Empirical Essays on Inequality

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Chapter 3: Are 'Good' Firms, Good for All Employees? An Investigation of Firm Fixed Effects at the Occupational Level

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1 Gender Differences in Fairness Evaluations of own Earnings in 28 European Countries

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

2.1 Introduction

The dynamics of occupational changes in the labour force is a central topic of economic research. In particular, technological change is historically identified as a critical explanation for major shifts in the workforce by creating and disrupting jobs.[1] Autor et al. (2003) propose the Routine-Biased Technological Change (henceforth, RBTC) hypothesis, which relates improvements in information and communications technologies (henceforth, ICT) to the de-routinization of the workforce. According to the RBTC hypothesis, the decreasing prices of technology since the 1980s 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. The 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 labour input has contributed to the de-routinization of jobs globally since the 1980s.

Acemoglu and Autor (2011) empirically investigate how de-routinization of jobs alters the distribution of skills. As routine jobs are typically middle-skilled jobs and non-routine jobs are mainly concentrated 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 de-routinization of jobs and job polarization opened the field to the 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 1980s. The authors define wage polarization as u-shaped earnings growth along the wage distribution, which results in a reduction in bottom-half and an increase in top-half inequality. Following their definition, overall distributional consequences depend

[1] See Vivarelli (2014) for a detailed literature.

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

on which two margins dominate.[3] Moreover, Autor and Dorn (2013) conclude from 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).

We recognize three main reasons for the debated nexus between job polarization and wage inequality. First, the global phenomena of de-routinization of jobs potentially have diverse distributional consequences as the number of routine and non-routine workers differs across countries. Hence, an extensive cross-country comparison can shed 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). However, focusing on averages disregards inequality within occupational classes (Hunt and Nunn, 2019; Taber and Roys, 2019; De La Rica et al., 2020). Accordingly, quantifying the nexus between job polarization and wage inequality requires a comprehensive assessment of 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 not only displaces workers in the middle but also at the bottom and 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 de-routinization of jobs.

This paper contributes to the literature by providing a direct test for the link between de-routinization of jobs and earnings inequality using harmonized data covering up to four decades in countries around the world. Specifically, our analysis sheds light on why de-routinization and job polarization do not translate into uniform patterns of earnings inequality. Furthermore, we discuss the drivers of the heterogeneous findings using appropriate decomposition techniques. Our analysis also adds to the discussion concerning the limits of mean comparisons of occupational groups (Böhm et al., 2019; Böhm, 2020; De La Rica et al., 2020; Hunt and Nunn, 2019; Taber and Roys, 2019) and the importance of variation within occupational groups for the overall earnings distribution in a large international comparison.

[3]In RBTC literature, polarization does not rely on the traditionally applied concepts of identification and alienation (Esteban and Ray, 1994). Instead, it refers to differentiated u-shaped growth patterns along the wage distribution. In this sense, the wage polarization notion used in RBTC literature is strictly bipolar, looks 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, 2015).

A novel and harmonized dataset for 35 countries, provided by the Luxembourg Income Study (LIS) and the Economic Research Forum (ERF), the LIS-ERF dataset, provides the empirical base for our analysis. The LIS is the largest available income database of harmonized microdata from countries worldwide. Technically, we estimate the Re-centered Influence Functions (RIF) decomposition method (Firpo et al., 2009, 2011, 2018) to measure, *ceteris paribus*, effects of de-routinization of jobs 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.

We show that that de-routinization occurs in 28 out of the 35 analyzed countries, albeit with varying levels of magnitude and timing. Compared to the US, which exhibits a steady decrease in routine jobs over time, many countries in our analysis experienced highly heterogeneous de-routinization processes over time. Our results support the RBTC hypothesis as suitable for explaining the observed shifts in employment shares in the workforce. However, de-routinization of jobs is ambiguously linked to inequality within and between occupational groups. Our results confirm that the variation in overall inequality primarily stems from variation within occupational groups. Applying the RIF decomposition method, we find that only four countries in our analysis exhibit earnings polarization following the definition of Acemoglu and Autor (2011). Moreover, we find that in all these couturiers the observed earnings polarization can *not* be attributed to de-routinization of jobs, confirming that job polarization has little explanatory power for the evolution of country-specific inequality.

We find that the weak link between de-routinization of jobs and earnings inequality stems predominantly from the heterogeneity within occupational classes. In particular, we observe that employees from a specific occupational class are not perfectly stratified but scattered along the earnings distribution. Consequently, de-routinization not only affects jobs at the middle of the earnings distribution, it also displaces workers in all earnings quantiles. Similarly, increasing shares of abstract and service occupations are not necessarily concentrated only at the top and bottom of the earnings distribution. Therefore, we conclude that shifts in occupational shares occurring within each quantile determine the overall effect of de-routinization of jobs on the earnings distribution, and these effects are, *a priori*, ambiguous.

The remainder of the paper is organized as follows: Section 2.2 provides a literature review. Section 2.3 discusses data sources and harmonization processes. Section 2.4 describes the methodology and the data-driven wave selection. Section 2.5 provides the main results. Section 2.6 discusses the assumptions and limitations of our analysis. Section 2.7 concludes.

2.2 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 are extensively studied in advanced and emerging economies. In their widely recognized work, Autor et al. (2003) find evidence of de-routinization of jobs between the 1960s and 2000s in the US. Goos and Manning (2007), analyzing different models of labour market changes for the UK between 1975 and 1999, conclude that the RBTC hypothesis of Autor et al. (2003) works best for explaining shifts in occupational classes. Autor (2019) updates these findings, describing an increasing wage divide 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), analysing 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); De Vries et al. (2020) find evidence for job polarization in developed countries around the world; Hardy et al. (2018) do so for Central and Eastern Europe. Mahutga et al. (2018) describe de-routinization of jobs primarily as a global north phenomenon. Their analysis is based on 38 aggregated LIS countries. Even though they use the same data source as in this paper, Mahutga et al. (2018) do not explore country-specific effects, a fundamental difference from our approach.

In sum, most existing research finds empirical evidence for job polarization due to ICT adaption in many countries. 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 other occupational categories characterized by low routine task intensity. Highly routinized employment experienced wage losses. The authors conclude that de-routinization of jobs 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 affluent 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[4] in the 1980s, while it was routine-biased[5] in the 1990s. In the 2000s, they only find a modest effect. Our results confirm and extend their analysis by adding a decade to the analysis. As this paper shows, we do not find that de-routinization of jobs is associated with wages and earnings polarization in the 2010s. Although our results do not exclude the temporary influences of ICT adaption on the earnings distribution in line with RBTC, we cannot observe a close nexus in the long run.

Another stream of the literature contests 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 consider variation in wages 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 adverse 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 labour-demand changes between occupations explain only a small part of changes in the wage distribution between 1979 and 2017 in the US, concluding that skill price changes within the occupation are far more critical. Massari et al. (2014) do not find wage polarization in Europe and only find weak polarizing effects of technological change. They suggest that the deterioration of labour 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 essential and significant part of wage differentials. However, they 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 necessarily translate into wage polarization. He suggests that the overall distributional effect is unclear if occupational groups are scattered and job displacement 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

[4]Wage growth strictly increases with skills.
[5]Wage growth was lower in the middle than at the tails of the skill distribution.

(2007), Böhm et al. (2019), Hunt and Nunn (2019), Böhm (2020), and De La Rica et al. (2020).

The importance of variation within occupational groups is increasingly addressed in the literature. In an international comparison of 19 countries, De La Rica et al. (2020) quantify wage-premiums (losses) to abstract (routine) tasks describing the relevance of variation within occupational groups. This connects to the finding of Consoli et al. (2023) showing that, within occupations, workers re-orientated away from routine tasks in the US between 1980 and 2010. Our analysis checks internationally how these within occupational dynamics contribute to earnings inequality.

2.3 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. The LIS and the ERF acquire, harmonize, and document micro-data from different national statistical institutions.[6] 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 focal variables: labour income and detailed job information are necessary to define quantiles and occupational classes used in the analysis.
2. Availability of repeated cross-sections: for each country, consistent information on earnings as well as earnings and occupations must be available over time.

Our working sample focuses on prime-age employed individuals aged 25-55. Missing values are imputed in all LIS and ERF countries, and the individual survey institute conducts the imputation in each country. Although the imputation procedures are not entirely standardized, we acknowledge high comparability across waves and countries, as guaranteed by LIS and ERF. Top- or bottom-coding procedures do not apply. Figure 2.1 shows a detailed overview of the country-specific waves used for the analysis.

2.3.1 Focal Variable - Earnings

Although most of the literature on the distributional analysis of the RBTC hypothesis focuses on hourly wages, our main variable of interest in the analysis is yearly

[6] 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`.

earnings. We opt for this for two reasons: First, LIS provides 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 chose the largest harmonized sample of countries possible. Second, the earnings information in LIS is more reliable than wages that suffer from higher item non-response rates. Nevertheless, in Section 2.8.4, we replicate the analysis using hourly wages as the dependent variable to provide closer comparability with the existing literature for the subset of countries where such information is available.

We rely on individual yearly gross and net labour incomes, 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 from self-employment.[7] We rely on gross income information if available. The income concept available for each country is provided in Appendix 2.8.1. We adjust the income variables for inflation using yearly Consumer Price Index data provided by the LIS, trimming the distribution at the 1st and 99th percentiles.

2.3.2 Focal Variable - Occupation

The literature on job polarization proposes two main approaches to characterize occupations according to their task requirements. The most frequently used approach relies on the Routine-Task-Index (RTI) (Autor et al., 2003; Autor and Dorn, 2013). It measures the intensity of routine tasks within a specific occupation assigning high (low) values for routine (non-routine) job categories.

The use of RTI-based classifications has several drawbacks for our analysis. First, RTI lacks a unique metric. Since numerous potential task scales exist, no obvious measure 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, the RTI index is a US-based measure.[8] Therefore, by applying the RTI in our cross-country perspective, we would assume that tasks are 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. Third, the RTI index works best with detailed occupational classification (3- or 4-digits information). However, in a cross-country framework such detailed information is usually missing.

[7] ERF countries, i.e., Egypt and Jordan, provide information on labour income at the household level. Therefore, for these countries, we proxy individual income by dividing the household income by the number of members in the household who receive a salary. In the decomposition exercise, we then restrict the analysis to household heads only.

[8] Developed for the US by Autor et al. (2003) and later refined in Autor and Dorn (2013), the RTI 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).

For these reasons, we cluster jobs into three main occupational classes, i.e., abstract, routine, and service. This classification is particularly convenient since it is easily interpretable and more flexible for cross-countries comparisons.

Our classification deviates in two ways from the one proposed in Acemoglu and Autor (2011). First, we merge the 'routine abstract' and the 'routine manual' into one 'routine' occupational class, as previously done by Massari et al. (2014) and Böhm (2020). Second, we do not drop agricultural occupations from our working sample. We argue that several countries under analysis rely considerably on the agriculture sector; hence, it would be inappropriate to exclude them. Table 2.1 presents a detailed overview of the alternative classifications.[9]

Occupational Class: Longmuir, Schröder, Targa	Occupational Class: Acemoglu and Autor	ISCO-88 Label	ISCO-88 Code	RTI
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 (2020). 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 that is typically different from the average non routine manual worker.

Table 2.1: Occupational classes based on 2-digts ISCO

[9] RTI index scores reported in the Table are taken from Mahutga et al. (2018).

The assignment of jobs to the occupational classes is based on a 2-digits ISCO-88 scheme,[10] as shown in columns three and four in Table 2.1. Unfortunately, the LIS-ERF dataset only provides harmonized information on occupations at the 1-digit level, which is not detailed enough to assign jobs to occupational classes according to our scheme.[11] Therefore, we classify workers using the country-specific, non-harmonized occupational variable. While, 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 conversion tables provided by Mahutga et al. (2018).[12] We, instead, rely on the cross-walks provided by Jann (2019) in order to convert ISCO-08 in 2-digits ISCO-88 occupational codes when available.

The main limitation of the class-based classification is that it neglects the routine intensity gradient between occupations: RTI scores in Table 2.1 range 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 an essential difference in the nature of the tasks performed by workers and, therefore, potential heterogeneity in the exposure to technological change and the risk of being subject to automation processes. In this sense, RTI scores can be interpreted as a measure of risk. Therefore, they are particularly suitable for sensitivity analysis to detect the differences in the degree of exposure to the risk of displacement effects between regional and local labour markets. Since we are interested in the distributional effects of *realized* de-routinization of jobs and not in the *potential* risk of layoffs, we argue that the aggregated occupational classes adequately characterize the composition of the workforce.

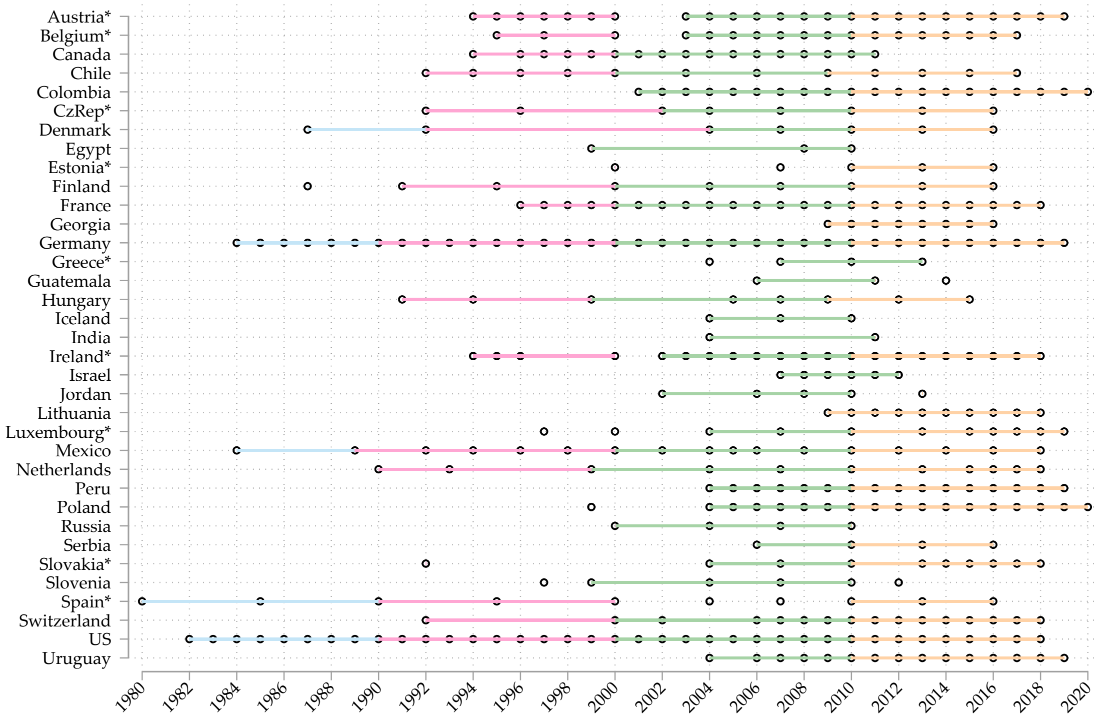
[10] The International Standard Classification of Occupations (ISCO) is the International Labour Organization (ILO) classification structure for organizing information on labour and jobs. The current version, known as ISCO-08, was published in 2008 and is the fourth iteration, following ISCO-58, ISCO-68,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

[11] 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 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 '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 '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.

[12] This is necessary for Canada, Finland, France, Hungary, India, Israel, Mexico, Russia, Spain, the US, and Uruguay. In some cases, complete harmonization from the national scheme 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 imputations typically involve around 1-5% of the employed workforce and are available upon request.

2.3.3 Wave selection

For most countries, the LIS-ERF database provides various cross-sectional waves. In our working sample, we select all the available waves with consistent information on earnings and occupational classification as defined in the previous sections.



Notes: The figure shows a detailed overview of the country-specific waves used for the analysis. For each country, dots represent waves with valid occupational classifications. Colored bars link survey waves used for the RIF decomposition exercises.

Figure 2.1: Countries and time frames in working sample.

Figure 2.1 shows a detailed overview of the country-specific waves used for the analysis. For each country, dots represent waves with valid occupational classifications. We use these waves to compute country-specific employment shares in service, routine, and abstract occupations. In our analysis, we consider the longest time-span available and, if available, decade-specific sub-periods: the 1980s indicated in light blue, the 1990s in pink, the 2000s in green, and the 2010s in orange. The selection of the base ($t = 0$) and last period ($t = 1$) depends on consistent earnings information. Note that in some countries the colored bars do not include all waves available. This is for two main reasons: either the time frame within the decade is shorter than 5 years or the earnings gross/net definition is not consistent over the entire time frame and, therefore, two waves cannot be directly comparable. As documented in

Appendix 2.8.1, the latter is the case for Austria, Belgium, Estonia, Czech Republic, Estonia, Greece, Ireland, Luxembourg, Slovakia, and Spain.

2.4 Methodology

In Section 2.4.1, we introduce the descriptive approach for analyzing de-routinization of jobs and present the methods used to investigate correlations between job polarization and overall inequality patterns across countries. Section 2.4.2 presents the unconditional RIF decomposition technique proposed by Firpo et al. (2009) that is subsequently applied in Firpo et al. (2011), which constitutes our empirical framework for testing the distributional consequences of de-routinization of jobs within each country under analysis. Section 2.4.3 provides the procedure to analyze the effects of occupational class-specific composition and returns.

2.4.1 Assessing De-routinization of Jobs and Earnings Inequality

We start our analysis by scrutinizing country-specific changes in workforce composition over time. Decreasing employment shares in routine occupations characterize de-routinization of jobs. Accordingly, we define employment shares as

$$ES_t^{Occ} = \frac{N_t^{Occ}}{N_t^{Service} + N_t^{Routine} + N_t^{Abstract}} \tag{2.1}$$

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. Decreasing $ES_t^{Routine}$ over time, indicates de-routinization of jobs in the country.

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

$$\Delta ES^{Routine} = \frac{ES_1^{Routine} - ES_0^{Routine}}{ES_0^{Routine}} \tag{2.2}$$

The larger the $\Delta ES^{Routine}$, the stronger the de-routinization process in that country between period $t = 0$ and $t = 1$.[13] Countries that did (not) experience de-routinization of jobs exhibit decreasing (increasing) employment shares $\Delta ES^{Routine}$.

We rely on inequality indices to study the connection between de-routinization and earnings inequality. An inequality index compresses all the information contained in the earnings distribution into a single number. Assume that all workers in an occupational class are homogeneous and, thus, all receive the same wage. Then a standard inequality measure would be a function of the employment shares of

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

the three occupational classes and their relative average earnings. Accordingly, the change in inequality would depend on the changes in the employment shares and changes in average earnings. If earnings are heterogeneous within occupational classes, the index would also depend on the inequalities within occupational classes.

We use the variation of the Theil index in the Routine-Service population as a measure of earnings inequality since it complies with the decomposition principle (Bourguignon, 1979), distinguishing inequality within and between occupational classes. In particular:

$$T_t = \frac{1}{N_t}\sum_{n=1}^{N}\frac{y_{it}}{\mu}ln\left(\frac{y_{it}}{\mu_t}\right) = \sum_{Occ=1}^{m}\frac{N_t^{Occ}\mu^{Occ}}{N_t\mu_t}ln\left(\frac{\mu_t^{Occ}}{\mu_t}\right) + \sum_{Occ=1}^{m}\frac{N_t^{Occ}\mu_t^{Occ}}{N_t\mu_t}T_t^{Occ} = T_t^b + T_t^w \tag{2.3}$$

Where y_i represents the worker earnings, mu the overall average earnings, and N the total sample size at time t. The sample is then divided into m occupational classes ($Occ = Service, Routine, Abstract$) that count N^{Occ} workers, where μ^{Occ} is the average earnings within that occupation at time t. T indicates the overall Theil Index in period t, T^b is the between component, and T^w the one within.

2.4.2 RIF-Regression Methods

Aside from the Theil decomposition, we are interested in a more detailed perspective of the changes in the earnings distribution. Therefore, we apply RIF regressions to estimate the distributional consequences of de-routinization in every country.

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 2.8.2.

The RIF-unconditional quantile decomposition allows for 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.

The decomposition for quantiles takes the following form:

$$\Delta^p = q_1^{p-} q_0^p = E[RIF(y, q_t^p, F)|t = 1] - E[RIF(y, q_t^p, F)|t = 0]$$
$$= \sum_i \overline{Occ_{i1}}(\widehat{\gamma}_{1,i}^p - \widehat{\gamma}_{0,i}^p) + (\overline{Occ_{i1}} - \overline{Occ_{i0}})\widehat{\gamma}_{0,i}^p + \tag{2.4}$$
$$+ \overline{X_1'}(\widehat{\beta}_1^p - \widehat{\beta}_0^p) + (\overline{X_1'} - \overline{X_0'})\widehat{\beta}_0^p$$

where q_t^p represents the p-quantile at time t of the earnings distribution, Occ_i is a set of occupational class dummies,[14] 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).[15] Time indexes $t = 1$ and $t = 0$ are defined over the longest time span available as explained in Section 2.3. If available, we replicate the decomposition exercise for decade-specific sub-periods, where $t = 1$ and $t = 0$ are the latest and earliest wave in the decade, with a minimum distance of 5 years in between. Colored bars in Figure 2.1 connect $t = 1$ and $t = 0$ in each available decade.

There are several advantages in 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 Δ^p;[16] the *composition effect* shows how much of the changes in Δ^p can be explained by over-time differences in the level of covariates.[17] Second, the methodology is designed for regression analysis on distributional statistics over the detailed list of covariates X. This means that, for each LIS-ERF country, it is possible to estimate how much of the variation in the statistic of interest can be explained by de-routinization, which is captured by the 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, and aging, etc. Third, these decomposition methods

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

[15]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.

[16]In our framework, a reason for this may be that returns to non-routine occupations grow at a faster pace than returns to routine occupations due to changes in relative labour demand.

[17]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 Δ^p of the pure re-allocation of jobs away from routine toward non-routine abstract and service occupations.

are robust to non-linearity in the wage setting equation once the counterfactual is re-weighted citepfirpo2018decomposing.

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 meaning 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 definitive remedy for this problem and some arbitrariness is unavoidable, even if normalization strategies are applied (Yun, 2008).[18]

For the sake of clarity, we do not provide confidence intervals for our RIF estimates the in results section; these are found in Appendix 2.8.3.[19]

In the following sections and in the results tables, we use the term *Total Change* to define the overall difference in the dependent variables, Δ^p. For RIF-quantiles, it is calculated as the difference in (log)-quantiles between two reference years. Moreover, we refer to *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).

2.4.3 Analysis of Occupational Composition and Return Effects

RIF decomposition measures the joint effect of occupational changes on earnings growth. Additionally, we expand the analysis describing 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;

$$s_{t,Q}^{Occ} = \frac{\sum_{i=1}^{N_Q^{Occ}} y_{i,t}^{Occ}}{\sum_{i=1}^{N_Q} y_{i,t}} \qquad if\ F(y_{i,t}) \leq Q, \tag{2.5}$$

[18]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 prove to be robust to different base group specifications; these are available upon request.

[19]In Figure 2.17, we provide confidence intervals based on robust standard errors. These should be interpreted as a lower-bound. 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.

where $s_{t,Q}^{Occ}$ 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:

$$\Delta\, s_Q^{Occ} = s_{1,Q}^{Occ} - s_{0,Q}^{Occ} \tag{2.6}$$

$$with\ \ \Delta\, s_Q^{service} + \Delta\, s_Q^{routine} + \Delta\, s_Q^{abstract} = 1,$$

where $\Delta\, s_Q^{Occ} > 0$ indicates that that the 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 in the composition of the workforce over time, we estimate the population share of each occupational class below each quantile Q of the (log) monthly earnings distribution y in period t=1 and t=0,[20]

$$ES_{t,Q}^{Occ} = \frac{N_t^{Occ}}{N_t^{Service}+N_t^{Routine}+N_t^{Abstract}} \quad for\ y \leq y_Q. \tag{2.7}$$

The changes of the composition below each quantile Q of the distribution is described as

$$\Delta ES_Q^{Occ} = ES_{1,Q}^{Occ} - ES_{0,Q}^{Occ}. \tag{2.8}$$

Positive (negative) values of ΔES_Q^{Occ} would imply that the concentration of workers employed in the occupational class has increased (decreased) below quantile Q over time.

Aside from composition effects, differences in occupational returns shape the overall *Occupational Effect*. To estimate how the returns of each occupational class evolved along the earnings distribution, we run the following unconditional quantile regressions $Q_{i,t}$:

$$Q_{i,t} = X_{i,t}'\beta_{t,Q} + \ \gamma_{t,Q}^{Service} * Service_{i,t} + \ \gamma_{t,Q}^{Abstract} * Abstract_{i,t} + \ \varepsilon_{t,Q}. \tag{2.9}$$

As $Service_{i,t}$ ($Abstract_{i,t}$) is equal to one if individual i belongs to the service (abstract) class, $\gamma_{t,Q}^{Occ}$ represent the return of the occupation in comparison to the

[20]We separate the distribution into 20 quantiles.

routine class in period t, at the quantile Q. 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 $\gamma_{t,Q}^{Service}$ and positive values for $\gamma_{t,Q}^{Abstract}$.

2.5 Results

This section provides the results of our analysis. We start by detailing our analysis using the US as a case study; subsequently, we turn to all countries in our sample. Our results are organized as follows: first, we provide descriptive evidence of whether de-routinization of jobs can be observed. Second, we discuss and confirm previous findings of job polarization focusing on differences *between* occupational classes. Third, we show the relative importance of the variation within occupational classes by applying the Theil decomposition. Fourth, we apply RIF decompositions, including variation within and between occupational classes, to analyse how de-routinization affects earnings distributions. Fifth, we examine the role of overlapping distributions and occupational compositions and returns to clarify our findings.

2.5.1 The Case of the US

2.5.1.1 The US: De-routinization and Job Polarization

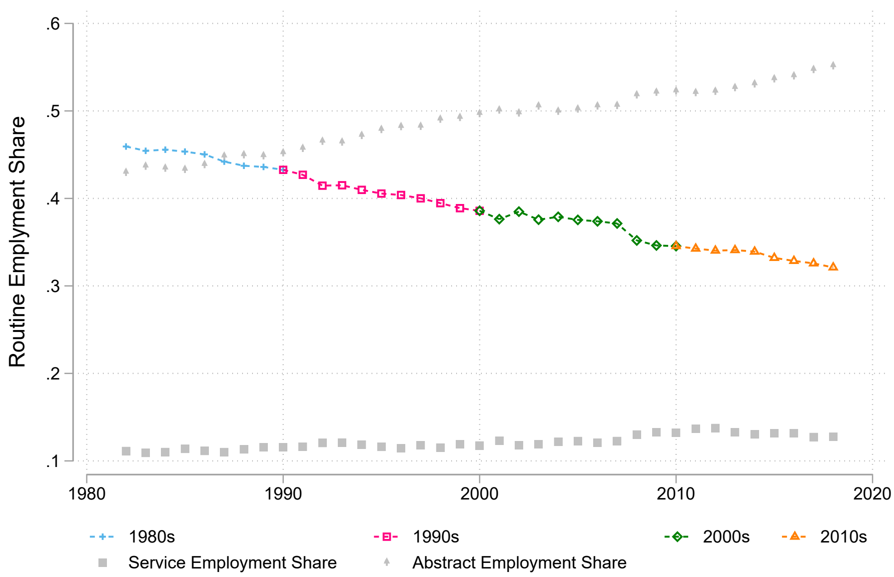
We start with a detailed discussion of de-routinization and its distributional consequences using the US as a case study. We choose the US because it is highly debated in the literature and provides a harmonized long-term data series.

We can confirm a long-lasting de-routinization process in the US labour market. Figure 2.2 presents the respective employment share of abstract, routine, and service occupations from 1982 to 2018. The figure shows a continuous decrease in routine jobs and an increase in abstract occupations. The share of service jobs shows a small increase starting from the end of the 2000s. This confirms that the US exhibits a long term de-routinization trend, which allows an in-depth analysis of the distributional consequences.

Given that de-routinization is observed, we further investigate whether we can observe job polarization in the US over time. We confirm the presence of job polarization if the share of workers with low and high earnings increase at the expense of those with an average remuneration. De-routinization implies job polarization if routine occupations are clustered in the center of the earnings distribution, i.e. the received average earnings (Acemoglu and Autor, 2011). The two panels in Figure 2.3 show the average earnings of service (on the left) and abstract occupations (on the right) normalized by the average of routine earnings in each year, respectively. Because of the normalization, the average routine earnings (in red) are equal to one in each period. Therefore, average earnings in service and abstract occupations are expressed as proportions of the average of routine earnings.

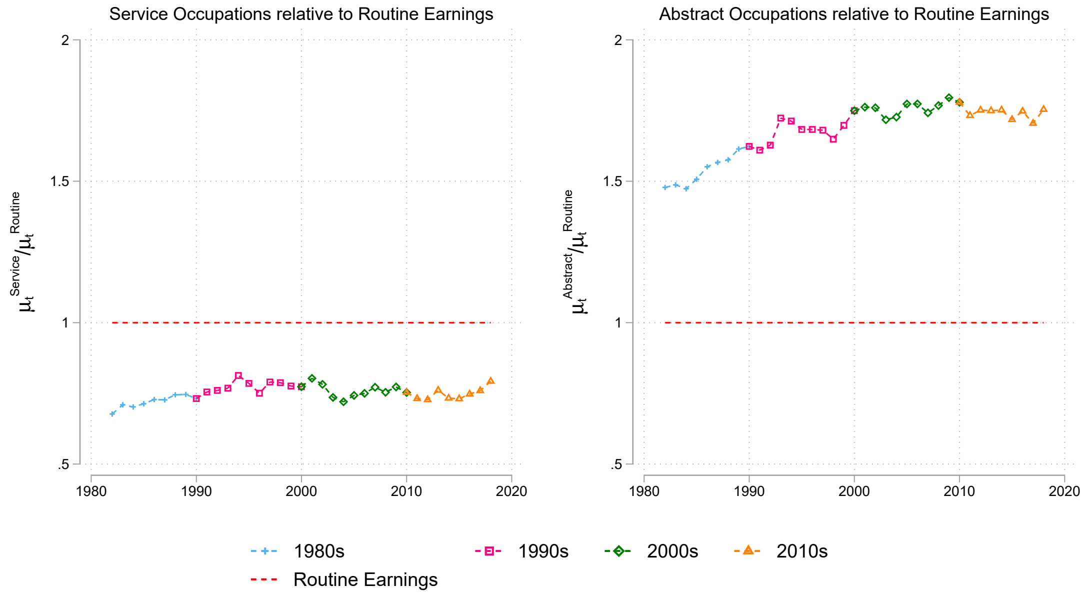
The figure displays a distinct hierarchy in average earnings across occupational classes, which is consistent over time. In all decades, we find that the average earnings of service occupations are below those of routine occupations. The average remuneration for abstract occupations is above that of routine occupations. On average, routine occupations are clustered in the middle of the earnings distribution: above service and below abstract occupations. While the difference between average service and routine earnings remained relatively constant, the right panel reveals that the average earnings of abstract occupations increased from 1.5 to around 1.75 between the 1980s and the beginning of the 2000s. This clear hierarchy between average earnings of the occupational classes is consistent with the RBTC framework and is similarly found in the existing literature (Acemoglu and Autor, 2011; Autor et al., 2003).

A shortcoming of the analysis of mean differences in occupational groups is that it ignores inequality within occupational classes. For analyzing distributional consequences of de-routinization, between-group differences are potentially insufficient to draw conclusions from if the variation within classes is large. Thus, as a next step we want to quantify whether variances within - or between - occupational groups are the determinants of overall earnings inequality.



Notes: Compiled by authors based on LIS data for the prime-aged, employed population. The figure shows the employment share for each occupational class between 1982 and 2018.

Figure 2.2: Employment shares in the United States



Notes: Compiled by authors based on LIS data for the prime-aged, employed population. The upper two plots provide the average earnings of occupational classes ($\mu_t^{Service}$; $\mu_t^{Abstract}$) divided by the average of routine occupations ($\mu_t^{Routine}$) in each year, respectively.

Figure 2.3: Job polarization in the United States

2.5.1.2 The US: Theil Decomposition

A tool that allows us to determine the relevance of within - or between- class variation is the Theil index. As detailed in the methodology section, the Theil index allows us to decompose overall inequality into a within and a between component. We provide the Theil index for earnings alongside the within and the between components for the US between 1982 and 2018 in Figure 2.4.

Most earnings inequality in the US stems from variation within occupational classes. The left panel in Figure 2.4 shows that, in all years, the within component explains nearly all the variation of the overall Theil. The right panel provides the relative share of the within component to the overall Theil. The within component represents constantly between 85 and 90 percent of the overall inequality in the observed years.

One could argue that the importance of the within component stems from the relatively broad definition of the three occupational classes. Hence, we apply the same Theil decomposition for less aggregated classifications of occupational classes, i.e. 24 ISCO-88 occupation categories and the original national occupational scheme, i.e., 4-digits Census Occupation Codes. The right panel of Figure 2.4 includes the relative importance of the within component for the less aggregated

Notes: Compiled by authors based on LIS data for the prime-aged, employed population. The left panel provides the Theil index as well as the within and between components for each wave in the US. The right panel provides the share of the within component for different occupational group specifications.

Figure 2.4: Theil index decomposition from 1982 to 2018 in the United States

classifications. For the 24 ISCO groups, around 80 percent of the overall earnings variation is explained by variation within these groups. Using up to 483 groups in the 4-digit definition, the within variation remains at levels between 65 and 70 percent. We, therefore, argue that the importance of the within-group component for overall inequality is robust to alternative definitions of occupational groups. Overall earnings inequality is mostly determined by inequalities *within* rather than *between* occupations. Hence, analyzing the distributional consequence of de-routinization needs to take changes both within and between occupational classes into account – which is the reason for applying RIF quantile decomposition in the next step.

2.5.1.3 The US: Distributional Consequences of De-routinization

We report the RIF quantile decomposition in Figure 2.5. The left panel provides the unconditional quantile-specific earnings growth, i.e. the *Total Change*, for the longest time span available and for decade-specific estimates.[21] The right panel presents the corresponding *Occupational Effect*, indicating 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.[22] We argue that if *Occupational Effect* and the *Total Change* are similar, de-routinization played a determining role in shaping the earnings distribution. We choose this graphical representation because it enables us to analyse two important dimensions: the (dis)connection of the *Occupational Effect* and the *Total Change*, as well as the evolution of overall inequality in the long-term as well as per decade.

We find long-term polarization in the US that cannot be attributed to changes within or between occupational classes. The left panel shows a u-shaped *Total Change* along earnings quantiles between 1982 and 2018. The decade-specific estimates reveal that this polarizing effect stems mainly from the 1990s, while the 1980s and the 2010s exhibit smaller earnings growth and the 2000s predominantly show a negative *Total Change* in earnings percentile growth. These findings are in line with previous findings by Acemoglu and Autor (2011) and Firpo et al. (2011). The right panel reveals that these *Total Changes* do not substantially correspond with *Occupational Effects*. The long-term *Occupational Effects* show slightly higher earnings growth for lower earnings quantiles and relatively constant growth for above the median. The estimates cannot explain the u-shaped *Total Change* patterns, while the earnings growth for the lower quantiles are barely explained by *Occupational Effects*.

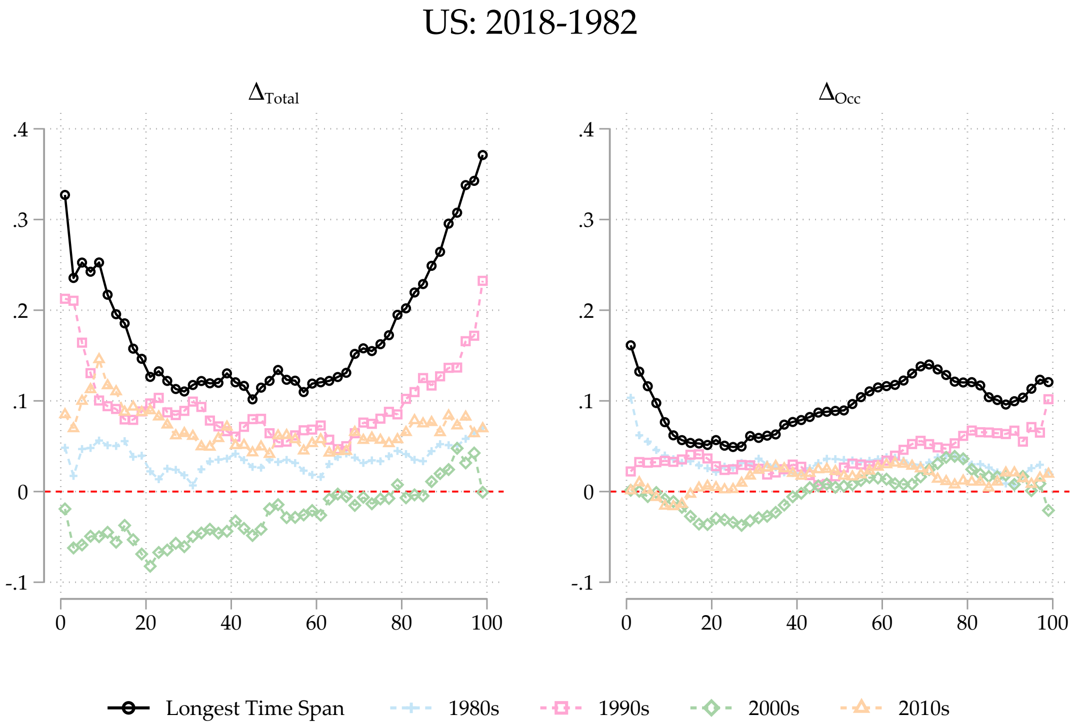
The disconnection between the *Total Changes* and *Occupational Effects* becomes even more striking when we consider the decade-specific effects. While most overall polarization seem to stem from the 1990s, the *Occupational Effect* does not explain the shape of the *Total Change* at all. Earnings growth from *Occupational Effect* remains relatively constant and increases slightly above the median. For the other decades, *Occupational Effects* are relatively small and close to zero.

We conclude that employment de-routinization *per se* cannot explain the observed overall polarization trend in the US.[23] Our results are in line with those of Hunt and Nunn (2019), Böhm et al. (2019) and Böhm (2020), showing the ambiguous distributional consequences of the RBTC framework: including within-group variation, the *Occupational Effect* does not correlate with the *Total Change*. Our

[21] *Total Change* refers to the term Δ^q in equation 2.4. For the sake of clarity, the figure provides the rolling average based on three percentiles.

[22] *Occupational Effect* refers to the term $\sum_i \overline{Occ_{i1}}(\widehat{\gamma}^p_{1,i} - \widehat{\gamma}^p_{0,i}) + (\overline{Occ_{i1}} - \overline{Occ_{i0}})\widehat{\gamma}^p_{0,i}$ in equation 2.4.

[23] We provide the figures with confidence intervals based on robust standard errors in Appendix 2.8.3. 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.



Notes: Compiled by authors based on LIS data for the prime-age, employed population. The left panel shows the total percentile earnings growth on the y-axis (*Total Change*), the left panel provides the counterfactual earnings growth (*Occupational Effect*) on the y-axis. Both panels show results for the US for the longest time span (1982 to 2018), the 1980s, 1990s, 2000s, and 2010s, based on RIF quantiles decomposition explained in Section 2.4.2. The x-axis provides the percentiles of the earning distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

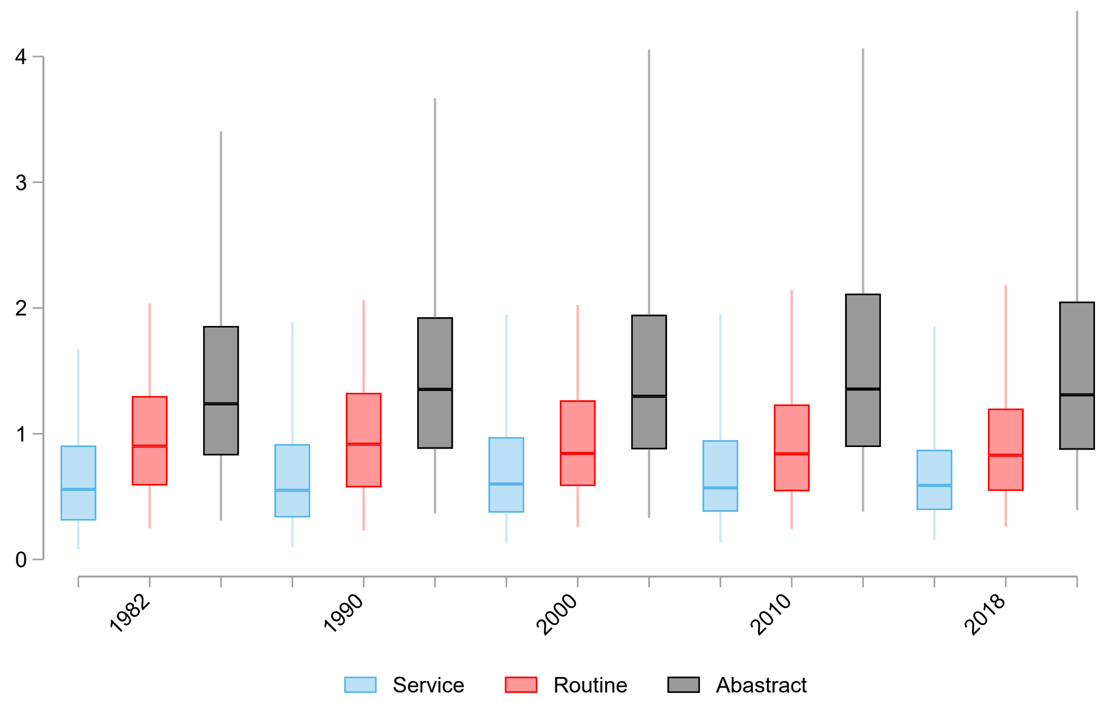
Figure 2.5: RIF decomposition for the United States

estimates also suggest that increased labour demand for non-routine occupations did not necessarily lead to higher returns for service workers at the bottom of the distribution. Moreover, the long-term *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.

2.5.1.4 The US: Overlapping Distributions, Composition and Return Effects

But why do *Occupational Effects* tell us little about overall percentile earnings growth? To answer this question, we discuss the role of overlapping distributions and potentially offsetting occupational compositions and return effects.

For the US, the occupational earnings distributions overlap substantially. Figure 2.6 shows the earnings distribution of each occupational group (service in light blue, routine in red, and abstract in back) via box-plots in 1982, 1990, 2000, 2010, and 2018. Earnings in each occupational group are normalized by the year-specific



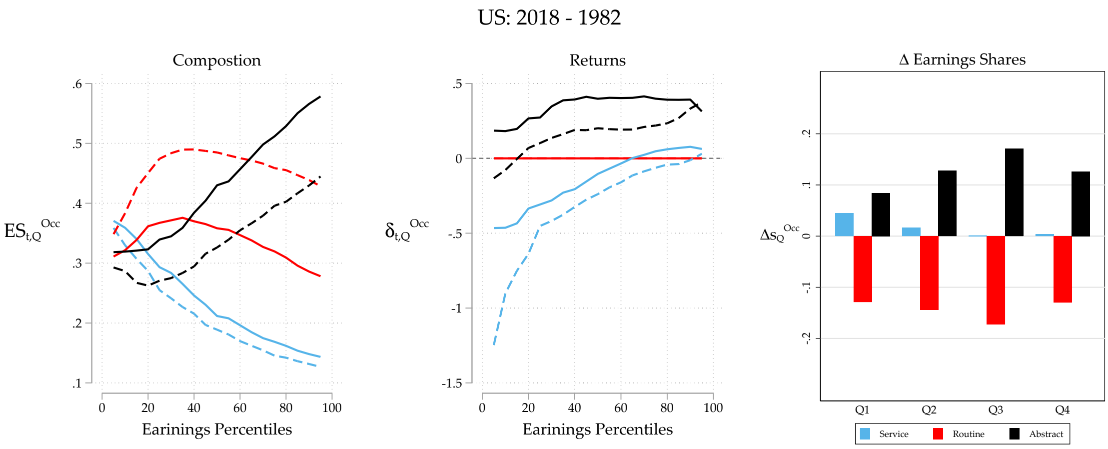
Notes. Compiled by authors based on LIS data for the prime-age, employed population. The y-axis shows the country-specific distribution of earnings in service (in light blue), routine (in red), and abstract (in black) occupational classes in 1982, 1990, 2000, 2010, and 2018. Individual earnings in each occupational class are normalized by the average *routine* earnings in that year. The occupation-specific distribution is represented by box plots where the vertical line extremes represent the 5th and 95h percentiles, the box includes earnings between the 25th and 75th percentiles, and the median is marked by the horizontal line.

Figure 2.6: Overlapping distribution in the United States

average routine earnings and, for each occupational group, the box-plots provide the 5th, 25th, 50th, 75th, and 95th percentiles. The figure reveals that abstract occupations show the highest median earnings but also the largest dispersion within the occupational classes in all years. This means that abstract jobs are not limited to the top of the distribution.

The degree of overlap is substantial in all decades analyzed. In particular, service earnings above the service median considerably overlap with routine earnings below the routine median. Conversely, the percentiles above the routine median overlap with the earnings below the abstract median. For the US, we conclude that employees from a certain occupational class are not perfectly stratified but scattered along the earnings distribution. Hence, de-routinization processes do not just shift jobs from the middle toward the tails, but it replaces routine occupations along the entire earnings distribution.

We add another perspective to the argument of overlapping occupational earnings distributions, by further de-composing the *Occupational Effect* into return and composition effects. Figure 2.7 provides three panels. The left panel presents the change of the composition of employment shares along the earnings distribution. The middle panel describes the returns along the earnings distribution with the routine class as base category. The right panel depicts the quartile-specific earnings share of the three occupational classes.[24] In all panels, blue represents the service class, red the routine class, and black the abstract class. Solid lines indicate the estimate for the end period, $t = 1$, while dotted lines indicate the estimates for the initial period, $t = 0$.



Notes: Compiled by authors based on LIS data for prime-age, employed population. The y-axis in the left panel depicts the changes in occupational composition over time. The x-axis provides the population ranked by the earnings distribution. The y-axis in the central panel shows the changes of occupational returns using the routine occupation as baseline category. Solid lines indicate the estimate for the end period, $t = 1$, while dotted lines indicate the estimates for the initial period, $t = 0$. Again, the x-axis provides the population ranked by the earnings distribution. The y-axis in the right panel provides the change of earnings shares by occupational class over time. The x-axis depicts the quartiles of the earnings distribution.

Figure 2.7: Occupational composition and return effects in United States

In the left panel, we observe that the share of employees in routine occupations has reduced along the whole 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. The middle panel show the hierarchy of returns between occupational classes has not changed substantially over time. The right panel shows that the earnings shares of routine jobs reduced in all quartiles of the distribution, while abstract jobs increased their earning shares. Thus, within each quartile, there are service (abstract) workers who replace routine workers and, therefore, reduce (increase) earnings growth.

[24] Formulas are discussed in detail in Section 2.4.3.

We conclude that composition effects – specifically replacement of routine jobs with abstract workers – drive the *Occupational Effect* in the US. The effect is positive and mainly flat along the earnings distribution mirroring the change in composition and returns. The slightly larger *Occupational Effect* for lower-earning quantiles can be explained by a relatively large increase of returns for abstract workers.

These results suggest several insights into the link between the de-routinization of jobs 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, de-routinization of jobs does not necessarily displace workers only in the middle of the earnings distribution. Additionally, we find that de-routinization of jobs does not displace routine workers only at the middle of the earnings distribution, as routine occupations have been displaced along all quantiles. Similarly, increasing demand for abstract and service occupations is not necessarily concentrated only at the top and bottom of the earnings distribution, respectively. We find evidence that service and abstract workers are represented at both the bottom and the top of the distribution. For the remainder of the paper, we show that this finding holds for most countries under analysis.

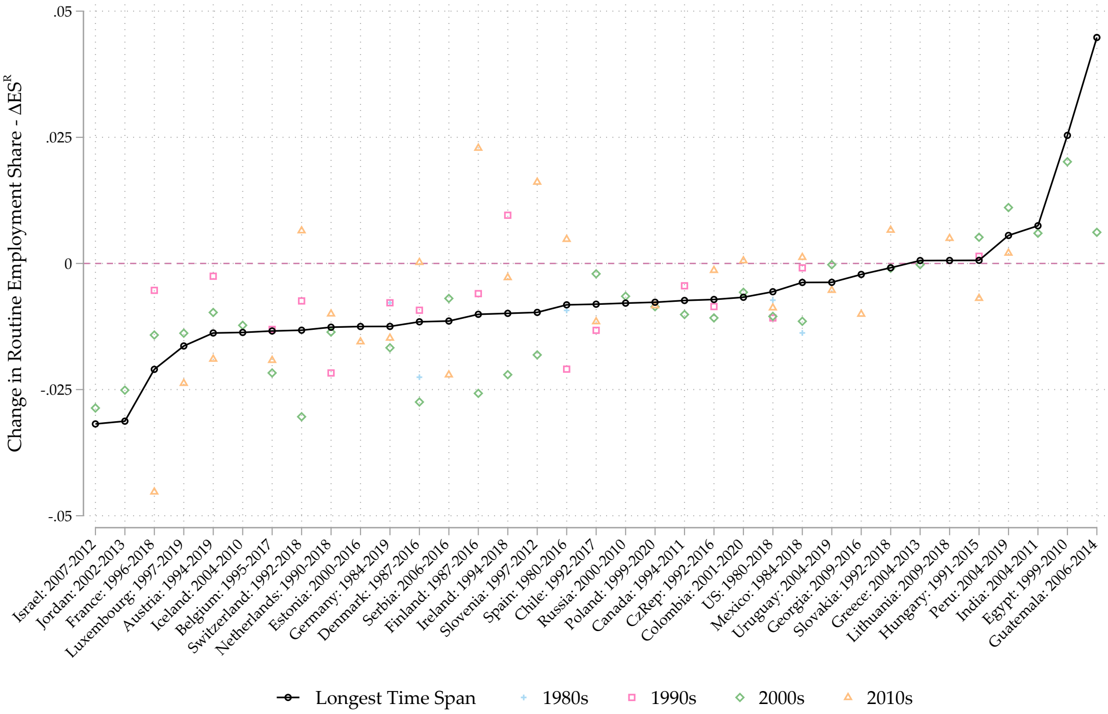
2.5.2 International Comparison of 35 Countries

2.5.2.1 International Comparison : De-routinization and Job Polarization

We now analyse to what extent the findings for the US are valid for the other countries in our sample. We start with a descriptive investigation of de-routinization for the longest time period and decade-specific estimates. As described in the data section, the observed periods differ and not all decades are available in every country. Again, we confirm the presence of de-routinization if the employment share decreases.

