De-routinization of Jobs and the Distribution of Earnings: A Cross-Country Comparison

M. Longmuir, C. Schröder, M. Targa;

Research Question:

Investigation of the distributional consequences of *job de-routinization* <u>internationally</u>.

Research Question:

Investigation of the distributional consequences of *job de-routinization* internationally.

- ***Job de-routinization -*** Acemoglu and Autor (2011)
  - Technological change leads to *automatization* of labor inputs that involve execution of routine task,
  - **decreasing demand for routine** intense jobs over time and **increasing** demand for complementary **non routine jobs**.

Research Question:

Investigation of the distributional consequences of *job de-routinization* internationally.

- ***Job de-routinization -*** Acemoglu and Autor (2011)
  - ➢ Technological change leads to *automatization* of labor inputs that involve execution of routine task,
  - ➢ **decreasing demand for routine** intense jobs over time and **increasing** demand for complementary **non routine jobs**.

- Job de-routinization might have ***distributional consequences*** because***:***
  - ➢ **Routine** jobs are typically **middle-skilled** jobs (e.g. office clerks and manufacturing workers)
  - ➢ **Non-routine** jobs are either:
    - at the **bottom** (service manual jobs)
    - at the **top** (abstract non-routine jobs) of the distribution.

Research Question:

Investigation of the distributional consequences of *job de-routinization* internationally.

- ***Job de-routinization -*** Acemoglu and Autor (2011)
  - Technological change leads to *automatization* of labor inputs that involve execution of routine task,
  - **decreasing demand for routine** intense jobs over time and **increasing** demand for complementary **non routine jobs**.

- Job de-routinization might have ***distributional consequences*** because***:***
  - **Routine** jobs are typically **middle-skilled** jobs (e.g. office clerks and manufacturing workers)
  - **Non-routine** jobs are either:
    - at the **bottom** (service manual jobs)
    - at the **top** (abstract non-routine jobs) of the distribution.

- **Large compositional changes of the work force might affect inequality *between* and *within* occupations.**

Research Question:

Investigation of the distributional consequences of *job de-routinization* internationally.

➢ **Large compositional changes of the work force might affect inequality *between* and *within* occupations.**

Previous literature results:

- Autor and Dorn (2013) for US find that **job de-routinization → earnings polarization**:
  - ➢ *U-shaped quantile growth curves,* tails growing faster than the middle of the distribution
  - ➢ They focused only on ***between* occupational dynamics**
- Despite massive literature, the distributional implication are still debated!

Main challenge:

Data support that allows cross-country analysis accounting:

1. 2-digits occupational information → allow to distinguish:
   - service occupations
   - routine occupations
   - abstract occupations
2. Long enough time horizon to track sensitive employment and wage changes

Data:

- We start with LIS dataset,
- Harmonize occupational codes at the 2-digit level.

➢ Final working sample of **35 countries**:
   - 22 core countries that we observe for more than 15 years
   - 13 other that we observe for less than 15 years → Appendix

Main challenge:

1. 2-digits occupational information, to distinguish:
   - Service jobs,
   - Routine jobs,
   - Abstract jobs.

LIS provides harmonized data only up to ISCO 1-digit.

We therefore harmonized the original country-specific information (usually 2 or digts), at the ISCO-88 level.

→ Main selection criteria to select countries and data waves into working sample.

Occupational Class: Present study	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
	—	Agricultural, fishery and related labourers	92	0.38

Notes. The table shows the correspondence between ISCO-88 2 digits codes and the main occupational classes as proposed in Acemoglu and Restrepo (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 1: Occupational classes based on 2-digits ISCO

<u>Main challenges:</u>

Data support that allows cross-country analysis accounting:

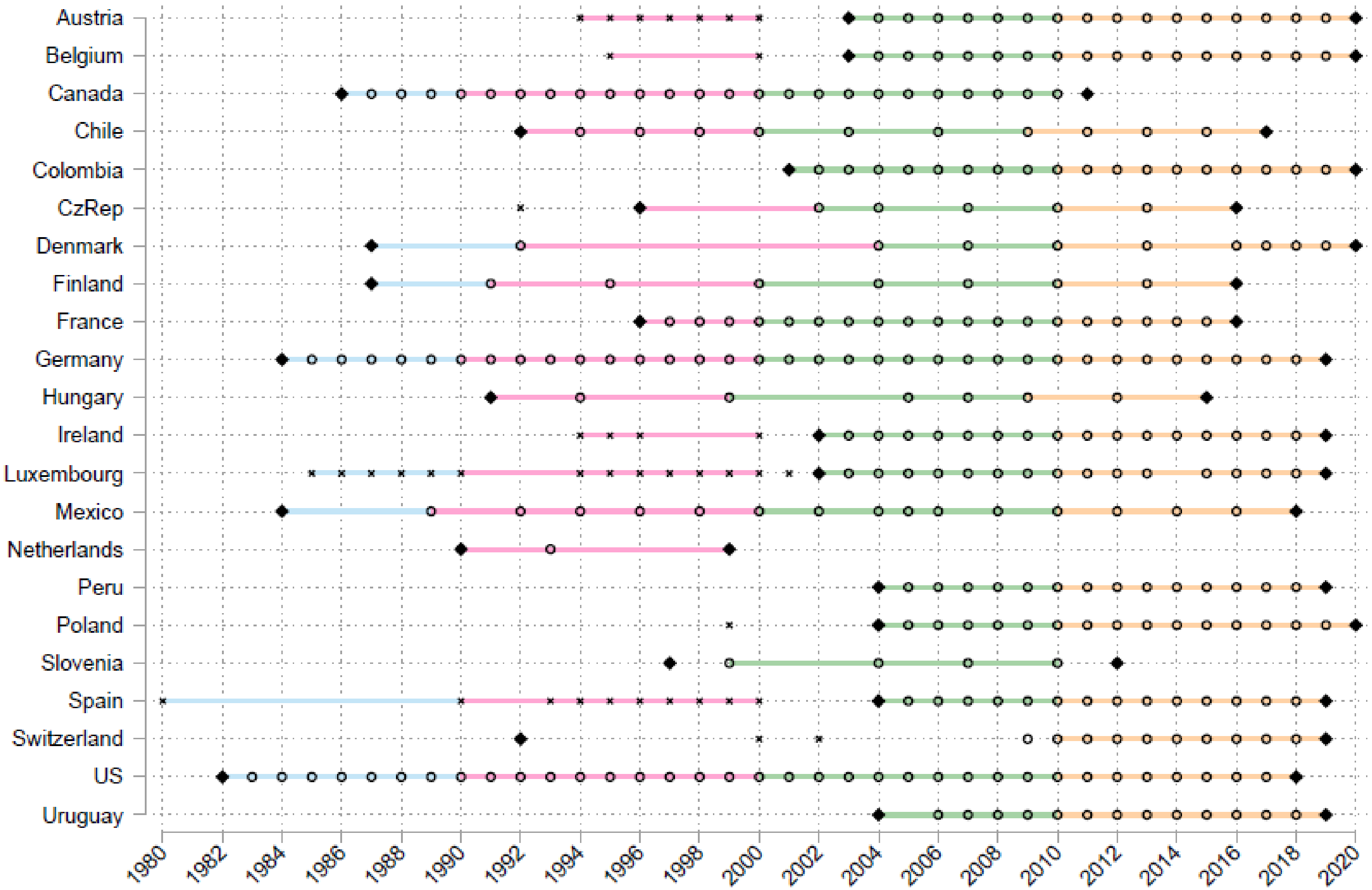
1. 2-digits occupational information → allow to distinguish:
    - service occupations
    - routine occupations
    - abstract occupations
2. Long enough time horizon to track sensitive employment and wage changes

<u>Data:</u>

- We start with LIS dataset,
- Harmonize occupational codes at the 2-digit level.

➢ <u>Final working sample of **35 countries**:</u>

  - **22 core countries** that we **observed for more than 15 years**
  - 13 other that we observe for less than 15 years → Appendix



Notes: The figure shows a detailed overview of the country-specific waves used for the analysis. Dots represent waves with consistent earnings definitions (gross/net). Crosses mark those years in the country series that deviate from the core earnings definition and, therefore, cannot be directly compared with the former. Diamonds define the earliest and latest waves for each country, as they have a consistent earnings concept. Colored bars link survey waves used for the decade-specific RIF decomposition estimations. The 1980s are indicated in light blue, the 1990s in pink, the 2000s in green, and the 2010s in orange.

Figure 1: Countries and Observed Time Horizons

Testing job de-routiniziation internationally

Are routine jobs vanishing?

Figure 1:

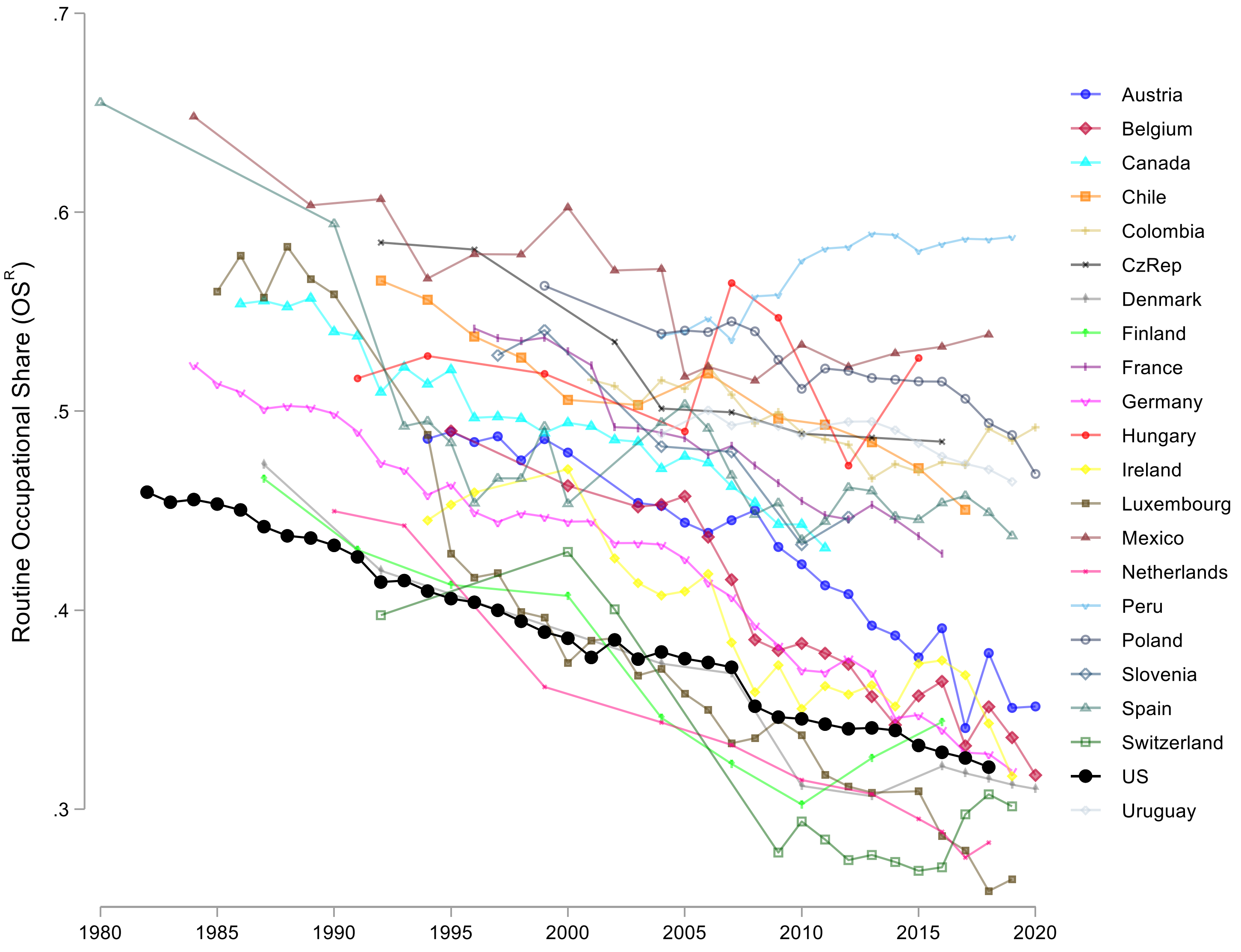
Overtime change in the **employme share of routine occupations.**

Result 1:

Job de-routinization is an internatio phenomenon.

➢ 20 of 22 core countries exhibit simil long run de-routinization trends

Exceptions: Hungary and Peru.



Notes: Compiled by authors based on LIS data for the prime-age, employed population. The y-axis shows the occupational share in routine occupation OS_t^R. The figure depicts the 22 core countries.

