational Classes Compostion and Returns

# Switzerland: 2007-1992

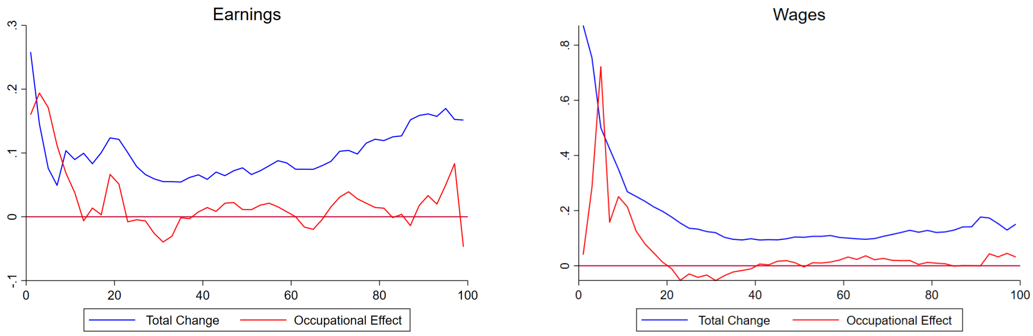



Employment and Income shares by Occupational Class

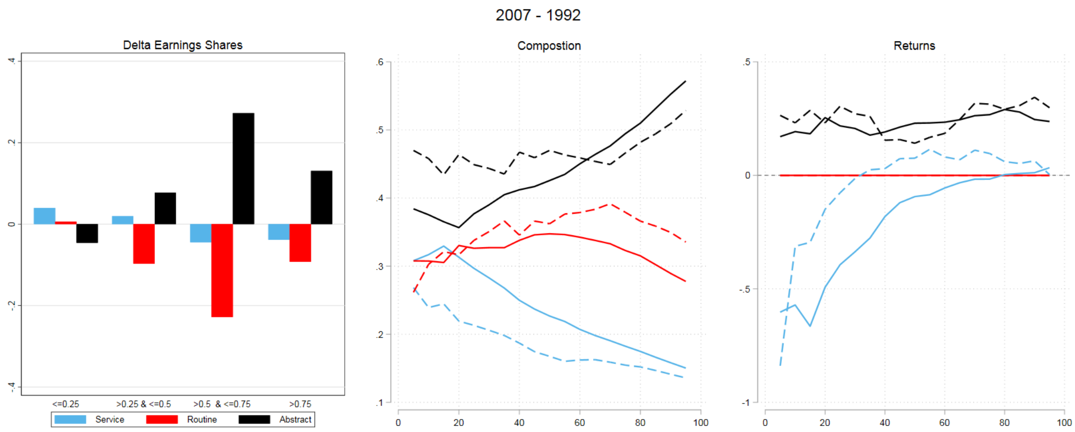



Theil Decompostion

| switzerland: 2007 - 1992 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.000480 | -0.00112 | 0.000640 |
| Specification Error | 9.00e-05 | 7.00e-05 | -0.000160 |
| Composition Effect | | | |
| Occ | -0.00067*** | 0.00040*** | 0.00026*** |
| Educ | -0.00045*** | -3.00e-05 | 0.00048*** |
| Female | 0.00010** | -1.00e-05 | -0.00009** |
| Age | -0.00041*** | 0.00019** | 0.00022*** |
| Reweighting Error | -0.000520 | 4.00e-05 | 0.00048* |
| Coefficent Effect | | | |
| Occ | 0.00156 | -0.00123 | -0.000320 |
| Educ | -0.000630 | 0.000810 | -0.000180 |
| Female | 0.00119 | 4.00e-05 | -0.00123 |
| Age | -0.00263 | 0.00352 | -0.000890 |
| _cons | 0.00286 | -0.00493 | 0.00207 |