Figure 2.8 shows the change in the share of workers employed in routine occupations on the y-axis and the countries ordered by the size of the change in the employment share on the x-axis for the longest time-span, respectively. For the sake of comparability, we annualize the change in employment share. Hence, e.g., in France, the share of routine jobs fell, on average, by around 2.2 percent per year between 1996 and 2018. Moreover, the decade-specific estimates show that most de-routinization was observed in the 2010s, with a reduction of nearly 5 percent, while it was close to zero in the 1990s.

The figure supports two major findings: first, we find that de-routinization occurs in most of the analyzed countries, albeit with varying levels of magnitude. De-routinization occurs in 28 of 35 countries, and we can observe seven countries – Greece, Guatemala, Hungary, India, Lithuania, Peru, and Slovakia - that do not show de-routinization processes. These countries are economies where recent indus-



Notes: Compiled by authors based on LIS data for prime-age, employed population. The figure summarizes the results of our analysis of de-routinization. The y-axis is the average percentage change of the employment share in routine occupations for the longest time span observed and each decade available. The x-axis specifies the country sorted by descending levels of de-routinization.

Figure 2.8: Changes in the employment shares of routine classes

trialization may explain increases in the production sector and, therefore, higher demand for routine jobs. This is in line with the findings of De Vries et al. (2020).

Second, many countries experienced decades of heterogeneous de-routinization processes, especially compared to the steady decrease observed in the US. In particular, we find that the intensity of job de-routinization varies between countries and decades. While some countries experienced strong de-routinization in the 2000s, e.g. Denmark, Finland, Germany, and Ireland, , others exhibited more de-routinization in the 2010s, e.g., Austria, France, Luxembourg,. In contrast, in some countries that experienced job de-routinization in previous decades started, employment shares in routine jobs started to grow again during the 2010s.[25]

Given that de-routinization is observed in most countries, in Figure 2.9 we investigate whether we can observe job polarization in our set of countries. Like for the US above, the y-axis provides the average service - (lower panel) and abstract earnings (upper panel) divided by average routine earnings. We scatter decade-

[25]This is, for example, the case for Finland, Slovenia, Spain, and Switzerland.

specific averages for every country, which are sorted, as in Figure 2.8, by decreasing levels of de-routinization. This representation incorporates two major advantages: first, we show that our findings are not dependent on the selection of the time frame. Second, changes over time can be observed.[26]

Our set of countries reveals a distinct hierarchy in average earnings across occupational classes for almost all decades. Service jobs are, on average, less renumerated than routine jobs.[27] Moreover, in all countries, we find that the average earnings of abstract occupations are above those of routine occupations. We conclude, similarly to the US, that routine occupations, on average, are clustered at the middle of the earnings distribution: below abstract and above service occupations. Thus, we can confirm a clear hierarchy between the average earnings of the occupational classes for almost all countries in all decades in our sample.

2.5.2.2 International Comparison: Theil Decomposition

In the case of the US, we show that the variation between occupational classes explains little of the overall variation. The successive analysis explores whether this can be generalized to the other countries in our sample. Therefore, we provide two panels in Figure 2.10 showing the overall Theil in the upper panel and the proportion explained by the within component in the lower panel. Again, the x-axis provides the countries ordered by decreasing levels of de-routinization.

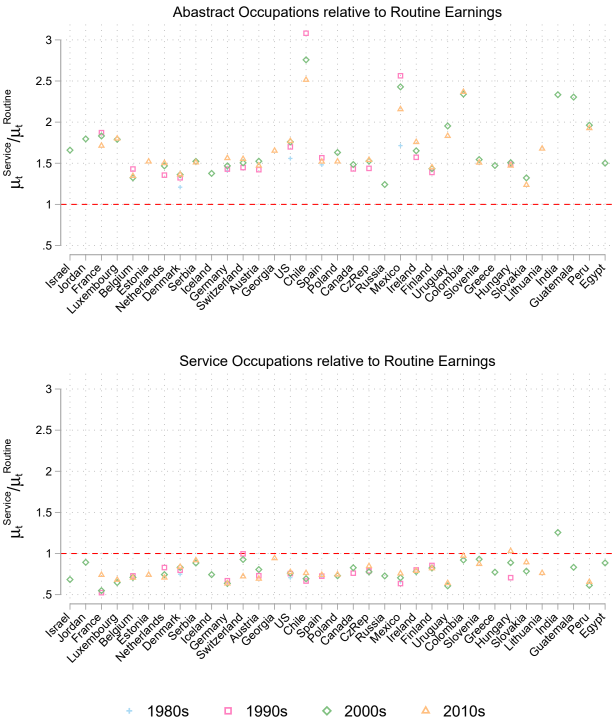
The upper panel in Figure 2.10 shows different levels of inequality across countries. The correlation between the level of de-routinization and inequality expressed by the Theil index remains, on this point, inconclusive: on one hand, we find more variation in inequality for countries with lower levels of de-routinization across decades, but on the other hand, lower levels of inequality can also be found for non-de-routinizing countries on the right, e.g., Slovakia, Egypt, Hungry, and Slovakia.

The lower panel in Figure 2.10 confirms the importance of the within component for all countries in our sample. For most countries and decades, the within component explains 80 percent or more of overall inequality. Moreover, the level of de-routinization does not seem to alter the importance of the within component.[28] We conclude that a focus on occupational class *averages* is potentially insufficient to explore the overall distributional consequences of de-routinization and that dynamics within occupations seem to play a major role in the evolution of the earnings distribution over time.

[26]For instance, service jobs in France lowered their average earnings gap to routine jobs, as the 2010s ratio is closer to one than in previous decades (left panel). Another example is Chile, with a very high earnings ratio between abstract and routine jobs (right panel). The panel shows, however, that the earnings ratio fell between the 1990s and the 2010s from around 3 to 2.5.

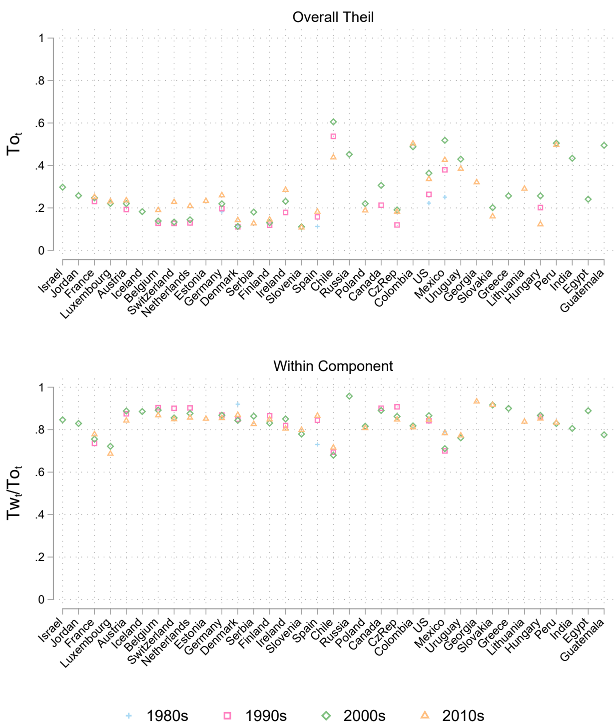
[27]Except in the case of India in the 2000s and Hungry in the 2010s.

[28]We show in Figure 2.16 in Appendix 2.8.3 that the measurement with 2-digits ISCO codes and the original country-specific occupational schemes still explain mostly more than 70 percent of the overall inequality.



Notes. Compiled by authors based on LIS data for the prime-aged, employed population. The two panels provide the average earnings of occupational classes divided by the average earnings of the routine occupations for each available decade. The x-axis is sorted by the level of de-routinization as described in Figure 2.8.

Figure 2.9: Employment average earnings normalized to the routine class



Notes. Compiled by authors based on LIS data for the prime-aged, employed population. The upper panel provides the overall Theil at the beginning of the decade. The lower panel provides the share of the corresponding within component. The x-axis provides the countries sorted by the level of de-routinization as described in Figure 2.8.

2.5.2.3 International Comparison: Distributional Consequences of De-routinization

So far, the international comparison shows a static description of earnings dispersion. To investigate the role of de-routinization for earnings distributions in more detail, we turn to our estimates from unconditional quantile decompositions, in the same manner as in our US case study. Specifically, we show that the weak link between the *Total Change* in earnings percentile and the counterfactual change from *Occupational Effect* is not limited to the US.

The RIF decompositions reveal various overall distributional outcomes, but no close link between de-routinization of jobs and changes in the earnings distribution over time. We discuss the country-specific trends concerning changes in the overall earnings distribution, i.e., increased and decreased inequality, polarization, and no change in inequality. Interpreting the magnitude and the sources for heterogeneous earnings percentiles growth for every single country, however, is not within the scope of this paper.

We start with countries exhibiting increasing inequality, where the *Total Change* is increasing over the earnings quantiles. Figure 2.11 includes estimates for these countries, i.e. Austria, Belgium, Canada, Czech Republic, Estonia, Finland, Germany, India, Mexico, Netherlands, Slovenia, Spain, and Switzerland. With the exception of India, we find evidence for overall de-routinization of jobs in all these countries; however, the *Occupational Effect* from the RIF decomposition does not explain the *Total Change* along the earnings quantiles. In some countries, like Estonia, Finland, Germany, Mexico, and Switzerland, *Occupational Effects* are positive at the bottom of the distribution. This is consistent with the RBTC framework, as lower earnings would have increased if only occupational changes had occurred. Nevertheless, other mechanisms offset the impact of de-routinization of jobs on the overall *Total Change*. In several countries, i.e., Czech Republic, Slovenia, and Spain, de-routinization effects are nearly zero along the entire distribution. If applicable, the figure also provides decade-specific estimates of the *Total Change*, and the *Occupational Effects*. However, similar to the US, they do not show a close link.

We categorize countries into the group of decreasing inequality if the *Total Change* indicates that lower quantiles are growing at a faster rate compared to upper quantiles. Figure 2.12 reports the respective RIF decomposition results. It includes Chile, Colombia, Egypt, France, Georgia, Guatemala, Hungary, Jordan, Luxembourg, Peru, Poland, Russia, Serbia, Slovakia, and Uruguay. Although we find evidence of de-routinization of jobs in most of these countries, except for Egypt, Hungary, and Peru, *Occupational Effects* are generally small and, again, they do not explain the decreasing *Total Change*.

In some countries, *Total Change* displays earnings polarization, which is a u-shaped pattern along the earnings quantiles. Figure 2.13 includes the countries Denmark, Ireland, Lithuania, and the United States. The u-shaped patterns of the

Total Change are very distinct in Denmark, Ireland, and the United States, while the decade-specific estimates suggest that earnings polarization was especially strong in all these countries in the 1990s. However, neither the longest time span, nor the decade-specific estimates of the *Occupational Effects* correspond with pattern of the *Total Change*. It also shows that the overall earnings polarization trend in the US is rather a specific case than a general result for our selection of countries.

Lastly, we define no change in inequality, if the *Total Change* is constant along the earnings quantiles. Figure 2.14 plots the results for Greece, Iceland, and Israel. Again, the *Occupational Effect* is equal to zero for most countries. An interesting comparison here is Greece and Israel, as they cover similar time frames, with no de-routinization in Greece and high levels of de-routinization in Israel. The *Occupational Effect*, nevertheless, is close to zero for all quantiles.

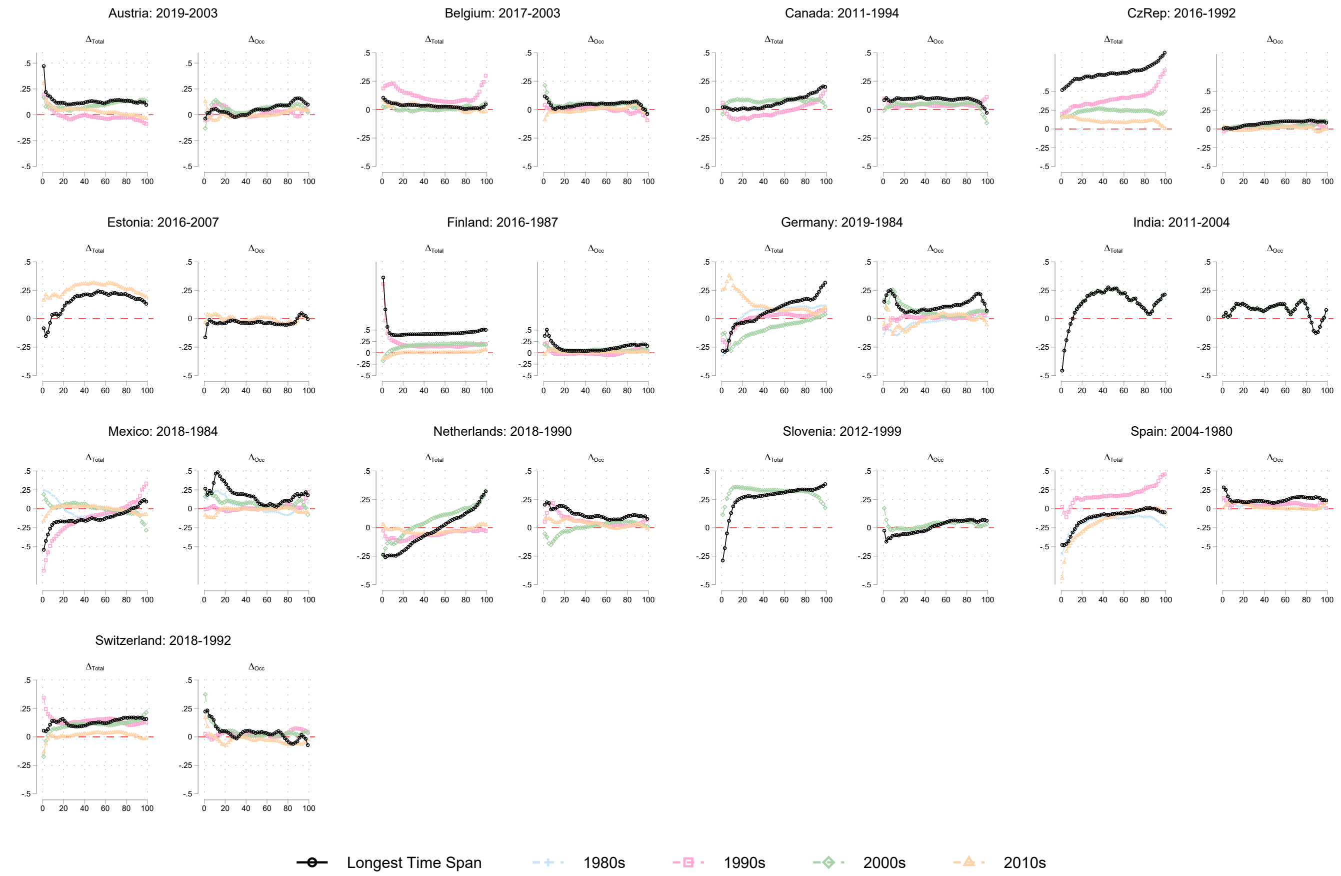
2.5.2.4 International Comparison: Overlapping Distributions, Composition and Return Effects

The remaining question is whether the reasons the weak link between de-routinization of jobs and changes in the earnings distributions discussed for the US also hold in our international comparisons. We, again, start with an empirical investigation of the theoretical argument by Böhm et al. (2019) and Böhm (2020), stating that earnings distributions of occupational classes can overlap. Consequently, de-routinization of jobs displaces workers in all quantiles, thus leading to adverse distributional effects.

Figure 2.15 reveals that class-specific earnings distributions overlap in all countries and in all decades. Generally, abstract occupations show the highest median earnings but also the largest dispersion within the occupational classes. This means that abstract jobs are not just at the top of the distribution, but are rather widely distributed. Moreover, earnings from routine and service occupations overlap substantially in nearly all countries. Our finding for the US, that employees from a certain occupational class are not perfectly stratified but scattered along the earnings distribution, also holds for the other countries in our sample. Therefore, we support the argument of Böhm et al. (2019) that the weak link between the *Total Change* and the *Occupational Effect* arises from simultaneous movements of different occupational classes within the same quantiles that can counteract and enforce each other resulting in ambiguous distributional effects.

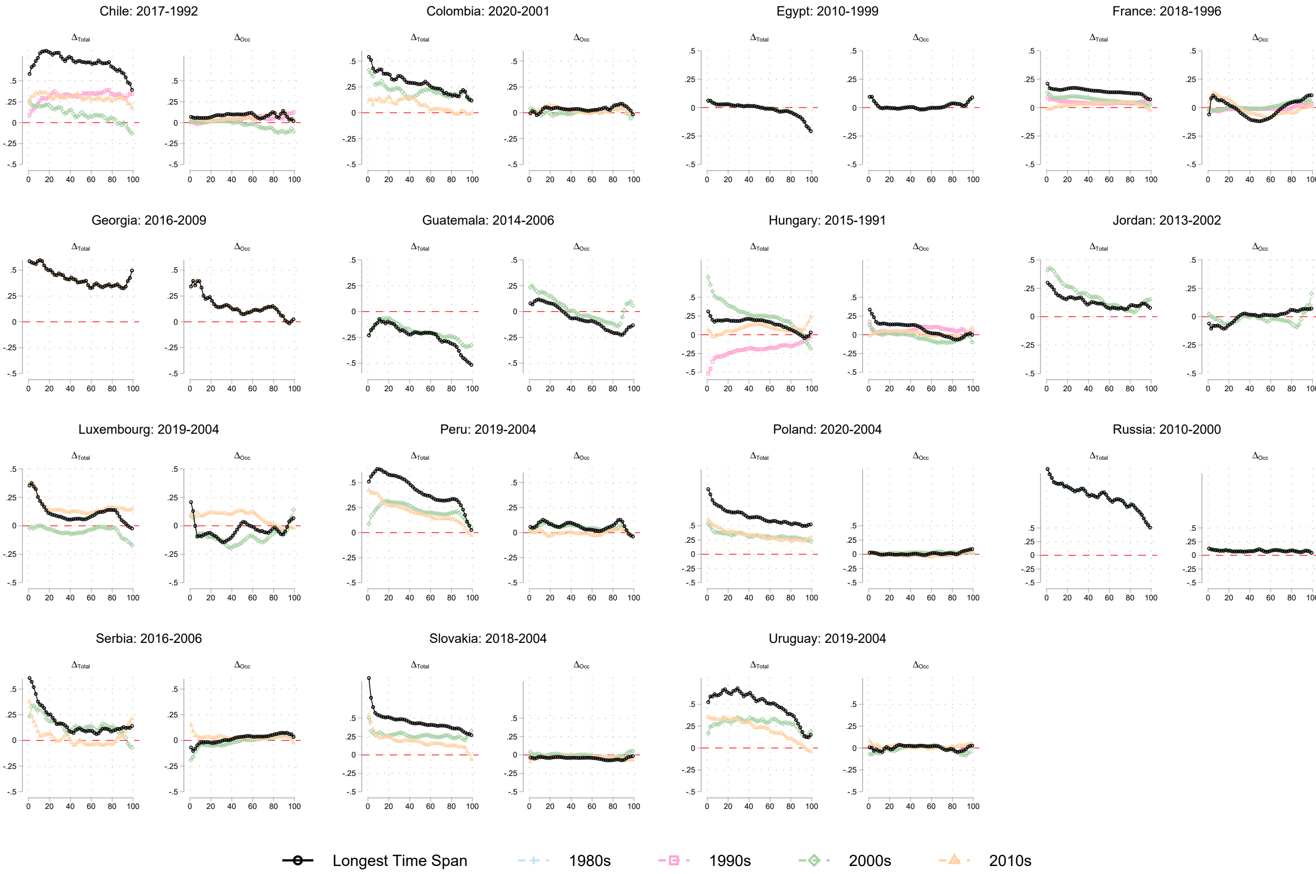
We also see that the findings of occupational composition and return effects in the US can be translated to the other de-routinizing countries in our sample. While there is a clear hierarchy in returns for occupational groups across earnings quantiles, the changes in occupational composition and returns are not limited to certain parts of the earnings distribution and, thus, de-routinization can lead to various distributional consequences.[29]

[29] We provide the three panels, as shown in Figure 2.7 for the US, for every country in Appendix 2.8.5.



Notes: Compiled by authors based on LIS data for prime-age, employed population. For each country, the first panel shows the total percentile earnings growth, *Total Change* (Δ_{Tot}), on the y-axis. The second panel provides the counterfactual earnings growth, *Occupational Effect* (Δ_{Occ}) based on RIF quantiles decomposition explained in Section 2.4.2. The countries depicted here exhibit increasing inequality in the *Total Change*. The x-axis provides the percentiles of the earning distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

Figure 2.11: Increased inequality - *Total Change* and *Occupational Effect* from RIF quantiles decomposition



Notes: Compiled by authors based on LIS data for prime-age, employed population. For each country, the first panel shows the total percentile earnings growth, *Total Change* (Δ_{Tot}), on the y-axis. The second panel provides the counterfactual earnings growth, *Occupational Effect* (Δ_{Occ}) based on RIF quantiles decomposition explained in Section 2.4.2. The countries depicted here exhibit decreasing inequality in the *Total Change*. The x-axis provides the percentiles of the earning distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

Figure 2.12: Decreased inequality - *Total Change* and *Occupational Effect* from RIF quantiles decomposition

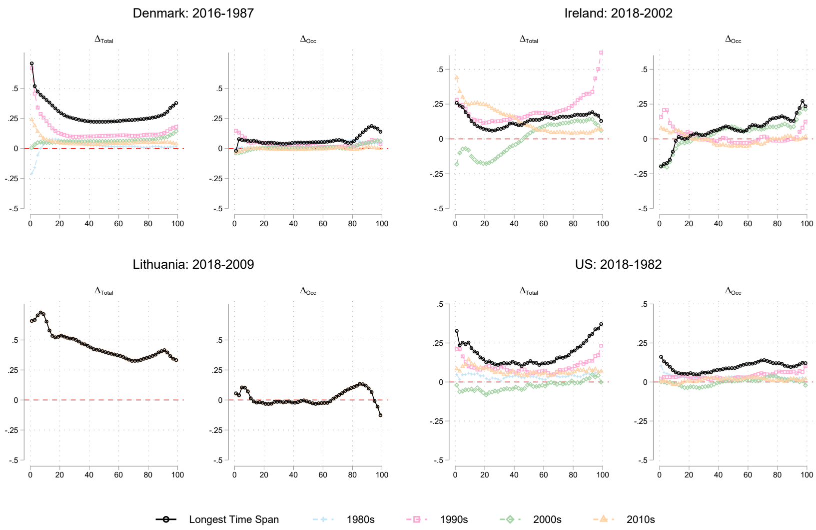
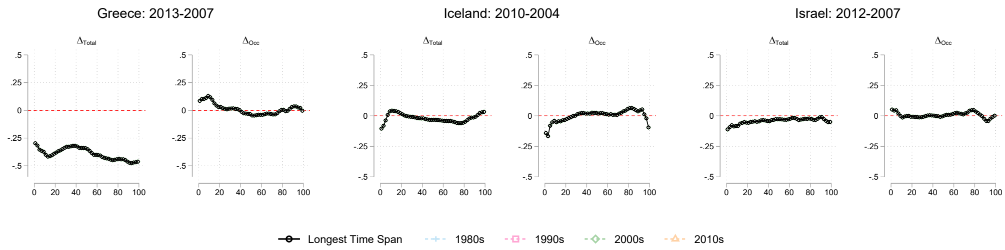
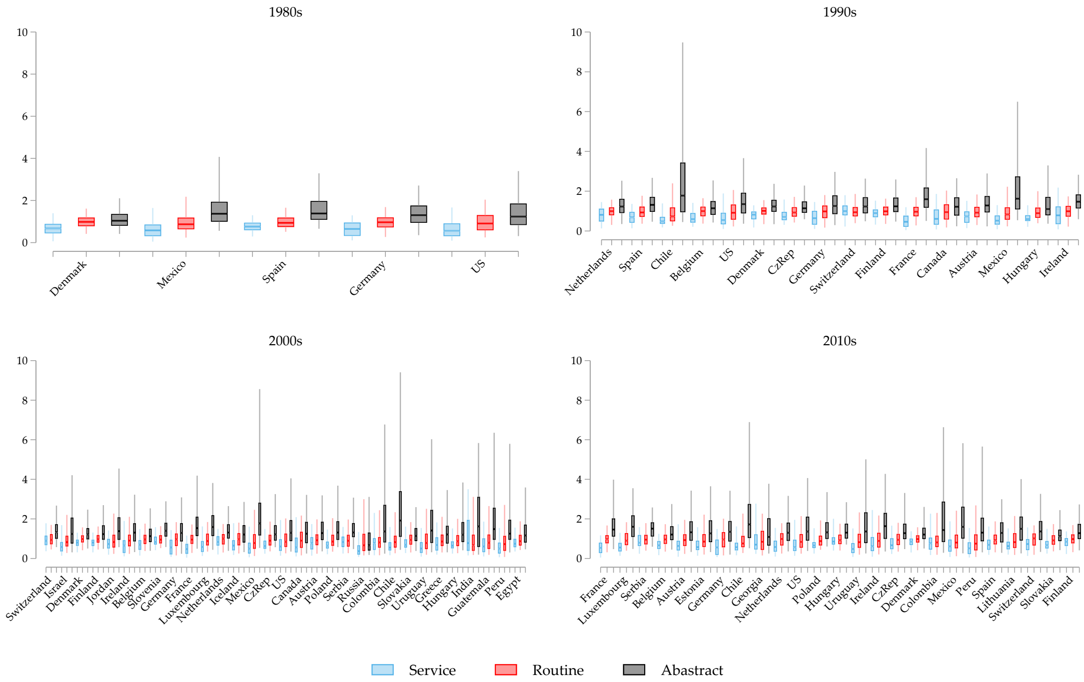


Figure 2.13: Polarization - *Total Change* and *Occupational Effect* from RIF quantiles decomposition



Notes: Compiled by authors based on LIS data for prime-age, employed population. For each country, the first panel shows the total percentile earnings growth, *Total Change* (Δ_{Tot}), on the y-axis. The second panel provides the counterfactual earnings growth, *Occupational Effect* (Δ_{Occ}) based on RIF quantiles decomposition explained in Section 2.4.2. The countries depicted here exhibit polarization and no change in the *Total Change*. The x-axis provides the percentiles of the earning distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

Figure 2.14: No change in inequality- *Total Change* and *Occupational Effect* from RIF quantiles decomposition



Notes. Compiled by authors based on LIS data for the prime-age, employed population. The four panel show the dispersion of earnings for the earliest year in the decade available. The y-axis shows the country-specific distribution of earnings in service (in light blue), routine (in red), and abstract (in black) occupational classes. Individual earnings in each occupational class are normalized by the country-specific average *routine* earnings in that year. The occupation-specific distribution is represented by box plots where the vertical line extremes represent the 5th and 95h percentiles, the box includes earnings between the 25th and 75th percentiles, and the median is marked by the horizontal line. The x-axis depicts the countries. The countries are sorted by the level of de-routinization in the respective decade.

Figure 2.15: Dispersion of earnings by occupational classes

2.6 Qualification and Extensions

The analysis applied in this paper requires several assumptions for its methodological approach and the comparability of the data for some countries needs to be treated cautiously.

A central assumption of the RIF decomposition is the in-variance of the conditional distribution. It means that there are no equilibrium effects between the two different periods (Firpo et al., 2009, 2011, 2018). This assumption is relatively strong and potentially violated in our analysis, as we include several time periods when structural changes took place. This is a major caveat of this approach, especially as job de-routinization is typically a long-lasting effect. This can potentially result in biased estimates and we cannot exclude that some long-run time frames are affected by this.

The results based on the RIF decomposition are sensitive to the choice of the base group. This arbitrary choice could potentially mean that the elements of the decomposition are also viewed as arbitrary.[30] In our main analysis, the base group is defined as 'male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industry, aged between 35 and 39 years'. We re-run our analysis for different base groups, but the implications remains the same.[31] Nevertheless, there is no standardized method for choosing the base group and we cannot avoid an arbitrary selection.

Although the literature refers to the counterfactual estimates as *effects*, the RIF decomposition is not suitable for causal interpretation (Firpo et al., 2009, 2011, 2018). The estimated counterfactual is a local approximation for the effect of changes in occupational classes on the quantiles growth over time. Fortin et al. (2011) argue that its accuracy depends on the application at hand. As we run the decomposition for each quantile of the earnings distribution, we see the interpretation of our results in the light of a local approximation as reasonable.

We do not provide confidence intervals for our estimates in our main analysis. The reason for this is the computational limits of bootstrapping the RIF results. Therefore, we only provide robust standard errors for the US. in Appendix 2.8.3. As discussed above, we choose this simplification for computational reasons, as otherwise we would have to run about 500 times (number of bootstrap replications) over 50 (number of estimated percentiles) RIF regressions per country for each time frame considered. The literature, especially in Firpo et al. (2011) and Firpo et al. (2018), typically does not provide confidence bands for quantile regressions, since they are mostly interested in the 'shape of the effect'. We do not think that is a strong argument and, therefore, we included intervals based on robust standard errors,

[30] Oaxaca and Ransom (1999) see this as an identification problem, Fortin et al. (2011) and Gelbach (2016) refer to it as a conceptual problem.

[31] Results are available upon request.

which are typically smaller than bootstrapped standard errors and should be seen as a lower bound.

Another shortcoming is that we do not include a formal test of polarization as provided in the polarization literature by (Esteban and Ray, 1994) and (Chakravarty, 2015). We do not apply it for two reasons: first, the analysis of polarization is not the main concern of this analysis, as we focus on various distributional consequences. Second, the RBTC literature typically refers to 'u-shaped patterns' of wage growth along the wage distribution. We follow this very generalized definition to be consistent with the literature. As we typically focus on the lower or upper part of the distribution, this should not affect our results and interpretation. Nevertheless, a fine-grained methodological connection of RBTC dynamics and the general polarization literature could be another interesting extension

Another concern is the comparability of the datasets. The LIS-ERF dataset is an internationally recognized and well received collection of surveys, but they are not perfectly harmonized, which effects the comparability of our vocal variables, i.e., earnings and occupation, between countries and over time. We apply a restrictive selection scheme, excluding several countries and waves from our analysis. The remaining 35 countries, however, still rely, to some extent, on net-earnings or mixed earnings information, as pointed out in Section 2.3 and Appendix 2.8.1. Nevertheless, the RIF decomposition in Section 2.5.2.3 only compares waves with the same earnings definition.

From a general perspective, one could also criticize that we argue against a theory without proposing an alternative explanation for the drivers of earnings inequality. Furthermore, the analysis focuses on occupational changes and neglects other labour market transitions over time. These would be interesting extensions for follow-up research in the future.

2.7 Discussion and Conclusion

This paper analyses whether de-routinization of the workforce can be observed internationally and if it explains changes in earnings inequalities within and between occupations. The database comprises 35 LIS-ERF countries characterized by different economic and political systems. We confirm shifts from routine-intense jobs toward non-routine occupations in 28 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, 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. Second, occupations overlap strikingly across the earnings distribution, despite a hierarchy in average returns, service, routine, and abstract. Therefore, de-routinization not only affects jobs in 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 the earnings distribution and these are, *a priori*, ambiguous.

Our analysis provides a broad map of the distributional consequences of the de-routinization of jobs and the importance of heterogeneity within occupational groups. The finding is pivotal, because it even holds for more than 4-digits occupational classifications as in the case of the US. Our analysis points toward the necessity to focus on occupational tasks rather than occupational groups, as it better accounts for variation within occupations. This is well-discussed by De Vries et al. (2020). However, our analysis is limited regarding changes in task prices as this requires more highly detailed occupational codes or other comparable metrics of workers' skill sets. Further empirical evidence on this matter, especially over-time decompositions of task prices along the earnings distribution, would be a fruitful extension to our work.

Our results highlight that de-routinization induced by ICT adoption is a process facing most countries. 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 de-routinization of jobs on inequality of labour market outcomes.

2.8 Appendix

2.8.1 Data Supplements - Income concepts

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

- Net earnings countries: Chile, Egypt, Georgia, Hungary, India, Mexico, Poland, Russia, Serbia, Slovenia, Uruguay.
- Gross earnings countries: Canada, Colombia, Denmark, Finland, France, Germany, Guatemala, Iceland, Israel, Jordan, Lithuania, Netherlands, Peru, Switzerland, US
- Austria, Belgium, Czech Republic, Estonia, Greece, Ireland, Luxembourg, Slovakia, Spain do not have harmonized earnings information across the whole time span. Thus, we separate gross from net earnings waves. Specifically, Austria and Belgium provide consistent information on gross earnings only after 2003. In the first wave available in Czech Republic (1992) and Slovakia (1992) earnings are defined as 'mixed, total income does not account for full taxes and contributions', while in all the later waves gross earnings are provided. Similarly, the first wave available in Estonia (2000) and Greece (2004) provides net earnings, while in all the later waves gross earnings are provided. Ireland switched from net to gross earnings after 2000, while Luxembourg and Spain after 2004.

2.8.2 RIF-Regression Methods

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

$$Y_{it} = g_t(X_i, \epsilon_i) \tag{2.10}$$

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 for estimating of a broad set of distributional parameters $v_t = v(F_t)$ including quantiles, variance, or the Gini Index under very general assumptions on the earnings setting equation 4.2. The central innovation is the use of Recentered Influence Functions (RIF). RIFs give the influence that each observation has on the calculation of $v(F_t)$ and have the property of integrating up to the parameter of interest $v(F_t)$. Therefore, it is possible to express group/time specific functions, v_1 and v_0, as conditional expectations:

$$v(F_t) = E[RIF(y_t, v_t, F_t)|X, T = t] \tag{2.11}$$

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

$$E[RIF(y_t, v_t, F_t)|X, T = t] = X_t'\widehat{\gamma}_t^v \tag{2.12}$$

$$\widehat{\gamma}_t^v = E[XX'|T = t]^{-1}E[RIF(y_t, v_t, F_t)|X, T = t] \tag{2.13}$$

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

$$\Delta^v = \bar{X}_1'(\widehat{\gamma}_1^v - \widehat{\gamma}_0^v) + (\bar{X}_1' - \bar{X}_0')\widehat{\gamma}_1^v \tag{2.14}$$

In the specific case of quantiles, RIF is defined as:[32]

$$RIF(t; q_t^p) = q_t^p + \frac{p - I[y \leq q_t^p]}{f_Y(q_t^p)} \tag{2.15}$$

$$E[RIF(y_t, q_t, F_t)|T = 1] = \frac{1}{f_Y(q_t^p)}Pr[Y > q_t^p|X = x] + (q_t^p - \frac{1-p}{f_Y(q_t^p)}) \tag{2.16}$$

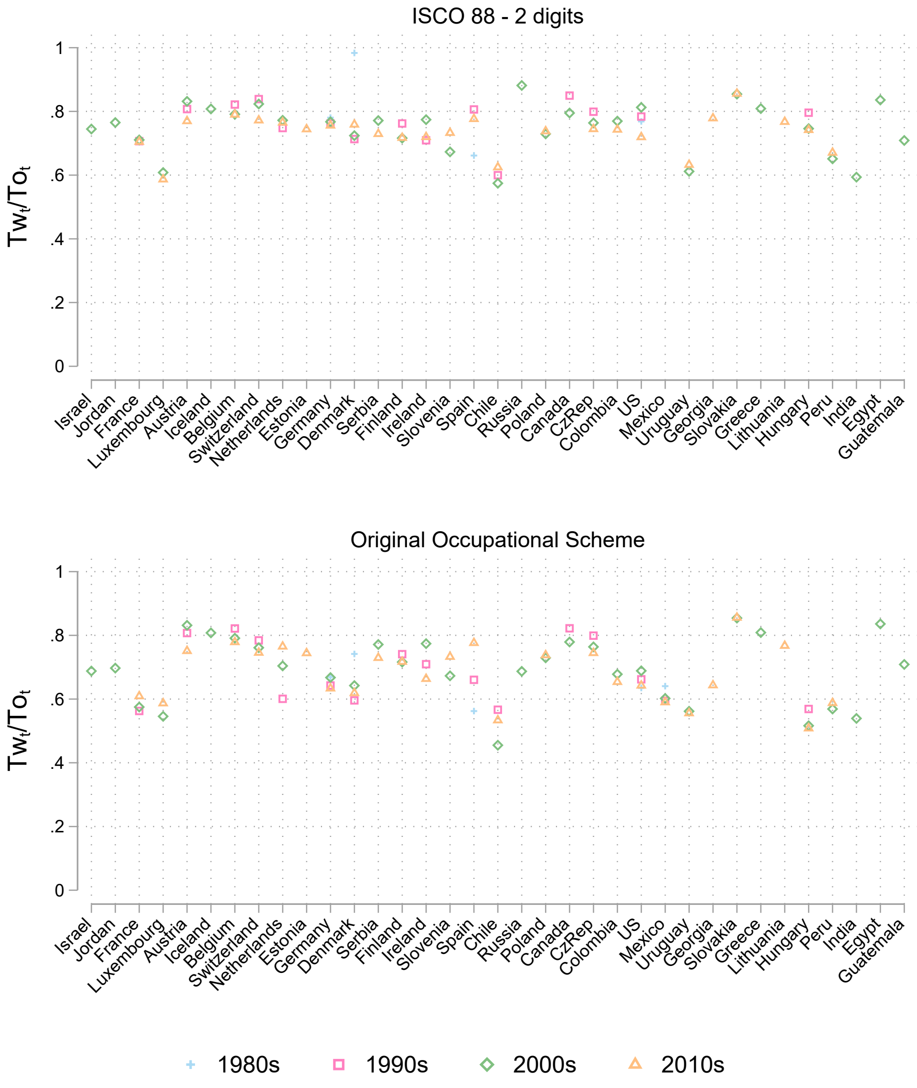
$$= c_{1,p}Pr[Y > q_t^p|X = x] + c_{2,p} \tag{2.17}$$

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 is found in Davies et al. (2017).

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

2.8.3 Auxiliary Tables and Figures

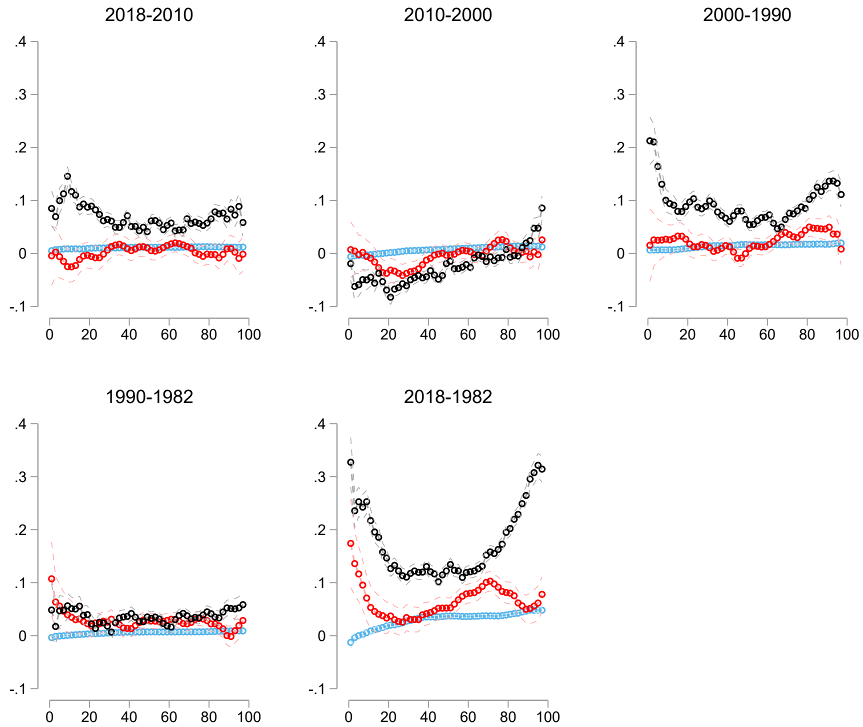
In Figure 2.16, we report the results for the Theil decomposition using alternative occupational classifications.



Notes. Compiled by authors based on LIS data for the prime-aged, employed population. The upper panel provides the share of the within component when the Theil is decomposed over 2-digits ISCO occupational classes. The lower panel provides the share of the within component when the Theil is decomposed over the original occupational classification ($occ1_c$), ranging from 2- to 4-digits depending on the country. The x-axis provides the countries sorted by the level of de-routinization as described in Figure 2.8.

Figure 2.16: Theil decomposition: within component under alternative occupational classifications.

In Figure 2.17, we report the results for the quantile decomposition on earnings and wages, respectively, for the US. The *Total Change* is shown in black, while the *Occupational Effect* is decomposed in *Composition* reported with light blue lines, and *Coefficient Effects* reported with red lines. Confidence intervals are shown at at the 95% significance level.



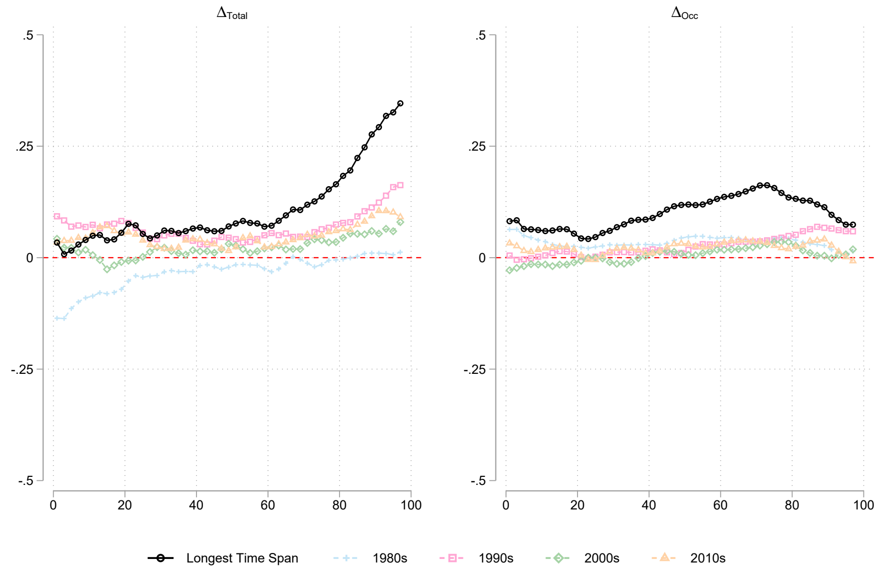
Notes: Compiled by authors based on LIS data for prime-age, employed population. The figure shows the total percentile earnings growth (*Total Change*, black line) and the *Occupational Effect* is decomposed in *Composition* (in light blue) and *Coefficient Effects* (in red) for the US based on RIF quantiles decomposition explained in Section 2.4.2. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years. Confidence intervals are provided at the 95% significance level.

Figure 2.17: Detailed quantile decompositions results for the United States

2.8.4 Robustness Checks - Wages instead of Yearly Earnings

This section replicates the analysis explained in Section 2.5.2.3 using hourly wages[33] as the dependent variable in order to provide closer comparability with the existing literature. Due to data constraints explained in Section 2.3, we can reproduce the analysis on hourly wages for a sub set of countries. We present in Figure 2.18 the results for the US.

In Figure 2.18, the wage decomposition for the US shows similar patterns as in Figure 2.5 for earnings. Episodes of wage polarization can be observed in the 1990s, characterized by large wage gains at bottom of the distribution. However our findings show that, over the longest time span available (2019-1982), we do not observe u-shaped *Total Change* for earnings. The wage gains experienced in the 1990s at the bottom of the wealth distribution are, in-fact, negatively compensated for by large and consistent wage losses experienced during the 1980s. Most notably, however, is the weak relation between the estimated *Total Change* and *Occupational Effects* robust to both earnings, as shown in Figure 2.5, and wages, Figure 2.18.



Notes: Compiled by authors based on LIS data for prime-age, employed population. This figure reports the RIF decomposition results of US for hourly wages. The graphs on the left-hand side show the total percentile earnings growth, *Total Change* (Δ_{Total}), on the y-axis. The graphs on the right-hand side provides the counterfactual earnings growth, *Occupational Effect* (Δ_{Occ}) based on RIF quantiles decomposition explained in Section 2.4.2. The x-axis provides the percentiles of the hourly wage distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

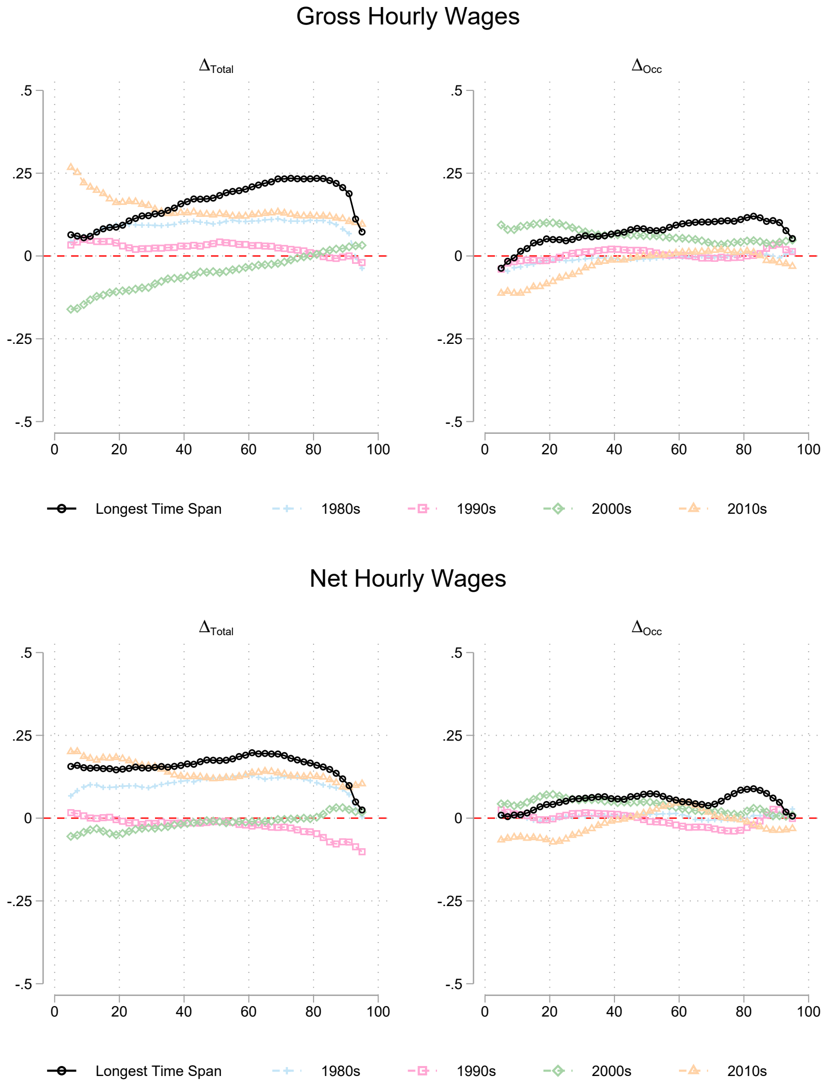
Figure 2.18: Quantile decomposition results for the United States - wages

[33] Our hourly wage variable is calculated dividing the personal labour income by the number of actual working hours usually worked during the week multiplied by 4.33.

Another concern is that we rely on mixed information of net and gross labour earnings in our sample. The robustness checks, however, do not suggest substantial differences between gross or net earnings, as both concepts reveal similar outcomes as in the main analysis above. 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 a very few countries provide both gross and net earnings information.

Figure 2.19 provides the quantile decomposition for gross (net) wage in the upper (lower) panel in Germany.[34] As above, the x-axis depicts the wage quantiles and the y-axis provides the quantile growth over the longest time span available for Germany (2017-1984) and for the intermediate decades. Both earnings concepts show similar patterns for the *Total Change* and the *Occupational Effect*. According to our estimates of the *Total Change*, inequality in gross wages increased more than inequality in net wages, especially due to high wage growth at the bottom of the net wage distribution. This might be due to re-distributional tax policies, which mitigate market outcome inequalities. Most notably, in both exercises, the *Occupational Effect* is weakly correlated with *Total Change*, thus confirming the robustness of our findings under different earnings concepts.

[34]The other countries, with both earnings concepts available, are Austria, Greece, Luxembourg, Panama, and Peru. The results are similar and available upon request.



Notes: Compiled by authors based on LIS data for prime-age, employed population. This figure reports the RIF decomposition results for gross and net hourly wage for Germany in the upper and lower panels respectively. The graphs on the left-hand side show the total percentile earnings growth, *Total Change* (Δ_{Total}), on the y-axis. The graphs on the right-hand side provides the counterfactual earnings growth, *Occupational Effect* (Δ_{Occ}) based on RIF quantiles decomposition explained in Section 2.4.2. The x-axis provides the percentiles of the hourly wage distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

Figure 2.19: Quantile decomposition results for gross and net hourly wages in Germany

2.8.5 Detailed Country Specific Results

This 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 2.3. Employment and income shares, alongside decomposition results for unconditional quantile regressions, are reported in country-specific tables and figures that are analogous to those in the main analysis. Note that Russia, Serbia, Slovakia, and Switzerland do not provide industry information. Therefore, we computed RIF decompositions without controlling for industry dummies.