Figure 2: Routine Occupational Shares Over Time

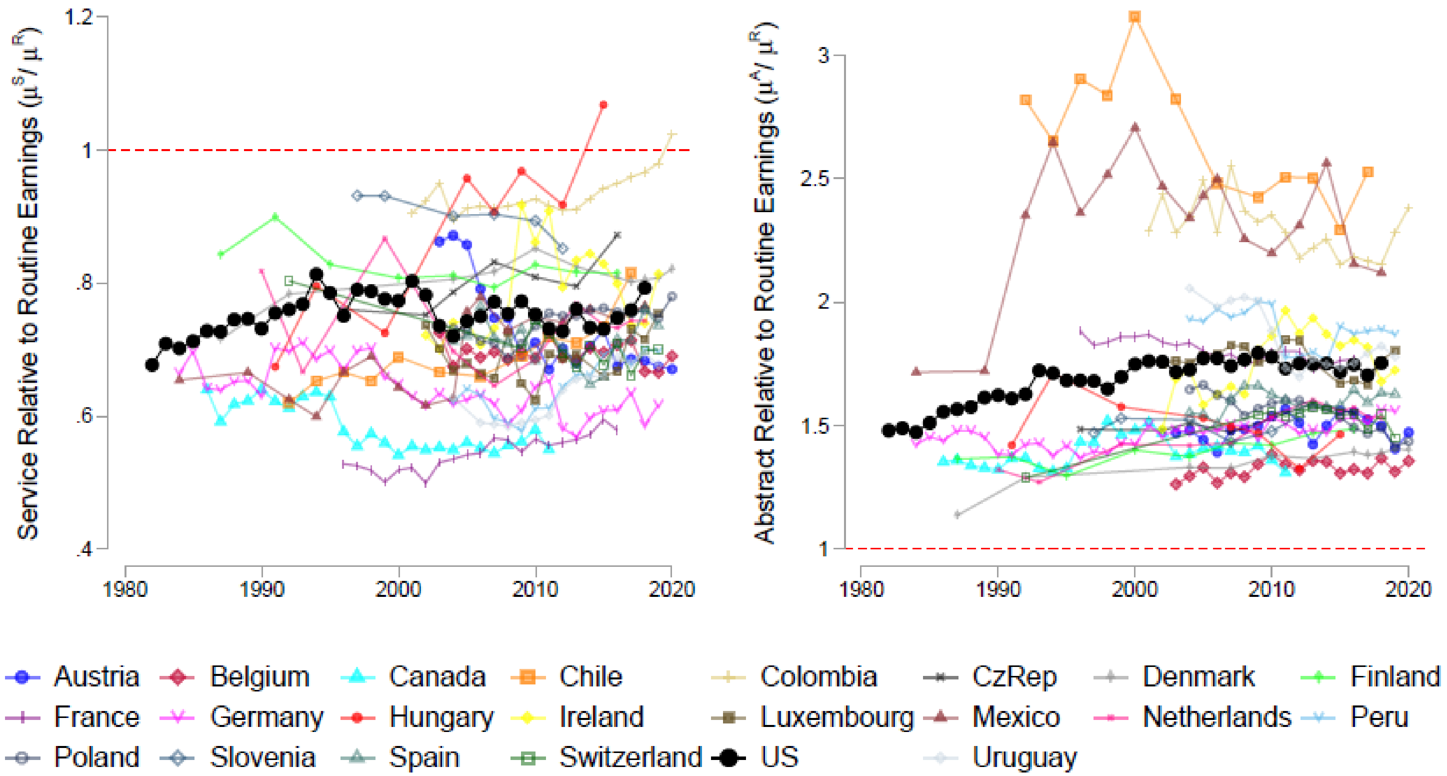
Figure 2:

We examine country-specific **average earnings in service (left) and abstract (right)** occupations **relative to routine jobs.**

Result 2:

Clear hierarchy in **average** earnings:
Service < Routine < Abstract

→ Job de-routinization is "hollowing out" the middle of the earnings distribution, rising concern for distributional consequences.



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

Figure 3: Job Polarization: Service and Abstract Compared to Routine Earnings

Figure 3:

Overtime change in the employment shar of **service**, **routine**, and **abstract** occupations.

→ **Routine jobs are replaced by both *service,* and abstract occupations.**

→ Since these occupations occupy different portions of the wage distribution

Acemoglu and Autor therefore talk about **wage polarization:**

→ **Reduced bottom tail inequality**

→ **Increased upper tail inequality**

<u>So far:</u>

Acemoglu and Autor focused on employment **shares** and **average** occupational earnings.

→ Their narrative focuses on ***between*** *occupational dynamics*

However, to assess overall distributional implications, we should focus on both ***between*** and ***within*** *occupational dynamics*.

Why is *within* occupational inequality important?

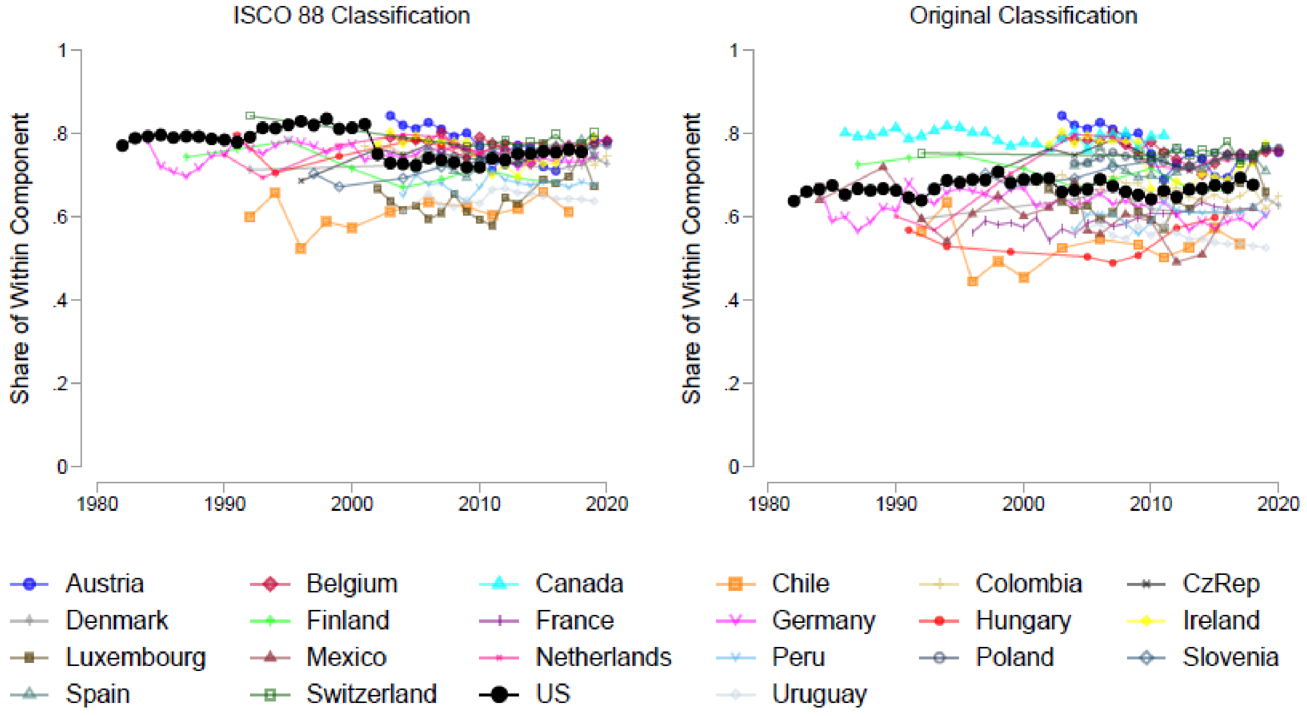
Figure 4:

Country-specific share of overall variance *within* occupations.

Result 3:

About ¾ of earnings inequality lies ***within occupations.***

- Result hold even if occupations are narrowly defined (3 digtis), as shown in the panel on the right.



Notes: Compiled by authors based on LIS data for the prime-aged, employed population. The left panel provides the share of the within component when the Theil is decomposed over 2-digits ISCO occupational classes. The right 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. Note that Canada, France, and Mexico rely on national occupational schemes that cannot be directly translated into ISCO 2 digits levels and are exlcuded from the left-hand panel.

Figure 7: The Theil Within Component: Different Levels of Aggregation

Figure 5:

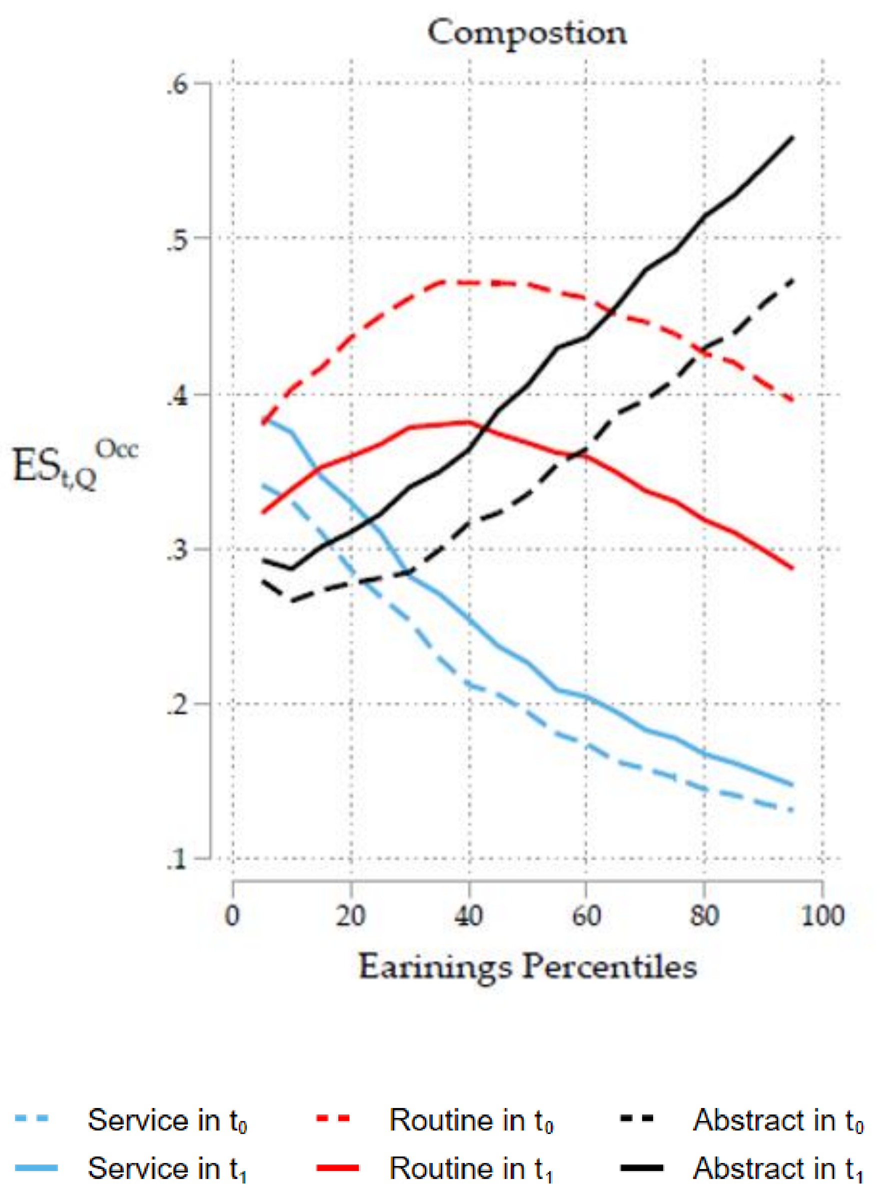
Compare Composition of different occupational classes along the earnings distribution **in US**, for **2018** (solid lines) and **1990** (dash lines).