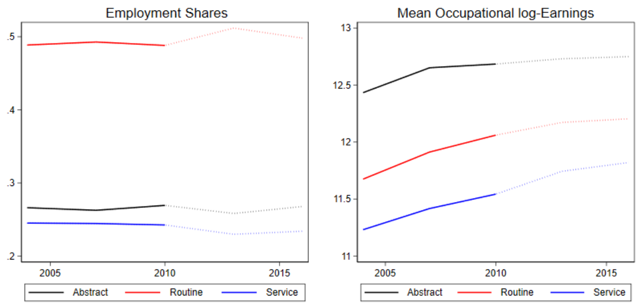



Quantile RIF Decompostion

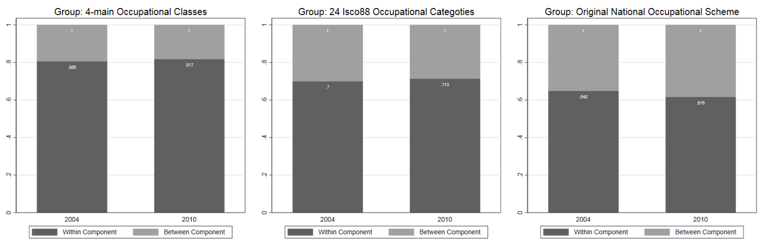



Occupational Classes Compostion and Returns

# Uruguay: 2010-2004



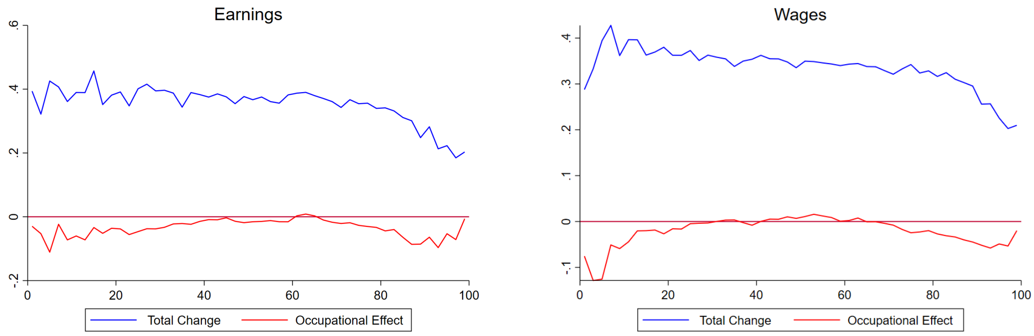

Employment and Income shares by Occupational Class



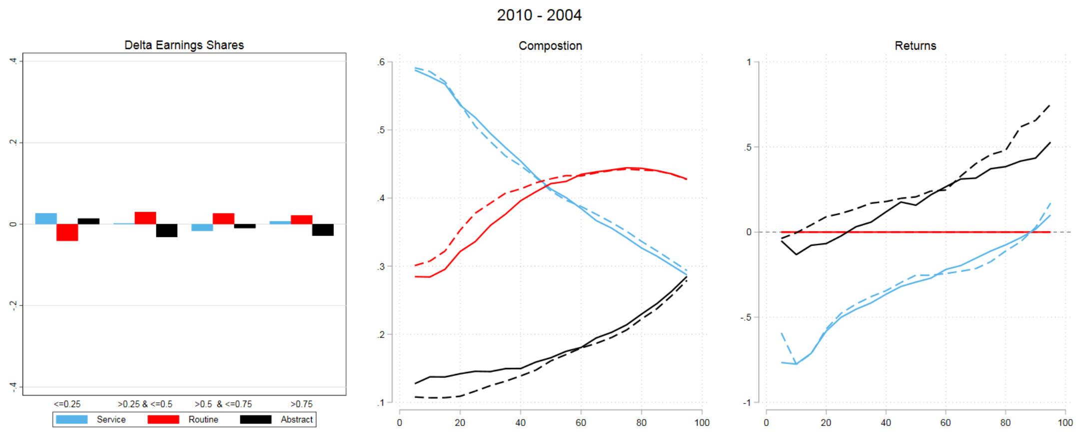

Theil Decompostion

uruguay: 2010 - 2004

| | <15 | 15-85 | >85 |
|---|---|---|---|
| Δ | 0.00058* | 0.00131*** | -0.00189*** |
| Specification Error | -1.00e-05 | 3.00e-05 | -3.00e-05 |
| Composition Effect | | | |
| Occ | -0.00012* | 3.00e-05 | 0.00010** |
| Educ | 0.00006*** | 0.00003* | -0.00009*** |
| Female | 0.00006*** | -0.00004*** | -2.00e-05 |
| Age | 0 | 0.00002* | -0.00002** |
| Ind | 0.00025*** | -0.00047*** | 0.00023*** |
| Reweighting Error | -0.00010* | 6.00e-05 | 4.00e-05 |
| Coefficent Effect | | | |
| Occ | -0.000420 | 0.00090* | -0.000480 |
| Educ | -0.000680 | -0.000370 | 0.00105* |
| Female | -0.000600 | -6.00e-05 | 0.00066** |
| Age | -0.000710 | 0.000580 | 0.000120 |
| Ind | -0.00357*** | -0.00237 | 0.00594* |
| _cons | 0.00643*** | 0.00296 | -0.00939*** |