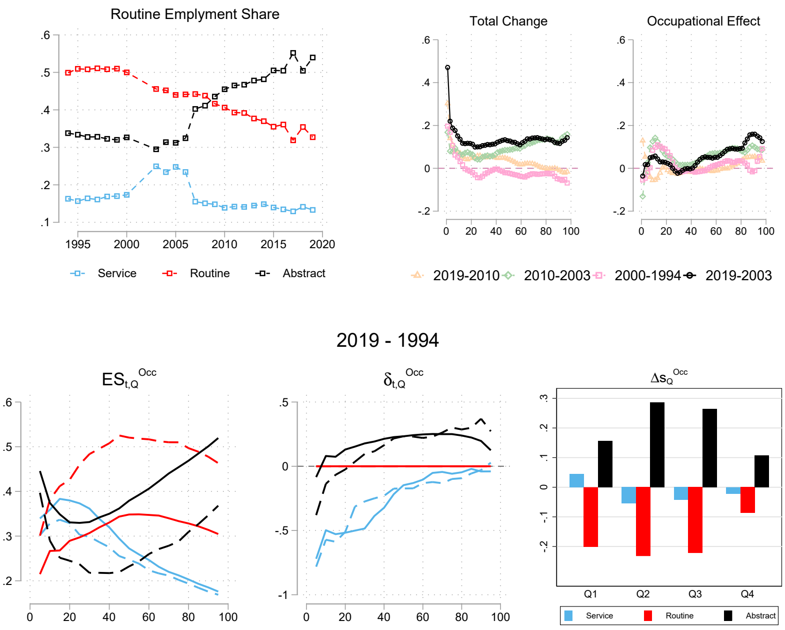
The following notes hold for the graphs and tables of all countries, respectively:

Upper-left figure: Employment shares by occupational class
Note. Compiled by authors based on LIS data for the prime-aged, employed population. The figure show the change of the employment share for each occupational class over time.

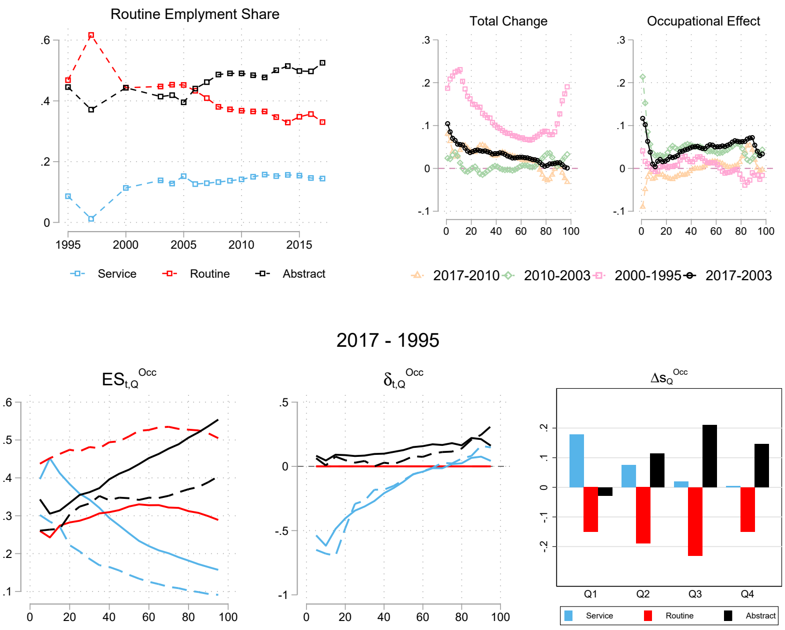
Upper-right figures: Quantile RIF decomposition
Note. Compiled by authors based on LIS data for the prime-age, employed population. The figure reports the RIF decomposition results for each country. The panel on the left-hand side show the total percentile earnings growth, *Total Change* (Δ_{Total}), on the y-axis. The graphs on the right-hand side provides the counterfactual earnings growth, *Occupational Effect* (Δ_{Occ}) based on RIF quantiles decomposition explained in Section 2.4.2. The x-axis provides the percentiles of the earnings distribution. The base group is represented by male workers, with a HS diploma, working in routine occupations in manufacturing, mining, or quarrying industries, aged between 35 and 39 years.

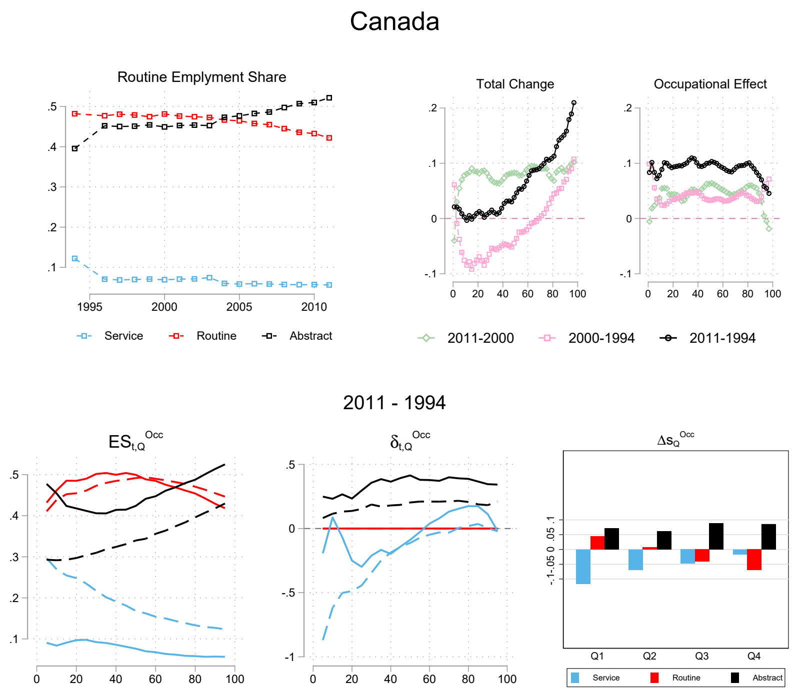
Lower figures: Occupational classes composition and returns
Note. Note. Compiled by authors based on LIS data for prime-age, employed population. The left panel provide the change of earnings shares by occupational class for the quartiles of the earnings distribution over time. The central panel depict the changes in occupational composition along the quintiles of 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. Methodlogy explained in Section 2.4.3

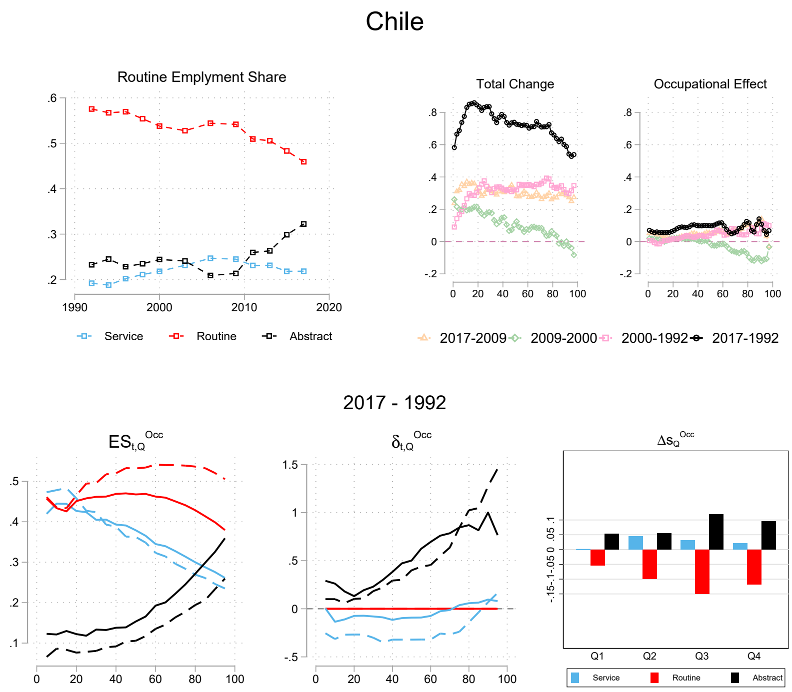
Austria



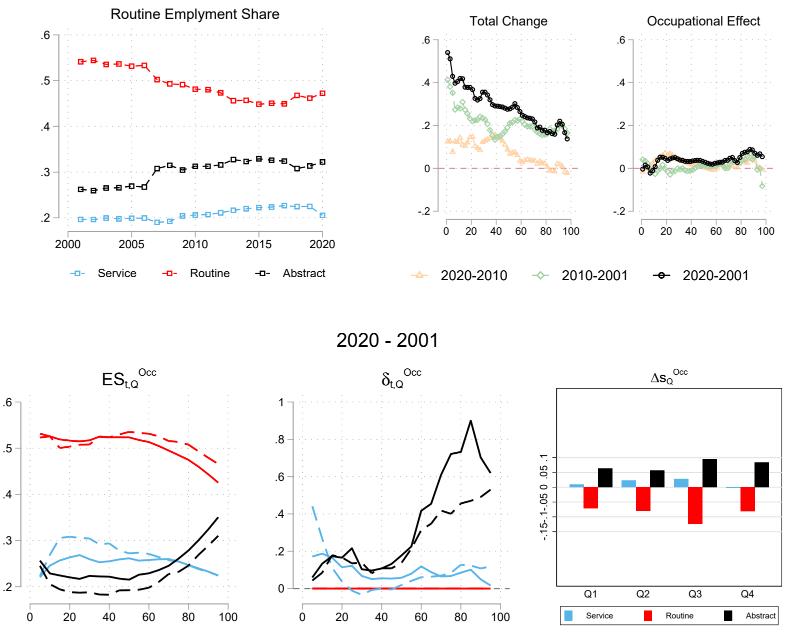
Belgium



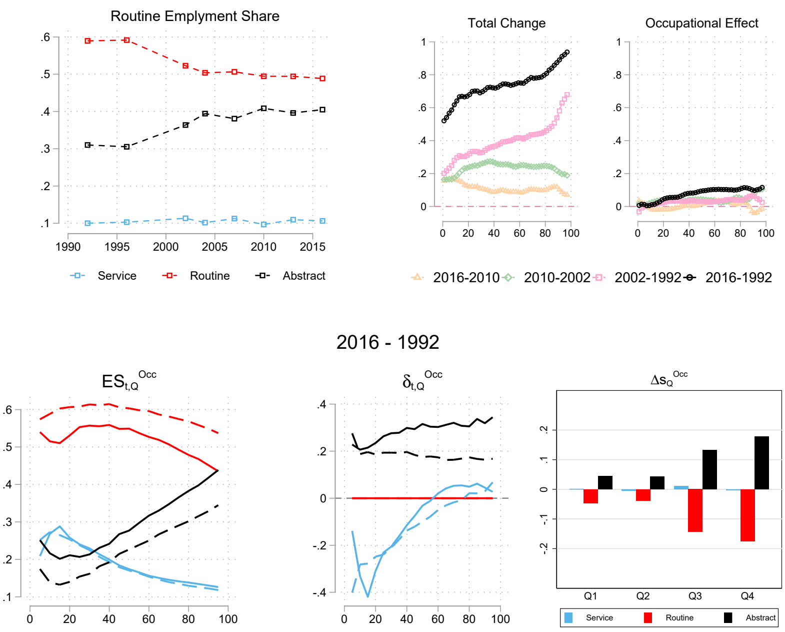

Canada
Routine Emplyment Share
Total Change
Occupational Effect
Service
Routine
Abstract
2011-2000
2000-1994
2011-1994
2011 - 1994
ES$_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4

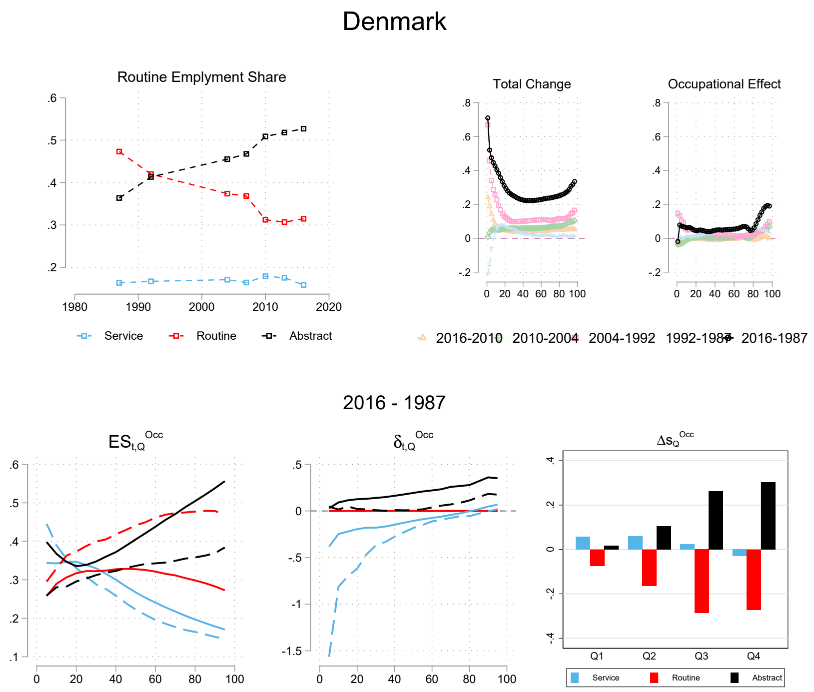

Chile
Routine Emplyment Share
Total Change
Occupational Effect
Service
Routine
Abstract
2017-2009
2009-2000
2000-1992
2017-1992
2017 - 1992
ES$_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4

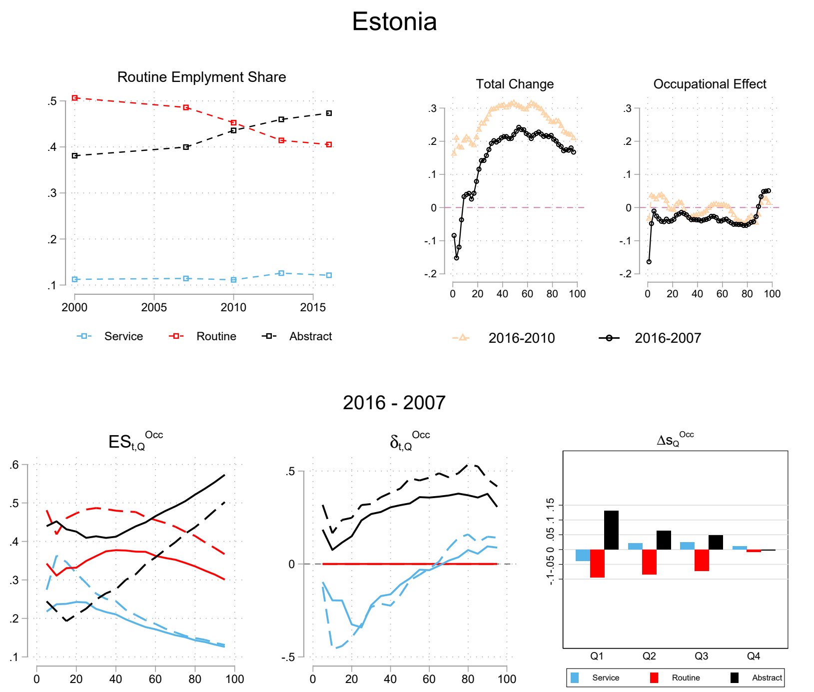
Colombia



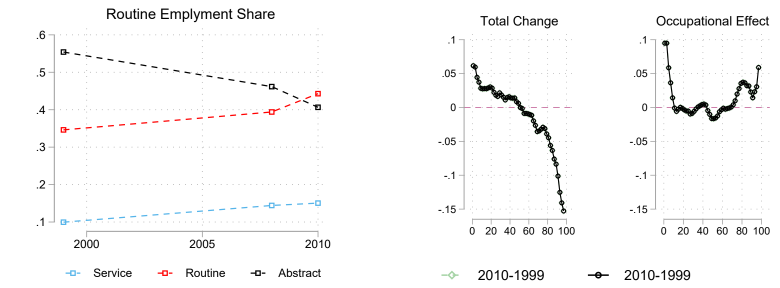
CzRep



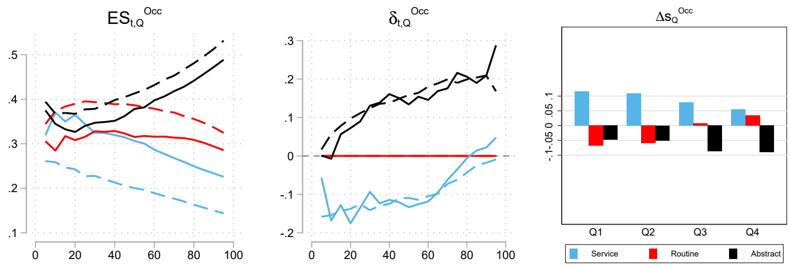

Denmark
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2016-2010
2010-2004
2004-1992
1992-1987
2016-1987
2016 - 1987
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4


Estonia
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2016-2010
2016-2007
2016 - 2007
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4

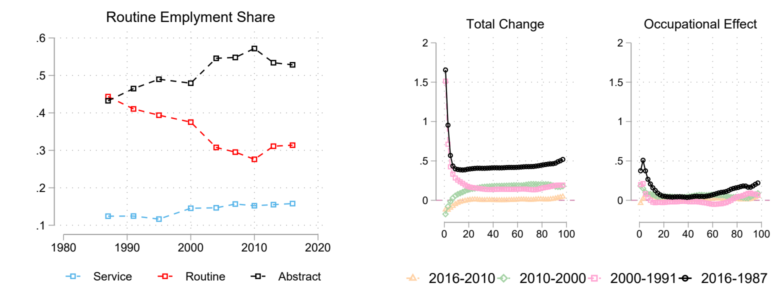
Egypt



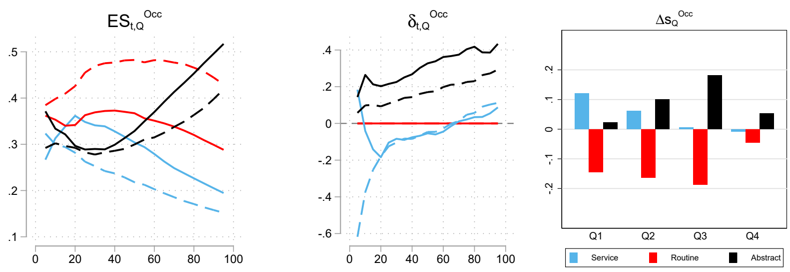
2010 - 1999

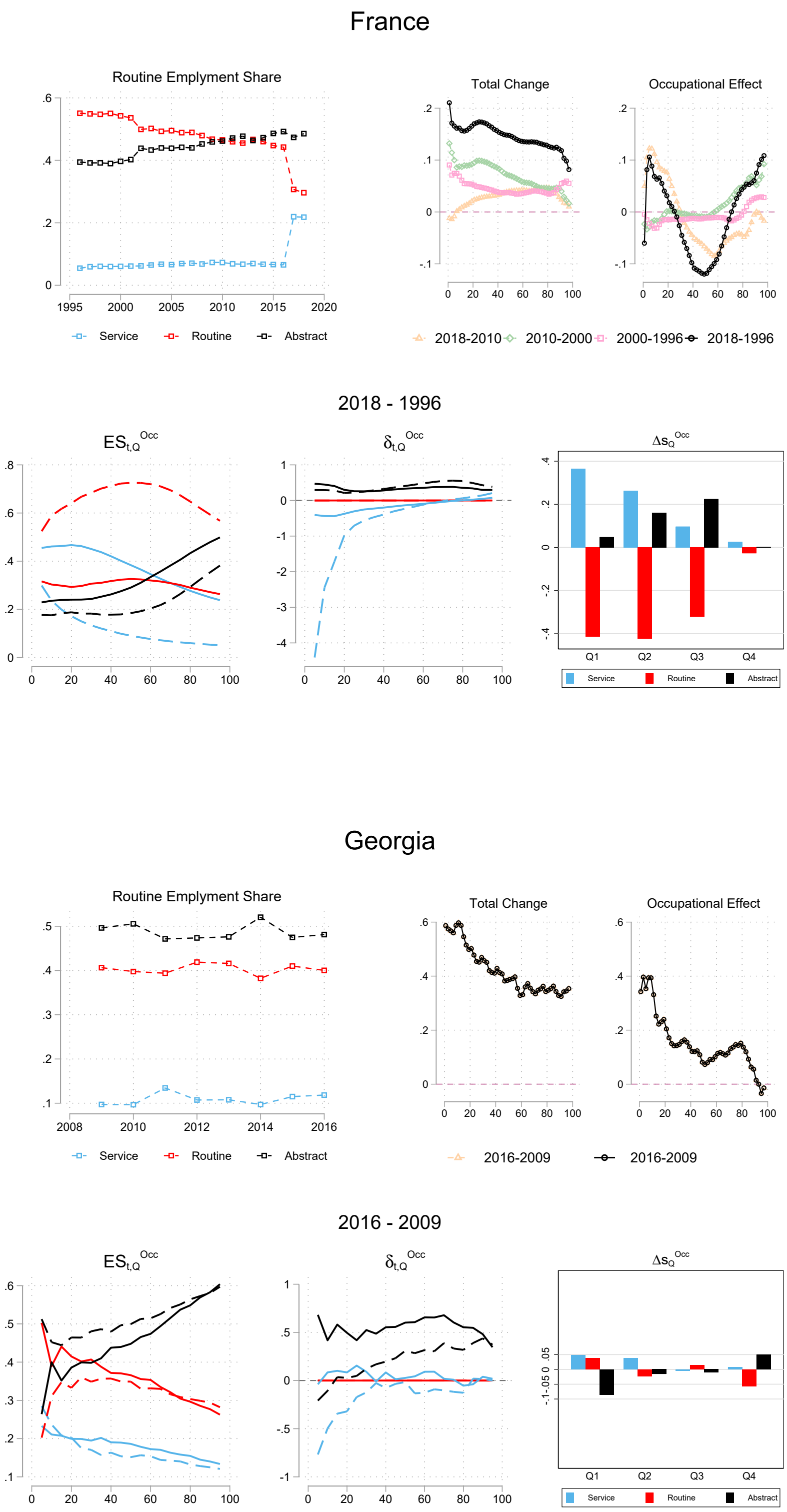


Finland

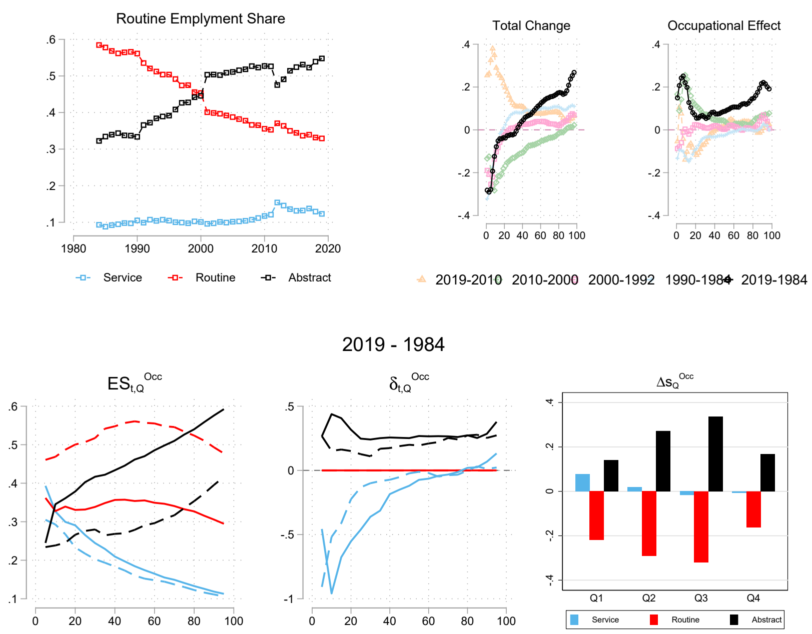


2016 - 1987

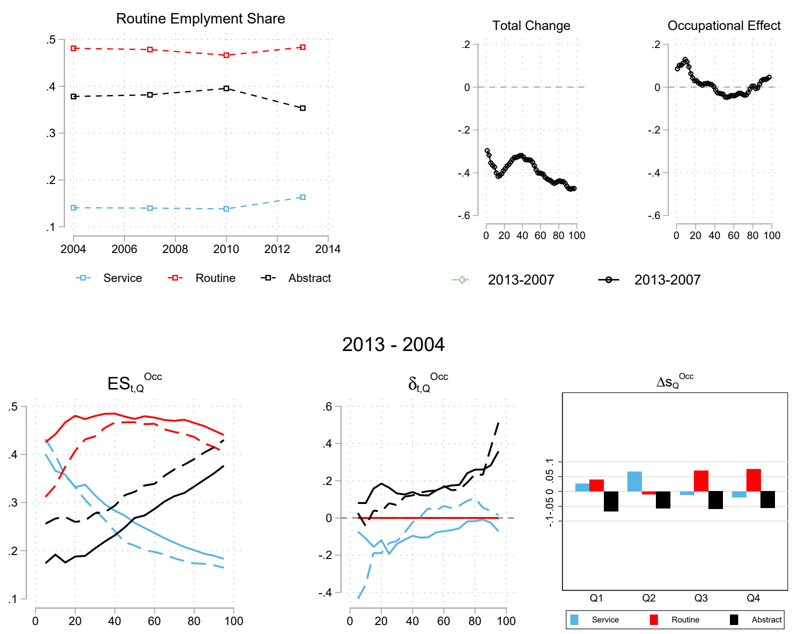


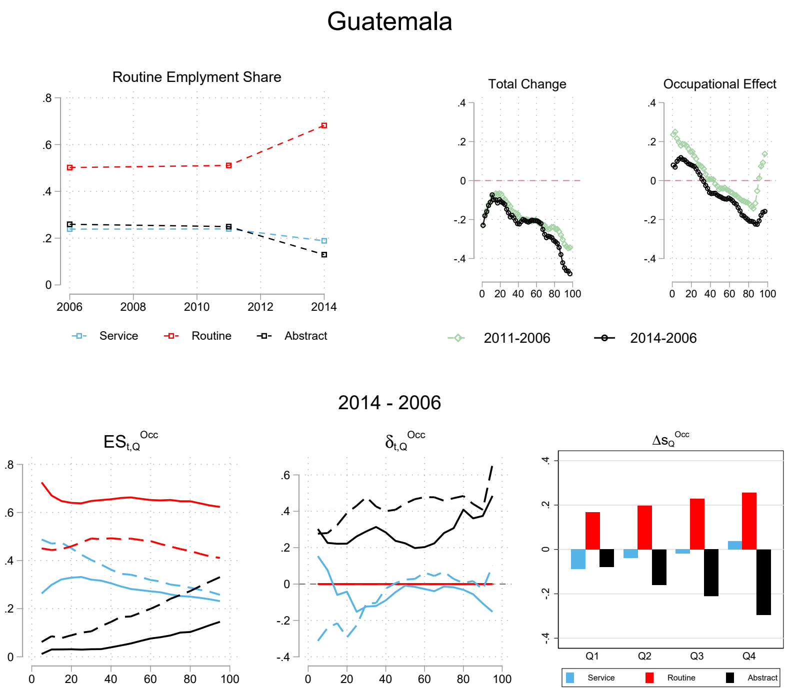

France
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2018-2010
2010-2000
2000-1996
2018-1996
2018 - 1996
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Georgia
Routine Emplyment Share
Total Change
Occupational Effect
2016-2009
2016-2009
2016 - 2009

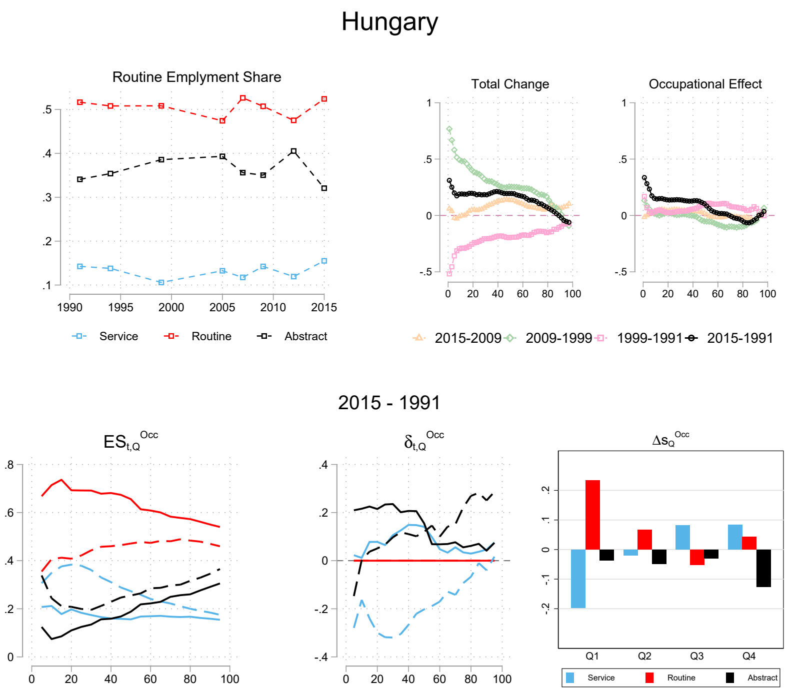
Germany



Greece




Guatemala
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2011-2006
2014-2006
2014 - 2006
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4


Hungary
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Service
Routine
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Total Change
Occupational Effect
2015-2009
2009-1999
1999-1991
2015-1991
2015 - 1991
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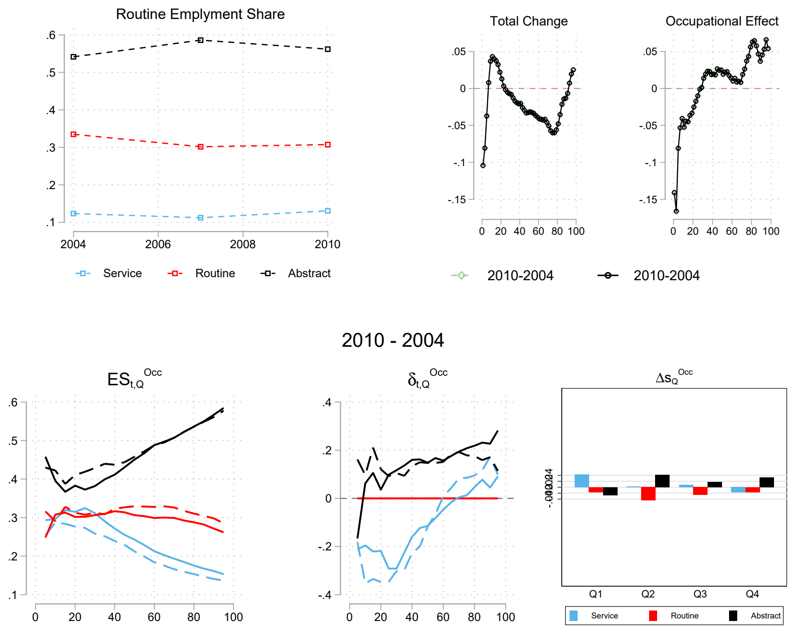
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4

Iceland



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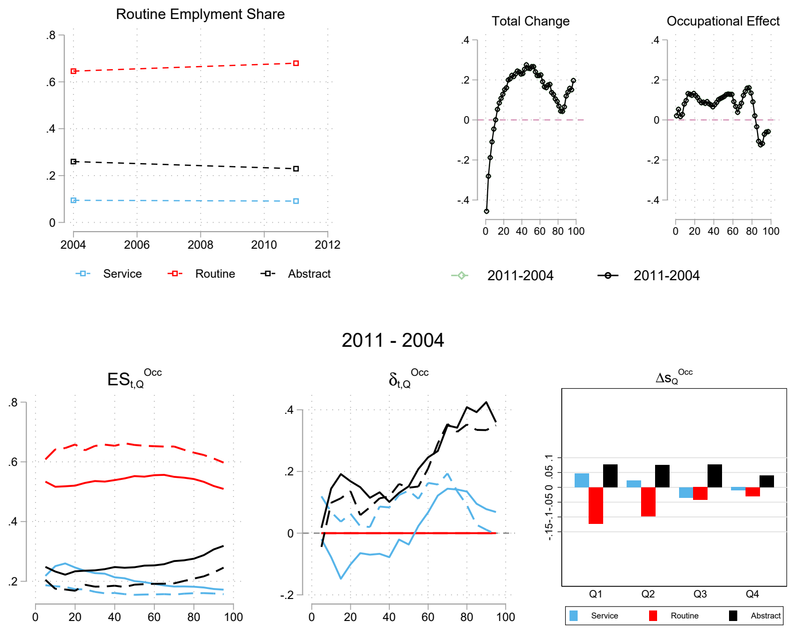

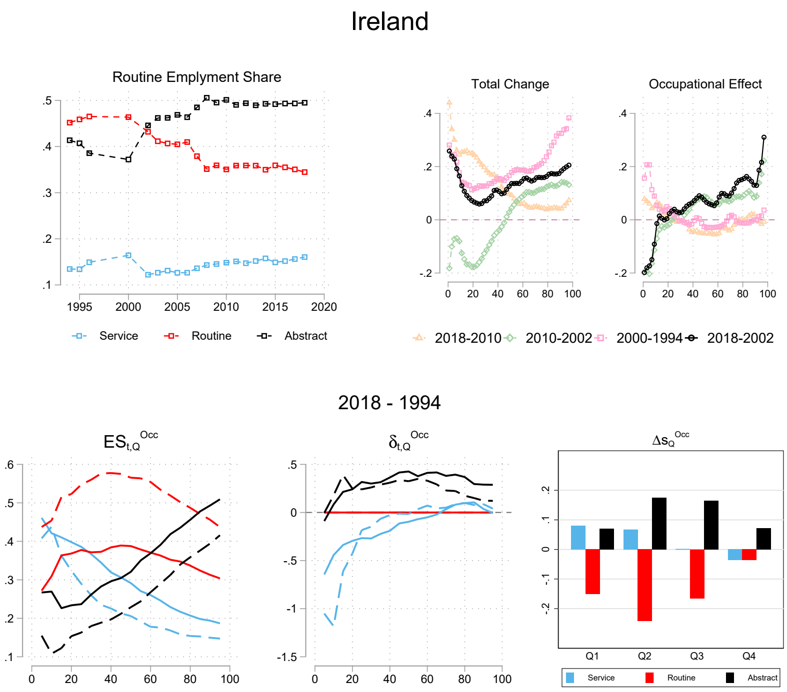
Ireland
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2018-2010
2010-2002
2000-1994
2018-2002
2018 - 1994
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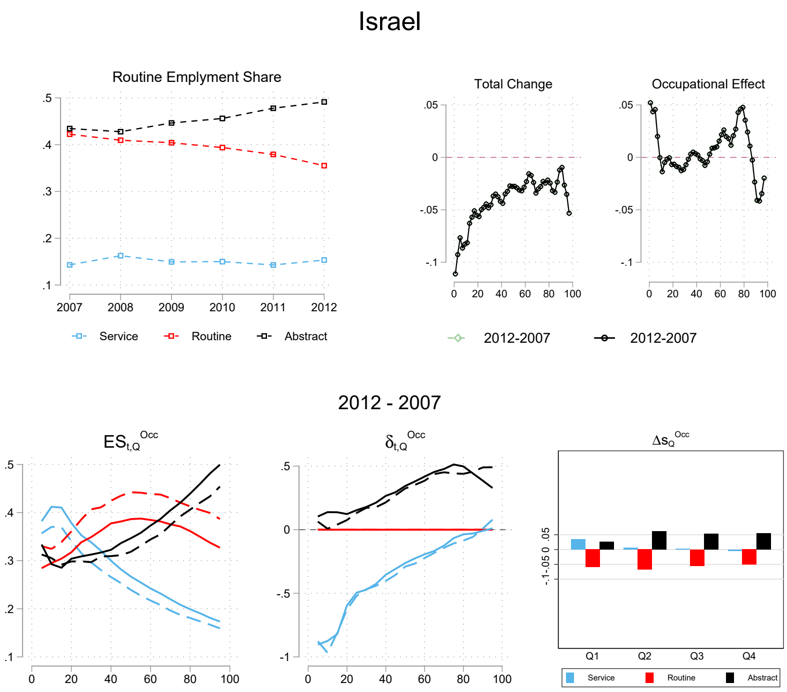
$\delta_{t,Q}^{Occ}$
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract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Service
Routine
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Total Change
Occupational Effect
2012-2007
2012-2007
2012 - 2007
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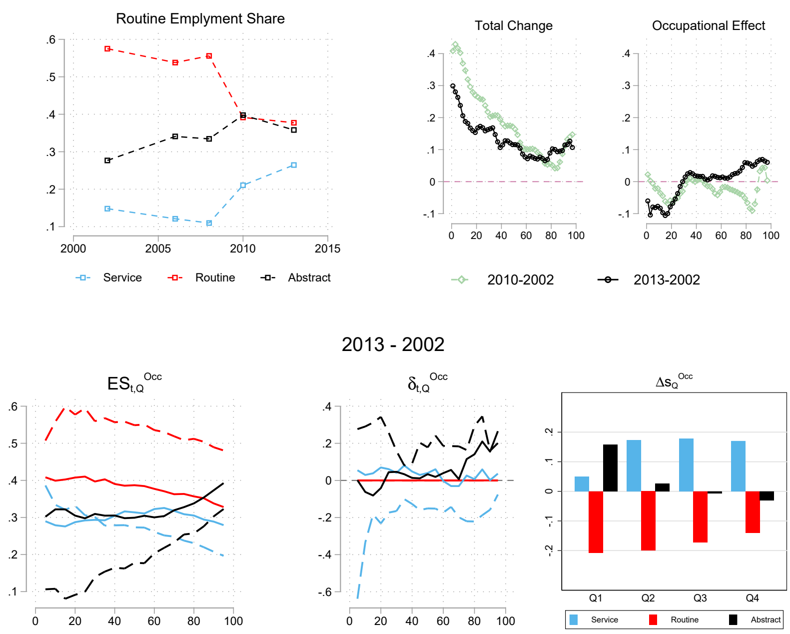
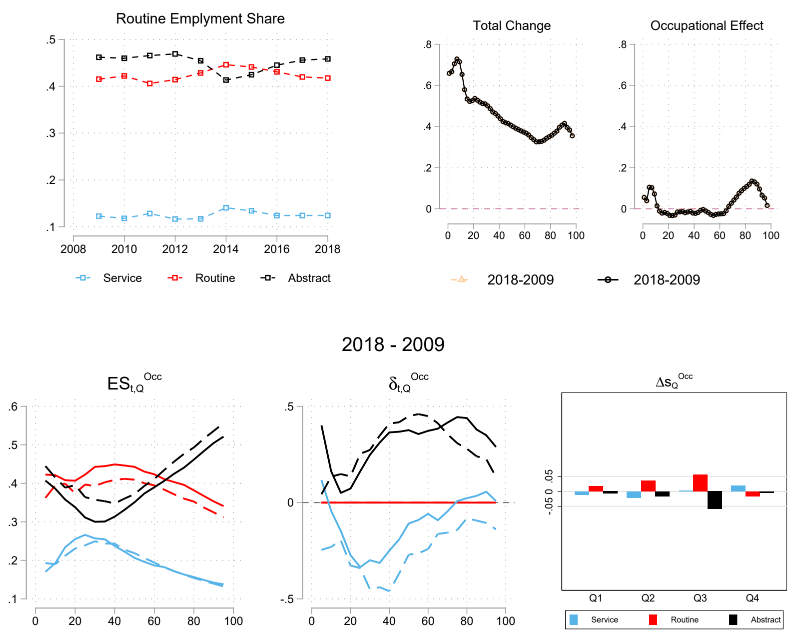
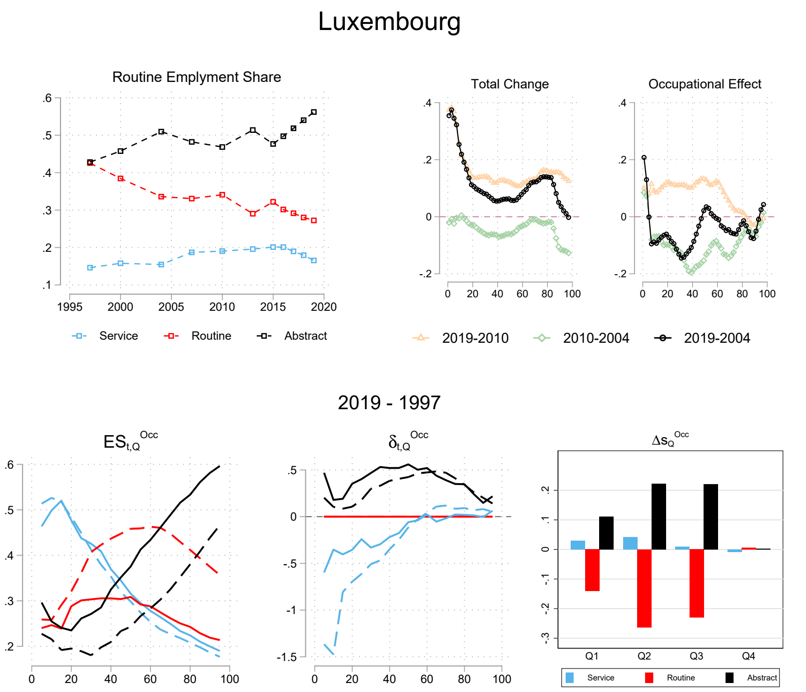
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract

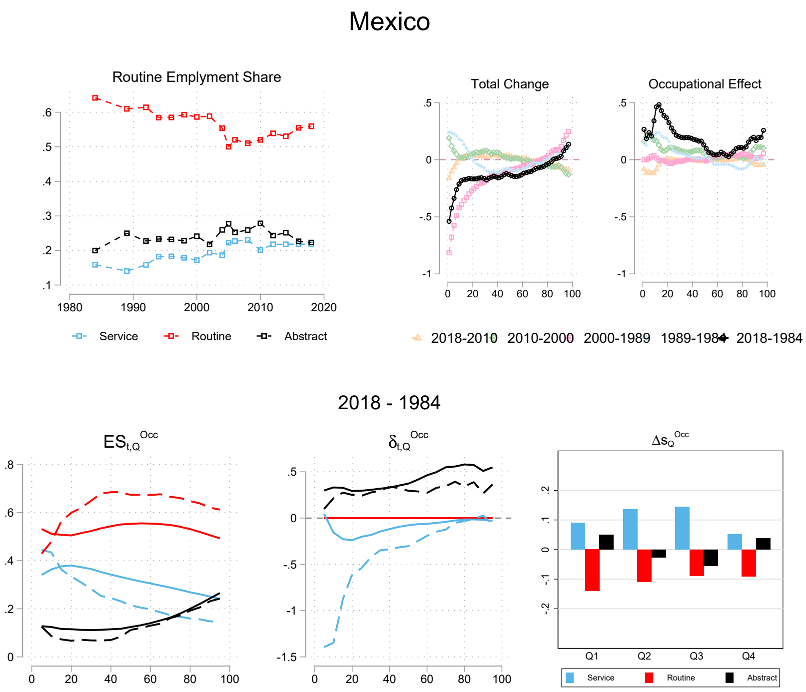
Jordan



Lithuania




Luxembourg
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2019-2010
2010-2004
2019-2004
2019 - 1997
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract


Mexico
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Service
Routine
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Total Change
Occupational Effect
2018-2010
2010-2000
2000-1989
1989-1984
2018-1984
2018 - 1984
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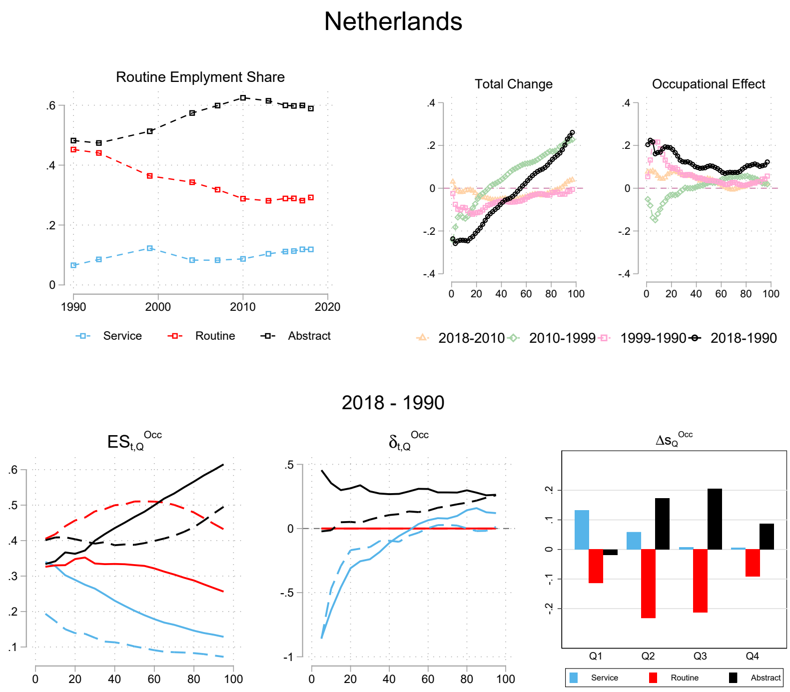
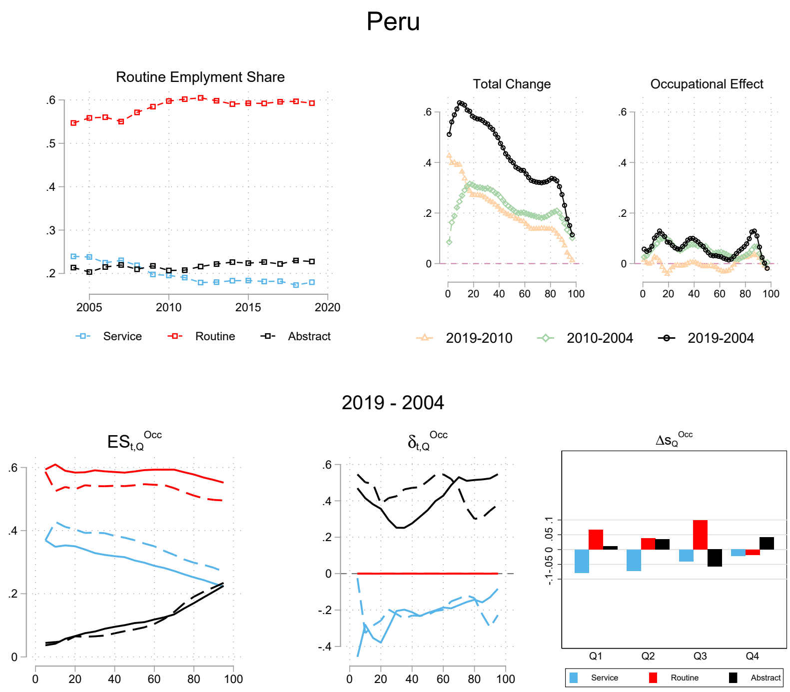
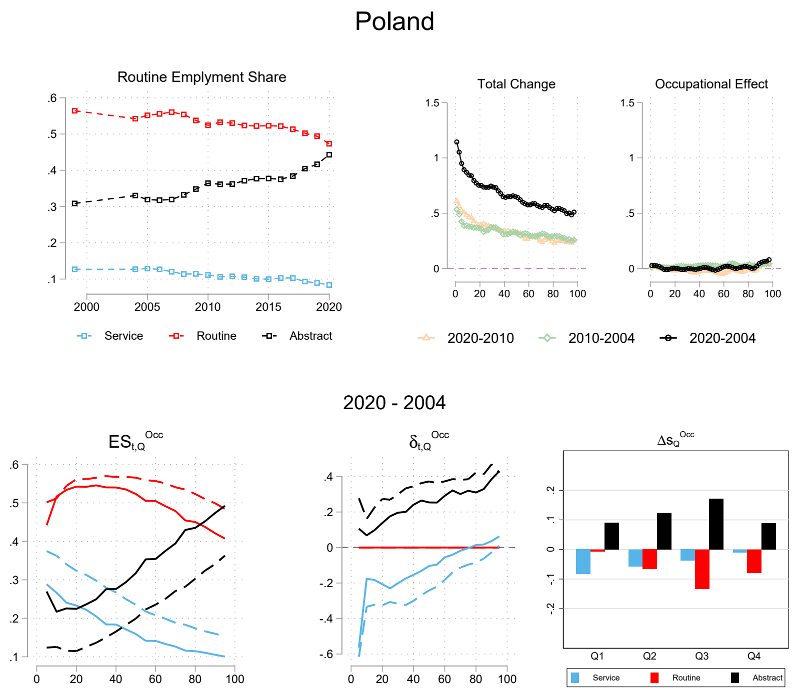
$\delta_{t,Q}^{Occ}$
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract


Netherlands
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2018-2010
2010-1999
1999-1990
2018-1990
2018 - 1990
Q1
Q2
Q3
Q4


Peru
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2019-2010
2010-2004
2019-2004
2019 - 2004
Q1
Q2
Q3
Q4


Poland
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Service
Routine
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Total Change
Occupational Effect
2020-2010
2010-2004
2020-2004
2020 - 2004
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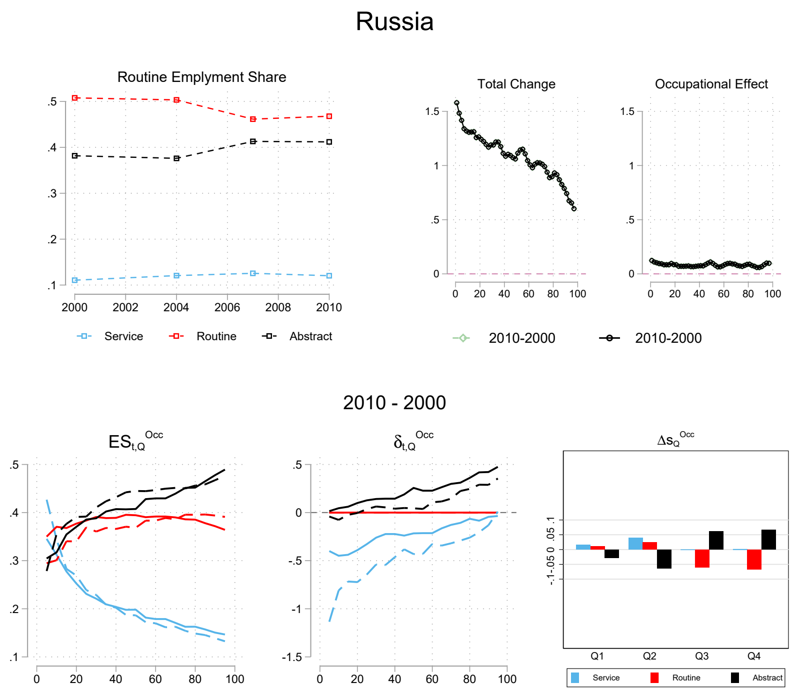
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract


Russia
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2010-2000
2010-2000
2010 - 2000
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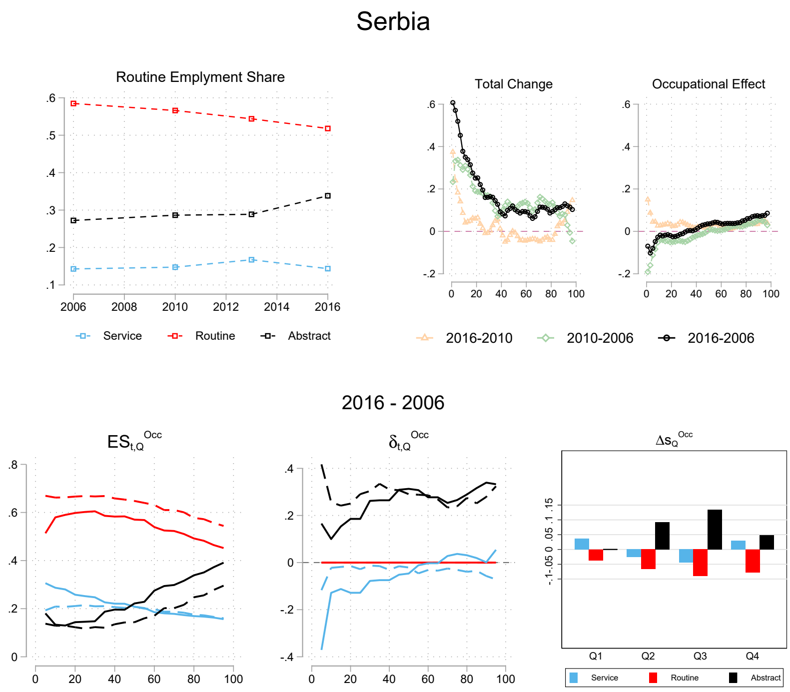
Δs_{Q}^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract



Serbia
Routine Emplyment Share
Service
Routine
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Total Change
Occupational Effect
2016-2010
2010-2006
2016-2006
2016 - 2006
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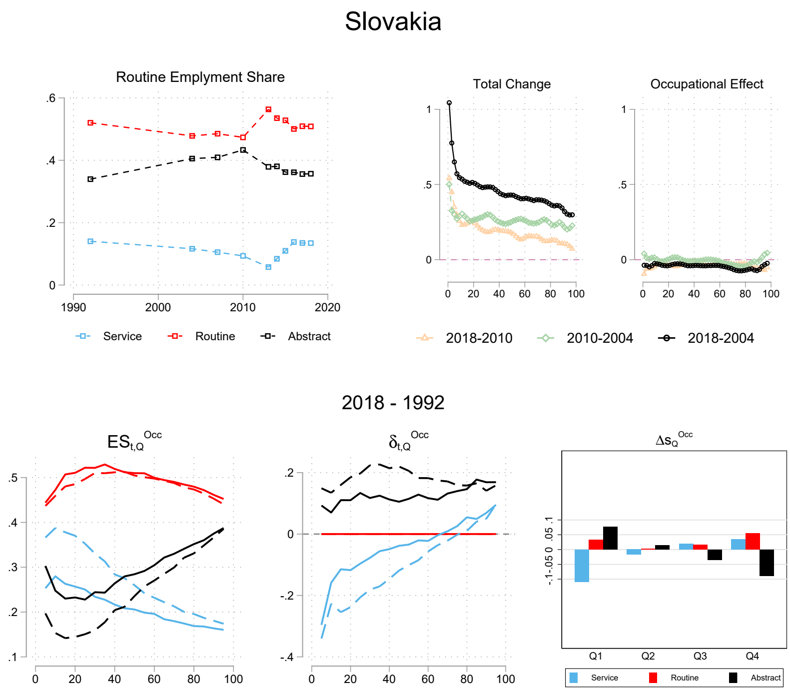
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract



Slovakia
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Service
Routine
Abstract
Total Change
Occupational Effect
2018-2010
2010-2004
2018-2004
2018 - 1992
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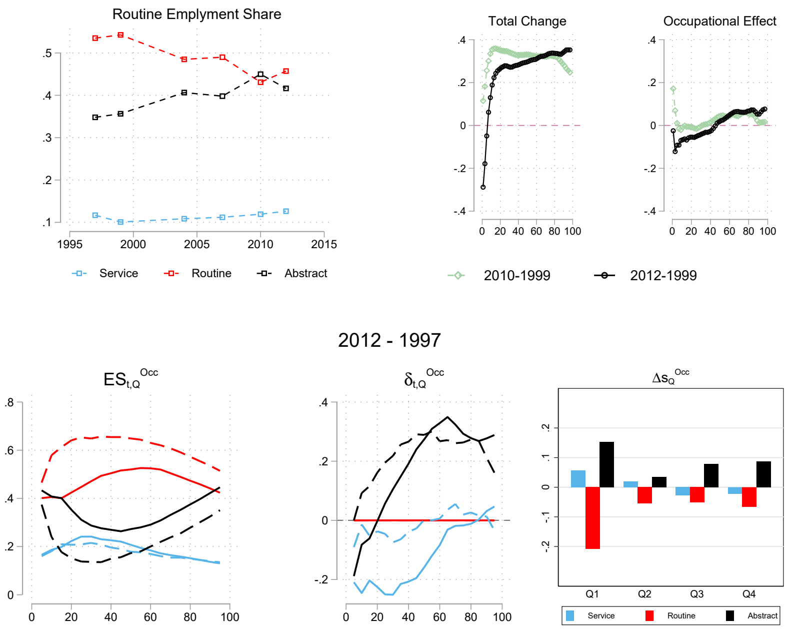
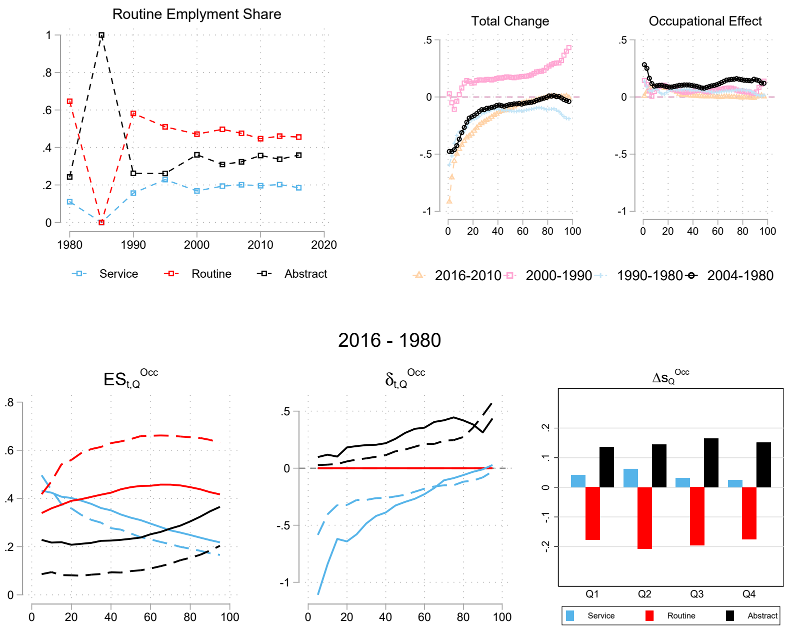
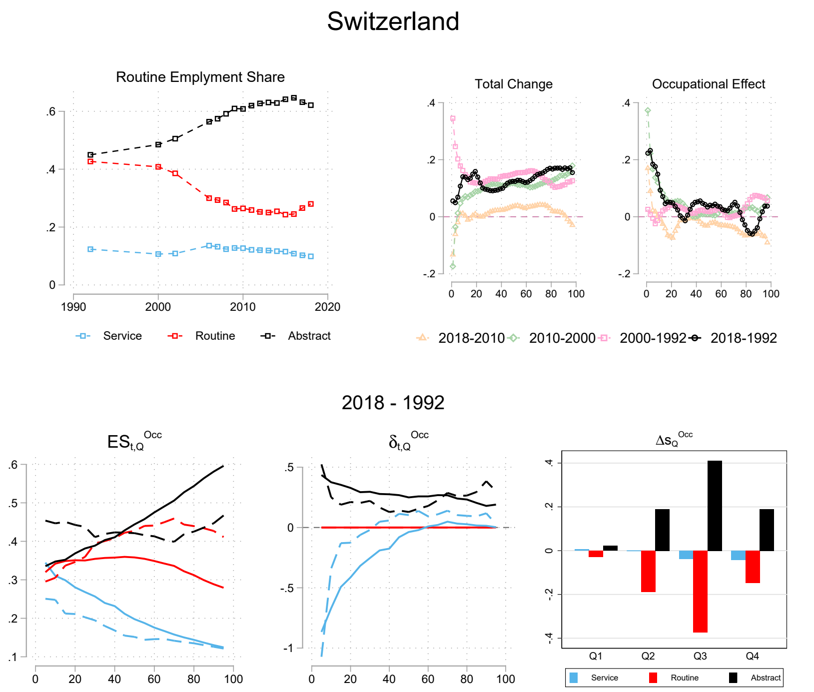
Δs_Q^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract

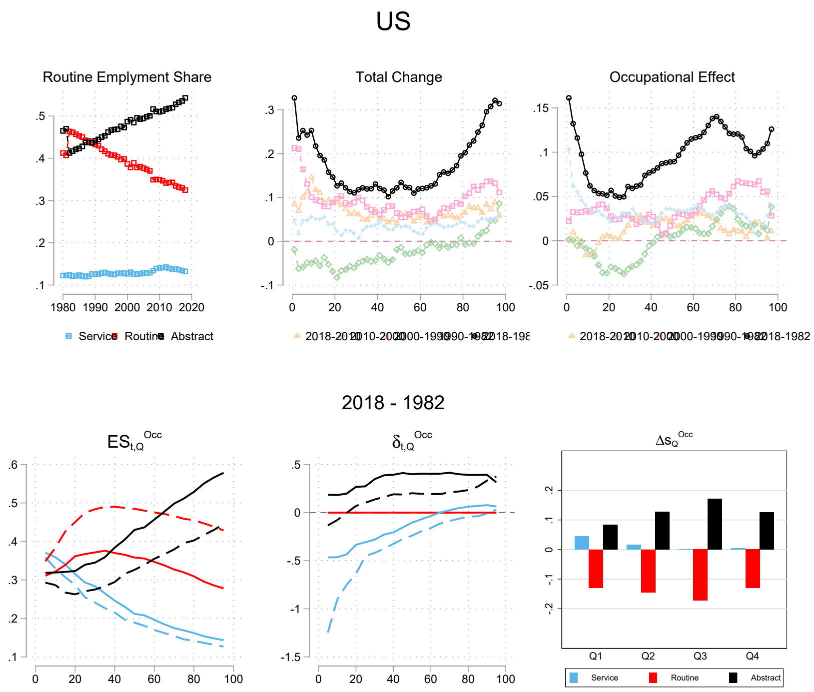
Slovenia

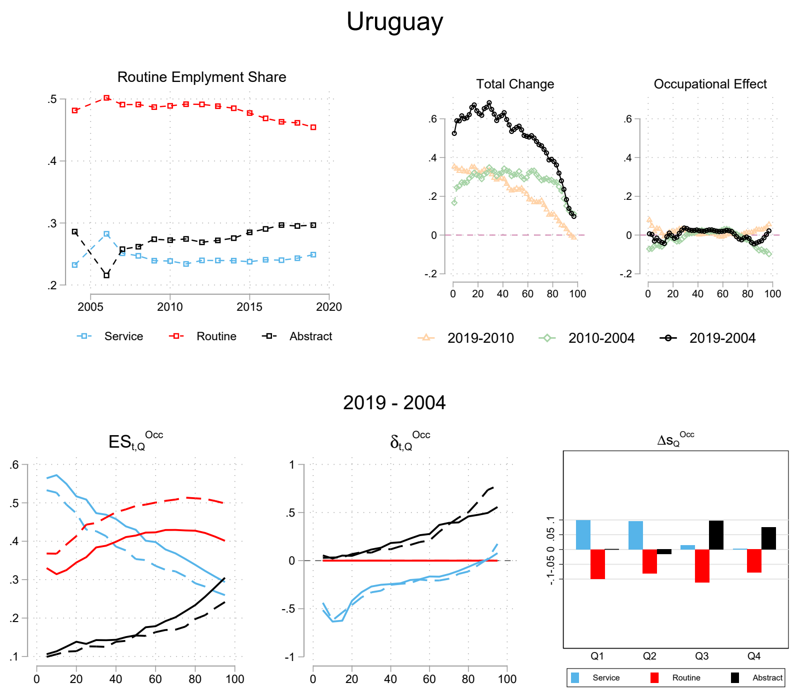


Spain




Switzerland
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2018-2010
2010-2000
2000-1992
2018-1992
2018 - 1992
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract


US
Routine Emplyment Share
Total Change
Occupational Effect
Service
Routine
Abstract
2018-1982
2018 - 1982
$ES_{t,Q}^{Occ}$
$\delta_{t,Q}^{Occ}$
Δs_Q^{Occ}
Q1
Q2
Q3
Q4
Service
Routine
Abstract


Uruguay
Routine Emplyment Share
Service
Routine
Abstract
Total Change
Occupational Effect
2019-2010
2010-2004
2019-2004
2019 - 2004
Q1
Q2
Q3
Q4

3 Are 'Good' Firms, Good for All Employees? An Investigation of Firm Fixed Effects at the Occupational Level

3.1 Introduction

A long tradition in the economic literature establishes that workers with similar skills earn different wages when employed in different firms (Slichter, 1950; Krueger and Summers, 1988; Van Reenen, 1996). In this sense, each firm applies a specific wage policy to its employees, determining employer-specific wage differentials independent of observed and unobserved worker characteristics.

While persistent wage premia are at odds with competitive labor markets in which wage levels are taken as given by firms, Card (2022) surveys four main empirical findings suggesting why employer wage-setting power is non-negligible: evidence on quit and recruiting responses to wages; evidence on the relationship between wages and firm productivity; evidence on the concentration of employment in small numbers of employers; and evidence of conspiracies and other forms of firm behavior targeted at suppressing firm-to-firm mobility and wage growth.

Abowd et al. (1999) (henceforth AKM), Goux and Maurin (1999), and Abowd et al. (2002) first propose an econometric model for the identification of firm premia as determinants of labor earnings, once differences in observed and unobserved characteristics of workers are controlled for. Subsequently, several papers show the existence of substantial heterogeneity in firm pay policies and that it contributes to the rise in earnings inequality in different countries since the 1990s (Card et al., 2013; Mueller et al., 2017; Devicienti et al., 2019; Song et al., 2019).

It is important to note that all these aforementioned studies implicitly assume that, within a firm, the same wage policy applies to all employees. The first to deviate from this assumption is Card et al. (2016): they show that firms apply different wage policies to male and female employees with women receiving only 90% of the firm-specific pay premia earned by men.[2] Kline et al. (2020) estimate age-specific firm wage premia and reject the hypothesis that older and younger workers face exactly the same vectors of firm effects.

In this paper I propose a new perspective on workplace heterogeneity, relaxing the implicit assumption of a unique premium distributed to all employees within a

[2]Similar results are found in Bruns (2019), Casarico and Lattanzio (2019), Palladino et al. (2021).

firm and allowing employers to set differential wage policies to different occupational classes, i.e. managers, blue collar workers, and white collar workers. To do so, I use administrative data covering the entire population of private-sector workers and firms in the Italian region of Veneto and estimate separate AKM models for managers, white, and blue collar workers in order to retrieve *occupation-specific* firm wage premia.[3] I then compare these estimates across occupational classes, firms, and time periods seeking to understand the role of firms in shaping inequality between and within occupations.

First, I show that occupation-specific firm pay policies predict well differences in wage levels between firms. Managers, white collar workers, and blue collar workers employed in the top 25% of the occupation-specific firm premium distribution earn, respectively, 32%, 40%, and 25% more than workers in the same occupational group employed in firms belonging to the bottom 25%. Such high heterogeneity in pay levels between firms is, however, coupled with great heterogeneity within firms and between occupational classes too. Once I compare the occupation-specific wage policies applied by firms, I observe that the same firm applies different wage policies to its employees depending on their occupation. Specifically, not only does the *level* of the firm premium differ between occupations, but also the *rank* that the same firm occupies along the occupation-specific wage policy distribution. In this sense, for example, the same firm may apply very advantageous wage policies for managers, while being relatively un-rewarding for blue and white collar workers with respect to the other firms in the market. Overall, I find no correlation between the manager, white collar, and blue collar workers firm policy distribution, suggesting that a high-paying firm for a given occupational class is, therefore, not necessarily as good for the other employees.

This first set of findings provides empirical evidence for a sophisticated wage strategy on the employer's side: while, on average, there exists a clear hierarchy in the returns of the different occupational classes, firms retain a high degree of flexibility in the way in which they remunerate their employees. Such flexibility translates into the possibility on the employer side to increase or reduce the occupational returns of their employees with respect to the market average.

Thus, in a second step, I quantify the gradient of occupation-specific remuneration schemes adopted by firms. To do so, I exploit the fact that, within a (dual) connected set of firms,[4] the AKM occupation-specific firms effects can be directly comparable. In this way, it is possible to rank employers according to the degree of differentiation they apply when setting their own occupation-specific policies. For

[3]Torres et al. (2018) apply a three-way fixed effects accounting for worker, firm, and job title fixed effects, finding that job title fixed effects explain on fifth of wage variance using Portuguese data over a 26-year interval. While such application accounts for the role of heterogeneity between occupations on inequality, it still does not address whether the same firm applies different occupation-specific wage policy.

[4]Section 3.2 provides all the methodological details.

example, in a firm that pays high firm wage premium to its white collar workers and low premium to its blue collar workers, the degree of differentiation will be higher than in a firm that pays similar wage policies to both occupational classes. While in the latter case the firm is equally sharing rents among white and blue collar workers; in the former the firm is discerning the premium to apply to the different occupational groups, applying more advantageous wage policy to its white collar workers than to its blue collar workers.

I apply regression-based models to identify the returns of the different occupational groups. I find large heterogeneity in the way employers remunerate their employees. For example, in 2001, the latest year of available data in my application, white collar workers were earning on average 28.5% more than blue collar workers, *ceteris paribus*. However, sorting firms according to the difference between white and blue collar fixed effects, this wage premium increases to 33.1% among the 60% most differentiating firms and to 42.1% in the top 20%. Most notably, my findings show that there is a correlation close to one between the rank of a firm along the occupation-specific fixed effect distribution and its rank along the distribution of firms sorted by increasing wage policy differentiation, meaning that the highest-paying firms for a given occupational group are typically those applying the largest differences in pay policies with respect to the other employees.

Eventually, I study the evolution of occupation-specific firm premia over two decades comparing the 1980s (1982-1991) with the 1990s (1992-2001). Results show that, in the Veneto region, the difference in returns between white and blue collar workers increased by 3 percentage points between the 1980s and 1990s, passing from 25 to 28%. However, such wage premium increase was larger in firms applying larger differences in their occupation-specific wage policies. Among the 20% firms with the largest fixed effect differences, the white collar premium increased by 7 percentage points, passing from 34% to 41%. These findings suggest that firm policy differentiation between occupational classes has increased over time. As final exercise, I explore whether such changes came together with increased sorting of high-type workers in high-type (occupation-specific) firm policies. To do so, I estimated different measures of sorting proposed by the existing literature (Card et al., 2013; Lopes de Melo, 2018; Kline et al., 2020) for white and blue collar workers and compare their evolution across time periods. While I find substantial heterogeneity in sorting intensity between firms, most of the over time changes in sorting intensity occurred in firms that are in the middle of the distribution. Most notably, among the 20% firms that apply the largest wage policy differences, sorting intensity did not change for both white and blue collar workers. Theses results suggest that the high increase in white collar returns experienced by these firms does *not* seem to be driven by a more effective selection of the labor force by employers. Taken together, these findings show that firms increasingly differentiate their occupation-specific wage policies over time *independently* from sorting patterns.

The remainder of the paper is organized as follows: Section 3.2 discusses the econometric models applied in the paper, Section 3.3 presents the data, and Sections 3.4 and 3.5 discuss the main results. Section 3.6 discusses several caveats of the analysis and potential extensions. Section 3.7 concludes.

3.2 Methodology

The identification of firm premia requires two-way fixed effect models as first applied by Abowd et al. (1999). For each worker i, employed in firm j in occupation *Occ(i) = Manager*, *White Collar*, *Blue Collar*, in a given year $t=1, ..., T$, I assume the following linear model:

$$w_{it} = \theta_i + \psi_j^{Occ(i)} + X'_{it}\beta^{Occ(i)} + \epsilon_{it} \tag{3.1}$$

where w_{it} is log-daily wage, θ_i is a worker fixed effect representing worker i´s portable earnings component, and $X'_{it}\beta^{Occ(i)}$ is a covariate index capturing occupation-specific returns to time-varying characteristics of workers (i.e. age, age squared, and tenure) and firms (i.e. firm size). $\psi_j^{Occ(i)}$ is the occupation-specific firm premium paid to all employees of firm j working in occupation *Occ(i)* during the analyzed period. Unlike simple firm-specific occupational average wages, $\psi_j^{Occ(i)}$ is a persistent earnings component related to firm j and can be interpreted as the wage policy employed in firm j for occupation *Occ(i)*, after controlling for observed and unobserved worker heterogeneity (Devicienti et al., 2019).

With respect to previous literature, I relax the assumption that $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$, allowing the same firm to have different wage policies with its managers, white collar workers, and blue collar workers. The identification of these firm effects is possible within a given *connected set* of employers linked by worker mobility (Abowd et al., 2002). Such a connected set contains all the workers who have ever worked for any of the firms in the group and all the firms at which any of the workers were ever employed. Within each group, all the parameters in equation 3.1 can be estimated by OLS and *J-1* firm fixed effects, $\psi_j^{Occ(i)}$, will be identified. I perform the analysis on the largest connected groups within the managers, white, and blue collar workers sub-samples separately. While the three sub-samples are mutually exclusive in time t at the individual level, the same firm is not necessarily part of all the three connected sets. For this reason, some exercises in the following analysis are conducted on the *triple* connected set, which comprises all those firms connected by worker mobility where I can identify a firm-fixed effect for each occupational class. In Section 3.5, I then focus only on the evolution of the white and blue collar firm wage premia over time. In this latter case, I refer to the sub-sample including all the firms where both ψ^{WC} and ψ^{BC} can be estimated as the *double* connected set. Table 3.1 in Section 3.3 and Table 3.5 in Appendix report the details of each working sample used in the analysis.

Estimating firm fixed effects on separated samples by occupational class implies that that firm fixed effects are estimated only by job-movers between different firms and within the same occupation. This means that workers changing firm *and* occupation, do not contribute to the estimation of $\psi_j^{Occ(i)}$. An alternative approach consists in estimating an AKM model where the firm fixed effects are interacted with the occupational class. In this case, $\psi_j^{Occ(i)}$ is estimated over the full connected set, exploiting mobility between both firms *and* occupations. While this latter approach increases overall mobility and, consequently, the resulting connected set will be larger, the estimation of the occupation-specific firm policy $\psi_j^{Occ(i)}$ is derived comparing workers employed potentially in all occupational classes, affecting the interpretation of the wage policy. In this paper, I opt for the most conservative approach and estimate $\psi_j^{Occ(i)}$ based on separated samples by occupation. Nevertheless, in Appendix 3.8.4 I include a replication of the results using the interacted fixed-effect model as robustness check.

For the model estimates to be unbiased, the error component ϵ_{it} is assumed to not be correlated with any of the elements in θ_i, ψ_j, and X_{it}.[5] This restriction implies that the assignment of workers to firms respects a strict exogeneity condition. This condition rules out the possibility that idiosyncratic shocks in wages might lead to mobility toward a certain type of firm. Card et al. (2013) discuss in detail three forms of endogenous mobility that might bias the identification process and suggest several tests to support the validity of the assumption in the data. Several papers provide evidence in support of the exogenous worker's mobility applying these tests to German data (Card et al., 2013; Bruns, 2019), to Portuguese data (Card et al., 2016), to US data (Song et al., 2019), as well as to Italian and Veneto data (e.g. (Devicienti et al., 2019; Casarico and Lattanzio, 2019; Fanfani, 2022; Di Addario et al., 2022). In the Appendix, I replicate the exogeneity tests proposed in the literature for the managers, white, and blue collar workers sub-samples, showing that the AKM assumptions also hold in my working sample.

Ensuring the exogeneity of the AKM regression, I can then consistently estimate $\psi_j^{Manager}$, $\psi_j^{WhiteCollar}$, and $\psi_j^{BlueCollar}$. Since my primary focus of interest is understanding whether firms pay different pay premia to different occupational classes, I run occupation-specific AKM models on the triple connected set and normalize the estimated $\psi_j^{Occ(i)}$ to the same (group of) firm(s) in the sample ensuring direct comparability between occupation-specific firm wage policies. In Card et al. (2016), the normalization involves the use of balance sheets data where the group of firms with the lowest value-added are used as reference. Alternatively, other papers Bruns

[5] Importantly, note that correlation between θ_i, ψ_j, and X_{it} is legit in the model, which allows for sorting of high-skill workers into firms with higher firm fixed effects.

(2019) and Casarico and Lattanzio (2019) use firms in the food and accommodation sector as reference, assuming no rent-sharing in these sectors. I follow Fanfani (2022) and select the largest firm in terms of employed workers as reference.[6]

I then sort firms based on their rank over the $\psi_j^{Occ(i)}$ distribution. Within the triple connected set, for each firm, I can cross-compare its rank over the distribution of $\psi_j^{Manager}$, $\psi_j^{WhiteCollar}$ and $\psi_j^{BlueCollar}$, thus allowing to test whether the same firm applies different wage policies to their employees depending on their occupation. In this way, it is easy to assess whether high-paying firms for one occupational class (e.g. white collar workers) are also advantageous for others (e.g. blue collar workers) with respect to the other firms in market.

In the case differences within firms are observed, it is possible to formally estimate the size of the within-firm wage differences between occupational classes. To do so, I adapt the model for the estimation of firm-specific gender gaps proposed by Fanfani (2022) to test within-firm occupational premia. Within both the triple and the double connected set, it is possible to sort employees according to the metric $\mu_j = \psi_j^{WC} - \psi_j^{BC}$, such that the cumulative distribution $F(\mu_j)$ defines quintiles of increasingly more favorable firms for white collar workers with respect to blue collar. Then, via standard regression methods, I evaluate the marginal effect on wages of being a white collar worker employed in one of the firms in the right tail of $F(\mu_j)$. Specifically, the model takes the following form:

$$lnw_{it} = b_{wc}1[g = WC] + \sum_{\tau=0.2,0.4,0.6,0.8} b_\tau T_\tau + X'_{i,t}\beta + 1[g = WC]X'_{i,t}\delta + \omega_j + \rho_i + \epsilon_{it}$$

$$\text{with} \quad T_\tau = 1[g = WC]1[\tau + 0.2 \geq F(\mu_j) > \tau] \quad \text{and} \quad \tau = 0.2, 0.4, 0.6, 0.8 \tag{3.2}$$

where w_{it} is the wage of worker i at time t is regressed on a full set of observable individual characteristics, X,[7] accounting for both worker, ρ_i, and firms fixed effects, ω_j.[8] Workers' observable characteristics are interacted with the occupational dummy $1[g = WC]$ distinguishing white from blue collar workers.

The coefficients of interests are the b_τ, which are associated with a given quintile τ of the worker i's employer along the cumulative distribution $F(\mu_j)$. b_τ can be interpreted as the marginal effects on white collar wages of working in a firm at the τ quintile of the distribution of μ_j with respect to being employed in a firm at the bottom 20% of $F(\mu_j)$, where the distance between white and blue collar wage policies is minimal. In this sense, b_τ measures the additional wage premia that white collar

[6]Results applying different normalization strategies deliver comparable results.
[7]I control for age, age squared, tenure and a full set of year fixed effects
[8]In this exercise firm fixed effects are common to both white and blue collar workers.

workers gain if employed in firms that have increasingly divergent wage policies respect to blue collar workers, *ceteris paribus*. The aim of the exercises is, therefore, to quantify the gradient of wage differences between occupational classes applied by firms and can be seen as a test on the relevance of occupation-specific AKMs in ranking employers wage policies. Note that the same exercises can be done for any pair of occupational classes within the TCS. Therefore, it is possible to estimate within-firm wage differences between managers and blue or white collar workers, sorting employees according to the metric $\psi_j^M - \psi_j^{BC}$ and $\psi_j^M - \psi_j^{WC}$, respectively.

In Section 3.5 I estimate equation 3.2 for two different time periods in order to test if b_τ evolved over time. As robustness check, I run a simpler model which allows a more direct comparison between the within-firm pay policies in the 1980s and in the 1990s. In particular, I first restrict the working sample to the latest wave available in both periods, i.e. 1991 and 2001. Then, I estimate the following model:

$$\begin{aligned} ln(w_{it}|i \in F(\mu_j > \tau) = b_{wc}^{\tau} 1[g = WC] + \\ + \delta_{wc}^{\tau} 1[g = WC] 1[t = 2001] + \\ + X_{i,t}' \beta^{\tau} + X_{i,t}' 1[t = 2001] \gamma^{\tau} + \omega_j + \epsilon_{it} \end{aligned} \tag{3.3}$$

where w_{it} is the daily wage of worker i employed at time t in a firm j belonging to the right tail of the distribution $F(\mu_j = \psi_j^{WC} - \psi_j^{BC} > \tau)$, with $\tau = \{0; 0.2; 0.4; 0.6; 0.8\}$. $1[g = WC]$ is a dummy that takes value 1 if the worker is employed as white collar, 0 if employed as a blue collar. Similarly, $1[t = 2001]$ is a dummy that takes value 1 if the job spell is observed in year 2001, 0 if observed in 1991. Therefore, coefficient b_{wc}^{τ} provides the average wage premium that white collar workers earned over blue collar workers in 1991 when employed in a firm belonging to $F(\mu_j = \psi_j^{WC} - \psi_j^{BC} > \tau)$. The equivalent effect for white collar workers employed in 2001 is $b_{wc}^{\tau} + \delta_{wc}^{\tau}$, while the coefficient δ_{wc}^{τ} measures the difference between the white collar premia observed in 2001 and 1991. Next, I include in the model a full set of observable individual characteristics, X[9] and a firms fixed effects, ω_j, common to both white and blue collar workers. Individual level observable characteristics are interacted with the time dummy $1[g = WC]$.

Lastly, it is important to note certain limitations of the AKM approach discussed by the literature. On one hand, new methodologies are proposed to overcome the restrictions on workers' mobility implied by the AKM framework. In particular, Bonhomme et al. (2019) propose a two-step estimation approach that relies on clustering similar firms into groups and then estimating the fixed effects at the cluster level. In their preferred specification, they rely on 10 major clusters. Such approaches solves potential biases induced by limited mobility across firms[10] and

[9] I control for age, age squared, tenure.
[10] See Appendix 3.8.3 for a detailed discussion.

allows for working with bigger working samples since the estimation does not rely on double (or triple) largest connected sets; however, it reduces the heterogeneity of fixed effects from the firm level to the cluster level. On the other hand, Kline et al. (2020) show that the variance of worker- and firm fixed effects estimated via standard AKM models are upward biased. The interpretation of *second* moments of parameters estimated through AKM can, therefore, be misleading if specific bias correction techniques are not applied.[11] In this regard, it is important to stress, however, that the models proposed in this paper only rely on *first* moments of the AKM parameters. Consequently, once shown that the exogenous mobility conditions holds for all the occupational classes under analysis, the AKM provides unbiased estimates of occupation-specific firm fixed effects, $\psi_j^{Occ_i}$, which allows for precisely ranking each firm j along the distribution of managers, white, and blue collar workers.

3.3 Data

I rely on the Veneto Workers Histories (VWH) database for all of my estimations. The VWH is a typical matched employer-employee database, where workers can be followed over time and across different employers. It is obtained from the administrative records of the Italian Social Security System and it includes the universe of workers employed in the private-sector in Veneto from 1975 through 2001.[12] For each year in the sample, the database collects information on the job spells of each worker ever employed in Veneto, providing detailed information on the worker's earnings, job spell length, occupation, contract, age, and gender, all alongside basic information on the employing firm. The VWH also include information on job spells of those workers who moved outside the Veneto region, as long as they remain employed in the private sector.[13] Workers employed in agriculture, public administration, public services (most notable in the health system and railway transportation), and those activities with 1-owner-employer are excluded from the sample. In the VWH, earnings are defined pre-tax, including all in-cash benefits but excluding all in-kind ones. For the estimations, I rely on (log) daily earnings expressed in 2003 euro prices.

The VWH dataset is particularly well suited for the intended analysis for several reasons. First, for each job spell, I can identify the occupational class of each

[11] In Appendix 3.8.3, I discuss the methodology in detail and replicate the variance decomposition in my working samples, with and without bias correction.

[12] See Tattara et al. (2007) for details.

[13] Following Devicienti et al. (2019), I include the universe of job spells available in the estimation sample of the AKM accounting for spells located both inside and outside the Veneto region. This avoids a loss in efficiency due to the exclusion of observable jobs mobility happening in the sample. Nevertheless, all results reported and discussed in the paper are computed considering only firms located in Veneto.

worker, i.e. apprentice, blue collar, white collar, middle-manager,[14] and executive. While these occupational classes are not very detailed, such classification allows occupation-specific sub-samples that are large enough to correctly estimate occupation-specific firm fixed effects as explained in detail in Section 3.2. Having more granular and specific occupational classification (e.g. ISCO 1 or 2 digit) will drastically reduce the number of same-occupation workers and firms connected by job mobility and, therefore, it will affect the general validity of the results. Secondly, the panel nature of the dataset allows to correctly track worker mobility across firms, tenure, and earnings growth, which are key elements for the correct estimation of worker and firm fixed effects. Finally, Veneto is an important and fairly large region in Italy, representing around 10 percent of the national GDP. It relies on a well-developed manufacturing sector, close-to-natural unemployment rate, and limited out-migration that make it quite comparable to other well-developed Western economies (Devicienti et al., 2019). For these reasons, the dataset is widely used and its reliability validated by many studies (Card et al., 2014; Bartolucci et al., 2018; Devicienti et al., 2019; Serafinelli, 2019; Kline et al., 2020; Fanfani, 2022).

I took several standard steps, in the AKM literature, to define the working sample. First, I selected workers aged 18-64 who are not in their apprenticeship and who are employed for at least four months (16 weeks) in a year. Second, in case of workers with multiple job spells in the same year, I consider only the longest job spell per year in terms of days worked. In case this is not enough to identify unique job spells per year, I kept the observation with the highest weekly earnings. Since my aim is to study occupational-specific firm effects, I only consider those firms that employ at least one manager.

In the rest of this paper, I focus primarily on the period between 1996 and 2001. The main reason is that I can only distinguish mid-managers (*quadri*) from white collar workers after 1996. This choice allows me to have greater support for the estimation of managerial firm fixed effects and reduce variability within the white collar sample refining the estimates. Nevertheless, in Section 3.5, I expand the analysis to the evaluation of occupation-specific firm fixed effects over the long run, estimating separate AKM models for 1982-1991 and 1992-2001.[15]

Table 3.1 reports main descriptive statistics for the 1996-2001 period. Starting from left, the first three columns describe the largest connected sets within the managers, white, and blue collar sub-samples respectively. These three subsets are mutually exclusive since I observe only one job spell per year and in each year a worker can only be classified as a manager (executive or middle-manager), as a white collar worker, or as a blue collar worker. The last column on the right depicts the triple connected set (TCS), which comprises all those firms where I can

[14] Before 1996 middle-managers, *quadri*, are not distinguishable from white collar workers.

[15] In this application, I consider managers as white collar workers and estimated two separated AKM models on the dual connected set of firms linked by white and blue collar workers mobility. Details are further explained in Section 3.5.

	Largest Connected Stes			Triple Connected Set		
	Mangers	*White Collars*	*Blue Collars*	*Mangers*	*White Collars*	*Blue Collars*
Share of women	.11	.44	.3	.095	.44	.31
Average age	45	36	37	45	37	37
Average daily wage (2003 euros)	228	91	64	240	88	65
Avarege Experenice (months)	216	149	154	210	154	156
Share of workers employed in firms with						
Employees <100	.36	.37	.37	.035	.016	.014
Employees 101-200	.11	.14	.17	.047	.029	.024
Employees 201-500	.13	.14	.18	.38	.32	.36
Employees >500	.4	.35	.28	.17	.18	.22
Share of workers employed as						
Manager	.33	.	.	.4	.	.
Mid-manager (*Quadro*)	.67	.	.	.6		.
White Collars	.	1	.	.	1	.
Blue Collars	.	.	1	.	.	1
Share of workers employed in						
Primary Sector	.0023	.006	.0051	.002	.0023	.0014
Secondary Sector	.48	.41	.69	.68	.5	.72
Tertiary Sector	.52	.59	.3	.32	.5	.28
N obs	150,156	1,494,131	1,923,199	85,426	763,919	1,165,771
N workers	42,403	426,222	569,453	24,999	236,419	351,113
N Firms	5,234	10,084	6,983	2,410	2,410	2,410
N workers: % of Overall Sample	.74	.96	.96	.44	.53	.59
N firms: % of Overall Sample	.38	.78	.7	.17	.19	.27

Notes: The sample is Tenure is censored at 1975. Average firms' size is non-weighted and measured by the average of the number of employees working for the company in each year.

Table 3.1: Descriptive statics

identify a firm-fixed effect for each occupational class. The TCS is, therefore, highly restricted since it comprises all those firms that, within the period of observation, are connected by mobility of both managers, white, and blue collar workers. This involves around 18% of the firms and 59% of the workers of the original working sample. Table 3.5 in Appendix 3.8.1 provides the main descriptive statistics for the 1982-1991 and 1991-2001 sub-samples.

3.4 Empirical Results - Time Period 1996-2001

3.4.1 Descriptive Evidence on occupation-specific firm fixed Effects

I begin by estimating equation 3.1 for each occupational class over the 1996-2001 period. I control for age, age-squared, tenure, and firm size.[16]

First, I want to see weather AKM firm fixed effects predict wage differences between workers employed at different firm types. To do so, after ψ^{Occ} is estimated in the largest connected sets, I report in Table 3.2 the average daily wages for managers, white collar workers, and blue collar workers employed in Veneto by quartiles of the occupation- specific firm fixed effects distribution. Similarly, Figure 3.1 plots the average (log-)daily wage of managers, white collar workers, and blue collar workers employed for subsequent years in firms at different quartiles of the ψ_j^{Occ} distribution over the estimation period of 1996-2001. The figure highlights a clear wage gradient over ψ_j^{Occ} quartiles for all occupational classes where the average worker pay is increasing with ψ_j^{Occ}. Moreover, the wage profiles evolve distinctly and in parallel, thus indicating that workers employed in firms belonging to different ranks of the ψ_j^{Occ} distribution earn substantially different wage *levels* but they do not experience different wage *growth*.

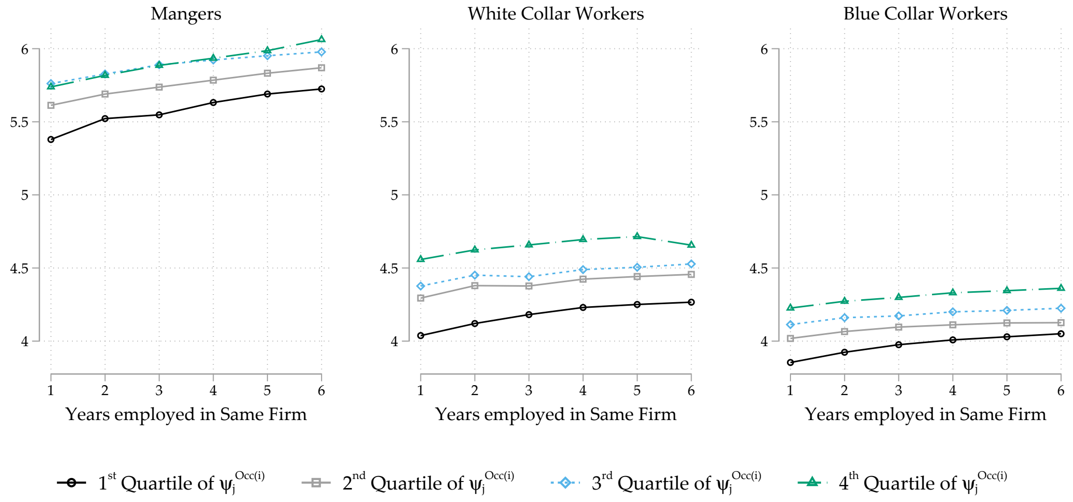
$\psi_j^{Occ(i)}$ Quartile	Managers	White Collar	Blue Collar
1^{st}	273.23	68.69	54.17
2^{nd}	335.26	85.86	60.91
3^{rd}	399.93	92.47	66.48
4^{th}	400.36	113.64	74.79
N workers	8,780	301,379	454,246
N firms	1,609	5,311	4,358

Notes: The table reports average daily wages in 2003 euros for managers, white collars and blue collars by quartiles of the occupation-specific firm fixed effects distribution. The estimated wages are based on job spells of workers working in firms located in Veneto and belonging to the three occupation specific largest connected sets. Among managers, mid-managers (*quadri*) are excluded form the estimation.

Table 3.2: Average daily wage along the distribution of $\psi_j^{Occ(i)}$.

Table 3.2 and Figure 3.1 confirm the existence of 'good' and 'bad' firms type *within* each occupational class: with respect to workers employed at the top of 25% of ψ_j^{Occ}, if employed in a firm belonging to the bottom 25%, managers earn 32% less, white collar workers 40% less and blue collar workers 28% less.

[16] I distinguish 5 classes of firms depending on the number of employees: firms with less than 10, between 10 and 20, between 21 and 200, between 201 and 500, more than 500 employees.



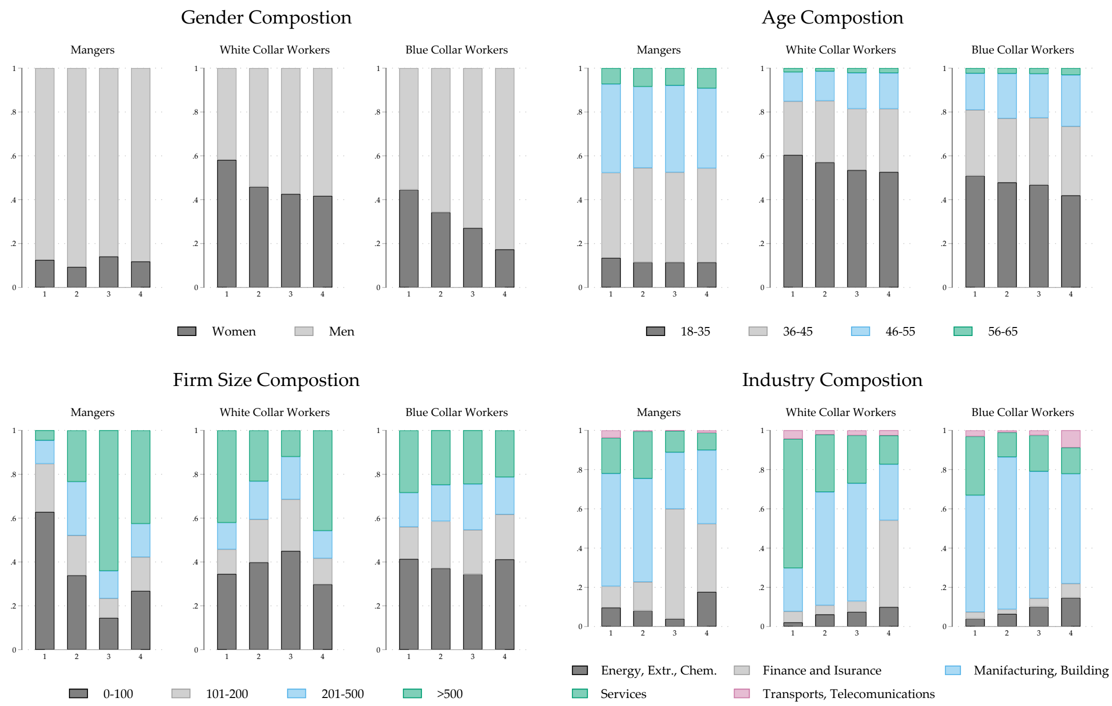
Notes. The figure plots for each occupational class the average daily wage of workers employed for subsequent years in firms belonging to different quartiles of the firm fixed effect distribution for the time period 1996-2001. Estimates are based on the occupation-specific largest connected set.

Figure 3.1: Daily wages along the occupation-specific firm fixed effects distribution.

I then explore whether workers' and employers' characteristics help predict the distribution of $\psi_j^{Occ(i)}$. Figure 3.2 shows for each occupational class, the workers' gender and age composition as well as the employers' size and industrial sector composition along quartiles of $\psi_j^{Occ(i)}$. In the upper-left panel of Figure 3.2 it is immediate to see a clear adverse selection of women along both ψ_j^{WC} and ψ_j^{BC}. These results are in line with gender-biased sorting of workers into firms largely documented by previous literature (Card et al., 2013; Bruns, 2019; Casarico and Lattanzio, 2019; Fanfani, 2022). Similarly, in the upper-right panel, I can see that the age composition of workers is skewed along $\psi_j^{Occ(i)}$. In particular, consistently with findings by Kline et al. (2020), workers younger than 35 are more likely to be employed at the bottom of the $\psi_j^{Occ(i)}$ distribution.

In the lower panels of Figure 3.2, I plot the composition of quartiles of $\psi_j^{Occ(i)}$ by 4 main firm size classes and 5 main industrial sectors.[17] It is possible to see that managers employed in bigger firms enjoy the highest $\psi_j^{Occ(i)}$, while for both white and blue collar workers, firm size does not seem to play a big role. Similarly, working

[17] I consider 4 main firm size classes based on the number of employees per year: firms with less than 100 employees; firms with between 101 and 200 employees per year; firms with between 201 and 500 employees per year; and firms with more than 500 employees per year. Next, I consider 5 main industrial sector groups: energy, extraction and chemical industries; manufacturing and building industries; finance and insurance; services; transport and telecommunications.



Notes. The figure plots for each occupational class the average daily wage of workers employed for subsequent years in firms belonging to different quartiles of the firm fixed effect distribution for the time period 1996-2001. Estimates are based on the occupation-specific largest connected set in year 2001.

Figure 3.2: Daily Wages along the occupation-specific firm fixed effects distribution.

$\mathbf{Pr}(i \in F(\psi_j) \geq \mathbf{0.5})$	**Managers**		**White Collar Workers**		**Blue Collar Workers**	
	β	*P-value*	β	*P-value*	β	*P-value*
Female	.017	.0013	-.044	0	-.16	0
Age above 45	.023	0	.056	0	.058	0
Firm with more than 200 employees	.092	0	.042	0	.04	0
Firm in finance and insurance sector	.057	0	.41	0	.026	0
Firm in Service Sector	-.14	0	-.13	0	.093	0
N Workers	24,763		301,379		454,246	
N Firms	1,927		5,311		4,358	
N person-year obs	80,916		988,881		1,518,028	

Notes: The table reports the results for a simple Probit model. The dependent variable equals one if the worker is employed in a firm at top-half of the $\psi^{Occ(i)}$ distribution. In the model we then control for worker's gender and age (dummy equal to one if worker is older than 45 years old), employers' size (dummy equal to one if firm has more than 200 employees) and two dummies indicating if the worker is employed in a firm operating in the finance or service sector. Year and province fixed effects are added as controls. The estimation sample comprises all workers and firms belonging to the occupation-specific connected sets and that are located in Veneto.

Table 3.3: Probability of working in a firm belonging to the top-half of ψ_j^{Occ} distribution.

in the financial (service) sector is related to the highest (lowest) firm wage policies for both managers and white collar workers.

Eventually, I formally test observable differences between low- and high-type firms with a probit model where the dependent variable takes value 1 if the worker is employed in a firm belonging to the top 50% of the firm-fixed effect distribution. I include a list of dummy variables distinguishing workers by gender, by age (older than 45 years old), by employer's size (more than 200 employees), by employer's industrial sector (one dummy for finance and one for service sector). I estimate separate models for the three occupation-specific, largest connected sets including year and province fixed effects. Model results are displayed in Table 3.3. The reported coefficients read as the difference in the probability of being employed in a 'good' firm (i.e. a firm that belongs to the top half of the $\psi_j^{Occ(i)}$ distribution) depending on the worker's gender and age and on the employer's size and industrial sector. For example, managers working in the financial (service) sector are 5.7 (14) percentage points more (less) likely to be employed in a high-paying firm, with respect to similar managers employed in other sectors.