The graph ordinate, shows the employment composition in each quantile:

$$\frac{N_t^{Occ}}{N_t^{Service} + N_t^{Routine} N_t^{Abastract}} \quad for \;\; y_i < q^{th}$$

Result 4:

Despite a clear hierarchy in returns, occupational classes are highly **overlapped** along the earnings distribution,

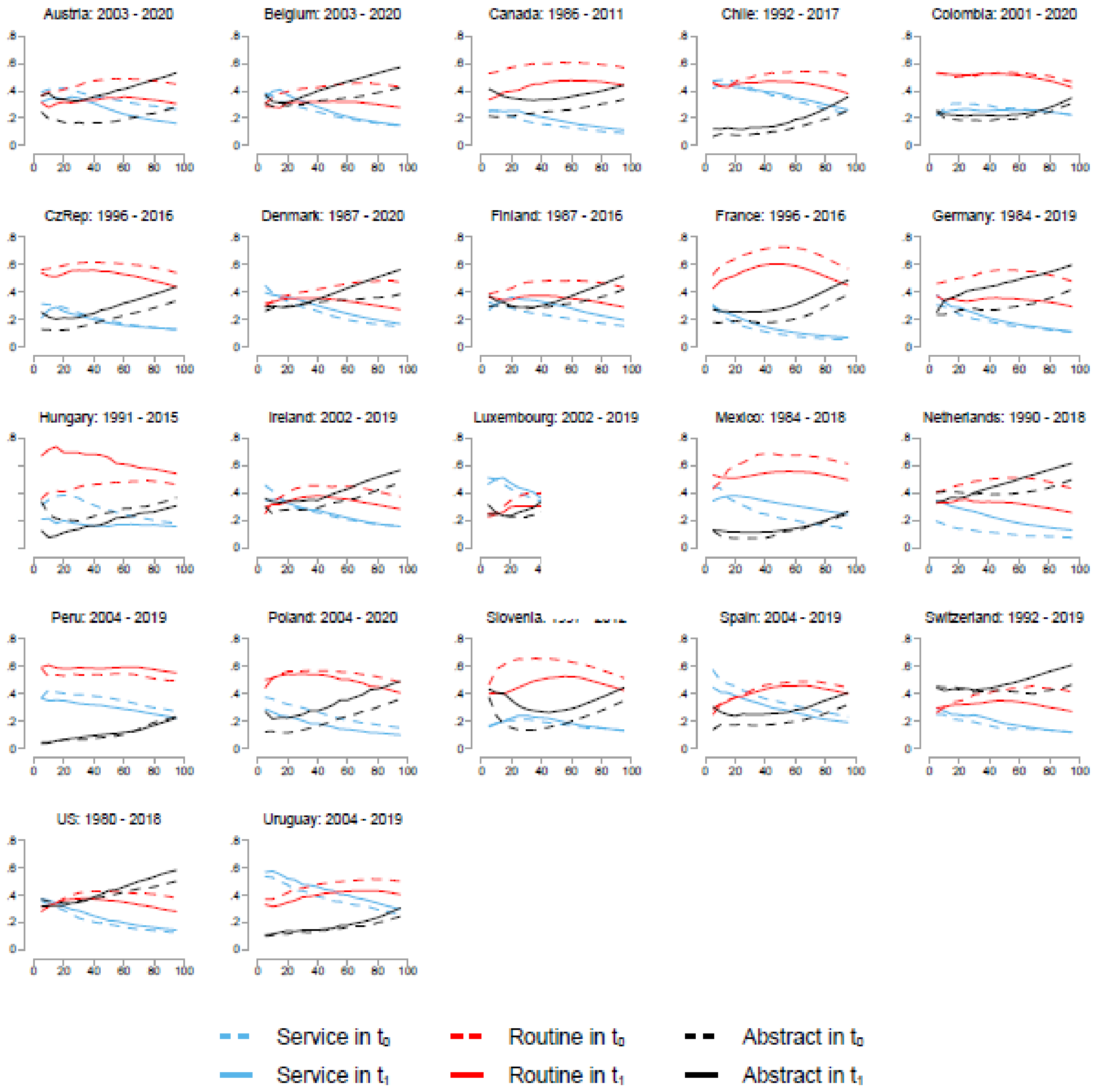


Result 4:

Despite a clear hierarchy in returns, occupational classes are highly **overlapped** along the earnings distribution,

→ Job de-routinization does not only affect the middle of the distribution but is replacing workers *everywhere*!