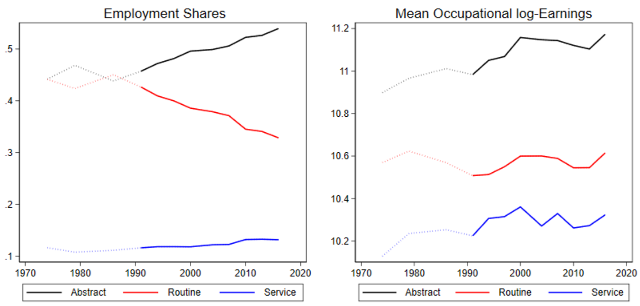



Quantile RIF Decompostion

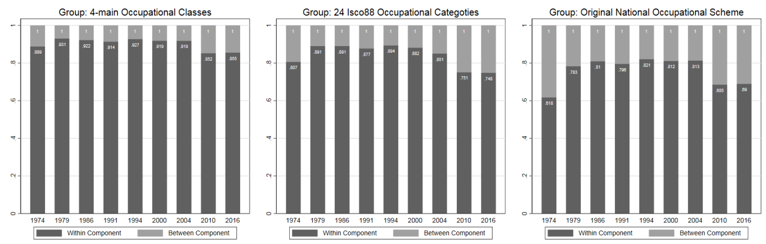



Occupational Classes Compostion and Returns

# US: 2016 - 1991

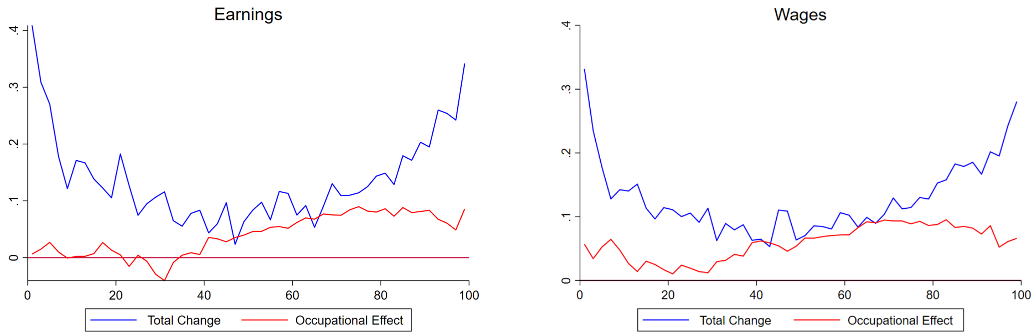



Employment and Income shares by Occupational Class

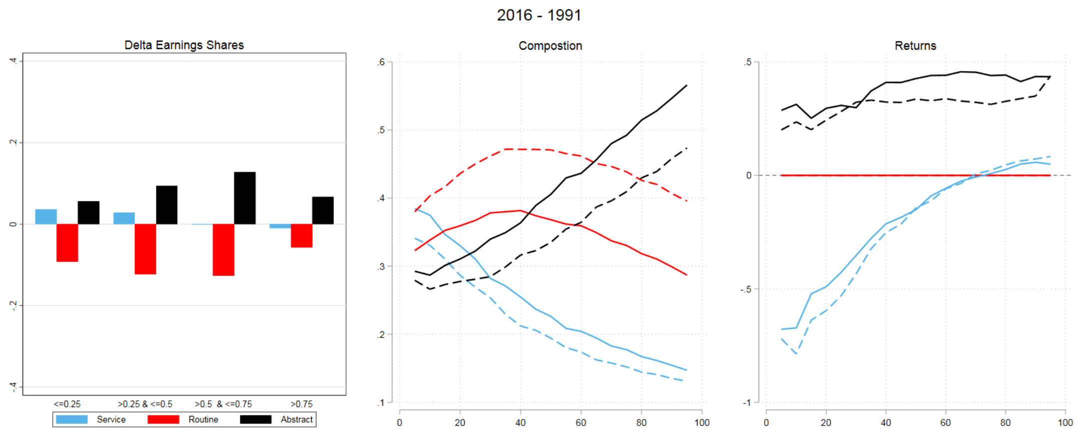



Theil Decompostion

| us: 2016 - 1991 | | | |
|---|---|---|---|
| | <15 | 15-85 | >85 |
| Δ | 0.00128*** | -0.00256*** | 0.00128*** |
| Specification Error | 0.00005* | 0.00010*** | -0.00014*** |
| Composition Effect | | | |
| Occ | -0.00022*** | 0.00011*** | 0.00010*** |
| Educ | -0.00025*** | 0.00018*** | 0.00008** |
| Female | -0.00001*** | -0.00000* | 0.00001*** |
| Age | -0.00006* | -2.00e-05 | 0.00008*** |
| Ind | -0.00029*** | -6.00e-05 | 0.00035*** |
| Reweighting Error | 2.00e-05 | -2.00e-05 | 0 |
| Coefficent Effect | | | |
| Occ | -0.000220 | 2.00e-05 | 0.000200 |
| Educ | 7.00e-05 | -3.00e-05 | -4.00e-05 |
| Female | 0.00048** | 9.00e-05 | -0.00057*** |
| Age | -0.000520 | 0.000120 | 0.000400 |
| Ind | 0.00130*** | -0.000540 | -0.000760 |
| _cons | 0.000940 | -0.00251*** | 0.00157* |




Quantile RIF Decompostion




Occupational Classes Compostion and Returns