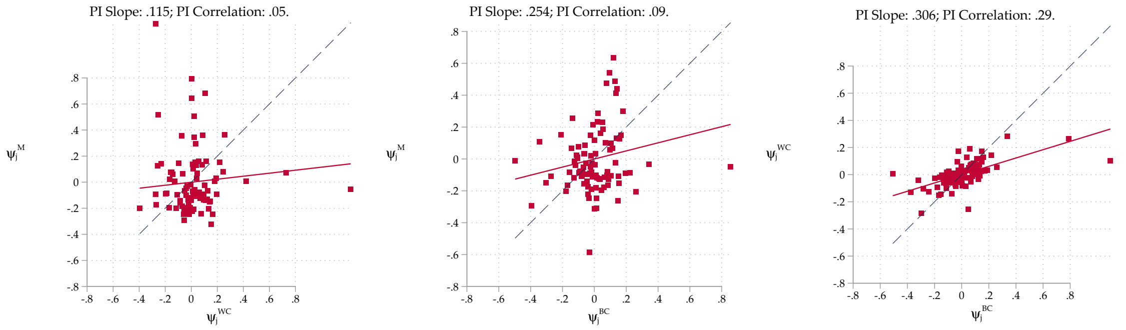
Overall, results in Table 3.3 are in line with the descriptive evidence from Figure 3.2 and show that a) there is evidence of differences in the worker and firm characteristics along the occupation-specific firm premia distribution and b) these differences are *not* common to each occupational class. While these results provide already some insights about potential heterogeneity in the policy applied within firms to different occupational, they do not answer the question of whether a single firm adopts different pay strategies for its employees based on the occupational class. I explore this specific question in the following paragraphs.

3.4.2 Same Firm different Wage Policies

Once I relax the assumption that $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$, it might be the case that, for example, firm j adopts advantageous pay policies for its managers with respect to the other firm in the market but, at the same time, the firm premium paid to blue collar workers working in j is relatively un-rewarding. In this case, firm j will be at the top of the $\psi^{Manager}$ distribution and at the bottom of $\psi^{BlueCollar}$ distribution. Thus, firm premia may differ not only by *level*, but also by *rank* between occupational classes. To test this, I estimate correlations in ranks across the different occupation-specific ψ^{Occ} distribution. I restrict the following analysis to the *triple* connected set (TCS), which comprises all those firms connected by worker mobility where I can identify a firm-fixed effect for each occupational class. Within the TCS, I can directly compare the rank and the level of ψ_j^M, ψ_j^{WC} and ψ_j^{BC} because they are estimated and normalized over the same support of firms.

The red lines in Figure 3.3 provide the coefficient of the person-year weighted projection of $\psi_j^{Manager}$ onto $\psi_j^{WhiteCollar}$ in the left panel, the projection of $\psi_j^{Manager}$

onto $\psi_j^{BlueCollar}$ in the central panel, and the projection of $\psi_j^{WhiteCollar}$ onto $\psi_j^{BlueCollar}$ in the right panel. The firm premia are estimated here using the triple connected set in order to have the same sub-sample of firms in each $\psi_j^{Occ(i)}$ distribution.[18] Under the assumption $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$ the estimated projection slopes should coincide with the 45 degree line. However, the low estimated correlations indicate that firms occupy substantially different ranks along the firm premia distribution depending on the occupational class.



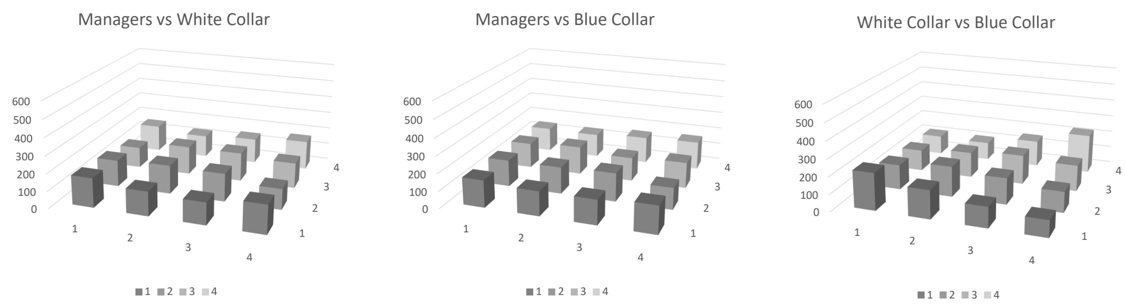
Notes. Estimation on the triple connected set over the period 1996-2001. Each set of firm fixed effect have been demeaned. $PIslope$ in the figure 3.3 indicates the coefficient of the projection of $\psi_j^{Manager}$ onto $\psi_j^{WhiteCollar}$ in the left panel, the projection of $\psi_j^{Manager}$ onto $\psi_j^{BlueCollar}$ in the central panel and the projection of $\psi_j^{WhiteCollar}$ onto $\psi_j^{BlueCollar}$ in the right panel. $PI\ correlation$ gives the person-year weighted sample correlation between occupation-specific firm premia.

Figure 3.3: Do firm premia differ between occupational classes?

As further test, in Figure 3.4, I take the 2,410 firms in the triple connected set and sort them based on their rank over quartiles of the $\psi^{Manager}$, $\psi^{WhiteCollar}$ and $\psi^{BlueCollar}$ distribution. I then cross-compare the ranks that the same firm has on the manager, white collar, and blue collar firm premia distribution. If firms would apply same pay strategies to all their employees, the bars in Figure 3.4 should be clustered along the main diagonal. Instead, firms are scattered across all the possible rank interactions.

The analysis above shows that once the assumption $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$ is relaxed, substantial heterogeneity emerges. Such variability lies be-

[18] The same test is applied in Kline et al. (2020) for checking whether firms premia differ between younger and older employees.



Notes. Estimation on the triple connected set over the 1996-2001 period. The figure counts firms over 16 cells of occupation-specific firm effects (4 quartiles per occupational group).

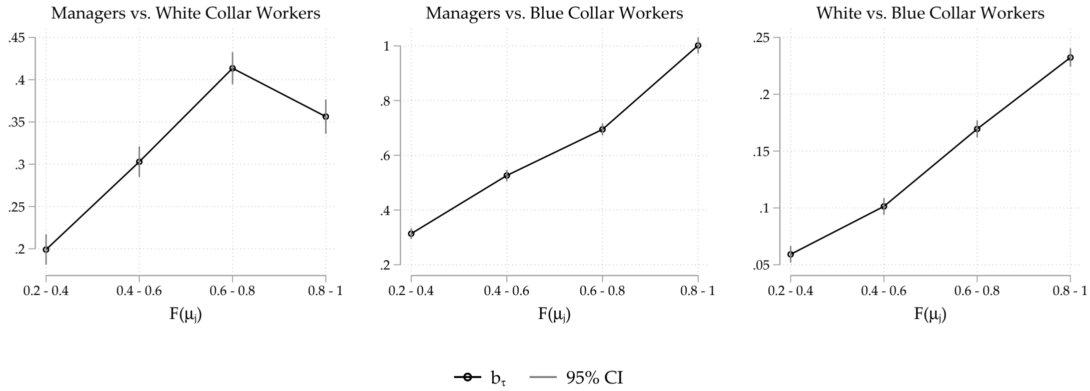
Figure 3.4: Joint Distribution of the occupation-specific Firms Premia.

tween *and* within firms since, as Figure 3.3 and 3.4 show, a single firm adopts diversified compensation strategies for its employees depending on their occupation.

An interesting aspect to investigate is the extent of the within-firm wage differences between occupational classes. As explained in Section 3.2, equation 3.2 adapts the model for the estimation of firm-specific gender gaps proposed by Fanfani (2022) to test within-firm differences in occupational returns. Firms in the TCS are sorted according to metric $\mu_j^{X-Y} = \psi_j^X - \psi_j^Y$ defining quintiles of increasingly more favorable firms for the occupational group X with respect to occupational group Y. The coefficient of interest is b_τ and measures the additional wage premia that occupation X gains if employed in firms that have increasingly more favorable wage policies for occupation X with respect to occupation Y, *ceteris paribus*. Figure 3.5 reports estimates of b_τ for each combination of occupational groups.

Results show that a relevant wage gradient exists between the occupation-specific wage policies applied by firms. In the case of white and blue collar workers (right-hand panel in Figure 3.5), b_τ is always positive and increasing along the distribution $F(\mu_j)$. Specifically, white collar workers earn an additional 6% wage premium on blue collar peers if employed between the first and second quintiles of $F(\mu_)$. This wage premium for white collar workers increases by 10% if employed in a firm between the second and third quintiles, by 17% between the third and fourth quintiles and by 23% if employed in the 20% most discriminatory firms, *ceteris paribus*. Similar patterns can be observed between managers and white collar workers (left-hand panel), and between managers and blue collar workers (middle panel).

Eventually, it is important to understand how $F(\psi_j)$ and $F(\mu_j)$ are related. In particular, I would like to know whether the firms that pay the highest wage policies

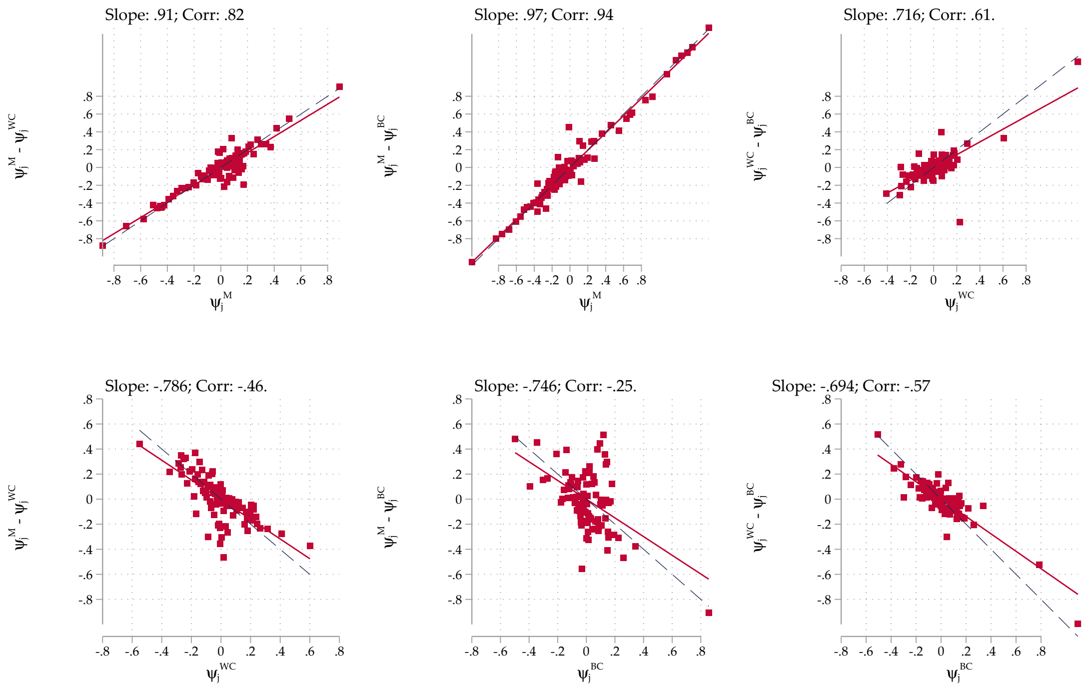


Notes. The figure reports estimation of b_τ according to model 3.2 for managers over white collar workers in the panel on the left, for managers over blue collar workers in the middle panel, and for white over blue collar workers in the panel on the right. Estimation on the triple connected set over the 1996-2001 period restricted to firms located in Veneto. Results for managers comprise both executive and middle-level managers (*quadri*).

Figure 3.5: Within-firm wage gradient.

to a given occupational class, are also those that are paying the largest differences in the wage policies. If this were the case, among white and blue collar workers, for example, $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$ and $F(\psi_j^{WC})$ would be positively related. Similarly for Figure 3.3, Figure 3.6 shows the projection of μ_j onto percentiles of ψ_j for the different combinations of occupation-specific firm fixed effects. In the three upper panels of Figure 3.6, correlation is confirmed to be strong and positive, suggesting that the 'best' firms for each occupational class are also those that are applying the largest occupation-specific wage policy differences with respect to the other occupational classes. For example, in the case of white and blue collar workers (upper right panel) it is immediate to see that those firms that have the largest policy differences (high $\mu_j = \psi_j^{WC} - \psi_j^{BC}$) are located at the top of the ψ_j^{WC} distribution and such correlation is close to one. In the three lower panels of Figure 3.6, instead, I show the correlation between $F(\mu_j)$ and the firm fixed effects of the occupational class that is penalized. Correlation is negative although in general lower. For example, $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$ and $F(\psi_j^{BC})$ are negatively related meaning that those firms where blue collar workers are the most disadvantaged with respect to white collar workers (large μ_j), are likely to be firms that are paying the lowest blue collar wage policy in the market.

These results corroborate the previous findings: not only do the same firms apply different wage policies to its employees, but the highest-paying firms for a given occupational group are likely to be among the least advantageous for the other employees.



Notes. Estimation on the triple connected set over the period 1996-2001. Each set of firm fixed effect have been demeaned. *Slope* in the Figure 3.6 indicates the coefficient of the projection of $\mu_j = \psi_j^M - \psi_j^{WC}$ onto ψ_j^M (ψ_j^{WC}) in the upper (lower) left panel, the projection of $\mu_j = \psi_j^M - \psi_j^{BC}$ onto ψ_j^M (ψ_j^{BC}) in the upper (lower) central panel and the projection of $\mu_j = \psi_j^{WC} - \psi_j^{BC}$ onto ψ_j^{WC} (ψ_j^{BC}) in the upper(lower) right panel. *Correlation* gives the person-year weighted sample correlation between μ_j and $\psi_j Occ$.

Figure 3.6: Correlation μ_j and ψ_j

3.5 Empirical Results - Long-run Analysis 1980s vs. 1990s

In the following section, I study the evolution of occupation-specific firm premia over time, assessing whether the role of firms in inequality changed between the 1980s (1982-1991) and the 1990s (1992-2001) in the Veneto region. Concepts and methodologies are the same applied for the 1996 - 2001 analysis explained above. The unique difference is that, because of data limitations, I cannot distinguish mid-managers (*quadri*) from white collar workers before 1996. In order to have consistent and comparable samples over time, in the following exercises managers are incorporated into white collar workforce. Consequently, for each firm in the data, I distinguish two, rather than three, occupation-specific wage policies, ψ_j^{WC} and ψ_j^{BC}. Therefore, in my working sample, I consider all those firms in VWH that have at least one white collar *and* one blue collar worker.[19] As before, I focus on unique job spells per year of workers aged 18-64 who are not in their apprenticeship and who are employed for at least four months (16 weeks) in a year. Table 3.5 in the Appendix summarizes the main descriptive statistics for both the 1980s and 1990s working-sub-samples in the occupation-specific largest connected sets and in the *double* connected set.[20]

3.5.1 Did firm policies changed over time?

I first estimate, in each period, two separate AKM models on the white and blue collar largest connected set. Figure 3.10 in Appendix 3.8.1 shows the average (log-) daily wage of blue and white collar workers employed for subsequent years in firms belonging to different quartiles of the firm fixed effect distribution. As for the short panel 1996-2001, I notice that firm fixed effects predict well the substantial heterogeneity in the wage *levels* across workers employed in the same occupational group. I then estimate within the DCS, new AKM models to retrieve ψ_j^{WC} and ψ_j^{BC} that are directly comparable within the same time frame. This allows for replicating Figure 3.3 and Figure 3.4 for both the 1980s and 1990s. The resulting figures are shown in Appendix 3.8.1 and confirm, like the previous section, a weak relationship between $F(\psi_j^{WC})$ and $F(\psi_j^{BC})$. Therefore, even in the long run, firms seem to have applied different wage policies to their employees depending on the occupational classes.

[19] In the previous section, the data restriction was much tighter since I only considered firms with at least one manager as eligible for the connected set.

[20] As for the triple connected set, the double connected set (DCS) comprise all those firms connected by white *and* blue collar workers mobility. Thus, within the DCS, it is possible to estimate both ψ_j^{WC} and ψ_j^{BC} for each firm j.

Thus, an interesting aspect to investigate is whether differences *within* firms have expanded, reduced, or remained constant over time. To do so, first I estimate model 3.2 in both time intervals and then compare the results. Figure 3.7 shows on the left side b_τ estimated in the 1990s in black and the b_τ estimated in the 1980s in light blue. The right panel of Figure 3.7 plots the over-time difference in the estimated coefficients. My results show that within firms, pay policies differentials increased in the 1990s with respect to the 1980s and such increase has been larger the higher $F(\mu_j)$. In other words, between the 1980s and 1990s the most advantageous firms in the market for white collar workers become increasingly less attractive for blue collar workers.

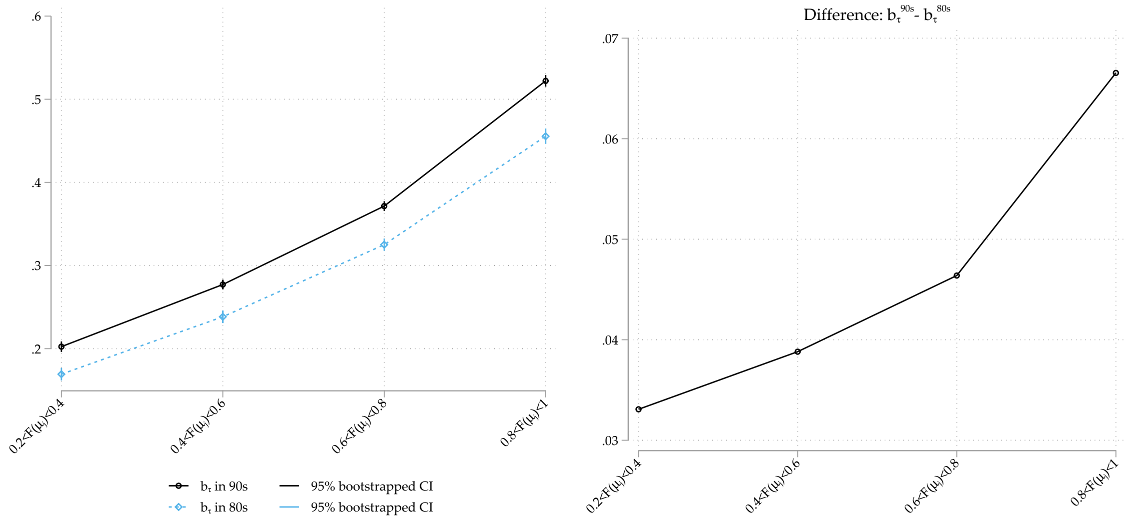
I further test these latter findings with the model in equation 3.3 that allows a more direct comparison of within-firm pay policies over time. Figure 3.8 shows for 1991 (left panel) and 2001 (middle panel) the returns earned by white collar workers employed in firms j belonging to the right tail of the distribution $F(\mu_j) > \tau$ with $\tau = \{0; 0.2; 0.4; 0.6; 0.8\}$. In the figure the right-hand panel reports the interaction coefficient representing the difference between the white collar premia observed in 2001 and 1991. Overall, in the Veneto region, the differences in returns between white and blue collar workers increased by 3 percentage points between 1991 and 2001, passing from 0.25 to 0.28. However, this wage premium increase was larger in firms with high wage policies differences $\mu_j = \psi_j^{WC} - \psi_j^{BC}$. In the top 20% of $F(\mu_j)$, the white collar premium increased by 7 percentage points confirming the findings in Figure 3.7.

3.5.2 Sorting

A key question to explore is whether the disproportionate increase in white collar returns along the distribution $F(\mu_j)$ is determined by increased sorting of workers into firms. In particular, sorting accounts for the degree of selection of high-type workers in high-type firms and it is usually measured by the covariance between firm and worker effects, $Cov(\psi_j^{Occ}, \theta_i)$, estimated from the occupation-specific largest connected sets.[21] More recently, several papers discuss a series of limitations of $Cov(\psi_j^{Occ}, \theta_i)$. Kline et al. (2020) show that, in a traditional AKM estimation $Cov(\psi_j^{Occ}, \theta_i)$ is typically downward-biased and this bias is negatively related with the number of movers within the connected set. Thus, the authors propose a bias-correction methodology that relies on the so called 'leave-one-out' estimator. Alternatively, Lopes de Melo (2018) proposed to proxy sorting using the correlation between the worker's fixed effect, θ_i, and the average fixed effect of coworkers, $\tilde{\theta^j}$.[22]

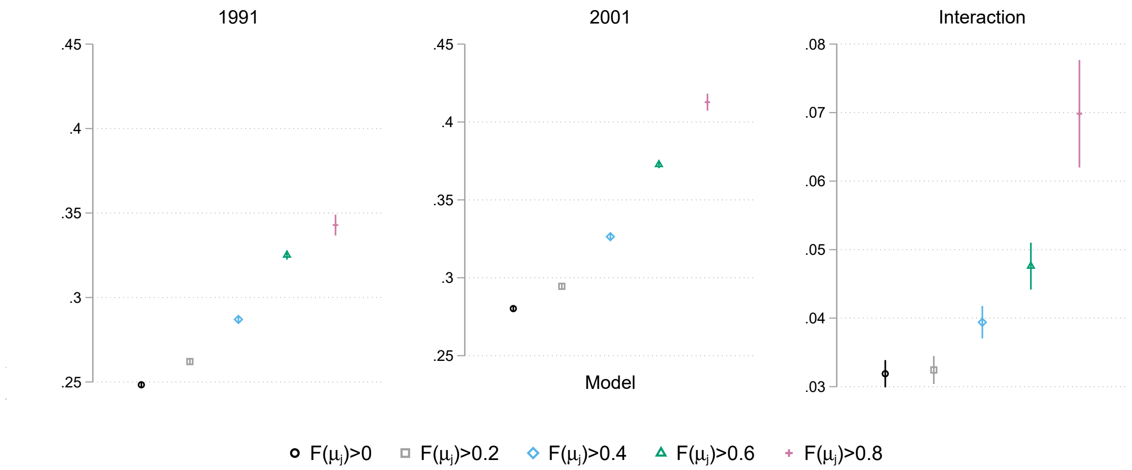
[21] Lopes de Melo (2018) provides a good overview of previous studies applying AKM models for estimation of sorting effects.

[22] One limitation of the measure is that it does not distinguish the sign of sorting, just its intensity (Lopes de Melo, 2018). I claim that this does not represent a limitation of the intended analysis,



Notes. The left panel of the figure reports estimation of b_τ according to model 3.2 for white collar over blue collar workers for the period 1992-2001 (in black) and for the period 1982-1991 (in light blue). Confidence intervals are obtained via bootstrapping (50 replications). The panel on the right reports the over time difference $b_\tau^{90s} - b_\tau^{80s}$. Estimation on the double connected set restricted to firms located in Veneto

Figure 3.7: Within-firm wage gradient over time.



Notes. The figure reports the estimates of the main coefficients of interest from model 3.3. Estimates of b_{wc}^τ are reported in the left-hand panel. Estimates of $b_{wc}^\tau + \delta_{wc}^\tau$ are reported in the middle panel. Estimates of δ_{wc}^τ are reported in the right-hand panel. The black marker corresponds to the overall effects, i.e. when $F(\mu_j) > 0$. The gray marker when $F(\mu_j) > 0.2$, the light blue marker when $F(\mu_j) > 0.4$, the green marker when $F(\mu_j) > 0.6$, and the pink marker when $F(\mu_j) > 0.8$. Estimation is restricted to white and blue collar workers employed in 1991 and 2001.

Figure 3.8: White collar workers returns conditional on $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$

Song et al. (2019) propose a measure of segregation, defined as the propensity of low- and high-type workers to be increasingly likely to be employed in different firms. Formally, the Segregation Index is calculated as the ratio between the variance of the average worker effect in each firm, $Var(\overline{\theta^j})$, and the variance of worker fixed effects, $Var(\theta_i)$. The higher the index, the more firms are differentiated by worker's ability.

Table 3.4 shows alternative measures for the sorting and segregation of workers into firms in the 1982-1991 and 1992-2001 periods for both white and blue collar workers. In the upper panel, the table reports measures for $Cov(\psi_j^{Occ}, \theta_i)$, $Corr(\theta_i, \widetilde{\theta^j})$, and the segregation index estimated on the occupation- and period-specific largest connected set. As mentioned in Section 3.2 and further discussed in Section 3.8.3 of the Appendix, $Cov(\psi_j^{Occ}, \theta_i)$ is typically downward biased when ψ and θ are calculated via the traditional AKM estimator. I, therefore, apply the bias correction proposed by Kline et al. (2020) (KSS) and report the results in the lower panel of the table. Note that the samples used for the estimation of the parameters in the upper and lower table are different. This is due to the fact that KSS bias-correction requires at least *two* movers per firms within the connected set for the identification of the relevant parameters. Section 3.8.3 provides a detailed discussion of the methodology.

In the upper panel, all the indicators show that sorting is slightly decreased within white collar workforce and increased within blue collar workers. Within the leave-one-out sample (lower panel), the KSS estimates confirm these findings, despite the presence of downward biases in the estimation of $Cov(\psi_j^{Occ}, \theta_i)$ via AKM in both periods and for both blue and white collar workers.

Increased sorting within blue collar workers might help explain the disproportionate increase in the white collar returns along the $F(\mu_j)$ distribution over time. As shown in Figure 3.13, $F(\mu_j)$ and $F(\psi_j^{BC})$ are negatively related, meaning that the most attractive firms for white collar workers are typically among the least attractive for blue collar workers. Increased sorting among blue collar workers, might, therefore, reflect a redistribution of high-type blue collar workforce away from high-$F(\mu_j)$ firms, which are the least attractive for blue collar workers, toward firms with larger ψ_j^{BC}. Such redistribution might then explain the increase of the white collar returns experienced in high-$F(\mu_j)$ firms between the 1980s and 1990s documented in Figure 3.7 and Figure 3.8.

To further examine this hypothesis, I next estimate $Corr(\theta; \tilde{\theta^j})$ along the distribution $F(\mu_j)$ and compare the estimates across time periods. This measure has the great

since the aim of the exercise is exactly to test whether the *intensity* of sorting changed between the 1980s and 1990s in Veneto. Bartolucci et al. (2018) develops an alternative sorting measure index based on firm profits rather than firm AKM fixed effects and provide tests for the sign of sorting. In their paper Bartolucci et al. (2018), using the same dataset as this study, show that both their index and correlation, proposed by Lopes de Melo (2018), are much better proxies for the degree of assortment between workers and firm types in labor markets than the covariance index.

Tradional AKM: Largest Connected Sets	White Collars			Blue Collars		
	1992-2001	1982-1991	Δ	1992-2001	1982-1991	Δ
$Var(w_{it})$	0.279	0.245	0.034	0.122	0.106	0.016
$Cov(\psi_j^{Occ}, \theta_i)$	-0.009	-0.018	0.009	0.005	-0.012	0.017
$Corr(\theta_i, \widetilde{\theta^j})$	0.441	0.462	-0.020	0.495	0.493	0.002
$Var(\overline{\theta^j})/Var(\theta)$	0.325	0.341	-0.016	0.337	0.330	0.007
N of Firms	58,836	50,206		74,428	62,830	
N Movers	210,984	149,892		493,211	340,989	
N of Person Year Observations	3,411,169	2,937,505		6,837,013	6,263,659	

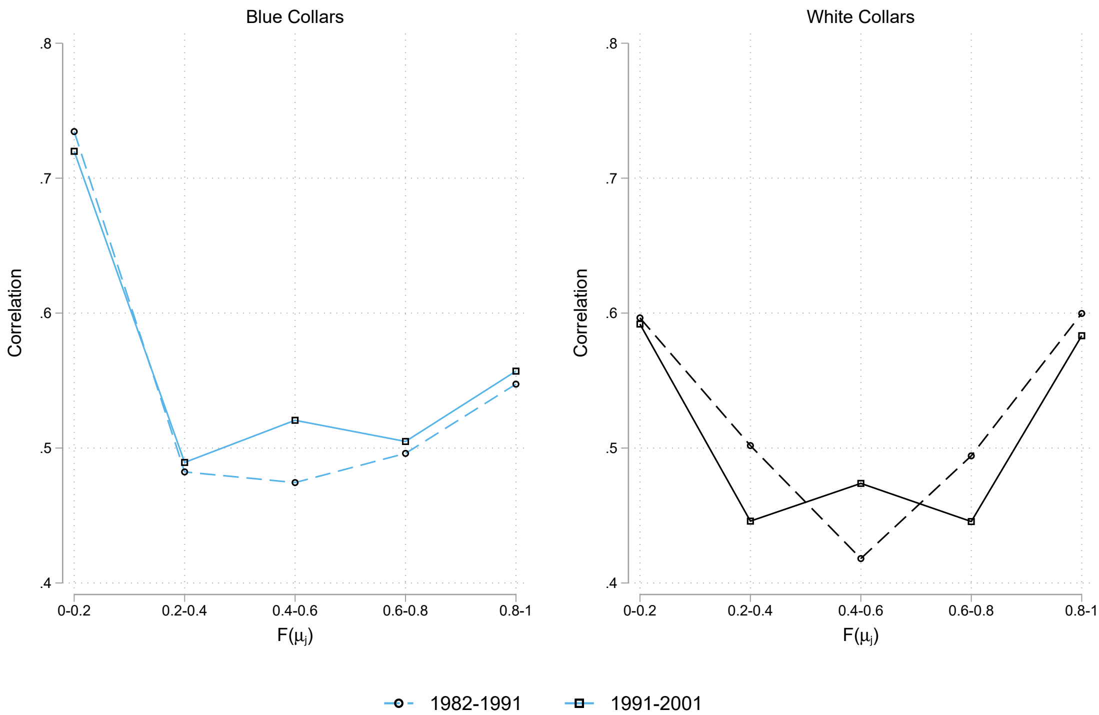
KSS Bias-Correction: Leave-one-out Set	White Collars			Blue Collars		
	1992-2001	1982-1991	Δ	1992-2001	1982-1991	Δ
$Var(w_{it})$	0.274	0.243	0.032	0.118	0.102	0.017
AKM Estimates (biased)						
$Cov(\psi_j^{Occ}, \theta_i)$	-0.002	-0.001	-0.001	-0.003	-0.009	0.006
KSS Bias-corrected Estimates (unbiased)						
$Cov(\psi_j^{Occ}, \theta_i)$	0.008	0.009	-0.001	0.001	-0.003	0.004
N of Firms	31,419	26,314		58,284	48,381	
N Movers	185,385	127,458		477,115	326,612	
N of Person Year Observations	2,976,557	2,580,635		6,407,268	5,875,702	

Notes: This table shows different measures of sorting over the 2001-1992 and the 1991-1982 period. The Table is divided in two main panels. The upper panel provides results on the occupation-specific largest connected sets as described in the main text. I report $Corr(\theta_i.\overline{\theta^j})$ and $Var(\overline{\theta^j})/Var(\theta)$. The former represents a measure of sorting as suggested by Lopes de Melo (2018). the latter is the segregation index adopetd in Song et al. (2019).The lower panel provides results on the Leave-one-out set and compares the biased estimates from traditional AKM with the biased-corrected estimates of $Cov(\psi_j^{Occ}, \theta_i)$ and $Corr(\psi_j^{Occ}, \theta_i)$ accroding to Kline et al. (2020)

Table 3.4: Sorting

advantage of being unbiased and it can be easily estimated at different quantiles of $F(\mu_j)$, providing a *local* proxy for sorting. Figure 3.9 shows the $Corr(\theta;\widetilde{\theta^j})$ for white and blue collar workers, estimated within quintiles of $F(\mu_j)$, over the 1982-1991 (dash line) and 1992-2001 (solid line) period. Substantial heterogeneity in sorting intensity emerges from the figure. Interestingly, for both white and blue collar workers, the major changes in sorting intensity happened at the middle of $F(\mu_j)$, while sorting is found to be unchanged among the firms with highly differentiated occupation-specific wage policies.

Overall, these findings provide evidence for an increased segmentation in the remuneration strategies applied by high- and low-paying firms rather than increasing sorting patterns of high- (low-) type workers into high- (low-) type firms. I interpret these findings as a signal of increased wage setting decision power by firms.



Notes. The figure report the estimates $Corr(\theta; \tilde{\theta^j})$ along the distribution $F(\mu_j)$ over the 1982-1991 (dash line) and 1992-2001 (solid line) periods within each quintile of $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$ for blue (on the left) and white (on the right) collar workers. Estimation is restricted to white and blue collar workers employed in firms located Veneto belonging to the double connected set in 1991 and 2001. Managers are included in the estimation of the AKMs and excluded from $Corr(\theta; \tilde{\theta^j})$.

Figure 3.9: $Corr(\theta; \tilde{\theta^j})$ over $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$

3.6 Qualifications and Extensions

As discussed in Section 3.2, the AKM model has some limitations.

First, unbiased estimates of workers and fixed effects rely on the exogenous mobility assumption, meaning that worker-firm matching processes are not affected by transitory shocks. While such assumption seems to be economically strong, Card et al. (2013) proposed some empirical tests to assess its credibility.[23]. Section 3.8.2 replicates the analysis for the white and blue collar workers sub-samples in the 1980s and 1990s, showing that the AKM assumptions also hold in my working sample.

Second, the AKM does not allow for interactions between firms and workers attributes, ruling out potential complementary patterns in earnings, meaning that, in the AKM framework, worker's i productivity does not depend on the employer j. However, it is reasonable to assume that the same worker might have very different productivity levels if employed at different firms. In their empirical model, Bonhomme et al. (2019) expand the AKM framework allowing complementary between firm and workers types finding, however, that those complementarities explain only a small part of the variance of log-earnings.

Third, wage policies adopted by the firm are assumed to be *fixed* over the whole estimation period. In Section 3.5, for instance, firm fixed effects are estimated over a 10 years time span. Firm premium might, however, change over time and adapt to productivity shocks, business cycles and major changes experienced within establishments. While I do not provide tests for the persistence of firm wage policies over time, Lachowska et al. (2022) and Engbom et al. (2022) empirically proved that firm wage effects show a remarkable degree of stability.

Fourth, identification of relevant parameters is only possible within the largest connected set, which is particularly restrictive in the case of the current occupation-specific application. In particular, as shown in Table 3.1, the *triple connected set* only comprises between 17 and 27% of the available firms in the sample, covering between 44 and 59% of the overall workforce (depending on the occupational group considered). The estimation sample is therefore a selected group of the general population of workers and firms. Findings might, therefore, be generalized applying appropriate re-weighting of workers and firms in order to resemble the general population observed in the data. Nevertheless, our main findings proved to be robust also in less selected estimation samples. In Section 3.5, the double connected sets used for the estimation of the occupation-sepcific AKM in the 1980s and 1990s cover between 81 and 86% of the overall withe and blue collar worker population as shown in Table 3.5. In Section 3.8.4 in the Appendix we estimate occupation-specific firm premia via interactions of firm and occupation fixed effects. In such context the

[23]These tests have been widely implemented and confirmed by literature using German data (e.g. Card et al. (2013); Bruns (2019)), Portuguese data (e.g. Card et al. (2016)), US data (e.g. Song et al. (2019)), as well as to Italian and Veneto data (e.g. Devicienti et al. (2019); Casarico and Lattanzio (2019); Fanfani (2022); Di Addario et al. (2022)

double connected set covers between 90 and 97% of the original workforce as shown in Table 3.9.

The current chapter investigates whether firm fixed effects differ at the occupational level. While my findings show that great heterogeneity exist both within and between firms, the current chapter does not answer *why* such differentiated wage policies exist within and between firms. Several extensions might improve the understating of the underlying mechanisms.

First, in the current application I rely on three broad occupational classes. The choice is driven by both data (no harmonized information is available in a greater detail) and methodological limitations (the tighter the occupational group, the less mobility for the identification of relevant AKM parameters). However, more detailed information on occupations might allow the investigation of compositional differences within firms in skill and tasks characteristics. Such differences might explain some of the observed heterogeneity in the wage policies within firms. For example, in a firm where automation technologies are heavily implemented routine tasks performed by workers might be poorly paid since the degree of sustainability between labor and capital is high. In the same firm, however, non-routine tasks might be highly rewarded due to complementary between the cognitive labour input and the technological supports. If in such firm the blue collar workers are more likely to perform mostly routine tasks (e.g. supervising robot machinery), while white collars mostly perform cognitive tasks (e.g. managing production and delivery of orders), then the different wage polices within such firm might be explained by differences in the price paid to the tasks performed by employees within the same firm.

Another potential extension could investigate the role of collective bargaining in shaping firms' behavior. In this regard, recent studies by Devicienti and Fanfani (2021) show great heterogeneity in how firms react to changes in reaction to changes in the level of contractual minimum wages set within the Italian system of industrial relations.

3.7 Conclusions

In this paper, I propose a new perspective on workplace heterogeneity departing from the implicit assumption in traditional AKM models that, within a single firm, the same wage policy applies to all employees. In particular, I allow employers to set differential firm premia for different occupational classes, i.e. managers, white collar, and blue collar workers. The main aim of the analysis is to understand whether good firms are actually good for all their employees.

Therefore, I estimate separate AKM models for managers, white collar, and blue collar workers using administrative data covering the full population of private-sector employees in the Veneto region in Italy. I show that the same firm applies different wage policies to its employees depending on the occupational class. This means that firm j can be highly rewarding for occupational class x and, at the same time, relatively under-rewarding for occupational class y with respect to the other firms in the market. Overall, I find no correlation between the manager, white collar, and blue collar workers firm policy distributions, thus providing evidence that the high-type firms are not 'equally good' for all their employees.

These findings suggest that despite there exists a clear hierarchy in the *average* returns earned by the different occupational classes, firms retain a high degree of flexibility in the way in which they remunerate their employees. Thus, I estimate the returns of the different occupational groups *within* firms. Ranking employers by the occupation-specific firm fixed effects reveals substantial heterogeneity in the occupational returns that workers get if employed in different firms. Most notably, I find that the highest-paying firms for a given occupational group are likely to be among the most discriminatory for the other employees.

Subsequently, I estimate the evolution of such within-firm wage differentials over 20 years time span. The difference in the average returns of white and blue collar workers increased by 3 percentage points between the 1980s and 1990s, passing from 25 to 28%. However, such wage premium increase was larger in firms applying larger differences in their occupation-specific wage policies: ranking firms according to the difference in the firm fixed effect applied to white and blue collars, in firms at the top 20% of the distribution I find that the white collar premium increased by 7 percentage points, passing from 34% to 41%. In order to explain this result, I explore whether such changes came together with increased sorting of high-type workers in high-type (occupation-specific) firm policies. If firms applying highly differentiated wage policies become more efficient in their recruitment process, this might help explain the increase in the occupational gap. However, while I find substantial heterogeneity in sorting intensity across firms, in those firms where I observe the largest increase in the white collar returns sorting intensity did not change over time. These findings seem to rule out the hypothesis of a tight correlation between increasing wage policy differentiation and improved recruiting ability at the firm level. I interpret these findings as a signal of increased wage setting decision power by firms. Specifically, my findings show that the choice of the employer is a key determinant for worker wage levels, with the consequences of such choices becoming more severe over time.

3.8 Appendix

3.8.1 Supplementary Figures and Tables

	1982-1991				1992-2001			
	Largest Connected Sets		**Double Connected Set**		**Largest Connected Sets**		**Double Connected Set**	
	White Collars	*Blue Collars*	*White Collars*	*Blue Collars*	*White Collars*	*Blue Collars*	*White Collars*	*Blue Collars*
Share of women	.41	.29	.4	.29	.45	.31	.45	.3
Average age	35	36	35	36	36	36	36	36
Average daily wage (2003 euros)	86	61	88	61	96	62	96	63
Avarege Experenice (months)	93	99	94	100	138	136	139	138
Share of workers employed in firms with								
Employees <100	.48	.58	.097	.08	.53	.64	.11	.1
Employees 101-200	.099	.11	.1	.12	.1	.1	.12	.14
Employees 201-500	.11	.13	.36	.45	.1	.11	.4	.47
Employees >500	.31	.18	.12	.14	.27	.15	.11	.12
Share of workers employed as								
Manager	.03	.	.032	.	.029	.	.029	.
White Collars	.97	.	.968	.	.971	.	.971	.
Blue Collars	.	1	0	1	0	1	0	1
Primary Sector	.0048	.0078	.0045	.0063	.0042	.0091	.0042	.0073
Secondary	.4	.68	.44	.68	.45	.66	.47	.66
Secondary	.59	.31	.55	.31	.55	.33	.52	.33
N obs	2,937,505	6,263,659	2,591,507	5,462,147	3,411,169	6,837,013	3,106,097	5,926,512
N workers	599,086	1,211,324	533,319	1,075,856	696,744	1,364,734	641,829	1,226,454
N Firms	50,206	62,830	42,017	42,017	58,836	74,428	51,766	51,766
N obs: % of Overall Sample	.98	.99	.86	.86	.99	.99	.91	.86
N workers: % of Overall Sample	.94	.98	.84	.87	.96	.98	.88	.88
N firms: % of Overall Sample	.65	.82	.55	.55	.69	.87	.6	.6

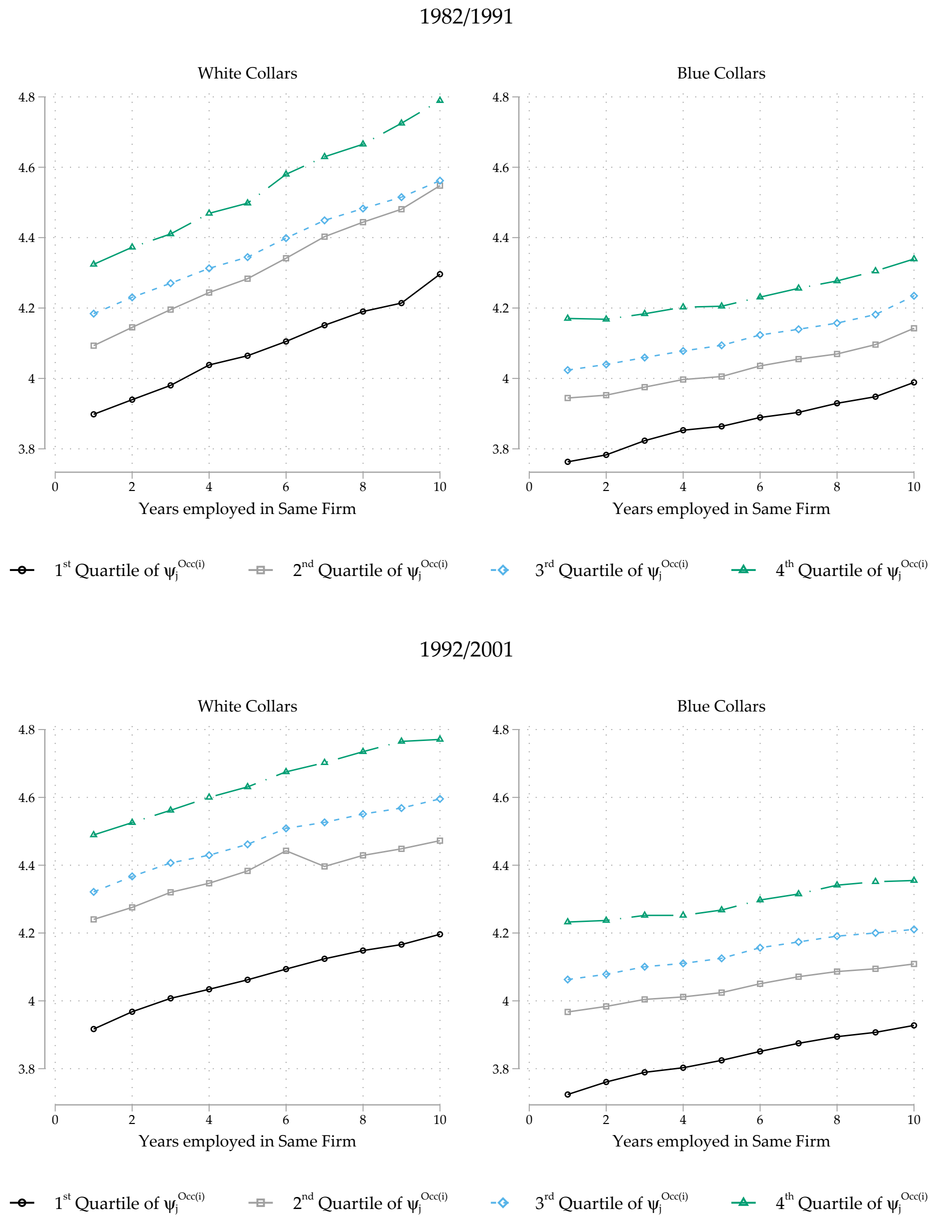
Notes: Tenure is censored at 1975. Average firms’ size is non-weighted and measured by the average of the number of employees working for the company in each year.

Table 3.5: Descriptive Statics

	1982-1991		1992-2001	
Quartiles of ψ_j^{Occ}	***White Collars***	***Blue Collars***	***White Collars***	***Blue Collars***
1^{st}	61.32	49.38	63.19	48.33
2^{nd}	79.14	56.79	88.17	58.02
3^{rd}	85.36	62.01	98.56	64.11
4^{th}	103.72	72.35	119.36	76.03
N workers	599,086	1,211,324	696,744	1,364,734
N firms	50,206	62,830	58,836	74,428

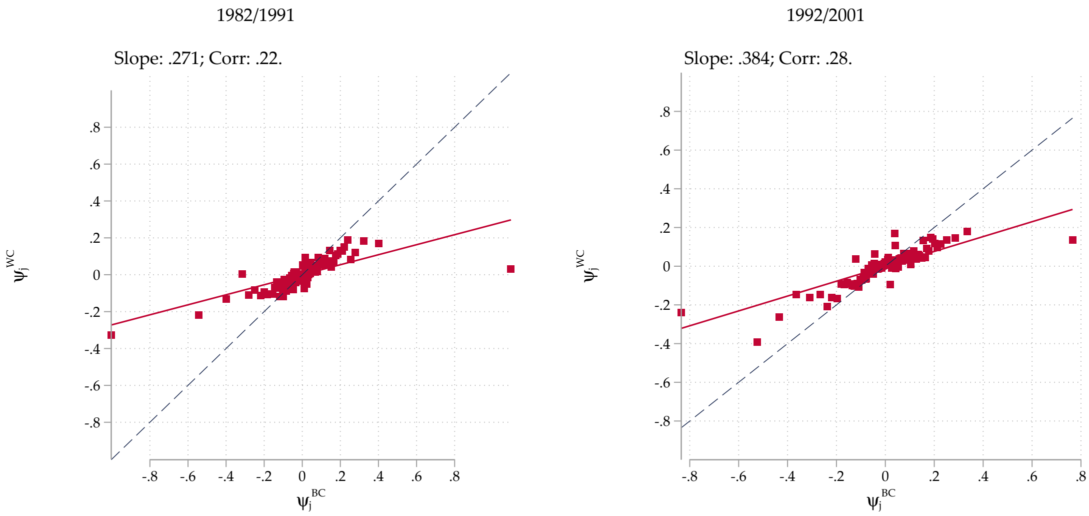
Notes: The table reports average daily wages in 2003 euros for managers, white collars and blue collars by quartiles of the occupation-specific firm fixed effects distribution. The estimated wages are based on job spells of workers working in firms located in Veneto and belonging to the three occupation specific largest connected sets. For managers, mid-managers (*quadri*) are excluded form the estimation.

Table 3.6: Average daily wage along the distribution of $\psi_j^{Occ(i)}$.



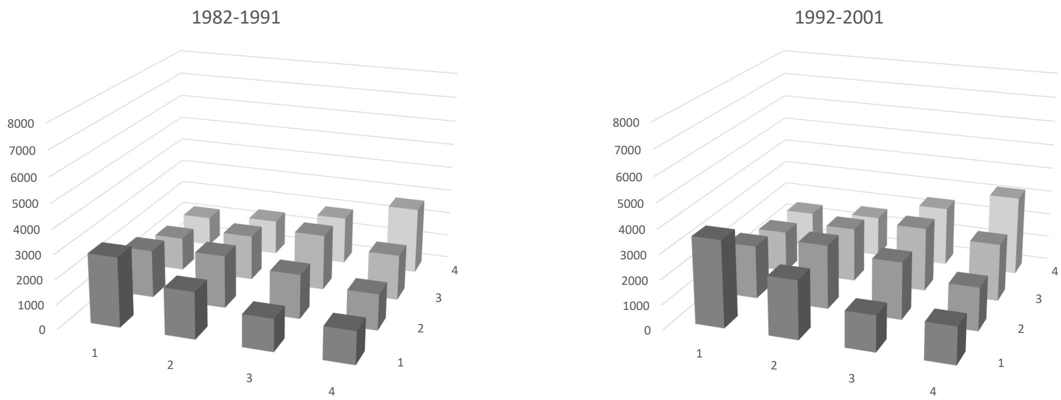
Notes. Estimation on the occupation-specific largest connected set over the 1982-1992 and 1992-2001 periods.

Figure 3.10: Average log-daily wage along $F(\psi)$.



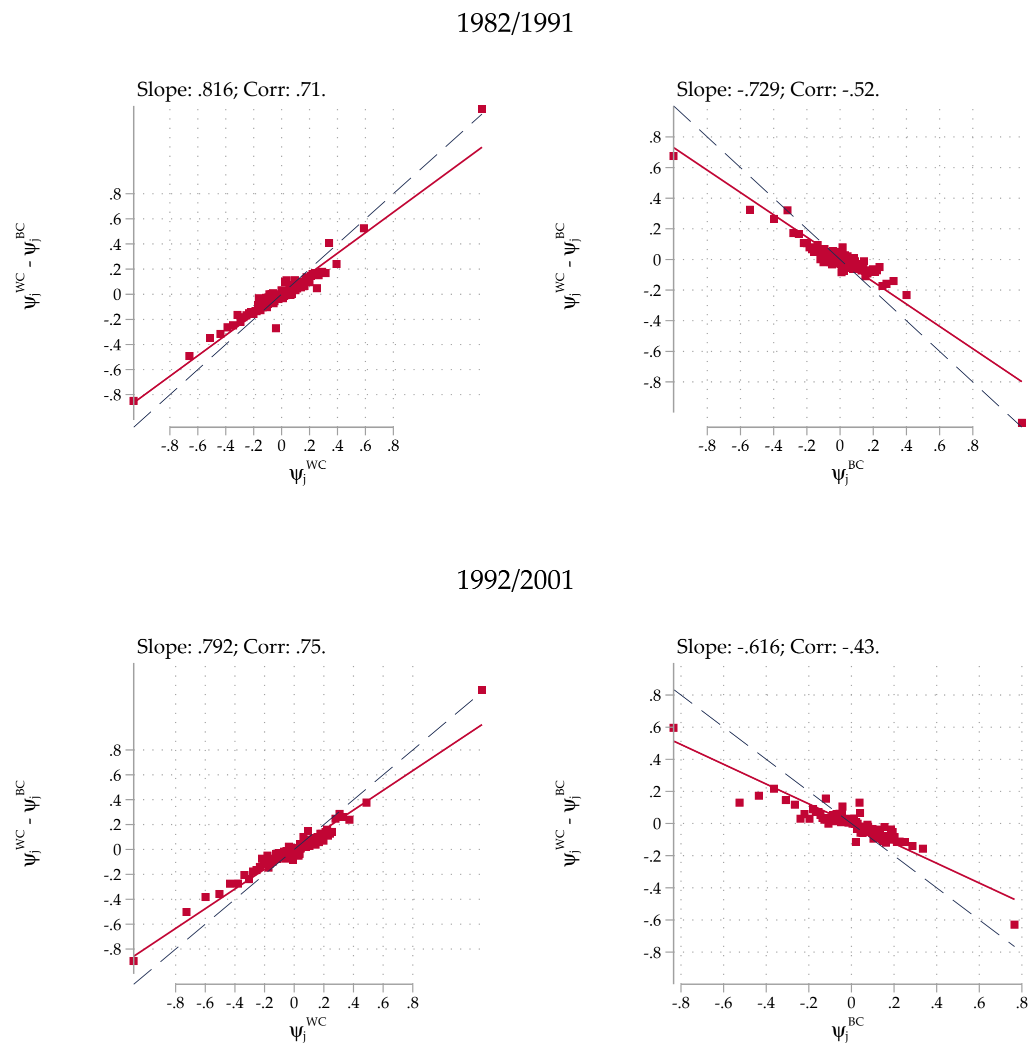
Notes. Estimation on the double connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. Each set of firm fixed effect have been demeaned. $PIslope$ in the Figure 3.3 indicates the coefficient of the projection of $\psi_j^{Manager}$ onto $\psi_j^{WhiteCollar}$ in the left panel, the projection of $\psi_j^{Manager}$ onto $\psi_j^{BlueCollar}$ in the central panel, and the projection of $\psi_j^{WhiteCollar}$ onto $\psi_j^{BlueCollar}$ in the right panel. $PIcorrelation$ gives the person-year weighted sample correlation between occupation-specific firm premia.

Figure 3.11: Do firm premia differ between occupational classes?



Notes. Estimation on the double connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. The figure counts firms over 16 cells of occupation-specific firm effects (4 quartiles per occupational group).

Figure 3.12: Joint Distribution of the occupation-specific firms premia.



Notes. Estimation on the double connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. Each set of firm fixed effect have been demeaned. *Slope* in the Figure 3.6 indicates the coefficient of the projection of $\mu_j = \psi_j^M - \psi_j^{WC}$ onto ψ_j^M (ψ_j^{WC}) in the upper (lower) left panel, the projection of $\mu_j = \psi_j^M - \psi_j^{BC}$ onto ψ_j^M (ψ_j^{BC}) in the upper (lower) central panel, and the projection of $\mu_j = \psi_j^{WC} - \psi_j^{BC}$ onto ψ_j^{WC} (ψ_j^{BC}) in the upper(lower) right panel. *Correlation* gives the person-year weighted sample correlation between μ_j and ψ_j.

Figure 3.13: Correlation μ_j and ψ_j over time.

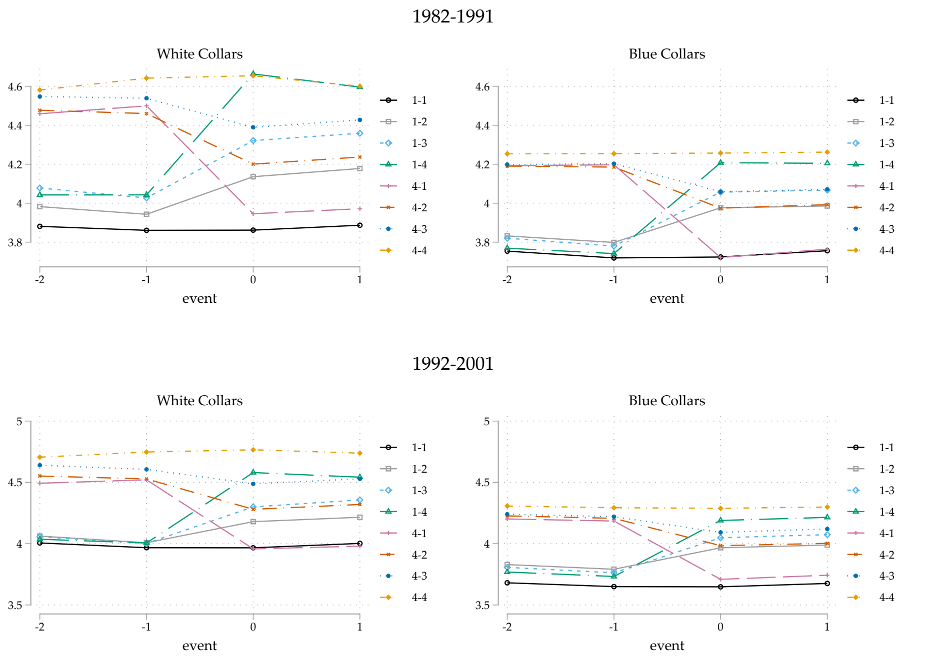
3.8.2 Conditional Random Mobility Assumption

Unbiased AKM estimation rely on *conditional random mobility* assumption. Specifically, given equation 3.1:

$$E[\epsilon_{it}|X_{it}, \psi_j, \theta_i] = 0 \tag{3.4}$$

Card et al. (2013) discusses three main channels through which conditional random mobility may be violated and proposes three main empirical tests. I replicate these tests on the largest connected sets for blue and white collar workers described in Table 3.5.

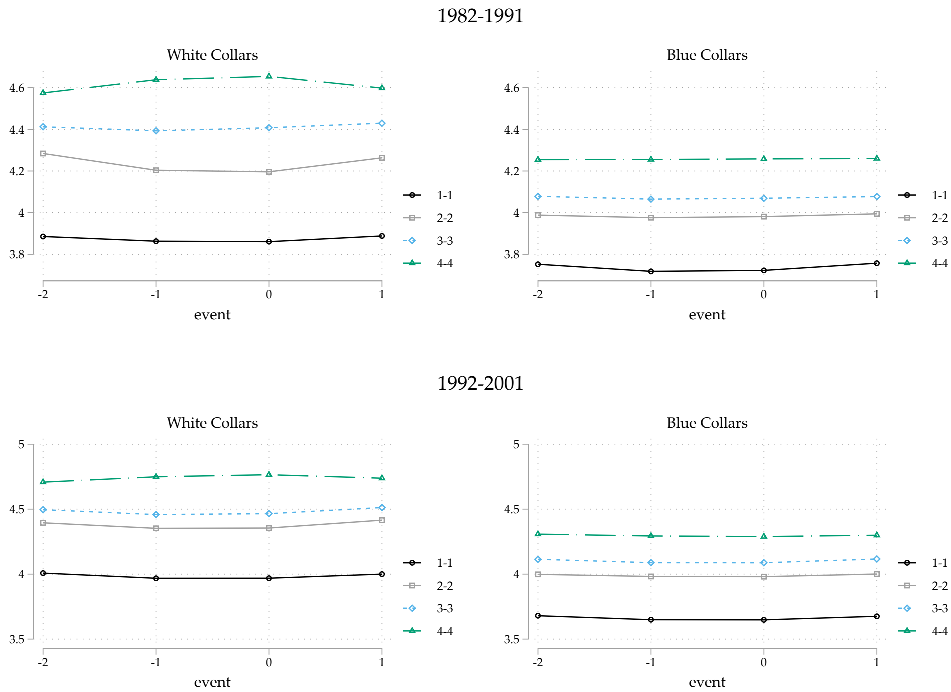
First, workers employed in firms experiencing negative shocks could decide to change job and join firms experiencing positive shocks. This would generate correlation between ψ_j and the probability that worker i is employed at firm j at time t . If this is the case, workers would experience a drop in earnings before the move, and a sudden rise in pay after. Figure 3.14 rules out this possibility. The figure shows average weekly wages for workers that changed firm between event -1 and 0. Job movers are differentiated depending on the quartile of their origin and destination firms. We see that for both withe and blue collar workers, there are no changes in the evolution of mean earnings before or after the move.



Notes. Estimation on the largest connected set over the 1982-1991 and 1992-2001 periods for both white and blue collar workers separately.

Figure 3.14: Average weekly earnings for movers across firm fixed effect quarterlies.

Second, workers could decide to change job would if they think that joining a new firm would deliver a better match between their personal characteristics and the firm characteristics compared to the firm of origin. Figure 3.15 reports the earnings evolution for the movers within the same quartile in the origin and destination firms. Flat earnings growth suggest that there are no match effects in mobility, thus ensuring that the conditional random mobility assumption is satisfied.



Notes. Estimation on the largest connected set over the 1982-1991 and 1992-2001 periods for both white and blue collar workers separately.

Figure 3.15: Average weekly earnings for movers across same firm fixed effect quarterlies.

Third, In Figure 3.16, I plot the average AKM residual in each of the 100 cells defined by the combination of worker and firm fixed effects deciles. If the model is missing some important match component between specific individuals and firms, I would expect to find high mean residuals in those cells that are threatened by miss-specification the most (Casarico and Lattanzio, 2019).

Notes. Estimation on the largest connected set over the 1982-1991 and 1992-2001 periods for both white and blue collar workers separately.

Figure 3.16: Average AKM residuals.

3.8.3 Variance Decomposition

3.8.3.1 Methodology

In the paper by Abowd et al. (1999), the following variance decomposition is proposed:

$$\begin{aligned} Var(w_{it})^{Occ} = Var(\theta_i + X'_{it}\beta^{Occ(i)})^{Occ} + Var(\psi_j^{Occ(i)})^{Occ} + \\ + 2Cov(\theta_i + X'_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})^{Occ} + Var(\epsilon_{it})^{Occ} \end{aligned} \tag{3.5}$$

Equation 3.5 decomposes total wage variation in the sum of the workers' ($Var(\theta_i + X'_{it}\beta^{Occ(i)})$) and firm premia heterogeneity ($Var(\psi_j^{Occ(i)})$) mediated by positive or negative sorting of workers types into types of firms adopting specific wage policies ($Cov(\theta_i + X'_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$).

While the main purpose of this paper is to study whether differences in the occupation-specific firm fixed effects, ψ^{Occ}, exists, previous literature greatly focuses on the covariance component $2Cov(\theta_i + X'_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$, which is typically interpreted as a measure of sorting of workers into firms.[24] Intuitively, rising assortment of high-type workers into high-type firms should be reflected in increasing covariance between worker and firm fixed effects. However, several papers discuss a series of limitations behind the covariance index and propose new methodologies for the estimation of sorting. First, non-monetary amenities might be related to the job choice of employees, such that equally productive workers may be employed by employers adopting very different wage policies. Second, high-type firms are *not* necessarily highly productive (Bartolucci et al., 2018) and firm fixed effects should rather be interpreted as capturing wage differentials paid by companies as results of frictions (Lopes de Melo, 2018). Thus, introducing these non-linearities between worker and firm types might undermine the economic interpretation of $2Cov(\theta_i + X'_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$ as a proxy of sorting. Lopes de Melo (2018) proposes to use the correlation between co-workers' fixed effects as a more precise measure for sorting in an economy, while Bartolucci et al. (2018) develop a novel indicator based on firm profits rather than firm AKM fixed effects. In their article, Bartolucci et al. (2018) showed that both indicators proved to more accurate proxies for the degree of assortment between workers and firm types in labor markets than the covariance index $2Cov(\theta_i + X'_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$.

Additionally, besides the difficult economic interpretation, (Andrews et al., 2008) formally show that the second moments of the AKM variance decomposition are biased and this bias can be particularly severe in situations where the mobility

[24] Lopes de Melo (2018) provides an overview of previous studies applying the same variance decomposition.

between firms is limited. In particular, the bias comes from the fact that the vector of estimated fixed effects, $\widehat{\theta_i}$ and ψ_j, suffer from standard least squares estimation error. While under the strict exogeneity assumption that these estimation errors are expected to be equal to 0, such that $E[\widehat{\psi_j} = \psi_j]$ is unbiased, the second moment $\widehat{\psi_j}^2$ ultimately depends on the variance of the error term σ_i. In the traditional AKM model, $Var(\psi_j)$ is calculated 'plugging-in' the OLS estimate $\widehat{\psi_j}$, so that:

$$Var(\widehat{\psi_j}) = Var(\psi_j) + \sum_{i=1}^{N} \mathbf{B}_{ii}\sigma_i^2 \tag{3.6}$$

where $\sum_{i=1}^{N} B_{ii}\sigma_i^2$ is the so called 'plug-in' bias and depends on the number of movers per firm.[25]

Bonhomme et al. (2019) propose a two-step estimation approach that relies on clustering similar firms into groups and then estimating the fixed effects at the cluster level. In their preferred specification, they rely on 10 major clusters. In their framework, thus, the authors exploit mobility between clusters of firms, and not of single firms, for the identification of the relevant parameters allowing for a higher degree of connection within the estimation sample. While this approach solves the limited mobility bias, it reduces the heterogeneity of fixed effects from the firm level to the cluster level.

Kline et al. (2020) (KSS), instead, proposed an alternative bias correction approach that consists in empirically computing $\sum_{i=1}^{N} B_{ii}\widehat{\sigma_i}^2$ in equation 3.6, where the *unbiased* estimator for σ_i^2 is calculated as

$$\widehat{\sigma_i}^2 = y_i(yi - x_i'\widehat{\rho}_{-i})^2 \tag{3.7}$$

$\widehat{\rho_{-i}}$ represents the OLS estimates of ψ_j, θ_i, and β in equation 3.1 when observation i is left out. The unbiased firm-fixed effect variance will, therefore consist in the bias-corrected plug-in estimate:

$$Var(\widetilde{\psi_j}) = Var(\widehat{\psi_j}) - \sum_{i=1}^{N} \mathbf{B}_{ii}\widehat{\sigma_i}^2 \tag{3.8}$$

Therefore, the KSS estimator allows for correcting the bias in the estimation of $Var(\widehat{\psi_j})$, $Var(\widehat{\theta_i})$, and $Cov(\widehat{\psi_j}, \widehat{\theta_i})$ within the so called *leave-one out* connected set, which requires dropping any firm associated with only one mover from the AKM largest connected. $\widehat{\rho}_{-i}$ can only be identified for firms connected by mobility of at

[25] $B_{ii} = x_i'S_{xx}^{-1}AS_{xx}^{-1}x_i$, where $S_{xx} = \sum_{i=1}^{N} x_i x_i'$, A is a known matrix equal to $A = \begin{pmatrix} 0 & 0 \\ 0 & A_{ff} \end{pmatrix}$ and $A_{ff} = \frac{1}{N}\sum_{i=1}^{N} /(f_i - \overline{f})(f_i - \overline{f})'$ with f_i denoting firm identifier. See Kline et al. (2020) and Lachowska et al. (2022) for details.

least *two* workers so that once worker i is removed from sample the connected set does not break its connectivity. It is, then, important to underline that estimation of $\widehat{\rho_{-i}}$ requires solving a system of NxT equations in N+J unknowns where, N represents the number of workers in the sample, T the number of years considered, and J the number of firms within the leave-one-out connected set. This computation is infeasible in large matched employer-employees data and it is based on a variation of the Johnson-Lindestrauss approximation algorithm developed by KSS and available as replication package in Matlab.

3.8.3.2 Results

Table 3.7 reports the estimates of the variance decomposition on the occupation-specific leave-one-out connected set for both time periods considered in Section 3.5. The table confronts the parameters identified with the *biased* AKM plug-in estimators and with the *unbiased* KSS estimators. Results show that the variance in wages increased for both white and blue collar workers between the 1980s and 1990s in the Veneto region. The largest source of wage heterogeneity comes from workers effects, while heterogeneity in firm wage policies, $Var(\psi_j)$, accounts for a minor share and it decreases over time. These results are consistent with findings by Devicienti et al. (2019) using the same data source but different working samples. Sorting is instead slightly decreased among white collar workers and increased among blue collar workers. KSS estimates confirm upward biases in $Var(\psi_j)$ and downward biases in the estimation of $Cov(\psi_j, \theta_i)$ via traditional AKM models. I report in Table 3.8 the estimates of the traditional AKM decomposition on the occupation specific largest connected set.

	White Collar Workers						Blue Collar Workers					
	1992-2001		**1982-1991**		**Δ**		**1992-2001**		**1982-1991**		**Δ**	
		%		%		%		%		%		%
$Var(w_{i,t}$	0.274	*100*	0.243	*100*	0.032	*0*	0.118	*100*	0.102	*100*	0.017	*0*
PLUG-IN ESTIMATES (BIASED),												
$Var(\psi_j)$	0.036	*13.000*	0.037	*15.221*	-0.001	*-2.221*	0.033	*27.906*	0.034	*33.808*	-0.001	*-5.903*
$Cov(\psi_j, \theta_i)$	-0.002	*-0.741*	-0.001	*-0.298*	-0.001	*-0.442*	-0.003	*-2.117*	-0.009	*-8.404*	0.006	*6.287*
$Var(\theta_i)$	0.178	*64.719*	0.238	*98.191*	-0.061	*-33.472*	0.194	*164.196*	0.287	*282.669*	-0.093	*-118.474*
$Corr(\psi_j, \theta_i)$	-0.026		-0.008		-0.018		-0.031		-0.086		0.055	
BIAS CORRECTED ESTIMATES (KSS)												
$Var(\psi_j)$	0.024	*8.795*	0.025	*10.461*	-0.001	*-1.666*	0.029	*24.388*	0.028	*27.831*	0.001	*-3.444*
$Cov(\psi_j, \theta_i)$	0.008	*2.864*	0.009	*3.818*	-0.001	*-0.954*	0.001	*0.719*	-0.003	*-3.162*	0.004	*3.881*
$Var(\theta_i)$	0.156	*56.828*	0.216	*88.978*	-0.060	*-32.149*	0.180	*152.050*	0.271	*266.332*	-0.091	*-114.283*
$Corr(\psi_j, \theta_i)$	0.128		0.125		0.003		0.012		-0.037		0.049	
N of Movers	185,385		127,458				477,115		326,612			
N of Firms	31,419		*26,314*				58,284		*48,381*			
N of Person Year Observations	2,976,557		*2,580,635*				6,407,268		5,875,702			

Notes: This table shows results from the variance decomposition specified in equation 3.5 using KSS-bias correction. The estimation sample is the leave-one-out connected set for white and blue collars in the 90s (1992-2001) and 80s (1982-1991). The table is divided in two main panels, the one on the left reporting results for white collars and the one on the right for blue collars. In each panel, the first and thirds columns report variance decomposition estimates for the 1992-2001 and 1982-1991 period respectively. The second and fourth columns display the variance decomposition components as share of total variance. The fifth and sixth column report over time differences.

Table 3.7: Variance decomposition - KSS correction

	White Collar Workers						Blue Collar Workers					
	1992-2001		1982-1991		Δ		1992-2001		1982-1991		Δ	
		%		%		%		%		%		%
Variance Decomposition												
$Var(w_{i,t})$	0.279	*100.000*	0.245	*100.000*	0.034	*0.000*	0.122	*100.000*	0.106	*100.000*	0.016	*0.000*
$Var(\theta_i + X_i, t\beta)$	0.205	*73.368*	0.177	*72.289*	0.028	*1.079*	0.057	*46.261*	0.047	*44.692*	0.009	*1.569*
$Var(\psi_j)$	0.045	*16.237*	0.046	*18.934*	-0.001	*-2.697*	0.036	*29.053*	0.037	*34.744*	-0.001	*-5.690*
$Var(\epsilon_{i,t})$	0.026	*9.345*	0.030	*12.258*	-0.004	*-2.913*	0.022	*17.893*	0.029	*26.942*	-0.007	*-9.049*
$Cov(\psi_j^{Occ}, \theta_i + X_{it}\beta)$	0.003	*1.051*	-0.009	*-3.480*	0.011	*4.531*	0.008	*6.792*	-0.007	*-6.378*	0.015	*13.170*
Alternative Sorting and Segregation Measures												
$Corr(\theta_i, \overline{\theta^j})$	0.441		0.462		-0.020		0.495	*0.493*	0.493		0.002	
$Var(\overline{\theta^j})$	0.047		0.062		-0.015		0.018	*0.023*	0.023		-0.005	
Segregation Index	0.325		0.341		-0.016		0.337	*0.330*	0.330		0.007	
$Corr(\psi_j, \psi_j^{Prev})*$	0.384		0.390		-0.006		0.386	*0.308*	0.308		0.078	
N firms	58,836		50,206				74,428		628,30			
N workers	696,744		599,086				1,364,734		1,211,324			
N movers	210,984		149,892				493,211		340,989			

Notes: This table shows results from the variance decomposition specified in equation 3.5 using traditional AKM models. The estimation sample is the largest connected set for white and blue collars in the 90s (1992-2001) and 80s (1982-1991). The table is divided in two main panels, the one on the left reporting results for white collars and the one on the right for blue collars. In each panel, the first and thirds columns report variance decomposition estimates for the 1992-2001 and 1982-1991 period respectively. The second and fourth columns display the variance decomposition components as share of total variance. The fifth and sixth column report over time differences.

Table 3.8: Variance decomposition - traditional AKM

3.8.4 Interacted Fixed Effects Model

In the main body of the paper I estimated occupation-specific fixed effects on separated samples by occupational classes. In practice this means to run 3 separate AKM models for different occupational groups over the same time period: one on the sub-sample including only managers, one on the sub-sample including only white collar workers and one on the sub-sample including only blue collar workers. As a consequence the largest connected set is identified only by job movers between different firms and within the same occupation. Workers changing firm *and* occupation, instead, do not belong to the connected set since they will belong to two different estimation samples before and after the job move. While this approach has the advantage of estimating the occupation-specific firm policy $\psi_j^{Occ(i)}$ exploiting comparisons of workers in the same occupational classes, it reduces the overall connectedness of the estimation samples since a non-negligible share of job movers moves between firms *and* occupational classes. Lower overall connectedness has two main consequences: first, it might reduce the sample size of the estimation sample since fewer job-movers potentially reduce the amount of connected firms; second, lower mobility might introduce biases in the estimation of $Var(\psi_j)$ and $Cov(\psi_j, \theta_i)$ (Andrews et al., 2008). Since in most of the analysis I rely on first moments of the AKM parameters, the latter limitation is not relevant for the current application.

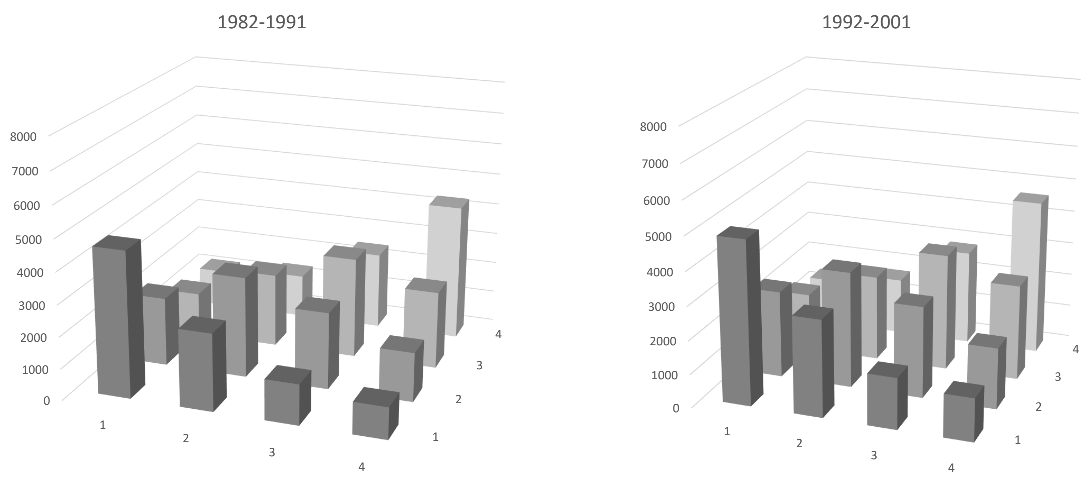
An alternative approach to the estimation of occupation-specific firm fixed effects consists in estimating an AKM model where the firm fixed effects are interacted with the worker's occupational class. In this case, $\psi_j^{Occ(i)}$ is estimated over the full connected set, exploiting mobility between both firms *and* occupations. While this latter approach increases overall mobility and, consequently, the resulting connected set will be larger, the estimation of the occupation-specific firm policy $\psi_j^{Occ(i)}$ is derived comparing workers employed potentially in all occupational classes, affecting the interpretation of the wage policy.

In the following paragraph, I replicate the exercises provided in the main body of the analysis for the period 1982-1991 and 1992-2001 distinguishing white collar (including managers) and blue collar firm fixed effects. Results are directly comparable with the findings explained in Section 3.5. Specifically, Table 3.9 summaries the main descriptive statics for the interacted samples in the 1980s and 1990s. Figure 3.17, replicates Figure 3.12, while Figure 3.18, replicates Figure 3.7.

	1982 - 1991				1992-2001			
	Largest Connected Set		**Dual Connected Set**		**Largest Connected Set**		**Dual Connected Set**	
	WC	*BC*	*WC*	*BC*	*WC*	*BC*	*WC*	*BC*
Share of women	.41	.29	.41	.29	.45	.3	.45	.3
Average Age	35	36	35	36	36	36	36	36
Average daily wage (2003 euros)	83	60	84	60	93	61	93	61
Average Experience (months)	94	99	94	1.0e+02	133	130	133	131
Share of workers employed in firms with								
Employees <100	.49	.58	.12	.095	.54	.64	.12	.11
Employees 101-200	.097	.11	.11	.13	.1	.1	.12	.15
Employees 201-500	.11	.12	.35	.45	.1	.11	.39	.46
Employees >500	.3	.18	.12	.13	.26	.15	.1	.12
Share of workers employed as								
Manager	.03	0	.03	0	.029	0	.029	0
White Collar Workers	1	0	1	0	1	0	1	0
Blue Collar Workers	0	1	0	1	0	1	0	1
Primary Sector	.005	.0078	.0048	.0066	.0044	.0092	.0042	.0089
Secondary Sector	.41	.68	.42	.68	.45	.66	.46	.66
Tertiary Sector	.58	.31	.58	.31	.54	.33	.54	.33
N obs	2,940,098	6,187,781	2,852,021	5,756,582	3,408,043	6,739,903	3,301,123	6,203,064
N workers	602,381	1,194,607	586,654	1,126,029	691,764	1,337,463	674,524	1,260,617
N Firms	58,739	66,218	53,536	53,536	67,522	76,732	62,126	62,126
N obs: % of Overall Sample	.98	.97	.95	.91	1	.98	.97	.9
N workers: % of Overall Sample	.95	.96	.92	.91	.95	.96	.93	.91
N firms: % of Overall Sample	.76	.86	.7	.7	.79	.89	.72	.72

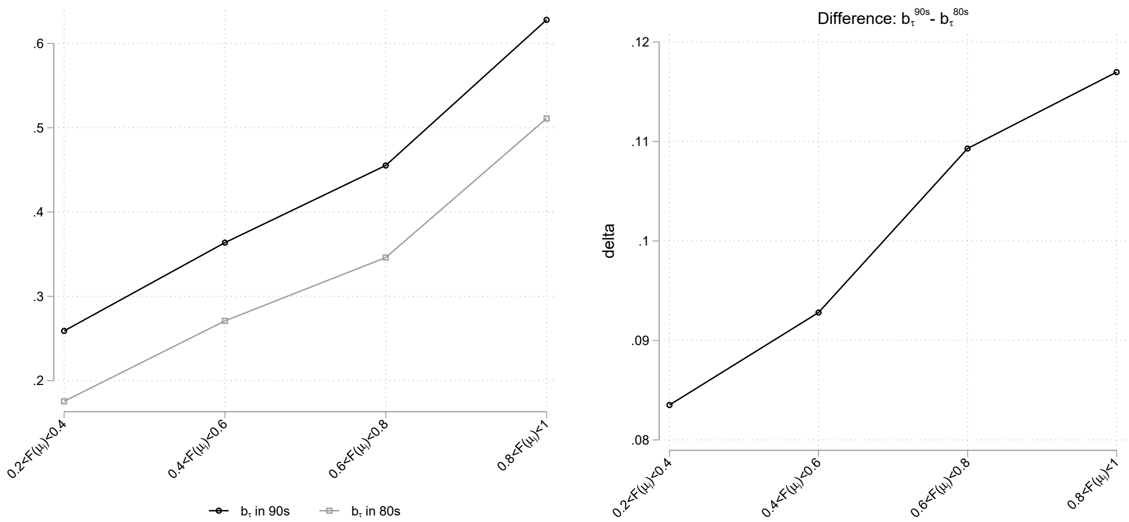
Notes: Tenure is censored at 1975. Average firms' size is non-weighted and measured by the average of the number of employees working for the company in each year.

Table 3.9: Descriptive Statics - Interacted Occupation Specific Fixed Effects



Notes. Estimation on the double connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. The figure counts firms over 16 cells of occupation-specific firm effects (4 quartiles per occupational group).

Figure 3.17: Joint Distribution of the occupation-specific firms premia - interacted fixed effects



Notes. The left panel of the figure reports estimation of b_τ according to model 3.2 for white collar workers over blue collar workers for the period 1992-2001 (in black) and for the period 1982-1991 (in light grey). The panel on the right reports the over time difference $b_\tau^{90s} - b_\tau^{80s}$. Estimation on the double connected set restricted to firms located in Veneto

Figure 3.18: Within-firm wage gradient over time - interacted fixed effects

4 A Study of the Chinese Communist Party (CCP) and Wealth Inequality in China

4.1 Introduction

[2]

Since the economic reform, the Chinese economy has experienced one of the world's biggest booms. Since the 1990s, China has witnessed a drastic transformation, going from a poor and egalitarian country to an upper middle-income country with levels of economic inequality close to that of the United States. Several studies find that political status and connection might play a key role in explaining existing inequalities, in both developed and developing countries (Johnson and Mitton, 2003; Khwaja and Mian, 2005; Faccio, 2006). In the context of China, there is growing interest among economists and other social scientists in measuring the economic returns of Chinese Communist Party (CCP) membership (Szelényi, 1987; Nee, 1989, 1991, 1996; Rona-Tas, 1994; Walder, 1996; Morduch and Sicular, 2000; Dickson and Rublee, 2000; Li et al., 2007; Appleton et al., 2009; McLaughlin, 2017; Gu and Zheng, 2018; Guo and Sun, 2019; Nikolov et al., 2020). Specifically, existing literature mostly focuses on estimating the returns of party membership on labour wages and earnings, recently generally agreeing about the existence of a wage premium for party members with respect to the non-CCP members (Ma and Iwasaki, 2021). Nevertheless, the size of such wage premium is still debated and there is not a general consensus regarding the causal mechanisms. Among the most recent studies, some confirm large and significant direct and indirect economic benefits for party members. McLaughlin (2017) estimates a party wage premium ranging from 7 to 29% using survey data from urban China, while Nikolov et al. (2020) using data from 1988 to 2013, confirm that CCP members earn about 20% higher monthly earnings than their non-member peers, and that these effects can be explained by members' improved access to government jobs, higher-ranking positions within a job hierarchy, and an overall improvement in social rank. Other studies, like Li et al. (2007), Gu and Zheng (2018), and Guo and Sun (2019) estimate that the economic returns to party membership are largely due to self-selection effect, since party membership is not random and more talented individuals might be positively selected to join the party. Nevertheless, Guo and Sun (2019) recognize party membership has important

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indirect effects and CCP members are found to be more likely to work in state-owned enterprises and obtain permanent urban residence.

While the correct causal estimation of the average effect of CCP membership on labour income remains the most debated issue in the literature, very little is known about the *wealth* differences between CCP and non-CCP households. A few exceptions, Meng (2007) and Xie and Jin (2015), using cross-sectional urban survey data, find a significant impact of CCP membership on the average household wealth. However, an in-depth investigation of the wealth differences and its evolution since 2003 is not provided, mainly due to data limitations.

In this paper, we aim to fill the gap in the literature by presenting the first comprehensive study about the wealth gap evolution in urban China between CCP and non-CCP households since the 1990s. Two main aspects distinguish our contribution.

First, we rely on two main data sources, the Chinese Household Income Project (CHIP) and the China Household Financial Survey (CHFS), that have been carefully harmonized in order to guarantee wealth information comparable over the period 1995-2017. The period under investigation is particularly interesting because China undertook a process of deep economic transformation. Private wealth experienced rapid and diffused growth, fostered by structural reforms (Novokmet et al., 2018; Piketty et al., 2019; Yang et al., 2021; Song et al., 2011). In particular, starting in the early 1990s, housing reforms initiated the privatization of housing wealth, which was previously publicly owned. Housing ownership was transferred at heavily subsidized prices to the occupying tenants, most of whom were employed in the public sector (Meng, 2007; Xie and Jin, 2015; Song and Xie, 2014). By 2002, 85% of urban housing was privately owned (Piketty et al., 2019) and the real estate market subsequently boomed.[3] The rapid growth experienced by the Chinese economy, however, came together with rising inequality. While a growing body of literature examines the evolution of *income* inequality in China (Zhang (2021)), only a few studies focus on the long term evolution of wealth inequality.[4] We, therefore, contribute to the current literature by introducing an important political dimension to the analysis of wealth inequality since the 1990s and by relying on a novel harmonized data framework.

Second, we apply unconditional quantile regression (UQR) to describe the heterogeneity in the returns of party membership along the income and wealth distributions. Our results show that the *average* wealth gap between CCP and non-CCP households remained substantial and stable between 1995 and 2017; however, the returns structure of political membership has deeply changed over time. While in 1995 the highest wealth advantages, in relative terms, for party members were

[3]Section 4.2.2 summarizes the main features of the housing reform, while a dedicated paragraph in Appendix 4.8.2 describes the history of China's urban housing in greater details.

[4]Among the few exceptions, see Piketty et al. (2019) and Li and Wan (2015)

concentrated at the middle of the distribution, in 2017 it is the lower class that benefits the most. We show that the privatization of the housing market, especially after the housing reform period, granted equal access to housing wealth to both CCP and non-CCP families, reducing the differences in the middle and at the top of the wealth distribution. However, strong differences between the housing investment of CCP and non-CCP households continue to persist at the bottom of the net wealth distribution, where CCP members are found to be more likely to own housing assets. We find that these differences are related to CCP households having better housing investments. In particular, we document that such persistent differences might derive from a privileged access to housing investment for CCP households, vis-à-vis non-CCP households, during the early stages of the real estate privatization process undertook in urban China during the 1990s.

While our analytical framework allows us to study in detail the observable wealth gap between CCP and non-CCP households, it is difficult to ascribe a *causal* interpretation of the party membership coefficient. As pointed out in the literature, party membership is not random. Further, un-observable characteristics of the household members, such as ability, ambition, and social networks, might lead more talented individuals to join the party and, at the same, these qualities are likely to correlate with individual earnings and, consequently, with household wealth. Positive selection of talented individuals as CCP members might, therefore, explain substantial income and wealth differences with the non-CCP counterpart. Aware of these limitations in the interpretation of the results, we believe that our findings still provide an important description of large and sizable inequalities within the Chinese society and we invite future research to investigate to what extent such gaps are driven by selection biases.

The remainder of the paper is organized as follows: Section 4.2 briefly summarizes the institutional background of party membership and briefly introduces the main features of the real estate privatization process. Section 4.3 discusses data sources and harmonization processes. Section 4.4 describes the methodology and Section 4.5 discusses the main results. Section 4.6 discusses several caveats of the analysis and potential extensions. Section 4.7 concludes.

4.2 Background

4.2.1 The Chinese Communist Party

Since 1949, the CCP has been the ruling and dominant party in China. At the end of 2016 the party counted over 89 million members making it the largest party in the world (Gu and Zheng, 2018). Membership is, however, conditional on a stringent selection process, where applicants have to successfully complete several evaluation steps including composing a formal motivation letter, demonstrate active participation in local political activities, follow specific classes, and pass a final assessment (Nikolov et al., 2020). The whole application process, therefore, requires special effort over an extended period of time, typically longer than 4 years (Ma and Iwasaki, 2021). Nevertheless, obtaining the CCP membership is considered to be the first step in becoming a part of the Chinese administrative elite (Nikolov et al., 2020).

Thus, the economic benefits could derive from several factors. First, party membership increases social capital via political connections and social networking. Most importantly, these connections might involve higher-status individuals who can provide referrals for high-status jobs (Bian, 1994). Secondly, some high-paying jobs are only available to party members, such as employment opportunities in local administrative offices or higher-level jobs in state-owned enterprises (Nikolov et al., 2020). McLaughlin (2017) documents that affiliation with the party brings higher paying jobs through the job assignment program, which was particularly pervasive before the 1990s.

4.2.2 Housing Reforms in China

The history of China's urban housing can be summarized into three significant phases: 1949-1978 (pre-reform period); 1979-1998 (housing reforming period); and 1999-present (post-reform period). While in the following paragraph we summarizes the main features of three phases, a more detailed explanation is provided in Appendix 4.8.2.

Since the Chinese Communist party came to power in 1949, urban private housing was gradually nationalized and, by 1978, 78.4% of the urban housing stock was publicly owned (侯淅珉, 1999, p.11). The housing units were allocated, usually free or at a highly subsidized price, to state employees as in-kind compensation. The quality (location, size, housing condition) of the allocated housing largely depended upon the worker's administrative rank (Song and Xie, 2014).

The mounting pressure in the public housing system at the end of 1970s, especially due to housing shortages, led to a series of housing privatization reforms in the following two decades. Nationwide housing reforms began in 1991, when the property rights of privatized housing were officially recognized. In this early phase, privatization of public housing occurred as the lump-sum transfer of wealth in the form of discounted sales of public housing apartments to residing tenants, who were mostly workers in the public sector. The private housing obtained during such privatization period are often called *welfare housing* ('福利房'), since these housing were initially distributed to the public as a type of welfare instead of a commodity. Since such allocation of public housing (location, size, condition) was concentrated in public sectors (i.e. governmental institutions and state-owned companies), based on the administrative rank of the employee, understandably the housing reform brought a windfall to those individuals working in the public sectors or having strong political connections (CCP members or government officials).

In 1998, the state council issued the official termination of in-kind allocations of publicly owned housing. According to the plan, after 1998, all newly built houses would be commercialized and old public housing would be gradually commercialized. The housing reform resulted in a vigorous and fast-growing urban housing market. By 2002, 85% of urban housing was privately-owned (Piketty et al., 2019). Consequentially, housing prices escalated rapidly, further triggering the problem of housing affordability. The central and local governments, therefore, implemented a large set of affordability-enacting polices that provided ground for the development of 'economically affordable housing' (经济适用房) designed to benefit all the low-to-medium income urban households, instead of only the employees of the state-owned enterprises and governmental institutions. These programs are still in place as of 2023. Nevertheless, the affordable housing system in China targets only urban residents who have city residence permits as part of its household registration system (commonly known as the *hukou* system). Migrant workers, floating populations, and others citizens without urban residence permits are not covered.

Another core policy for the transition is the establishment of the housing fund for urban employees at the end of 1990s, which was designed for the purpose of housing purchase and renovation. The Housing Fund is a form of social insurance paid by both employers and employees and it ranges from 10% to 40% (depending on the city) of employee's gross wage. Such funds are allocated in the employee personal account and can only be withdrawn for housing related expenses (i.e. down payment, construction, purchase, property renovation, and paying back a mortgage). According to the 2017 National Housing Fund Report[5], in 2017, the total housing fund stock, income, and outflow account for 6.3%, 2.3%, and 1.6% of China's GDP, respectively. In 2020, 50% of the employees registered in the housing fund system worked in the public sectors, whose employees cover only 13% of total employees in urban China.[6]

4.3 Data

4.3.1 Data and Variables Definition

Our analysis is based on two national representative surveys, namely the Urban Chinese Household Income Project (UCHIP) and the China Household Financial Survey (CHFS).

[5] published by Ministry of Housing and Urban-Rural Development, Ministry of Finance, and People's Bank of China *(Link)*.

[6] National Housing Provident Fund 2020 Annual Report

UCHIP surveys are repeated cross-section surveys drawn from a much larger sample of the Urban Household Survey conducted annually by the National Bureau of Statistics. More precisely, we use urban samples of two CHIP waves in 1995 and 2002. The 1995 survey covers 11 provinces consisting of 6,835 households, while the 2002 survey covers 12 provinces consisting of 6,931 households.

CHFS is the largest panel survey on household income and wealth in China, conducted by the Southwest University of Finance and Economics biennially since 2011. Since the first wave (CHFS 2011), the sample size has been continuously expanding. So far micro data from the first 4 waves are publicly accessible, namely CHFS 2011, 2013, 2015, and 2017. In the 2017 wave, the sample comprises more than 40,000 households from 367 counties in 29 provinces. Because of a major sample re-design, we excluded the first CHFS wave from our working sample.

Both surveys provide detailed information on household wealth including financial assets and debts, housing wealth, assets for household production and business activities, as well as information on income and expenditure. Together, CHIP and CHFS represent a unique source of information for analyzing wealth composition and distribution in urban China over a 20 year time span.

In our analysis we define:[7]

- *Household Total Income* as the sum of total net wages and salaries, pensions and annuities, net income from self-employment, farming and business activities, rental income, income from financial actives (interests and dividends), income from governmental transfers, as well as income from donations and presents. In both samples, information refers to the total revenues earned in the year before the interview.

- *Gross Household Wealth* as the sum of all assets owned by the household. Specifically, we distinguish six main assets categories: safe and risky financial wealth, housing wealth, housing funds, business wealth, and other assets. Safe financial wealth includes cash, deposits, and funds owned by the household. Risky financial wealth includes the current market value of bonds, financial products, loans, and stocks owned by the household. Housing Wealth is defined as the sum of the current market value of the three most valuable houses owned by the household. Business wealth includes the share of assets owned by the family invested in business activities, including individual business, leasing, transportation, online stores, and enterprises. Other Assets includes the current value of land and agricultural machinery. We exclude from the household wealth both durable goods and social security wealth.

[7] Table 4.6 in Appendix 4.8.1 defines the main wealth and income aggregates in our sample highlighting whether differences exists between the definitions applied in CHIP and CHFS.

	CHIP		CHFS		
	1995	**2002**	**2013**	**2015**	**2017**
N of Individuals	16,396	16,415	50,444	70,235	67,477
N of HHs	6,931	6,835	19,192	25,613	27,244
Average Age	43.55	45.00	46.27	47.39	49.95
% of Females	0.51	0.51	0.51	0.51	0.51
% of High-Educated	0.08	0.09	0.13	0.15	0.13
% of Low-Educated	0.65	0.63	0.54	0.48	0.54
% of Employed Individuals	0.90	0.62	0.58	0.57	0.58
% of CCP Individuals	0.24	0.27	0.17	0.20	0.18
Non-missing Rate	*1.00*	*0.98*	*0.73*	*0.70*	*0.72*
% of HHs with at least one CCP	0.46	0.50	0.29	0.28	0.27
Non-missing Rate	*1.00*	*1.00*	*1.00*	*1.00*	*0.99*

Notes: Estimations are based CHIP (1995, 2002) and CHFS (2013, 2015, and 2017). We include in the calculation all individuals aged 20 belonging to the urban sample. Estimates are weighted using sample weights.

Table 4.1: Descriptive statistics.

- *Household Debt* consists of the outstanding loans owned by the household from housing, financial investments, education, medical care, business, and agricultural activities owned by the household.

- *Net household wealth* as the consolidated value of the household balance sheet by subtracting debt from assets.

From the CHFS waves, we have detailed information on household consumption. Therefore, we express total household consumption as the average yearly expenditure for food, utilities, necessities, housing related expenses, transportation, communication, entertainment, clothing, education, travels, and medical reasons. Thus, we are able to define household savings as the difference between income and consumption.

We adjust all data for inflation using the consumer price index (CPI) and report results in 2017 euros.[8] Throughout the analysis, we rely on the household sample weights provided by CHIP and CHFS. We eventually trim the distribution at the 1st and 99th percentile of the net wealth distribution in each year in order to avoid outliers.

Table 4.1 provides the main descriptive statics of our working sample, where we include all individuals surveyed who are older than 20. The first two columns

[8] We use the CPI time series provided the World Bank.

provide information on the CHIP sample for 1995 and 2002, respectively. The central three columns report information on the CHFS sample for 2013, 2015, and 2017, respectively.

4.3.2 Definition of the CCP Status

Party membership is asked in both CHIP and CHFS. However, some differences between the two data-sources must be clarified.

First, while in CHIP party affiliation of each household member is collected, in CHFS, instead, party membership is asked only to the survey respondent and to the respondent' s partner. If the respondent changes between one survey wave and the other, the new respondent's and the new partners' information is provided, while the older respondent and older partner party membership information is registered from the previous survey wave. Nevertheless, missing rates, as shown in Table 4.1, range between 27-30% among the population older than 20 years old. This is due to the fact that CHFS does not provide party membership information about other individuals living in the HH besides the respondent and the respondent's partner.[9] While such limitation might increase some sample selection issues, in Figure 4.7 in Appendix 4.8.1 we show that no substantial differences exist in the main socio-economic characteristics between the full sample and the sub-sample with available CCP information. The majority of cases with missing information on political affiliation comes from individuals between 15 and 29 years old living at their parents' house who are not likely to be party members and who are not likely to be primary breadwinners in the household. The sub-population with missing information on political affiliation that is older than 30 is marginal and it is represented by adult individuals, other than the partner, who live together with the respondent.

Based on the political affiliation of the respondent and the respondent's partner in each year, we classify an household as CCP if at least one of the two is affiliated with the CCP.[10] Because of the missing information about the political affiliation of the other adults in the household, in the CHFS waves we might underestimate the presence of CCP members within the household and identify as non-CCP households where only members other than the respondent or the respondent' s partner are affiliated with CCP (false negative).[11] We claim, however, that the risk of incurring false negatives is limited. In our sample, only 9-11% of the total households are

[9] CHFS then asks all respondents younger than 60 whether their parents are CCP members or not. However, the same information is not provided for partners.

[10] In the case a household is in the sample for more survey waves and the survey respondent changes over time, we identify a household as CCP if at least one individual currently living in the household has ever declared to be a CCP member.

[11] Cases of false positively are instead unfeasible, as long as the household provided truthful information.

registered as non-CCP and at the same time comprise adults other than the respondent and respondent's partner that might be CCP members and, therefore, at risk of being falsely identified. Moreover, it is important to stress that interviewers in CHFS are explicitly asked to choose the family member who knows best about the family's economic condition as the survey respondent. Thus, it is reasonable to assume that if, in a household, there are adults other than the respondent and the respondent's partner, their contribution to the household wealth is marginal. Therefore, incorrect identification of the political status of a household might happen in a small minority of cases and, among these cases, the contribution to the household wealth of falsely identified members should be limited. Nevertheless, we invite the reader to read our findings as lower-bounds.

The second important difference between CHFS and CHIP comes from the sample design. The CHFS urban sample covers not only urban residents, but also rural-urban migrants, defined as Chinese citizens with household registration in rural areas and engaging in non-agricultural industries in an urban area for 6 or more months. UCHIP 2002, instead, only covers urban residents.[12]

This aspect might be a concern in terms of comparability of the CCP population over time, since the share of CCP members among rural residents is much lower than among urban residents.[13] In order to investigate the impact of rural-urban migrants, we estimate the share of CCP in urban China using the 2013 CHIP survey (CHIP 2013) by excluding and including rural-urban migrants. Including the migrants in the estimation, the share of CCP members in CHIP 2013 among individuals aged 20 is 18.2%, in line with estimates from CHFS 2013 shown in in Table 4.1. Excluding the migrants from the sample, the CCP share among the urban residents in CHIP 2013 is 19.5%, thus demonstrating that the influence of rural-urban migrants is quite limited.

The drop in the CCP share between 2002 and 2013, from 27 to 19.5% of the urban population, can instead be explained by the rapid process of urbanization experienced in China since the 1990s. The share of people living in urban areas rose from 17.9% in 1978 to 57.4 percent in 2016, including a rapid acceleration in urbanization since 2003 (Yang et al., 2019). Through urbanization, citizens formerly living in rural areas are able to acquire urban residence. Since CCP membership among the rural population is much lower than in urban areas, the intense urbanization process contributed to mechanically reducing the CCP share in urban areas.

[12]UCHIP 1995 also included rural-urban migrants in the sample, however the size of the rural-urban migration sample in 1995 is small.

[13]According to CHIP 2013 and CHFS 2013, the share of CCP members in rural areas is between 5 and 6% of the total rural population, versus 17% in urban areas.

4.4 Methodology

We apply Unconditional Quantile Regressions (Firpo et al., 2009, 2018) at the HH-level in order to understand the (descriptive) effect of CCP along the net wealth distribution once controlling for HH socio-demographic characteristics. Unconditional Quantile Regressions consists in regressing recentered influence functions (RIF) of the unconditional quantile on a set of covariates. Influence functions measure the dependence of given distributional statistics on the values of any observation in the sample and are typically used for robustness analysis in statistics. By definition, influence functions have zero expected value. Adding back the target statistics to the influence function (re-centering) yields the RIF. Since RIF can be calculated for most of the distributional statistics, it is possible to create a vector that assigns to each observation in the sample its influence on the statistics of interest - in our specific case, the percentiles of the net wealth distribution - and run OLS regression on a set of covariates. The estimated regression coefficients can be interpreted as the marginal effect on the unconditional quantile of a small location shift in the distribution of covariates, holding everything else constant. We provide a detailed explanation of the methodology applied to quantile regression in Appendix 4.8.3.

The main regression model takes the following form:

$$NW_t^q = E[Rif(NW_it, q_t^q)] = \alpha^q + \delta^q CCP_{it} + X_{it}'\beta^q + \epsilon_{it}^q \tag{4.1}$$

Where NW_t^P is q-th percentile of the Net Wealth distribution in time t, CCP_{it} is our key covariates of interest and represents a dummy equal to one if at least one member of the HH is a CCP member, and X_{it} is a vector of household characteristics. We follow Gradín (2016) and define these characteristics as within-household proportions in order to take into account the situation of all household members and not only the household head or survey respondent. We control for the household age composition by measuring the number individuals aged 0-15, 16 -24, 25-34, 35-44, 45-54, 55-64, and 65-older as a proportion of the number of household members. Similarly, we control for the proportion of adults in the household who are married or in a consensual union and for the share of adults who have completed low, medium, or high education. As for labour-related variables, we consider the share of adult women in the household who are actively working, the share of adults who work as self-employed, the share of those who work in the public sector, and the share of those who work in highly paid abstract occupations (as managers, legislators, technicians, or other professionals). We estimate equation 4.1 on the urban CHIP and CHFS year-specific samples, trimming the distribution of net wealth at the 1st and 99th percentiles.

δ^q is the unconditional quantile partial effect (UQPE) of CCP membership on the q-th percentile of the net wealth distribution and represents the key coefficient of interest for the analysis. The coefficient should read as the effect on quantile q of marginally increasing the probability of observing CCP members in the sample. If, for example, δ^q is equal to 0.5, it means that, if the proportion of CCP households increases by 1%, the net wealth at the q-th percentile would increase by 0.5% (0.01*0.5*100).

While the model in equation 4.1 provides a simple framework to estimate and show the net wealth gap between CCP and non-CCP households across the whole distribution, it is not informative about the sources of such wealth gaps. We then explore in greater details if substantial differences emerge between CCP and non-CCP households in housing investment, which represents the main private wealth component in urban China.

We first study whether significant differences between CCP and non-CCP households exist in the probability of owning real estate. To do so, we run a probit model where the dependent variable takes value 1 if, at time t, household i owns housing assets, 0 otherwise. We control for the household's political affiliation, CCP_{it} and the vector of household characteristics X_{it}, as defined in equation 4.1. We test the model in all CHIP and CHFS survey waves and across different net wealth bins separately (i.e. in the bottom 50%, mid 40%[14], and top 10% of the net wealth distribution). The key parameter of interest is the estimated CCP_{it} coefficient, which reads as the difference in the probability of owning a house between CCP and non-CCP households in a given year at the bottom, at the upper-middle and at the top of the net wealth distribution.

Then, among those households that own housing assets, we study whether CCP and non-CCP households differ in the type and quality of housing investment. We exploit detailed information provided in CHFS, since interviewed households were asked if the (most valuable) house they own was privately purchased on the real estate market, inherited or donated, self-built, or obtained via housing policy programs. Most notably, in the case of a household getting their house via a policy program, we are able to distinguish weather the house was purchased during the housing reform in the 1990s (welfare housing) or if it happened later via the affordable housing programs.[15] Thus, among those households owning an house, we run separate probit models for each of the possibilities in which the households could get the house according to the CHFS questionnaire. We control for the household's political affiliation, CCP_{it}, the vector of household characteristics X_{it}, and 29 province fixed-effects.

We then try to quantify whether the different purchasing options (private market, self-build, policy programs during and after the housing reform) affect the value of housing wealth in order to better characterize the observable differences in housing investment strategies between CCP and non-CCP households. To do so, we exploit

[14] We refer to mid 40% as the portion of the net wealth distribution between the 50-th and 90-th percentile.

[15] See Appendix 4.8.2 for a detailed timeline of housing reforms in China.

information on the price paid when the house was originally purchased and the current value of the house.[16] We then regress the CPI-adjusted house (log-) purchasing price and current (log-) value on CCP membership. We control for a set of dummies indicating whether the house was obtained via welfare housing, via post-reform policy programs, if it was inherited or self-built. These dummy coefficients read as the percentage difference in the outcome variable (purchasing price or current value) of getting the house via the corresponding channel with respect to the purchase of the house via the real estate market that serves as the reference category. We further control for a set of 29 provincial dummies, a set of year-dummies for indicating when the house was purchased, and the vector X_{it} of HH-characteristics.

Subsequently, we study whether CCP and non-CCP households differ in the availability of housing funds. In CHFS, respondents are asked to declare their current housing funds accounts and what was the average housing funds contribution in the year before the interview. Thus, we are able to test through OLS regression differences in current housing funds availability and in contributions between CCP and non-CCP members. Besides party membership, we control for gender, education, age, occupation, and type of employer of the respondent. We include a set of 29 province fixed effects. The coefficient associated with party membership reads as the percentage difference in the average value of the current housing funds account and the value of the average housing funds contribution between CCP and non CCP members.

4.5 Results

4.5.1 Wealth in China - Descriptive Statistics

The following paragraph describes the evolution of private wealth and wealth inequality in Urban China over the observation period of 1995-2017. The upper panel of Table 4.2 reports the average household net wealth expressed in 2017 euros by income groups, as well the evolution of Gini index in urban China in 1995, 2002, 2013, and 2017 based on two national representative household survey, namely CHIP and CHFS. Building on these results, the lower panel of Table 4.2 reports the growth rate of household net wealth in Urban China from the period from 1995 to 2002, 2002 to 2013, and 2013 to 2017.

In 1995, average net wealth per household in urban China was about €6,000. Average net wealth within the top 5% of the distribution was about €39,000, within the bottom 50% of the distribution was €1,160, about one-fifth of the overall average. The 1995–2002 period saw a significant rise the absolute wealth levels in all wealth groups, though the real rate of wealth growth becomes increasingly lower toward the top of the wealth distribution. Average net wealth per household in 2002 increased

[16] All monetary unites are at 2017 prices. We use the CPI time series provided by the World Bank.

	Average HH Ner Wealth			
	1995	**2002**	**2013**	**2017**
Full Population	6,024	24,069	104,628	138,607
Bottom 50%	1,160	7,893	18,640	25,813
Millde 40%	6,731	29,767	108,876	143,668
Top 10%	27,564	82,924	518,208	682,705
Top 5%	38,765	104,745	711,143	941,472
Gini	0.59	0.49	0.64	0.64
N HHs	6,719	6,629	17,237	24,011
	Annual growth rate of Net Wealth			
	1995-2002	***2002-2013***	***2013-2017***	***1995-2017***
Full Population	22.6%	16.8%	4.8%	15.2%
Bottom 50%	34.4%	7.8%	5.6%	15.0%
Millde 40%	24.1%	14.8%	4.7%	14.8%
Top 10%	17.0%	22.2%	4.7%	15.5%
Top 5%	15.3%	23.3%	4.8%	15.4%
	Share of total accumulated growth			
	1995-2002	***2002-2013***	***2013-2017***	***1995-2017***
Full Population	100%	100%	100%	100%
Bottom 50%	21.1%	6%	11%	9%
Millde 40%	49.9%	39%	41%	41%
Top 10%	29.0%	55%	48%	49%
Top 5%	17.3%	38%	34%	34%

Notes: Estimations are based CHIP (1995, 2002) and CHFS (2013, 2015, and 2017). Wealth is ranked using the net wealth level in each survey year. Only households living in urban areas with non-negative net wealth are included. Durables are not treated as fixed assets and excluded from net wealth. Monetary units are expressed in 2017 euros.

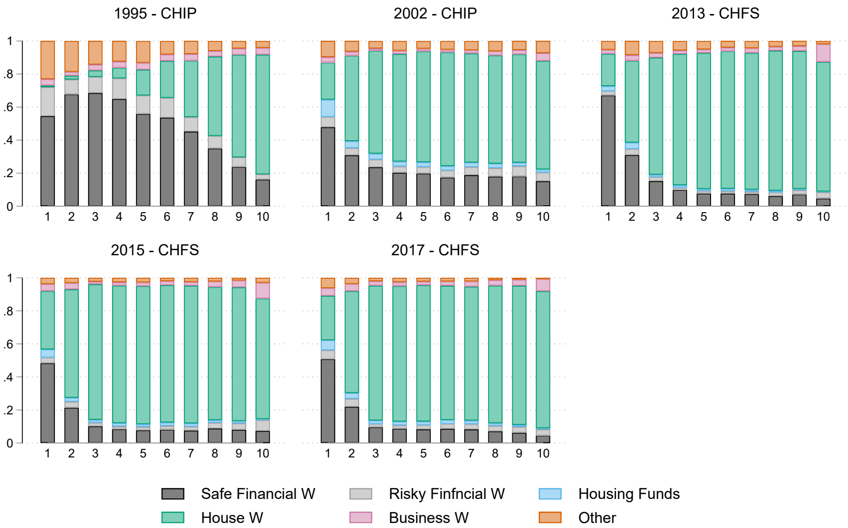
Table 4.2: Net wealth in China 1995-2017

to €24,000. The annual growth rate was about 34% within the bottom 50% of the distribution, 24% in the middle 40% (between the 50-th and 90-th percentile) and 17% in the top 10%. The Gini coefficient decreased correspondingly from 0.59 to 0.47. The significant rise in household wealth as well as the decrease of the wealth inequality in this period is mainly due to the rapid privatization of public housing between 1998 and 2003, when occupying tenants, mainly working in the public sector, were allowed to purchase the housing allocated to them by their working unit (Meng, 2007). Since access to privatization programs was relatively equal for urban residents working in the public sector, the rapid increase in housing wealth among the urban residents led to a drop in household wealth inequality between 1995 and 2002.

Between 2002 and 2013, urban China was characterized by a rapid increase in household wealth and a drastic widening of the wealth inequality due to the booming real estate market and the rapid escalation of housing prices (Knight et al., 2017; Li and Wan, 2015). In 2013, overall average net wealth per household was €104,700; but within the bottom 50% of the distribution it was €18,600 and within the top 5% of the distribution it was €711,100. From 2002 to 2013, the annual growth rate of real wealth for the top 5% was 23.3%, whereas this figure fell to 14.8% for the upper-middle 40% and 7.8% for the bottom 50%. The Gini coefficient increases sharply from 0.49 in 2002 to 0.64 in 2013.

From the 2013 to 2017, we observe a moderate increase in household wealth with a stabilized trend of wealth inequality. In 2017, overall average net wealth per household increased to €138,600; within the bottom 50% of the distribution, it increased to €25,800, while within the top 5% of the distribution, it increased to €941,500. Annual growth rate of real wealth for the bottom 50% of the distribution was 5.6%, which is slightly higher than the growth rate in the upper-middle 40%, the top 10%, and top 5% of the distribution, which are about 4.8%.

In order to better characterize the rapid expansion of Chinese private wealth, Figure 4.1 shows, for each year in our sample, the composition of private wealth by deciles of the gross wealth distribution. In particular, gross wealth is divided into six main components, i.e. safe and risky financial wealth, housing funds, housing wealth, business wealth, and other assets, as described in Section 4.1. From Figure 4.1, it is easy to see that, as consequence of the housing reform, between 1995 and 2002 housing became the predominant asset across the whole distribution. In particular, housing ownership went from 28% in 1995 to 62% in 2002, stabilizing around 84-89% in the 2013-2017 period, as reported in the first column of Table 4.3. However, between 2002 and 2013, the relevance of real estate assets increased substantially, accounting for 61% of gross wealth in 2002 and 84% in the 2013-2017 period. This strong increase in the house values during the post housing reform period is consistent with the estimates of Li and Wan (2015).



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. Wealth is ranked using the gross wealth level in survey year. Only households living in urban areas with non-negative gross wealth are included. Durables are not treated as fixed assets and excluded from gross wealth. Wealth is ranked using the gross wealth level in survey year. Monetary units are expressed in 2017 euros.

Figure 4.1: Total gross wealth composition by decile

	Overall	Bottom 25%	Bottom 25-50	Middle 40%	Top 10%
CHIP 1995					
Housing Onwership	0.28	0.11	0.12	0.41	0.59
Housing Wealth Share	0.50	0.06	0.09	0.44	0.69
N of HHs	*6,795*				
CHIP 2002					
Housing Onwership	0.62	0.26	0.66	0.76	0.80
Housing Wealth Share	0.61	0.35	0.60	0.62	0.64
N of HHs	*6,704*				
CHFS 2013					
Housing Onwership	0.84	0.46	0.94	0.99	0.99
Housing Wealth Share	0.84	0.62	0.81	0.84	0.84
N	*17,053*				
CHFS 2015					
Housing Onwership	0.89	0.59	0.97	0.99	1.00
Housing Wealth Share	0.81	0.73	0.82	0.81	0.82
N	*22,139*				
CHFS 2017					
Housing Onwership	0.88	0.59	0.97	0.99	1.00
Housing Wealth Share	0.85	0.68	0.81	0.83	0.88
N of HHs	*23,723*				
How Did you get the house? (Share)					
Self-built	0.28	0.48	0.30	0.24	0.15
Real Estate Market	0.48	0.28	0.46	0.52	0.60
Pre-reform: welfare housing	0.14	0.13	0.15	0.14	0.16
Post-reform: affordable housing	0.04	0.03	0.04	0.05	0.05
Inheritance	0.05	0.07	0.05	0.04	0.04
N of HHs	*19,713*				

Notes: Estimations are based CHIP (1995, 2002) and CHFS (2013, 2015, and 2017). Wealth is ranked using the net wealth level in each corresponding survey year. Only households living in urban areas with non-negative net wealth are included. Durables are not treated as fixed assets and excluded from net wealth. Monetary units are expressed in 2017 euros. Information on the housing parchment option is available only for CHFS survey waves. In the lower panel of the table information on 2017 wave are provided.

Table 4.3: Descriptive information on housing in the estimation sample

4.5.2 CCP Premia - Descriptive Statistics

So far we described the evolution of private wealth in China. We now turn our attention to analyze the evolution of the socio-demographic and economic differences between CCP and non-CCP households in urban China over the 1995-2017 period.

We first investigate whether substantial differences exist in the socio-demographic characteristics between CCP members and non-members. To do so we run separate probit models for each survey wave in our working sample, where the dependent variable takes value 1 if the individual is member of the party, 0 otherwise. We control for individuals' gender, education level, age, and employment status.[17]

Table 4.4 summarizes the results. Estimates show that in urban China, CCP members are more likely to be men, older than 50, with high education in all survey waves under observation. In particular, the possibility for CCP members with higher education background has been rising significantly over time. Among employed individuals, we observe that CCP members are more likely to work in the public sector and in managerial occupations. Such results are consistent with main findings in the existing literature (Dickson and Rublee, 2000; Appleton et al., 2009; Yan, 2019).

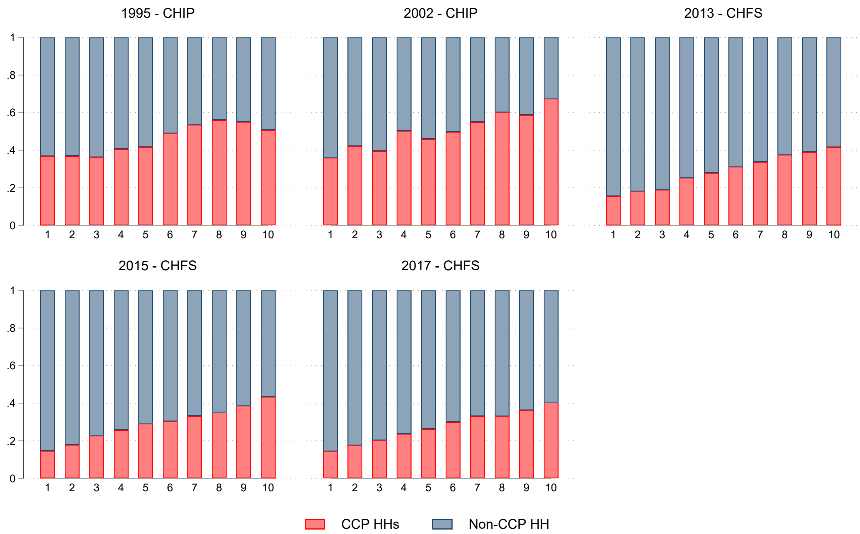
	CHIP		CHFS		
	1995	**2002**	**2013**	**2015**	**2017**
Female	-0.11***	-0.09***	-0.09***	-0.11***	-0.11***
Low Education	-0.09***	-0.15***	-0.16***	-0.17***	-0.17***
High Education	0.06***	0.07***	0.16***	0.17***	0.15***
age 20-30	-0.17***	-0.18***	-0.05***	-0.07***	-0.07***
age 30-40	-0.07***	-0.09***	-0.03***	-0.03***	-0.03***
age 50-60	0.05***	0.09***	0.05***	0.04***	0.04***
age above 60	0.05***	0.17***	0.19***	0.19***	0.16***
Not in the Labour Force or Unemployed	0.03	-0.02	−0.01*	-0.02***	-0.03***
Currently working as Self-emplyed	0.04	-0.09***	-0.03***	-0.04***	-0.04***
Currently working as Managers	0.39***	0.28***	0.14***	0.16***	0.23***
Currently working in the Public Sector	0.12***	0.04***	0.11***	0.12***	0.10***
N	13,782	11,062	36,795	47,758	48,594

Notes: Table reports the estimates from wave-specific Probit models. Estimations are based CHIP (1995, 2002) and CHFS (2013, 2015, and 2017). Only individuals aged 20 and above living in urban areas are included. Sample weights are applied to estimation. Statically significant effects at the 10%, 5%, and 1% significance level are indicated with ∗, ∗∗, ∗ ∗ ∗ respectively.

Table 4.4: Socio-economic determinants of CCP membership

[17] In particular we distinguishing whether the individual is outside the labour force, unemployed, or, in case the individual is currently employed, if the worker is self-employed, employed in the public sector, or employed in managerial occupations.

Figure 4.2 shows the concentration of households with at least one CCP member along the net wealth distribution. The share of CCP households is increasing along deciles of the net wealth distribution in all the years considered in our analysis indicating the presence of large wealth gaps.[18]. In 2017, for example, 27% of the urban CCP households had at least one CCP member. The CCP share, however, ranges from 14% in the first decile of the net wealth distribution to 40% in the last. As explained in Section 4.3.2, the drop in CCP share between 2002 and 2013 can be attributed to the rapid process of urbanization experienced in China combined with minor sampling differences between CHIP and CHFS.



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. Wealth is ranked using the net wealth level in the corresponding survey year. Only households living in urban areas with non-negative net wealth are included. Durables are not treated as fixed assets and excluded from net wealth. The CCP share is highlighted in red.

Figure 4.2: CCP share over the Net Wealth Deciles

The skewed distribution of the CCP households along the net wealth distribution indicates a large and significant wealth gap.[19] Figure 4.3 shows the evolution of the average and median un-adjusted wealth gap between 1995 and 2017. Solid lines report the level of average net wealth in 2017 euros of CCP (in red) and non-CCP households (in blue) over time. The dashed line, instead, reports in each year the estimate of the un-adjusted wealth gap and the relative bootstrapped confidence intervals. Table 4.7 in Appendix 4.8.1 complements the figure showing

[18]Similar findings can be seen across the total household total income distribution as shown in Figure 4.8 in Appendix 4.8.1

[19]Wealth gaps are calculated as the difference between CCP and non-CCP averages over the non-CCP average.

un-adjusted gaps in different wealth and income components between CCP and non-CCP households observable across our working sample.

The figure confirms large and persistent wealth and income differences. These differences in average wealth gaps strongly increase between 1995 and 2002, going from 20% to around 45%; it then slightly increases between 2002 and 2013 and remained stable thereafter. Wealth gaps at the median, instead, remain large (around 60%) and relatively stable across the entire observational period.

In order to explore the sources of such gaps in detail, Figure 4.4 explores average housing wealth (on the left) and participation in housing investments (on the right) of CCP and non-CCP households.

From figure 4.4, it is possible to see that housing wealth between 1995 and 2002 contributed to fostering the increase in the wealth gaps between CCP and non-CCP households. While, in 1995, we do not observe differences in the housing investment values between CCP and non-CCP households (dashed line in the left-hand panel), after the urban housing reform (1994-2002), CCP households own consistently higher housing assets. From 0 in 1995, the housing wealth gap increased to about 30% in 2002 and stabilized around 40-42% during the 2013-17 period. At the same time, housing ownership between CCP and non-CCP household remained stable over the observation period, with CCP households more likely than non-CCP households to own housing wealth by 6 to 8 percentage points (dashed line in the right-hand panel). Nevertheless, the sharp increase in the difference of housing asset value between CCP and non-CCP, suggests that CCP households were able to get the most valuable houses during the housing reform period, generating a substantial and persistent wealth gap in the average value of housing assets.

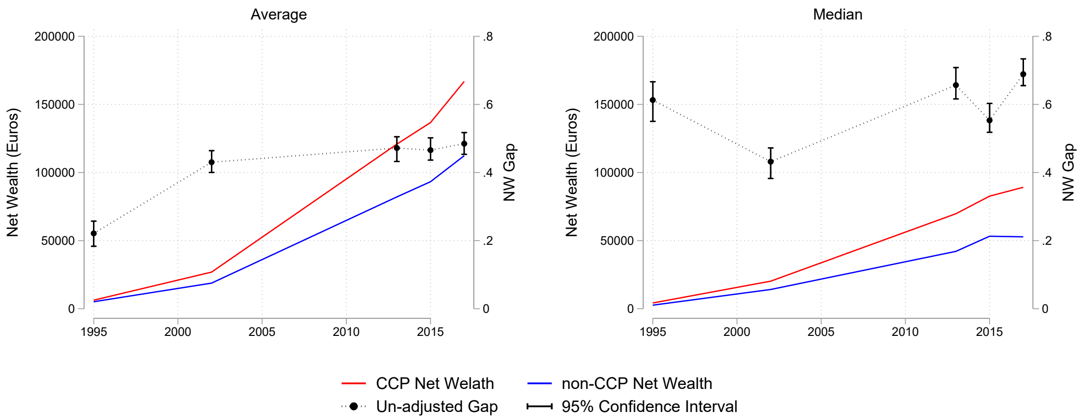
4.5.3 Estimating the CCP Premium along the Wealth Distribution

4.5.3.1 Unconditional Quantile Regression

The wealth gaps reported in Figure 4.3 and discussed in the previous paragraph do not account for (a) potential compositional differences in socio-demographic characteristics between CCP and non-CCP households, or for (b) potential heterogeneity along wealth distribution. In the following section, we then apply UQR, as explained in Section 4.4, in order to qualify whether these gaps are statically significant and homogeneous across the whole net wealth distribution once we control for differences in the socio-demographic characteristics between CCP and non-CCP households.[20]

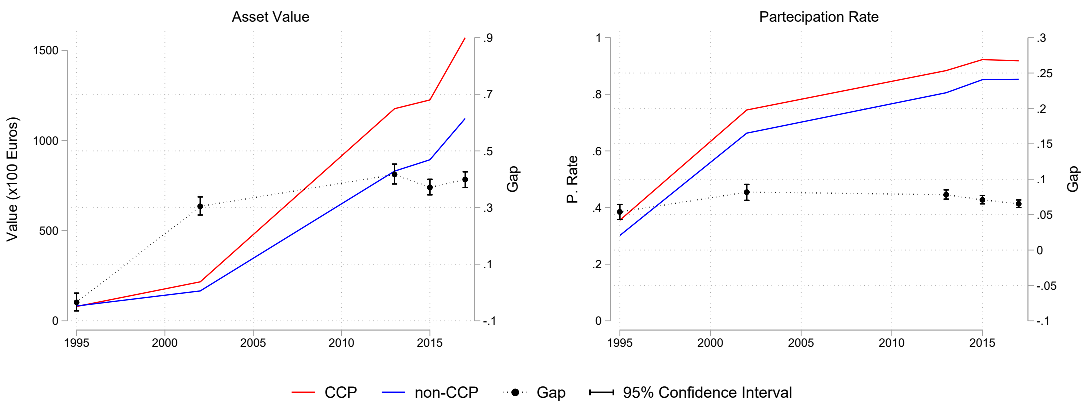
Figure 4.5 reports in blue the unconditional partial effect of CCP membership on the percentiles of the 1995, 2002, 2013, 2015, and 2017 net wealth distributions

[20] Appendix 4.8.4 provide a detailed discussion on CCP premia on individual labour earnings and on HH total income.



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. The left-hand panel show evolution of average net wealth in 2017 euros with a solid red (blue) line for CCP (non-CCP) households living in Urban China. The dashed line reports the wealth gap calculated as the difference between average net wealth in CCP households and non-CCP households over the average net wealth in non-CCP households. Bootstrapped (500 repetitions) confidence intervals are displayed. The right-hand panel replicates the one on the left using median instead of average wealth.

Figure 4.3: Un-adjusted CCP wealth gap



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. The figure shows asset value (on the left) and participation rates (on the right) of CCP and non-CCP households for housing wealth. Solid red lines refer to CCP households, while solid blue lines refer to non-CCP ones. The dashed lines report the gap in participation rates and in asset value for each outcome considered. Asset Value is expressed in in 2017 euros (x100). Bootstrapped (500 repetitions) confidence intervals are displayed.

Figure 4.4: Housing wealth value and participation rates of CCP and non-CCP households

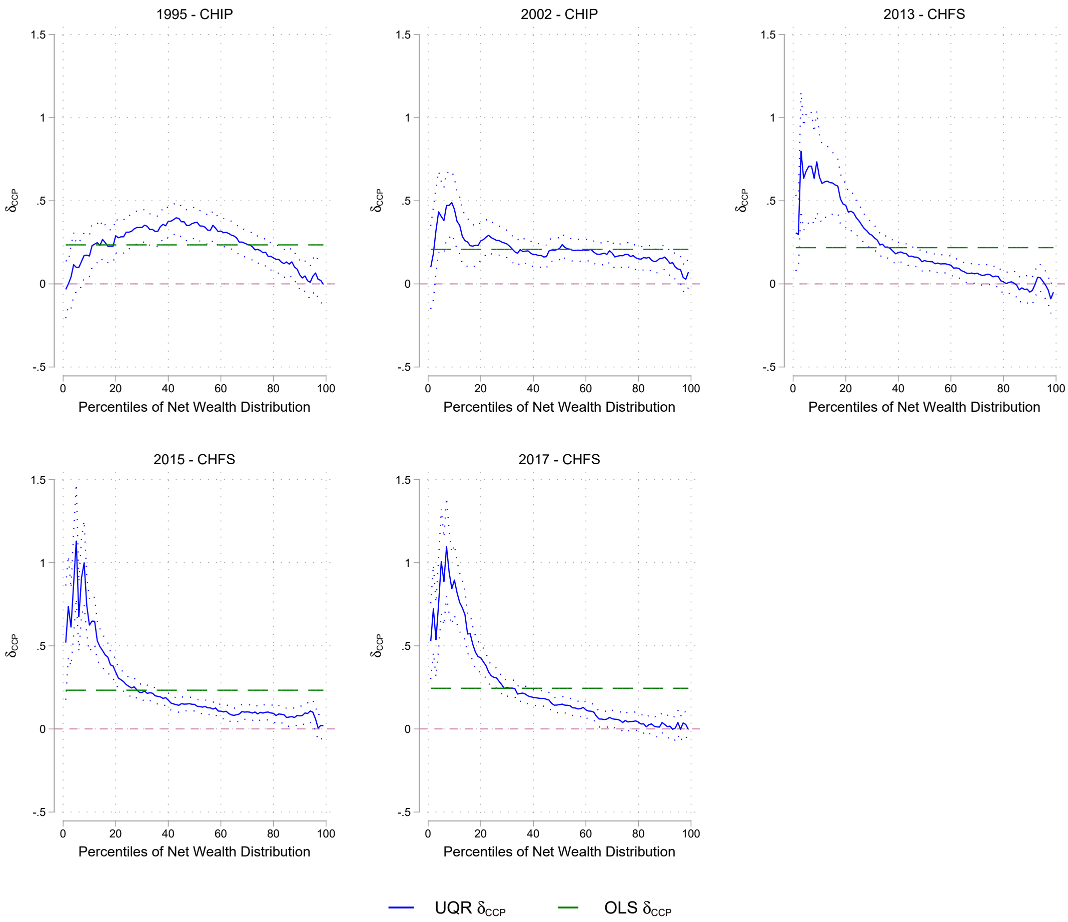
and the respective 95% confidence intervals.[21] The dashed green line represents the OLS estimate of equation 4.1.

While OLS predicts an average 21-24% net wealth gap that remained constant across all the period of observation, the unconditional quantile regression coefficients show highly heterogeneous CCP premia along the net wealth distribution. Interestingly, in 1995 the CCP coefficient presents an inverse-U shape, indicating that the greatest advantages, in relative terms, for CCP households were concentrated at the middle of the net wealth distribution and faded away in the tails. The interpretation of the unconditional quantile regression coefficients suggests that, if the share of CCP household marginally increases in a given percentile, the net wealth in that percentile would increase generating the highest returns for percentiles at the middle of the distribution. Starting in the 2002, however, the CCP premium at the middle of the net wealth distribution started to fall, while the effect in the bottom tail started to become more important. After 2013, the estimated CCP coefficients show a clear decreasing pattern along the net wealth distribution, pointing to greater advantages for households in the bottom 50% of the net wealth distribution. The same pattern is observed in 2015 and 2017.

These results show that between 1995 and 2017 , although the *average* wealth gap between CCP and non-CCP household did not change, the returns structure from political membership has deeply changed. In the mid-1990s, the largest returns were at the middle of the net wealth distribution, while, as of 2017, it is the lower class that benefits the most, in relative terms, from the party membership. These findings are particularly interesting if compared with the unconditional quantile regression on household labour incomes shown in Figure 4.10 in Appendix 4.8.4.2. According to our findings, the average CCP premia on labour HH increased between 1995 and 2002, increasing from 13% to 16%, then decreasing thereafter and stabilizing around 7-8% in the 2010s. Thus, our findings suggest that income gaps between CCP and non-CCP households are lower than wealth differences. Moreover, different from net wealth, CCP returns on income are highly constant across the income distribution, showing little heterogeneity.

In the following paragraphs we explore potential mechanisms that can explain why the net wealth return structure of CCP membership changed between 1995 and 2017. In particular, we study in greater detail if substantial differences emerge in housing investment between CCP and non-CCP households and how this evolved over time. The attention to housing assets is justified by the deep transformation experienced by urban China over the period under observation. Between 1995 and 2017, housing investment was fostered by a series of structural reforms, ultimately becoming the main driver of private wealth growth, as previously shown end discussed in Figure 4.1 and in Table 4.3.

[21] Figure 4.9 in Appendix 4.8.1 provides the unconditional quantile estimates for the coefficients of the other covariates in equation 4.1.



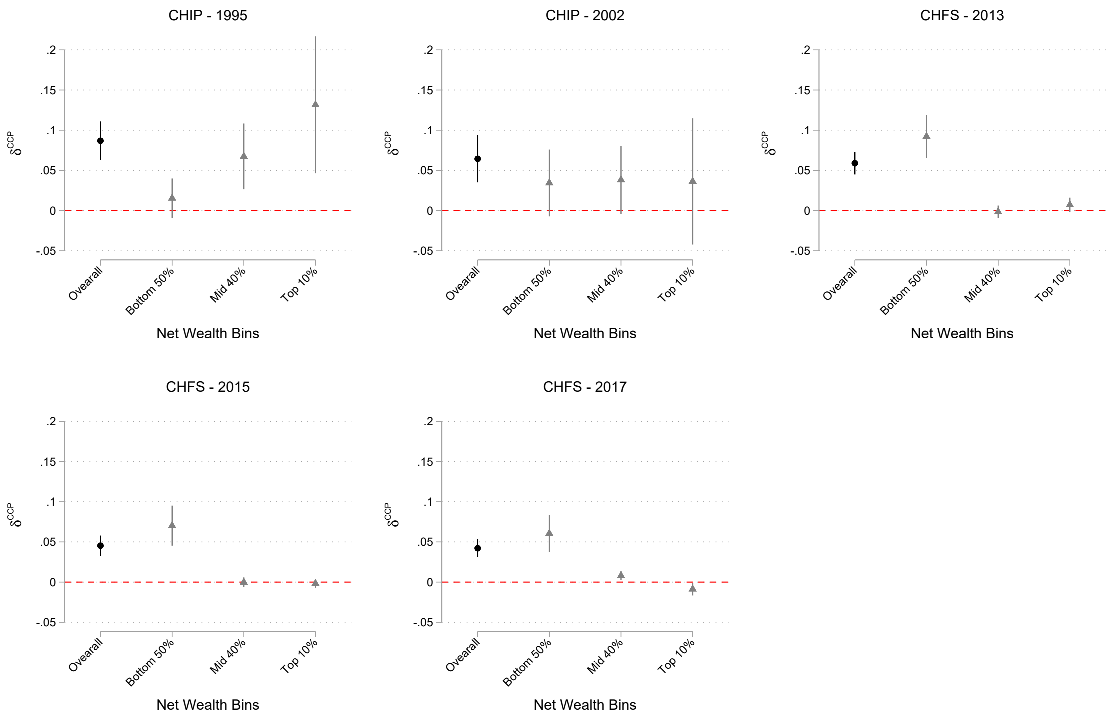
Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. The figure displays the estimated UQR coefficient for Party membership in blue with the relative Confidence intervals. The green dash line shows estimates from OLS regression.

Figure 4.5: Unconditional quantile regression - CCP memebership

4.5.3.2 CCP Membership and Housing Market

We first estimate whether CCP membership is correlated with a higher probability of owning an house, once socio-demographic characteristics of the household are accounted for. Housing accounts for the lion's share of household wealth composition in urban China. However, at the bottom of the net wealth distribution, where RIF effects are the strongest, housing ownership is more dispersed. Therefore, in the bottom 50% of the distribution, if CCP members are more likely than non-members to own housing assets, this might explain the high CCP returns found via UQR.

Figure 4.6 reports the CCP coefficient estimated in each bin of the wave-specific net wealth distribution and the corresponding confidence intervals at 95% signif-



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. The figure reports the effect of CCP membership on the probability of owing housing assets estimated via year-specific probit models. In each panel, the round marker shows results on the overall yearly-specific sample, while the triangle-shaped markers show results for sub-samples of the net wealth distribution (i.e. bottom 50%, middle 40% and top 10%).

Figure 4.6: Difference in the probability of owning an house between CCP and non-CCP households for different net wealth bins.

icance level. The coefficient reads as the difference in probability of owning an house between CCP and non-CCP households, *ceteris paribus*. In the figure, each year-specific panel reports, with a round marker, the CCP coefficient calculated on the *full* sample, while the effects at the different net wealth bins are shown with triangle-shaped markers.

In 1995, overall, CCP households were 8.6 percentage points more likely to own housing assets than non-CCP households. However, this estimate masks great heterogeneity and our results show that the statically significant differences can be found only in the top-half of the net wealth distribution. It is important to remember that, in 1995, the housing reform was in an early stage and only 28% of households in urban China owned private housing; see Table 4.3. In the 2000s, at the beginning of the post-reform period, the differences in the housing ownership started to change substantially. In 2002, already 62% of households in urban China owned some housing assets, with the differences between CCP and non-CCP households starting to reduce. On average, in 2002, CCP households were 6.5 percentage points more likely to own housing assets than non-CCP households. Moreover, versus 1995, in 2002 the CCP-ownership premium is found to be relatively constant across the whole distribution. After 2013, 85-89% of households in urban China owned housing assets. While, the CCP households are still more likely to own housing assets than non-CCP households, statically significant differences can only be observed at the bottom of the net wealth distribution.

Thus, according to Figure 4.6, between 1995 and 2017, the CCP housing ownership premium flipped. In 1995, housing ownership was rare and CCP membership was only correlated with an increased probability of owning some housing assets in the top-half of the distribution. In the 2013-2017 period, instead, housing ownership is diffused and CCP membership is correlated with increased probability of owning some housing assets only in the bottom-half of the distribution. At the bottom of the net wealth distribution, housing investment remains dispersed: in 2017 more than 40% of households in the bottom 25% of the net wealth distribution did not own their house, while in the top half of the distribution, housing ownership is around 98%. In such a scenario, the fact that CCP households are more likely to own their house at the bottom of the distribution with respect to non-members helps explain the high CCP returns found in Figure 4.5.

Another important aspect to analyze in order to better characterize the net wealth gap between CCP and non-CCP households, is whether substantial differences exist in the *type* and *quality* of the housing assets that the two groups own. We begin our investigation exploiting detailed information provided in the CHFS 2013, 2015, and 2017 survey waves, where the interviewed households were asked if the (most valuable) house they own was privately purchased on the real estate market, inherited or donated, self-built, or obtained via public housing policies. In the latter case, the CHFS also distinguishes between houses obtained through governmental programs during (1979-1998) and after (1999 onwards) the housing reform period. As explained in Section 4.2.2 and further described in the dedicated Appendix 4.8.2, keeping the two periods separated is important. The reform period was characterized by *welfare housing*, where publicly-owned houses were allocated to urban workers depending on the worker's administrative rank (Song and Xie, 2014) and households living in publicly-owned houses were allowed to buy the house at an advantageous transaction price with respect to the actual market price. Thus, in such a scenario, party membership might have represented a strong political connection in order to obtain and later purchase the house at a favorable price. After 1998, the 'economically affordable houses' program was introduced and it was designed to benefit all low-to-medium income households. Therefore, in such a context, the political advantage from party membership become less relevant.

The type of housing investment (private market, self-build, policy programs during and after the housing reform) might affect its quality and determine substantial differences in the purchasing price and current market value of the house. Thus, we want to understand whether CCP and non-CCP had differing accesses to the real estate assets they own and, if this is the case, what are the consequences in term of current value.

First, we run a separate probability model for each investment option in order to test differences between CCP and non-CCP households conditional on a rich set of covariates, as explained in the mythological section 4.4. The upper panel of Table 4.8 reports the average partial effect (APE) of CCP membership on the different investment options for 2013.[22] The coefficients read as the difference in probability between CCP and non-CCP households of getting their house via the model-specific outcome. The third column reports the overall effect, while columns 4 to 7 report the effect estimated within three main net wealth bins, i.e. the bottom 50%, the upper-middle 40% and the top 10%.

Results show relevant and statically significant differences in the way CCP and non-CCP households obtain their houses. We observe that CCP households are less likely to self-build their house and more likely to inherit, while no statically significant differences are found in the access to the private real estate market. Most notably, the greatest differences between CCP and non-CCP households are in the access to housing policy. We find that, among those households that got their current house before 1998, CCP households are overall 12 percentage points more likely to have obtained their current house through welfare housing than non-CCP households. These differences are statically significant and constant across the entire net wealth distribution.[23] However, such differences vanish among those households that obtained their house via a policy program after 1999.[24]

These findings confirm large disparities in the targeted group of the housing policy programs before and after 1998, showing that in 2013 and later CHFS waves, CCP households are more likely to have obtained their house via welfare housing.[25]

We then test whether statically significant differences exist in the purchasing price and current value of houses obtained via the different investment options (private market, self-build, policy programs during and after the housing reform) via OLS, controlling for a rich set of covariates as explained in Section 4.4. The key parameters of interest are four dummy variables, equal to one depending if

[22]Similar results are obtained for 2017 and available in Table 4.8 in Appendix 4.8.1.

[23]As robustness check, we run the same probability models on the sub-set of CCP and non-CCP households that have at least one adult working in the public sector and the CCP premia is confirmed. Results are available upon request.

[24]We did not include in the estimation those households that declared to have their house in 1998 in order to avoid potential overlaps.

[25]While it might be tempting to interpret such findings as the result of a privileged access to the housing market guaranteed to CCP households via housing policy before 1998, we invite the reader to interpret the results with caution. Due to data limitations, we know how and when households obtained their houses, but we do not know when CCP membership was achieved. Therefore, we are not able to disentangle if, at the time of the housing investment, the political affiliation of the household was different than what is observed in 2013.

Probit - How did HHs got the main house?	**Average Partial Effect**	**Overall**	**Bottom 50%**	**Middle 40%**	**Top10%**	**N**
RE market	CCP	0.01	0.00	-0.00	0.10***	13,583
Housing Policy - before 98	CCP	0.12***	0.11***	0.12***	0.09**	4,475
Housing Policy - after 98	CCP	-0.01	-0.03**	0.00	0.01	8,503
Self-built	CCP	-0.08***	-0.06***	-0.09***	-0.09***	13,583
Inerhitance	CCP	0.03***	0.01	0.04***	0.01	13,583
OLS	β	**Overall**	**Bottom 50%**	**Middle 40%**	**Top10%**	**N**
Purchasing Price of House	Housing Policy - before 98	-0.03***	-0.32***	-0.09***	-0.05***	9,822
	Housing Policy - after 98	-0.02***	-0.21	-0.03***	-0.03***	9,822
	Self-built	-0.02***	-0.32***	-0.04***	-0.02***	9,822
	Inerhitance	.	.	.	.	.
Current Value	Housing Policy - before 98	0.01**	0.21***	-0.00	-0.00	13,326
	Housing Policy - after 98	-0.01***	-0.20***	-0.01***	-0.01**	13,326
	Self-built	-0.01***	-0.36***	-0.01***	-0.00	13,326
	Inerhitance	-0.00	-0.18***	0.00	0.00	13,326
OLS	β	**Overall**	**Bottom 50%**	**Middle 40%**	**Top10%**	**N**
(log-) Current Housing Funds Account	CCP	0.02	-0.04	0.10	-0.03	3,527
(log-) Average Housing Fund yearly Contribution	CCP	0.12***	0.01	0.15***	0.13**	4,238

Notes: Estimations are based on CHFS 2013. Wealth is ranked using the net wealth level in each survey year. Only households living in urban areas with non-negative net wealth are included. Statically significant effects at the 10%, 5%, and 1% significance level are indicated with $*$, $**$, $***$ respectively.

Table 4.5: Housing investment - 2013 sample

the house was self-build, inherited, or obtained via a policy program during or after the housing reform, respectively. The estimated coefficients are reported in the middle panel of Table 4.8 and they read as the percentage difference in the outcome variable (purchasing price or current value) of getting the house via the corresponding investment channel with respect to purchasing the house via the real estate market, which serves as reference category.

We find significant differences in both the purchasing price and the current value of houses obtained via the different investment channels. Obtaining an house via housing policy (both before and after 1998) is significantly cheaper than purchasing it via the private real estate market and these differences are particularly large for the bottom 50% of the net wealth distribution. The same holds true for houses that are self-built. Nevertheless, the most interesting results concern the comparisons of current value of houses obtained through the different purchasing options. While small differences can be observed overall, for the bottom 50% of the net wealth distribution, the different purchasing options determine very different outcomes. Most notably, the current value of houses obtained via hosing public policy differ substantially if the house was obtained before (via welfare housing programs) or after 1998 (via the affordable housing program). As of 2017, welfare housing is found to be the most valuable source of housing investment for households belonging to the bottom 50% of the net wealth distribution. Specifically, those households that obtained a house via welfare housing and belong to the bottom 50% of the net wealth distribution in 2013 are found to own houses that are about 21% *more* valuable than houses purchased via the private market. At the same time, those households that obtained their house via affordable housing are found to own houses that are about 20% *less* valuable than houses purchased via the private market by similar households. Self-built houses are found to be, instead, the least valuable source of housing investment. In the top 50% of the net wealth distribution such differences vanish. Results using the net wealth distribution in 2017 are reported in Table 4.8 in Appendix 4.8.1 and confirm these findings.

All together, these results show that, at the bottom of the net wealth distribution, CCP households are (a) more likely to own real estate assets than non-CCP households and (b) the houses that they own are more valuable. In particular, we find that CCP households are more likely than non-CCP households to have acquired their current houses during the housing reform period, obtaining (currently) high-value houses at much cheaper prices than what is offered in the private real estate market. Non-CCP households, instead, invested more in self-built housing that, according to our estimates, represents the least remunerative source of housing investment, especially at the bottom of the net wealth distribution. These effects fade out in top half of the net wealth distribution where the differences between CCP and non-CCP households, as well as the differences between the different channels of housing investments decline.

Next, we explore whether substantial differences exists between CCP members and non-members in their availability of Housing Funds. Given that we know that CCP members are positively selected into better paid jobs (see Table 4.4), then party membership might be correlated with greater housing funds availability, which represents an important income source that CCP members might rely on for investing in housing wealth.

The lowest panel in Table 4.8 reports the OLS estimates of the CCP membership dummy on the (log-) current balance of housing funds and on the average (log-) monthly housing funds payment, once households characteristics are controlled for. The third column of Table 4.8 reports estimates on the overall sample, while, in columns 4 to 7, we complement the analysis looking at potential heterogeneity across the net wealth distribution: below the median, between the median and the 90th percentile, and above the 90th percentile.

According to our estimates, CCP households pay a 12 percentage points higher housing funds contribution than non-CCP ones. This finding can be explained by the positive selection of CCP individuals into better jobs and confirmed by higher contributions, *ceteris paribus* . We confirm heterogeneous effects of the CCP memberships along the net wealth distribution. Statically significant differences can only be found in the top half of the net wealth distribution, where CCP households are found to pay between 13 and 15 percentage points higher housing funds contribution. Nevertheless, such greater contribution among CCP households does not translate into larger housing fund accounts versus non-CCP households. We interpret this finding as suggestive evidence that CCP households at the top of the distribution use their funds relatively more than non-CCP households.

4.6 Qualifications and Extensions

This section qualifies the results of this chapter by discussing data restrictions, methodological limitations, and their implications for our results. Despite the high effort in the harmonization of two high-quality representative samples (CHIP and CHFS), several data limitations might trigger some concerns.

First, wealth information are self-reported by the survey respondents. While surveys have the great advantage of providing detailed background socio-economic characteristics of the household, self-reported valuations might suffer from measurement error, especially regarding current market value evaluations of assets (e.g. the current value of the house). Moreover, it is well documented that survey data typically mis-report wealth at the top of the distribution.[26] Unfortunately, the lack of comparable external data sources for private wealth in China makes the validation of our findings difficult.

Second, as discussed in Section 4.3.2, in the CHFS survey waves, the information on political affiliation is only available for the survey respondent and respondent's partner, potentially generating false negative problems (i.e. households where some members other than the respondent and the respondent's partner are affiliated with CCP, but do not appear in the data). In the paper, we show that the risk of false negatives is, however, limited, with only 9-11% of all households potentially wrongly classified. Nevertheless, further robustness checks might help to further investigate the problem.

Third, neither CHIP nor CHFS provide information on *when* the individual joined the party. Such information might be crucial to distinguish between 'junior' CCP members, who joined the party only recently, and 'senior' members. Since, according to previous literature, the membership premium derives from the increased social capital and political network of CCP individuals with respect to non-CCP ones, it is reasonable to assume that the wealth benefits from party membership will increase with the seniority in the party. Thus, detailed information about the timing of the affiliation would improve the quality of the estimation and allow for a more rigorous investigation of the potential determinants of the party premium.

Methodologically, instead, the principle limitation of the study is that it is difficult to ascribe a *causal* interpretation to our findings. The study lacks a structured identification strategy that consistently accounts for potential selection biases in party membership. As documented in previous literature and in Sections 4.2.1 and 4.5.2 of the current study, party membership is not random: un-observable characteristics of the household members might lead more talented individuals to join the party. Thus, in such a scenario, net wealth gaps in earnings and wealth might be partially explained by differences in the average ability between CCP and non-CCP members. In Section 4.8.4.1 in the Appendix, we show that large differences in

[26] See for example Schröder et al. (2020).

labour earnings persists when potential endogeneity in the CCP membership is accounted for, consistent with McLaughlin (2017). Such findings corroborate the idea that political affiliation *causally* determine economic returns for CCP members, despite potential positive selection biases. In our study, however, the identification of wealth gap has not accounted for potential selection biases and we invite the reader to interpret our findings as a first description of important and large inequalities.

There are several interesting extensions to the current study. One relevant extension would be to exploit the panel dimension of CHFS. It is, therefore, possible to construct a balanced household panel from 2013 to 2017 and then study the net wealth growth between savings and capital gains following Saez and Zucman (2016). With such framework it would be possible to study whether differences in the wealth accumulation components exist between CCP and non-CCP households. Another potential extension that exploits the panel dimension of CHFS consists of identifying wealth gaps through a diff-in-diff approach using households that joined the CCP (treatment) within the period of observation then comparing pre- and post-treatment outcomes of treated and un-treated households. While such an approach might help to improve the causal interpretation of our findings, two main limitations prevent the implementation of the exercise. First, the number of households joining the party during the observational period is extremely limited and does not provide enough statistical power for a meaningful estimation of the effects. Secondly, even if the sample size was big enough to guarantee a consistent estimation, it is reasonable to assume that wealth benefits for CCP members realize over the medium to long term. The time span (4 years) provided by CHFS might, therefore, be too short to grasp relevant and sizable wealth effects. Nevertheless, implementation of such approach could potentially be done in future exploiting new and enriched data sources. Finally, it would be interesting to analyze net wealth of first and second CCP generations, exploiting information on parental CCP affiliation. Such analyses might improve the understanding of long-term consequences of the CCP premium.

4.7 Conclusion

In this paper, we examine the evolution of the wealth gap between CCP and non-CCP households in urban China since the 1990s. For our investigation, we rely on two main data sources, the CHIP and the CHFS, which we carefully harmonized in order to provide a comparable data framework that ranges over a period of deep economic transformation for China. Next, we apply unconditional quantile regressions to study potential heterogeneity in the CCP economic returns along the net wealth distribution and its evolution over time. Overall, CCP households are estimated to enjoy net wealth premiums between 21 and 24 percentage points higher than non-CCP households. However, while the average wealth gap is constant over the

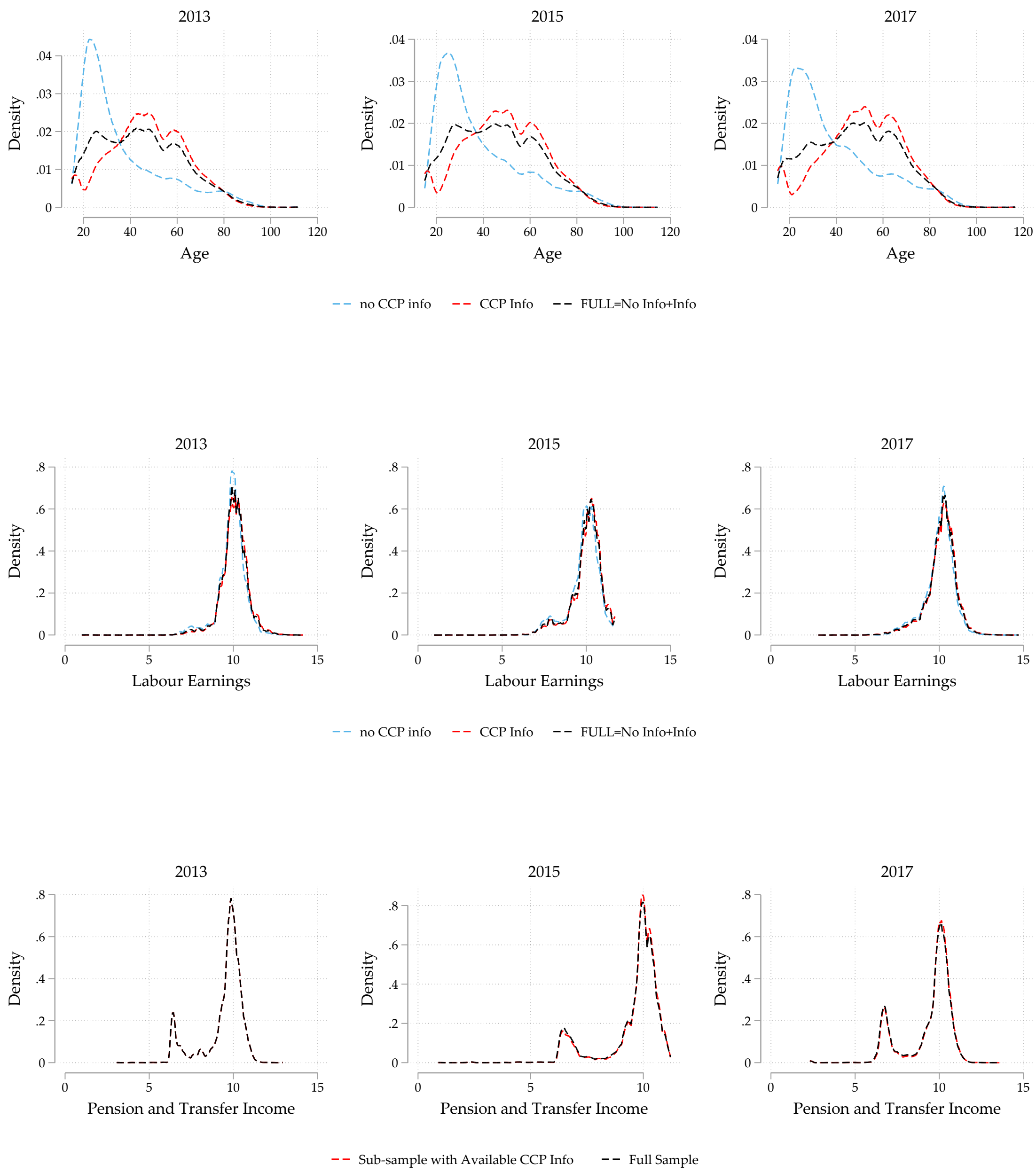
1995-2017 period, the returns structure of political membership has deeply changed over time. While in the 1990s, the highest wealth advantages for party members, in relative terms, were concentrated at the middle of the distribution, in 2017 the largest differences in wealth between CCP and non-CCP households are found to be in the bottom 50% of the distribution.

We show that the privatization of the housing market, especially after the housing reform, granted equal access to housing wealth for both CCP and non-CCP families, reducing the differences in the middle and at the top of the wealth distribution. However, strong differences between the housing investment of CCP and non-CCP households continue to persist at the bottom of the net wealth distribution, where CCP are found to be more likely to own housing assets than non-CCP households and the houses that they own are more valuable.

In conclusion, this article represents the first in-depth descriptive analysis of the net wealth gap between CCP and non-CCP households in urban China, documenting large and persistent inequalities. We invite future research to investigate to what extent such gaps are robust to potential selection biases embedded in CCP membership.

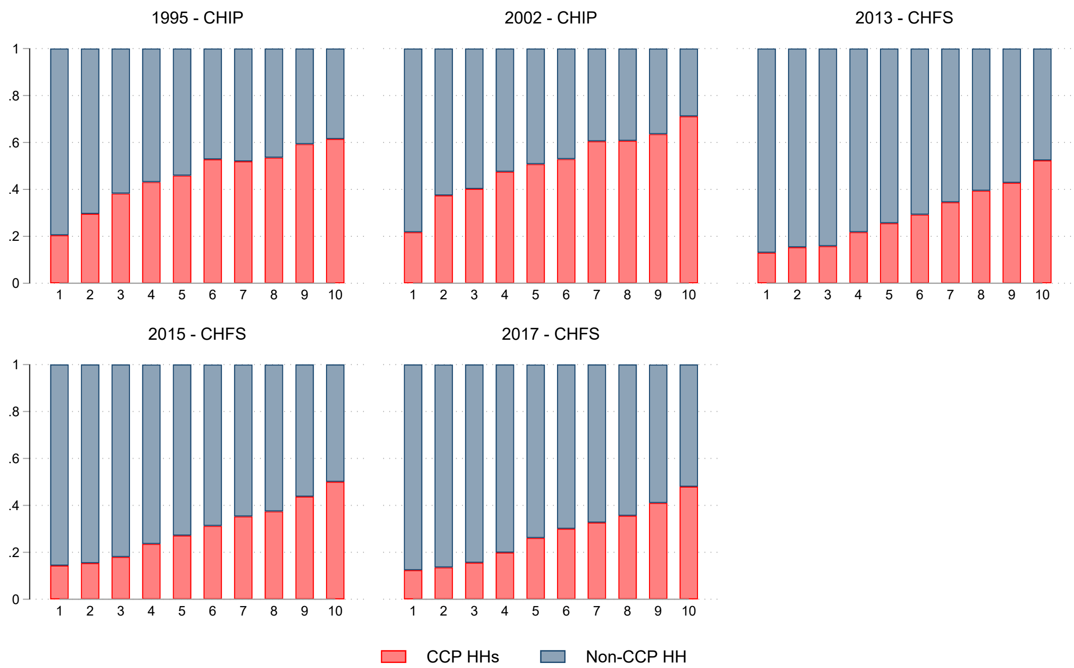
4.8 Appendix

4.8.1 Figures and Tables



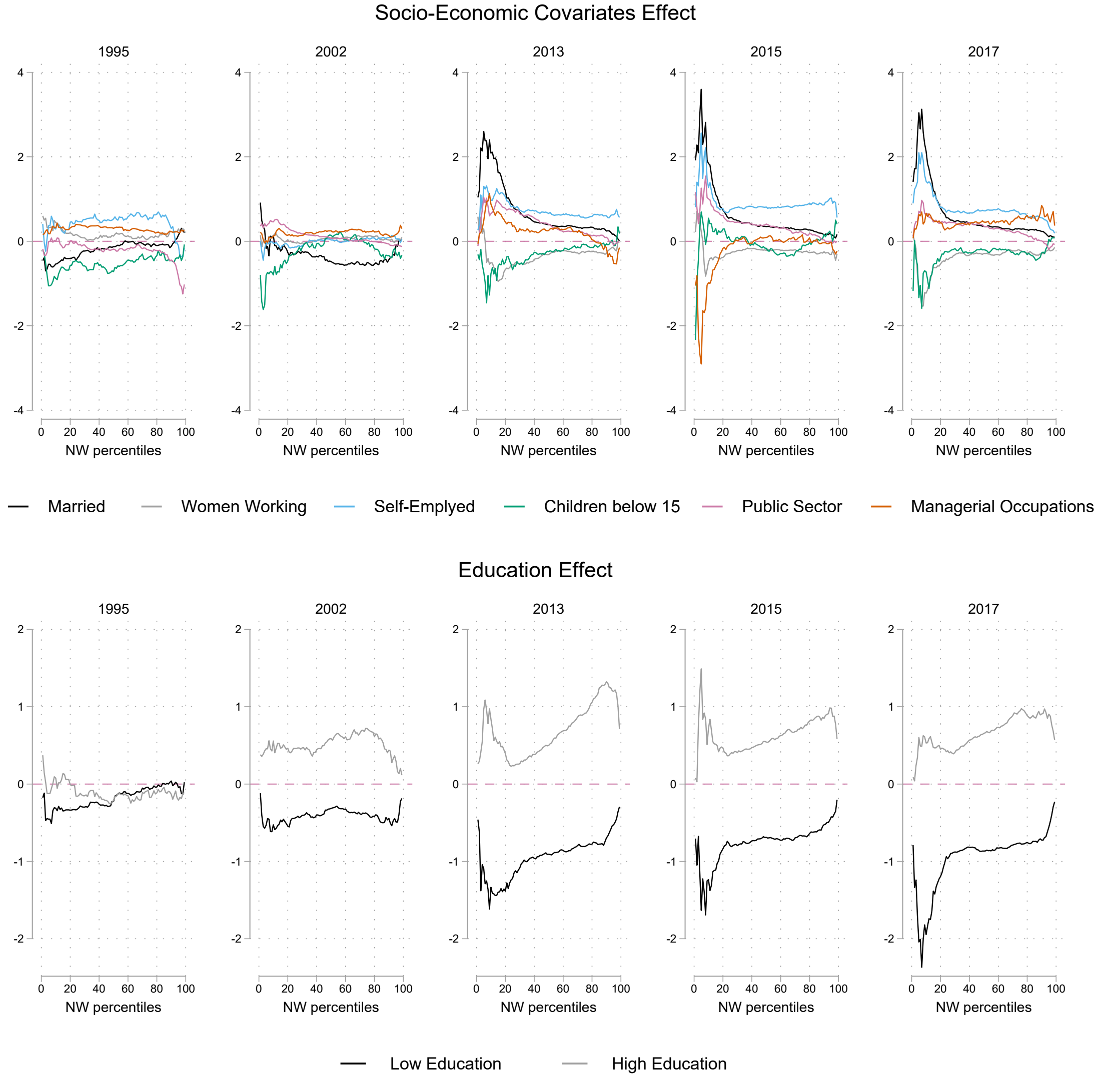
Notes: Compiled by authors based on CHFS (2013, 2015, and 2017) urban sample. All calculations are weighted with sample weights. For each year in CHFS, the figure shows the distributions of age, labour earnings, and pension incomes for the full sample (black line), the sub-sample that have available party membership information (red line), and for the sub-sample in which party membership is not available (light blue line).

Figure 4.7: Validation



Notes. Compiled by authors based on CHFS data for the household population in urban China.

Figure 4.8: CCP distribution over the total HH income deciles



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban sample. All calculations are weighted with sample weights. The figure compliments Figure 4.5 and displays the estimated UQR coefficient for the covariates X in equation 4.1.

Figure 4.9: Unconditional quantile regression - covariates effect

Wealth Aggregate	**Wealth Component**	**Description**	**Differences between CHFS and CHIP**
Gross Wealth	*Safe Finacial Wealth*	Cash, Deposits and Funds (excluding the housing fund) owned by the HH.	
	Risky Financial Assets	Bonds, Financial products, loans and Stocks owned by the HH	
	Housing Funds	Current account of housing Funds	
	Housing Wealth	Current market value of the most valuable 3 houses owned by the HH.	
	Business Wealth	Family share of the total assets (at current market value) invested in production and operation of industry and commerce, including individual business, leasing, transportation, online stores, and enterprises. Assets include project-related shops, cash deposits, inventory, office equipment, machinery, or mechanical means of transportation;. these do not include the value of the project-related houses owned by business owner.	
	Other Assets	Land Assets, Assets invested in agricultural machinery	
Debt	*Financial Debt*	Outstanding debt for the investment in financial products (stocks, bonds, financial products,. . .)	Not available in CHIP
	Educational Debt	Outstanding debt for investment in education	
	Housing Debt	Outstanding debt on the 3 most valuable houses owned by the HH	
	Production Debt	Outstanding Debt for agricultural and business related activists owned by the HH.	
	Medical Debt	Debt for medical care	Exculded from CHIP. Infomration is discntinuos across CHFS waves.
Net Wealth	*Gorss Welath - Debt*		

Income Aggregate	***Income Component***	**Description**	**Differences between CHFS and CHIP**
Total Income	Net Labour Income	deducted by insurances and housing fund, bonuses, subsidies, and subsidy in kind received last year	In CHIP we only heve Pre-tax infomramtion
	Transfer Income	Income from pension and annuity and governamental subsidies received last year	In CHIP it is deduced by income tax, social contribution, subsidies and housing fund contribution
	Business Income	After-tax income from business related actives in which the HH is directly involved.	In CHIP the infomration is availbel only pre-tax
	Other Income	It includes the after-tax income from agricultural activities in which the HH is directly involved, income from rents, income from financial activites, presents and donations received.	In CHIP it is only availabe the income from rents and dividends
Consumption		Average monthly consumption in food, utilities, necessisties housing related expences, transportations, comumunication, entratinment, cloths expenses. (multipleyed by 12). Yearly expences in education, travels, for medical reasons.	In CHIP it is not avaialble

Table 4.6: Variable defintion

	CHIP		CHFS		
	1995	**2002**	**2013**	**2015**	**2017**
Net Wealth	0.24	0.44	0.51	0.52	0.52
Gross Wealth	0.24	0.44	0.52	0.53	0.52
Safe Financial Wealth	0.31	0.42	0.82	0.67	0.69
Risky Financial Wealth	0.42	0.31	0.49	0.49	0.61
House Funds		0.28	0.75	0.67	0.63
House Wealth	-0.00	0.32	0.43	0.42	0.44
Business Wealth	0.06	0.11	-0.09	0.38	0.24
Total HH Income	0.25	0.38	0.49	0.43	0.49
Total HH Labour Income	0.18	0.36	0.39	0.31	0.41
Total HH Transfer Income	0.54	0.57	0.96	0.79	0.89
Total HH Business Income	-0.88	-0.19	-0.18	0.19	-0.05
Total HH Debt	0.23	0.62	0.63	0.52	0.54
Total HH Consumption			0.24	0.18	0.25
Total HH Savings			0.34	0.33	0.37
Δ Housing Ownership	0.06	0.08	0.08	0.06	0.06
N HHs	6,795	6,705	17,053	22,139	23,723

Notes: Estimations are based CHIP (1995, 2002) and CHFS (2013, 2015, and 2017). Only households living in urban areas with non-negative net wealth are included. Variables definition is available in Table 4.6. Outcome gaps are calculated as difference of the yearly-specific average outcome between CCP and non-CCP households over the average outcome non-CCP households. The sample is trimmed at the 1-st and 99-th percentile of the yearly-specific Net wealth distribution.

Table 4.7: Un-adjusted wealth and income gaps

Probit - How did HHs got the main house?	**Average Partial Effect**	**Overall**	**Bottom 50%**	**Middle 40%**	**Top 10%**	**N**
RE market	CCP	0.03***	0.08***	0.01	-0.01	19,494
Housing Policy - before 98	CCP	0.06***	0.07***	0.05**	0.07*	6,007
Housing Policy - after 98	CCP	0.01	0.01	0.01	-0.01	12,806
Self-built	CCP	-0.06***	-0.09***	-0.04***	-0.01	19,494
Inerhitance	CCP	-0.02***	-0.03***	-0.02***	-0.01*	19,494
OLS	β	**Overall**	**Bottom 50%**	**Middle 40%**	**Top 10%**	**N**
Purchasing Price of the House	Housing Policy - before 98	-0.02***	-0.75***	-0.05***	-0.02***	
	Housing Policy - after 98	-0.02***	-0.91***	-0.04***	-0.02***	
	Self-built	-0.01***	-0.46***	-0.01***	-0.01***	
	Inerhitance	.	.	.	.	
						15,988
Current Value	Housing Policy - before 98	0.01***	0.23***	0.01**	0.00	
	Housing Policy - after 98	-0.01***	-0.26***	0.00	-0.00*	
	Self-built	-0.01***	-0.50***	-0.01**	0.00***	
	Inerhitance	-0.02***	-0.54***	0.00	0.00	
						18,825
OLS	β	**Overall**	**Bottom 50%**	**Middle 40%**	**Top 10%**	**N**
(log-) Current Account in Housing Funds	CCP	0.17***	0.16**	0.18***	0.11	6,263
(log-) Average Housing Funds Contribution	CCP	0.11***	0.03	0.13***	0.14***	6,544

Notes: Estimations are based on CHFS 2017. Wealth is ranked using the net wealth level in each survey year. Only households living in urban areas with non-negative net wealth are included. Statically significant effects at the 10%, 5%, and 1% significance level are indicated with $*$, $**$, $***$ respectively.

Table 4.8: Housing investment - 2017 sample

4.8.2 Historical Perspective on Hosing Reforms in China.

The history of China's urban housing can be divided into three significant phases: 1949-1978 (pre-reform period); 1979-1998 (housing reforming period); 1999-present (post-reform period).

4.8.2.1 Housing socialist transformation (1949-1978): nationalization and public housing.

Nationalization: Before 1949, housing in China was mostly private owned. After the Chinese Communist party came to power, urban private housing was gradually nationalized. Until 1955, the share of private housing in urban China was still significant. For example, the ratio of private to total housing was 54% in Beijing, 66% in Shanghai, 54% in Tianjin, 78% in Jinan, 61% in Nanjing, and 86% in Suzhou (侯淅珉, 1999, p.9). The socialist transformation of private housing was completed only at the end of 1958. In addition to retaining part of the privately-owned self-occupied housing, most of rental housing was confiscated. By 1978, 78.4% of the urban housing stock was publicly owned housing (侯淅珉, 1999, p.11).

Public housing: As urban housing became predominately owned by the state or state-run work units, the state took responsibility for providing and managing urban housing. The housing units were allocated, usually free or at a highly subsidized price, to state employees as in-kind compensation. The quality (location, size, housing condition) of the allocated housing largely depended upon the worker's administrative rank (Song and Xie, 2014). Given such heavy subsidies, the nominal rent collected did not even cover the cost of basic maintenance of the housing, thus housing investment decreased considerably while urban living conditions were continuously deteriorating. The living area per capita in urban China decreased from 4.5 sqm in the early 1950s to 3.6 sqm in the 1970s (Tong and Hays, 1996).

4.8.2.2 Housing reforming period (1979-1998): from public housing to privatization

The mounting pressure in public housing system at the end of 1970s, especially the housing supply shortage, led to a series of housing privatization reforms in the 1980s and 1990s. In the early stage of urban housing reforms in 1980s, the government took a progressive approach by implementing experimental reform in selected cities (Wang and Murie, 2000), while nationwide housing reform began in 1991, when the property rights of privatized housing were officially recognized. In 1994, the government established a more comprehensive framework to facilitate the privatization of public housing stocks. Dwelling units previously owned by public employers were **sold** to residing employees at heavily subsidized prices. Meanwhile, private firms were allowed to enter the real estate industry and construct commercial houses for the first time. Consequentially, in the late 1980s, the real estate industry and private housing markets started to grow rapidly, with the per capita housing floor space rising from 5.2 sq meters in 1985 to 8.5 sq meters in 1996 Fu et al. (2000, p. 64). By 2002, 85% of urban housing was privately-owned (Piketty et al., 2019). Box 4.8.2.2 summarizes the major house reform policies adopted in this period.

Box C.2: House Reform Policies (1983-1998)

- In 1983, the State Council issued a regulation on urban private housing, which establishes the first legal protection for households to own, purchase, sell, and rent private homes in urban areas. ('Regulations on urban private housing', State Council [1983], No.194).
- In 1988 housing commercialization was officially announced as the goal of housing reform by the State Council. ('Implementation plan for a gradual housing system reform in cities and towns', State Council [1988] No. 11)
- In 1991, the property rights of privatized housing were officially recognized. ('The resolutions of the state council about actively and appropriately carry out urban housing reform', State Council [1991] No. 30)
- In 1994, the State Council further deepening the housing reform by advocating a transition from in-kind allocation of publicly owned housing (福利房) to commercial urban housing (商品房). ('The decision on deepening the urban housing reform', State Council [1994] No. 43)
- In 1998, the State Council announced the official termination of in-kind allocations of publicly owned housing. ('A notification on further deepening the reform of the urban housing system and accelerating housing construction', State Council [1998] No. 23)

In this phase, privatization of public housing substantially occurred as lumpsum transfer of wealth in the form of discounted sales of public housing apartments to residing tenants, who were mostly workers or officials in the public sector. The private housing obtained during this privatization period is typically called purchased public housing (已购工房) or Housing-reform house (房改房), while in our research we use the term ***welfare housing***, since these housing were initially distributed to the public as a type of welfare instead of a commodity. Since the initial allocation of the public housing (location, size, condition) was concentrated in public sectors (i.e. governmental institutions and state-owned companies), based on the administrative rank of the employee, understandably the housing reform has typically brought a windfall to those individuals working in the public sectors or having strong political connections (CCP members or government officials).

Another core policy for the transition is the establishment of the housing fund for urban employees at the end of 1990, which was designed for the purpose of housing purchase and renovation.[27] The housing fund has played the significant role in both housing reform and development of real estate' markets in China. However, there has been a growing concern on regressive distributional function (Lu and Wan, 2021). Similar to the privatization of public housing, since the establishment of housing fund system, its coverage concentrates on public sectors, which is almost

[27]The rates of housing fund range from 10% to 40% of employee's gross wage, split equally between employer and employee.

entirely located in urban China. Despite the expansion of the system to the private sector in the following decades, its coverage is still highly skewed. In 2020, residents in rural China and self-employed workers were still excluded from the system. In 2020, 50% of the employees registered in the housing fund system work in the public sectors, whose employees covers only 13% of total employees in urban China.[28]

4.8.2.3 Post housing reform period (1999-present)

In 1998, the state council issued the official termination of in-kind allocations of publicly owned housing. According to the plan, after 1998 all newly built houses would be commercialized and old public housing would be gradually commercialized. The volume of private housing built as a share of the total annual flow supply more than doubled from 30.7% in 1997 to 72.4% in 2007 (Li et al., 2020).

The housing reform resulted in a vigorous and fast-growing urban housing market; consequentially, housing prices escalated rapidly after 2003, further exacerbating the problem of housing affordability. The central and local governments, therefore, implemented a large set of affordability-enacting polices[29] that provided ground for the development of the 'economically affordable housing' (经济适用房).[30] The price of 'economically affordable housing' is substantially lower than the market price,[31] and, compared to welfare housing, the 'economically affordable houses' are designed to benefit all low-to-medium income urban households and not just the employees of the state-owned enterprises and governmental institutions. Nevertheless, in 2023 the affordable housing system in China is targeted only at urban residents who have city residence permits as part of its household registration system (commonly known as the hukou system). Migrant workers, floating populations, and others without urban residence permits are not covered.

[28] National Housing Provident Fund 2020 Annual Report.

[29] In 2007, the State Council issued 'Several Opinions on Solving the Housing Difficulties of Urban Low-income Households'; in 2008, the Central Work Conference on Economic Policy of the CCP emphasized the critical importance of alleviating housing poverty and developing the real estate market.

[30] See 'Notice of the Ministry of construction, the National Development and Reform Commission, the Ministry of State Land and Resources and the People's Bank of China about Issuing the Administrative Measures for Economically Affordable Houses' (2004)

[31] In order to construct the 'economically affordable housing', governments usually appropriate state-owned land to real estate developers at zero or very low price and then direct them to take responsibility of the finance and construction. The profit for real estate developers is capped around 3% to make sure the affordability of the 'economically affordable houses' for most low-to-medium households. For example, as a type of 'economically affordable housing', 'Capped Price Housing (限价房)'is sold at around 70% of the market price.

4.8.3 RIF-Regression Methods

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

$$Y_{it} = g_t(X_i, \epsilon_i) \tag{4.2}$$

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, variance, and the Gini Index under very general assumptions about the earnings setting equation 4.2. 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:

$$v(F_t) = E[RIF(y_t, v_t, F_t)|X, T = t] \tag{4.3}$$

In the specific case of quantiles, RIF is defined as:[32]

$$RIF(t; q_t^p) = q_t^p + \frac{p - I[y \leq q_t^p]}{f_Y(q_t^p)} \tag{4.4}$$

$$E[RIF(y_t, q_t, F_t)|T = 1] = \frac{1}{f_Y(q_t^p)} Pr[Y > q_t^p|X = x] + (q_t^p - \frac{1 - p}{f_Y(q_t^p)}) \tag{4.5}$$

$$= c_{1,p} Pr[Y > q_t^p|X = x] + c_{2,p} \tag{4.6}$$

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-centred by a constant $c_{2,p}$.

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

$$E[RIF(y_t, v_t, F_t)|X, T = t] = X_t' \widehat{\gamma}_t^v \tag{4.7}$$

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

$$\widehat{\gamma}_t^{\nu} = E[XX'|T=t]^{-1}E[RIF(y_t, \nu_t, F_t)|X, T=t] \tag{4.8}$$

X_t is a vector of covariates that entails dummies for the occupational class, as described in the sections above, and socio-demographic controls. γ_t^{ν} represents the unconditional marginal effect of X on $\nu(F_t)$, and has to be interpreted as the marginal effect on the unconditional quantile of a small location shift in the distribution of covariates, holding everything else constant.

4.8.4 CCP premia on Income

4.8.4.1 CCP average Premia

In this section, we replicate previous literature analysis on CCP labour earnings premia. We do so to show that previous literature results are confirmed using CHFS. To isolate the influence of membership on wages and earnings, we estimate regressions models that control for the observable characteristics of the individual. We begin with a simple OLS regression that takes the following form:

$$ln(y_{it}) = \alpha + \delta CCP_{it} + X'_{it}\beta + \epsilon_{it} \tag{4.9}$$

where y_{it} is net monthly labour earnings of currently employed workers, CCP_{it} is a dummy indicator for worker's party membership, X_{it} is a vector of covariates including age (5 main classes), a gender dummy, a married dummy, a dummy indicating the presence of children in the HH, worker's education dummies (3 main class), occupation (5 classes), and a public sector dummy. We use the same model to test also hourly wage premia, using hourly wages as y_{it}. We test equation 4.9 on currently working individuals living in urban China.

OLS presents different problems. First, as seen in the Probit tables 4.4, CCP members are more likely to be highly educated, work in public sector, and in high-paying occupations. This evidences suggest the presence of relevant selection biases in the membership process. In particular, if the likelihood to join the CCP is determined by unobservable characteristics, the OLS estimates will be biased.[33] Two main empirical strategies are proposed by previous literature in order to deal with such potential endogeneity problems:

[33]Exploiting the panel structure of our data, theoretically individual fixed effects models should solve these issues. However, this cannot be applied to the case of CCP membership since only a marginal fraction of the sample become CCP members within the time span in the data, having too little variation to exploit for a consentient estimation.

- *Propensity Score Matching (PSM)*: it consists of first estimating a propensity score, i.e. the probability of being a CCP member, using linear probability models. Then, based on the propensity scores, observations are matched and distinguished into a control group (i.e., non-party members) that is directly comparable to the treatment group (i.e., party members) based on observable characteristics. Next, the CCP premia is estimated as the average treatment effect. Such methodology should resolve problems of selection due to observable characteristics and is widely used in the literature on CCP premia estimation (McLaughlin, 2017; Guo and Sun, 2019; Nikolov et al., 2020).

- *IV with Endogenous Dummy regressor*: IVs are designed to solve selection based on observable characteristics. Following Appleton et al. (2009); McLaughlin (2017); Nikolov et al. (2020), we instrument the individual's party affiliation with parental membership and apply two-stage least squares (Wooldridge, 2002). Parental membership is claimed to be a valid instrument since it is likely to predict individual membership via either demand factors (for example, parents act as role models) or supply factors (parents vouch for one's character) (Appleton et al., 2009), and may not have strong direct effects on own wages. Both Appleton et al. (2009) and McLaughlin (2017) provide extensive tests for the validity of the instrument. CHFS asks about parental CCP membership only to the direct survey respondent, implying a considerable sample restriction in the estimation of the 2sls.

Results for OLS, IV and PSM are displayed in the Table 4.9.

First, It is immediate to see that in all the specifications CCP premia are found positive and statistically significant. Specifically, OLS and PSM estimates range between 5 and 10%.

Second, IV estimates are much higher. Similar results are found in McLaughlin (2017), with the author explaining that *'the instrumental variable estimator does not measure the average treatment effect, but estimates the local average treatment effect (LATE) for the sub-population of treated individuals for whom parental party membership causes them to be members.[. . .] If there is a concern that the OLS estimate is biased upward because of the ability and family background omitted variables, the IV estimate should be smaller in magnitude. However, it appears that the IV estimate is not consistent with the upward bias concern in OLS because IV estimates are larger compared to OLS estimates'* (page 11).

Overall we learn that CCP membership does generate positive earnings and wage premia and, although there are might be selection mechanisms in CCP affiliation, OLS estimates can be considered trustworthy. Results are in line with the literature (McLaughlin, 2017; Nikolov et al., 2020).

	2013		2015		2017	
	δ	N	δ	N	δ	N
(log-) Monthly Gross Labor Earnings						
OLS	0.08^{***}	10,709	0.09^{***}	14,359	0.05^{***}	14,024
IV	0.80^{***}	5,198	0.97^{***}	6,543	0.48^{***}	6,167
PSM	0.10^{***}	10,709	0.06^{**}	14,359	0.07^{***}	14,024
(log-) Hourly Gross Wage Earnings						
OLS	0.07^{***}	10,395	0.09^{***}	14,065	0.04^{***}	14,022
IV	0.60^{***}	5,031	0.74^{***}	6,430	0.26^{*}	6,150
PSM	0.10^{***}	10,395	0.05	14,065	0.05^{**}	14,022

Notes: Table reports the estimates from wave-specific OLS, PSM and IV models. Estimations are based on CHFS (2013, 2015, and 2017). Only individuals currently working aged 15 and above living in urban areas are included. Earnings and wages are trimmed at the 1-st and 99-th percentiles and do not include negative values. Sample weights are applied to estimation. Statically significant effects at the 10%, 5%, and 1% significance level are indicated with $*$, $**$, $***$ respectively.

Table 4.9: CCP premia on individual labour eranings and wages.

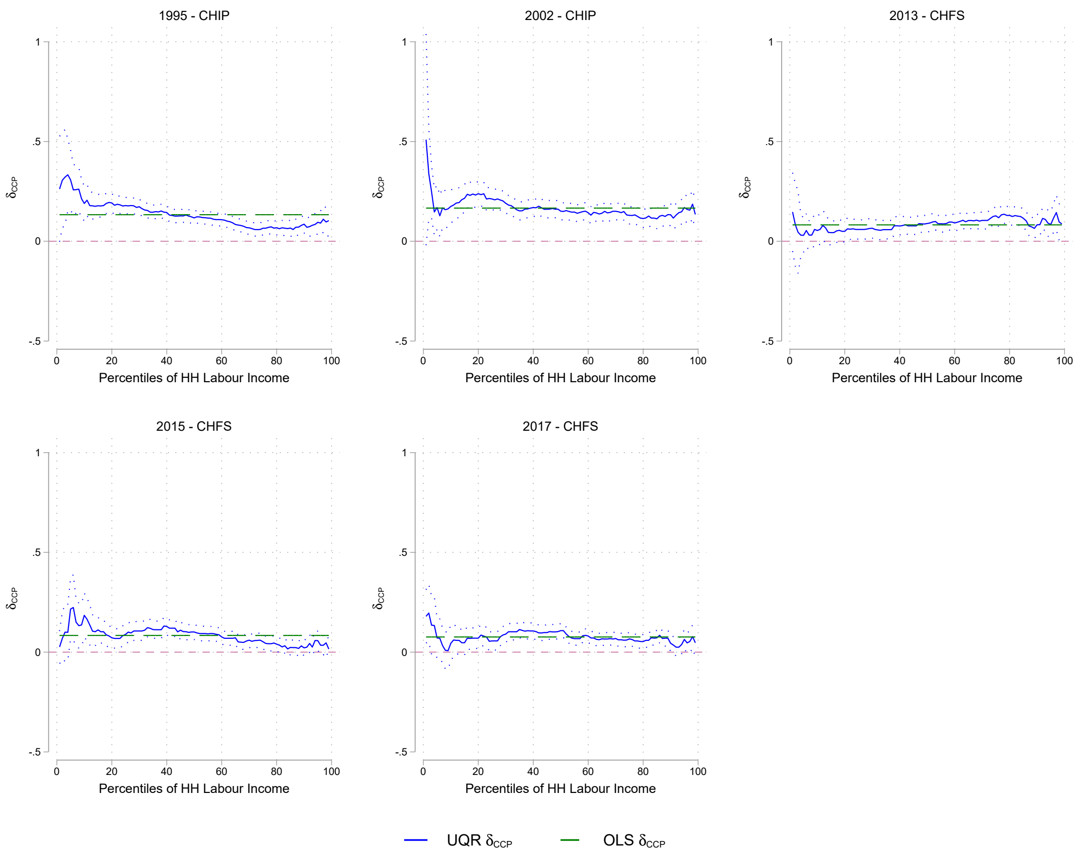
4.8.4.2 CCP heterogeneous Returns

We next focus on the CCP returns on HH labour income for households that are currently active in the labour market. To do so, we apply RIF unconditional quantile regressions at the household level that take the following form:

$$Y_t^q = E[Rif(Y_{it}, q_t^q)] = \alpha^q + \delta^q CCP_{it} + X_{it}'\beta^q + \epsilon_{it}^q \tag{4.10}$$

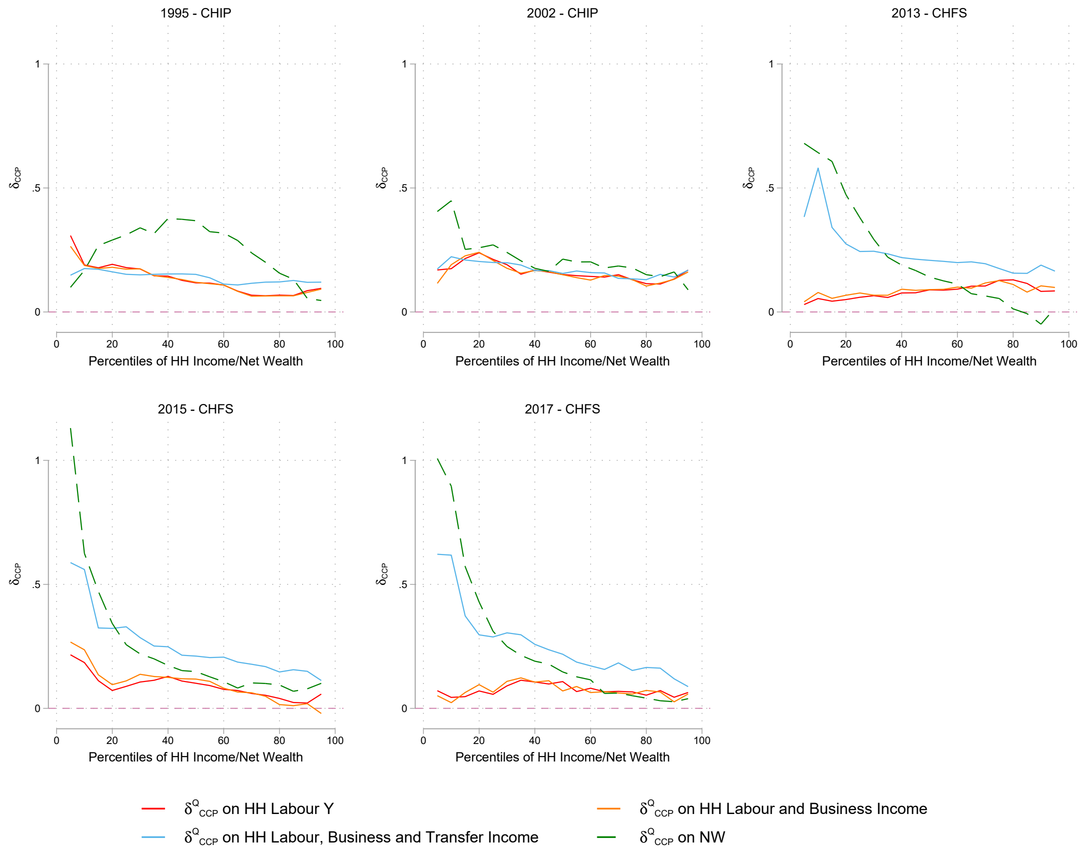
where Y_t^q is q-th percentile of the household income distribution, CCP_{it} is a dummy indicating if at least one individual belonging to household is a CCP member, and X_{it} is defined as in equation 4.10.

In Figure 4.10 we report with solid blue lines the estimated δ^q coefficients and the relative 95% confidence intervals from equation 4.10. We report OLS estimates with dashed green lines. Interestingly, we observe a $7-13\%$ CCP premia on HH income that is constant across the whole distribution and relatively stable across the years analyzed. Figure 4.11 compares the CCP returns on different HH Income aggregates. In particular, in red we report UQR estimates of CCP membership on HH labour income; in orange estimates on HH labour and business income; and in light blue estimates on total HH incomes (from labour, business, transfers, and other sources). The dash green line reports estimates on HH Net Wealth as estimated in Figure 4.5. Interestingly, the CCP premia doubles once we also account for pension incomes and the CCP effect decreases along the household income distribution with the largest returns concentrated at the bottom of the distribution. While these findings corroborate the evidence of positive returns for CCP members, they also suggest that the effect is stronger for older generations that are now retired versus those that are still active in the labour market.



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. The figure displays the estimated UQR coefficient for party membership in blue with the relative confidence intervals. The green dash line shows estimates from OLS regression.

Figure 4.10: Unconditional quantile regression on HH labour income - CCP membership



Notes: Compiled by authors based on CHIP (1995 and 2002) and CHFS (2013, 2015, and 2017) urban samples. All calculations are weighted with sample weights. The figure displays the estimated UQR coefficient for Party membership in blue with the relative Confidence intervals on different HH income aggregates: labour HH income in red, labour and business HH income in orange, total HH income in light blue. The dash green line reports estimates on HH Net Wealth as in Figure 4.5. The green dash line shows estimates from OLS regression.

Figure 4.11: Unconditional quantile regression CCP membership effects

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Summary

This dissertation consists of four empirical chapters which contribute to the fields of labor economics and inequality research.

The first chapter examine whether gender differences exist in fairness evaluation of own earnings. Previous studies found that women tend to evaluate their own pay more favorably than men. Contented women are speculated to not seek higher wages, thus the 'paradox of the contented female worker' may contribute to persistent gender pay differences. We extend the literature, by investigating fairness evaluations of own earnings and underlying conceptions of fair earnings, providing a closer link to potential subsequent wage demands than previous literature. Using European Social Survey (2018/19) data, we find no evidence that women evaluate their own earnings more favorably than men. In 15 out of the 28 analyzed countries, women actually report more intense levels of perceived unfairness. Studying fair markups on unfair earnings, i.e., the relative distance between the earnings received and earnings considered fair, we find that women report the same, if not lower, fair markups compared to men in most countries; thus indicating limited potential for perceived unfairness as a driving force to reduce the gender pay gap in Europe.

The second chapter studies the link between technological change, employment and earnings inequality. In particular, the 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 for complementary non-routine occupations, i.e., low-skilled service and high-skilled abstract jobs, has increased. These changes in the labor force composition imply a polarization of jobs along the skills distribution. Here we quantify the polarization of jobs and its importance for earnings distributions using a novel dataset of 35 countries. We find strong evidence for job polarization in most countries but no clear-cut distributional consequences. This weak link stems from variation *within* rather than *between* occupational classes and heterogeneous intensities of de-routinization along the earnings distribution.

The third chapter investigates how heterogeneity in firm wage policies shape inequalities *within* and *between* occupational groups. A long-standing line of literature in labor economics recognizes that workers with similar characteristics and skills earn different wages in different firms. In a decentralized economy, where the wage setting power is at the firm-level, these differentials are ascribed to firm-specific pay policies, hence the 'firm wage premium'. Differently form previous literature, I allow firms to set differential wage policies to different occupational classes, i.e. managers, blue collar, and white collar workers. Using matched employer-employee administrative data from the Veneto region in Italy, I show that within the same firm, different occupations receive different firm premia so that the high-type firms are not

'equally good' for all their employees. Ranking employers by the occupation-specific firm fixed effects reveals substantial heterogeneity in the wage policies applied to the different occupational groups within the same firm. Specifically, I show that the highest-paying firms for a given occupational group are likely to be among the least advantageous for the other employees. Eventually, examining the evolution of occupation-specific firm policies over two decades, this chapter provides empirical evidence that within-firm wage differentials between white and blue collar workers increased among Veneto employers in the 1990s with respect to the 1980s.

The fourth chapter analyzes wealth inequality in China. In particular, in the context of China, there is growing interests among economists and other social scientists in measuring the economic returns of the Chinese Communist Party (CCP) membership. Previous literature has mostly focused on the estimation of returns of party membership on labour wages and earnings. In this chapter, we aim to fill the gap in the literature by presenting the first comprehensive study about the wealth gap evolution in urban China between CCP and non-CCP households over the last three decades. Our results show that the *average* wealth gap between CCP and non-CCP household remained substantial and stable over the time period 1995-2017, however, the returns structure of political membership has deeply changed over time. While in the 1990s the highest wealth advantages, in relative terms, for party members where concreted at the middle of the distribution, today is the lower class that benefits the most. We then show that the the privatization of the housing market, especially after the housing reform, granted even access to housing wealth to both CCP and non-CCP families, reducing the differences in the middle and at the top of the wealth distribution. However, strong differences between the housing investment of CCP and non-CCP households persist still today at the bottom of the net wealth distribution, where CCP are found to be more likely to own housing real estate assets than non-CCP households and the houses that they own are more valuable.

Zusammenfassung

Diese Dissertation besteht aus vier empirischen Kapiteln, die einen Beitrag zu den Bereichen Arbeitsökonomie und Ungleichheitsforschung leisten.

Im ersten Kapitel wird untersucht, ob es geschlechtsspezifische Unterschiede bei der fairen Bewertung des eigenen Verdienstes gibt. Frühere Studien haben ergeben, dass Frauen dazu neigen, ihr eigenes Gehalt positiver zu bewerten als Männer. Es wird vermutet, dass diese zufriedenere Einstellung von Frauen dazu führt, dass sie keine höheren Löhne anstreben, so dass das "Paradoxon der zufriedenen Arbeitnehmerin" zu den anhaltenden Lohnunterschieden zwischen den Geschlechtern beitragen könnte. Wir erweitern die Literatur, indem wir Fairness-Bewertungen des eigenen Verdienstes und die zugrundeliegenden Vorstellungen von fairem Verdienst untersuchen und so eine engere Verbindung zu potenziellen späteren Lohnforderungen herstellen als die bisherige Literatur. Anhand der Daten der European Social Survey (2018/19) finden wir keine Hinweise darauf, dass Frauen ihren eigenen Verdienst positiver bewerten als Männer. In 15 der 28 untersuchten Länder berichten Frauen sogar über ein höheres Maß an Unfairness. Bei der Untersuchung des „fairen Aufschlags auf den ungerechten Verdienst“, d. h. des relativen Abstands zwischen dem erhaltenen -und dem als gerecht empfundenen Verdienst, stellen wir fest, dass Frauen in den meisten Ländern den gleichen, wenn nicht sogar einen geringeren fairen Aufschlag als Männer angeben. Für die Verringerung des geschlechtsspezifischen Lohngefälles in Europa scheint daher die wahrgenommene Ungerechtigkeit als treibende Kraft nur begrenztes Potenzial zu verfügen.

Das zweite Kapitel untersucht den Zusammenhang zwischen technologischem Wandel, Beschäftigung und Einkommensungleichheit. Insbesondere die Hypothese des routinebasierten technologischen Wandels (RBTC) von Acemoglu und Autor (2011) besagt, dass Automatisierungsprozesse Arbeitnehmer, die mittelqualifizierte Routineaufgaben ausführen, ersetzt haben. Infolgedessen ist die relative Nachfrage nach komplementären Nicht-Routineberufen, d. h. gering qualifizierten Dienstleistungen und hoch qualifizierten abstrakten Tätigkeiten, gestiegen. Diese Veränderungen in der Zusammensetzung der Erwerbsbevölkerung führen zu einer Polarisierung der Beschäftigungsverhältnisse entlang der Qualifikationsverteilung. In diesem Kapitel quantifizieren wir die Polarisierung der Beschäftigungsverhältnisse und ihre Bedeutung für die Einkommensverteilung anhand eines neuen Datensatzes aus 35 Ländern. In den meisten Ländern gibt es deutliche Hinweise auf eine Polarisierung der Beschäftigungsverhältnisse, aber keine eindeutigen Folgen für die Einkommensverteilung. Dieser schwache Zusammenhang ist eher auf Unterschiede innerhalb der einzelnen Berufsklassen, als zwischen ihnen, zurückzuführen sowie auf die heterogene Intensität der De-Routinisierung entlang der Einkommensverteilung.

Im dritten Kapitel wird untersucht, wie die Heterogenität der Lohnpolitik der Unternehmen die Ungleichheiten innerhalb und zwischen Berufsgruppen beeinflusst. In der arbeitsökonomischen Literatur wird seit langem anerkannt, dass Arbeitnehmer mit ähnlichen Merkmalen und Fähigkeiten in verschiedenen Unternehmen unterschiedliche Löhne erhalten. In einer dezentralisierten Wirtschaft, in der die Lohnsetzungsmacht auf Unternehmensebene liegt, werden diese Unterschiede auf die firmenspezifische Lohnpolitik zurückgeführt, auch „Firmenlohnprämie“ genannt. Anders als in der bisherigen Literatur nehme ich für die Unternehmen eine unterschiedliche Lohnpolitik für verschiedene Berufsgruppen, d. h. Manager, Arbeiter und Angestellte, an. Anhand von Verwaltungsdaten aus der Region Venetien in Italien, die detailierte Daten von Arbeitgebern und Arbeitnehmern enthält , zeige ich, dass innerhalb desselben Unternehmens verschiedene Berufe unterschiedliche Firmenprämien erhalten, so dass die Unternehmen mit hohem Lohnniveau nicht für alle ihre Beschäftigten „gleich gut“ sind. Ein Ranking der Arbeitgeber nach den berufsspezifischen festen Effekten des Unternehmens zeigt eine erhebliche Heterogenität in der Lohnpolitik, die auf die verschiedenen Berufsgruppen innerhalb desselben Unternehmens angewandt wird. Konkret zeige ich, dass die Unternehmen mit den höchsten Löhnen für eine bestimmte Berufsgruppe wahrscheinlich zu den am wenigsten vorteilhaften für die verbleibenden Berufsgruppe gehören. Durch die Untersuchung der Entwicklung der berufsspezifischen Unternehmenspolitik über zwei Jahrzehnte hinweg liefert dieses Kapitel schließlich empirische Belege dafür, dass die unternehmensinternen Lohnunterschiede zwischen Angestellten und Arbeitern bei den Arbeitgebern in Venetien in den 1990er Jahren im Vergleich zu den 1980er Jahren zugenommen haben.

Im vierten Kapitel wird die Vermögensungleichheit in China analysiert. Insbesondere im Zusammenhang mit China wächst das Interesse von Wirtschaftswissenschaftlern und anderen Sozialwissenschaftlern an der Messung der wirtschaftlichen Erträge der Mitgliedschaft in der Kommunistischen Partei Chinas (KPCh). Die bisherige Literatur konzentrierte sich hauptsächlich auf die Schätzung der Erträge der Parteimitgliedschaft auf Arbeitslöhne und -einkommen. In diesem Kapitel wollen wir eine Lücke in der Literatur schließen, indem wir die erste umfassende Studie über die Entwicklung der Vermögensunterschiede zwischen KPCh- und Nicht-KPCh-Haushalten im städtischen China in den letzten drei Jahrzehnten vorstellen. Unsere Ergebnisse zeigen, dass der durchschnittliche Vermögensunterschied zwischen KPCh- und Nicht-KPCh-Haushalten im Zeitraum 1995-2017 substanziell aber stabil geblieben ist, dass sich jedoch die Ertragsstruktur aus der politischen Mitgliedschaft im Laufe der Zeit stark verändert hat. Während in den 1990er Jahren die höchsten relativen Vermögensvorteile für Parteimitglieder in der Mitte der Verteilung zu finden waren, profitiert heute die Unterschicht am meisten. Wir zeigen dann, dass die Privatisierung des Wohnungsmarktes, insbesondere nach der Immobilienreform, sowohl KPCh- als auch Nicht-KP-Familien einen gleichmäßigen Zugang zu Immobilienvermögen ermöglichte, wodurch die Unterschiede in der Mitte und an der Spitze der Vermögensverteilung verringert wurden. Allerdings bestehen auch heute noch starke Unterschiede zwischen den Immobilieninvestitionen von CCP- und Nicht-CCP-Haushalten am unteren Ende der Netto-Vermögensverteilung, wo CCP-Haushalte mit größerer Wahrscheinlichkeit Wohnimmobilien besitzen als Nicht-CCP-Haushalte. Außerdem habe die Immobilien, die sie besitzen, einen höheren Wert.

Publications

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Erklärungen

Erklärung gemäß §4 Abs. 2

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

(Unterschrift, Ort, Datum)

Erklärung gemäß §10 Abs. 3

Ich habe meine Dissertation soweit im Folgenden nicht anders vermerkt selbständig verfasst. Folgende Hilfsmittel wurde benutzt

- Statistik: Stata, MATLAB, Excel
- Schriftsatz und Formatierung: LaTeX

Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

(Unterschrift, Ort, Datum)