→ Distributional effects are, *a priori,* **ambiguous**



Testing distributional consequences accounting for both *between* and *within* occupational dynamics.

Methodology:

RIF-decomposition based on unconditional quantile regression (Firpo et al., 2009)

It allows to study determinants of wage quantiles growth in each country between period T=1 and T=0

$$\boldsymbol{Total\ Change\ in\ quatile\ p} = \Delta^{p} = q_1^p - q_0^p = E\left[RIF\left(y, q_t^p\right)|T=1\right] - E\left[RIF\left(y, q_t^p\right)|T=1\right] =$$

$$\sum_i \left[\left(\overline{Occ_{i1}} - \overline{Occ_{i0}}\right)\hat{\beta}_{i,0}^p + \overline{Occ_{i1}}\left(\widehat{\beta_{i,1}^p} - \widehat{\beta_{i,0}^p}\right)\right] + \left(\overline{X_1} - \overline{X_0}\right)\widehat{\gamma_0^p} + \overline{X_1}\left(\widehat{\gamma_1^p} - \widehat{\gamma_0^p}\right) =$$

$$= \boldsymbol{Occupational\ effect} + \boldsymbol{Covariates\ Effect}$$

Occ_{it} is a set of occupational class dummies (*i= service, routine, abstract*)

X is a set of controls (gender, age, education, industry affiliation).

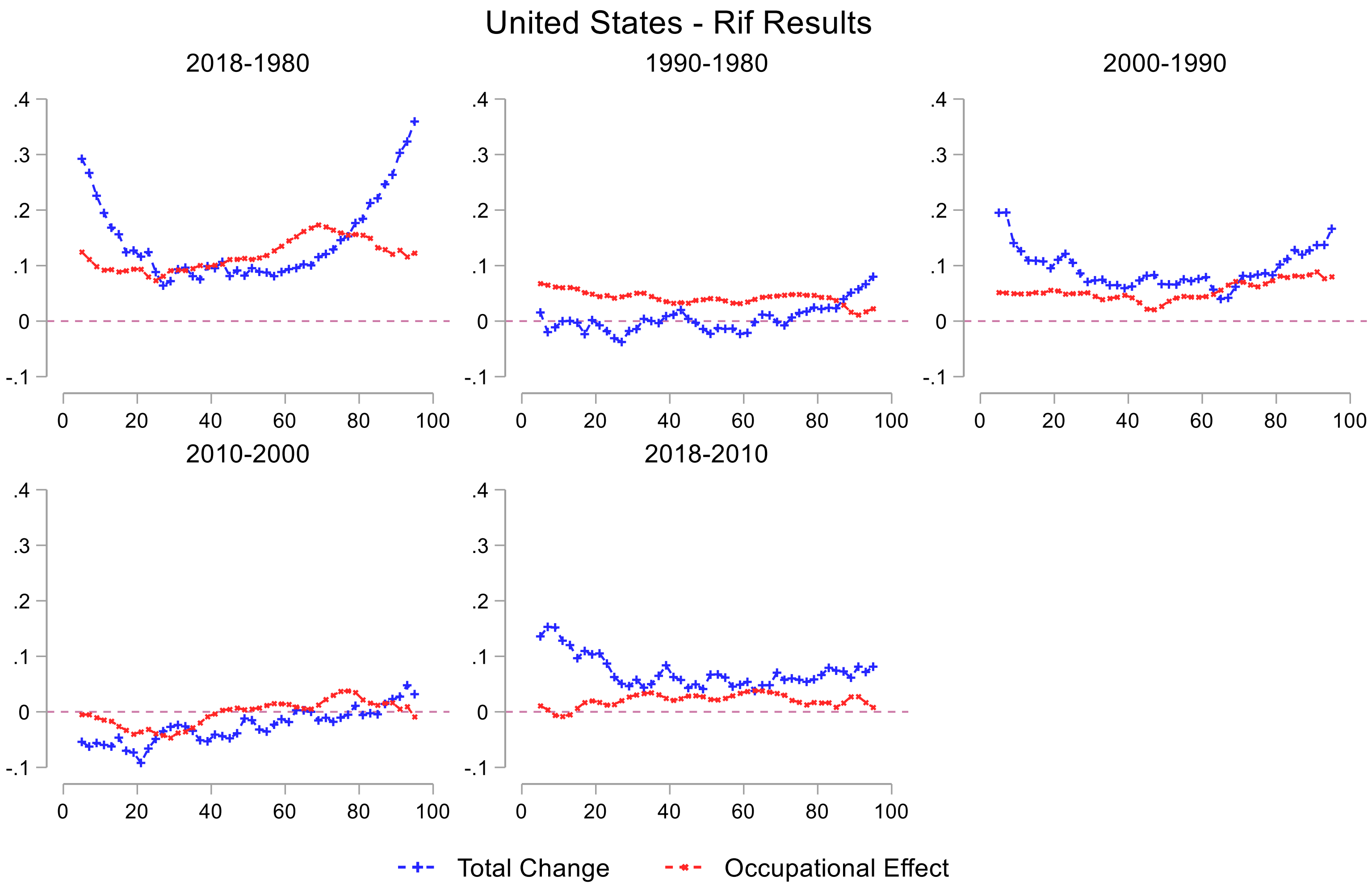
Two advantages:

1. Counterfactual interpretation of $\boldsymbol{Occupational\ effect}$
2. Accounts for variation ***between*** and ***within*** occupational classes.

Figure 6:

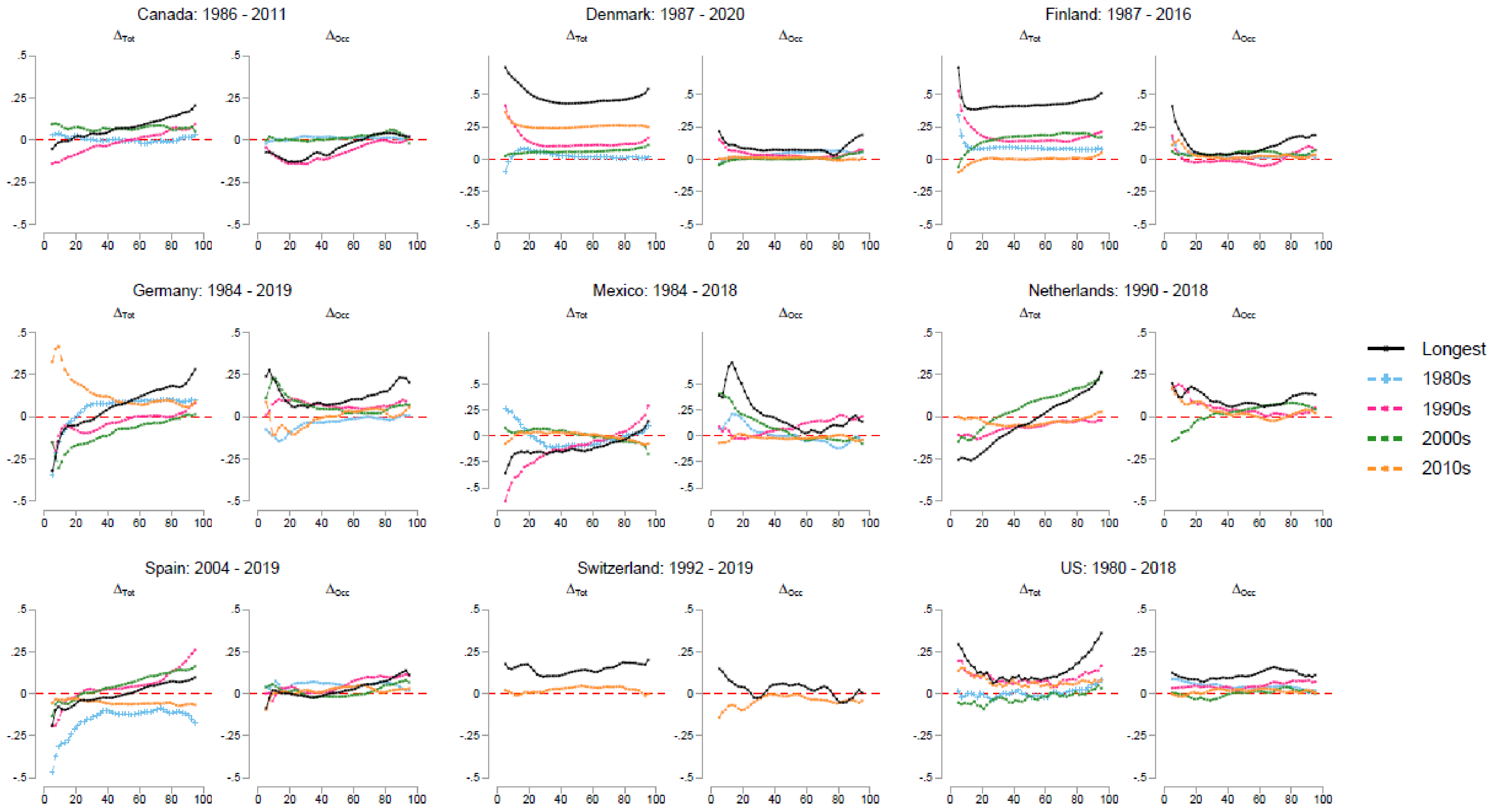
RIF decomposition based on UQR for **US**.

- Total Change: observed wage change at quantile *q*
- Occupational effect: counterfactual wage change at quintile q if only changes in occupational composition and returns would have happened.



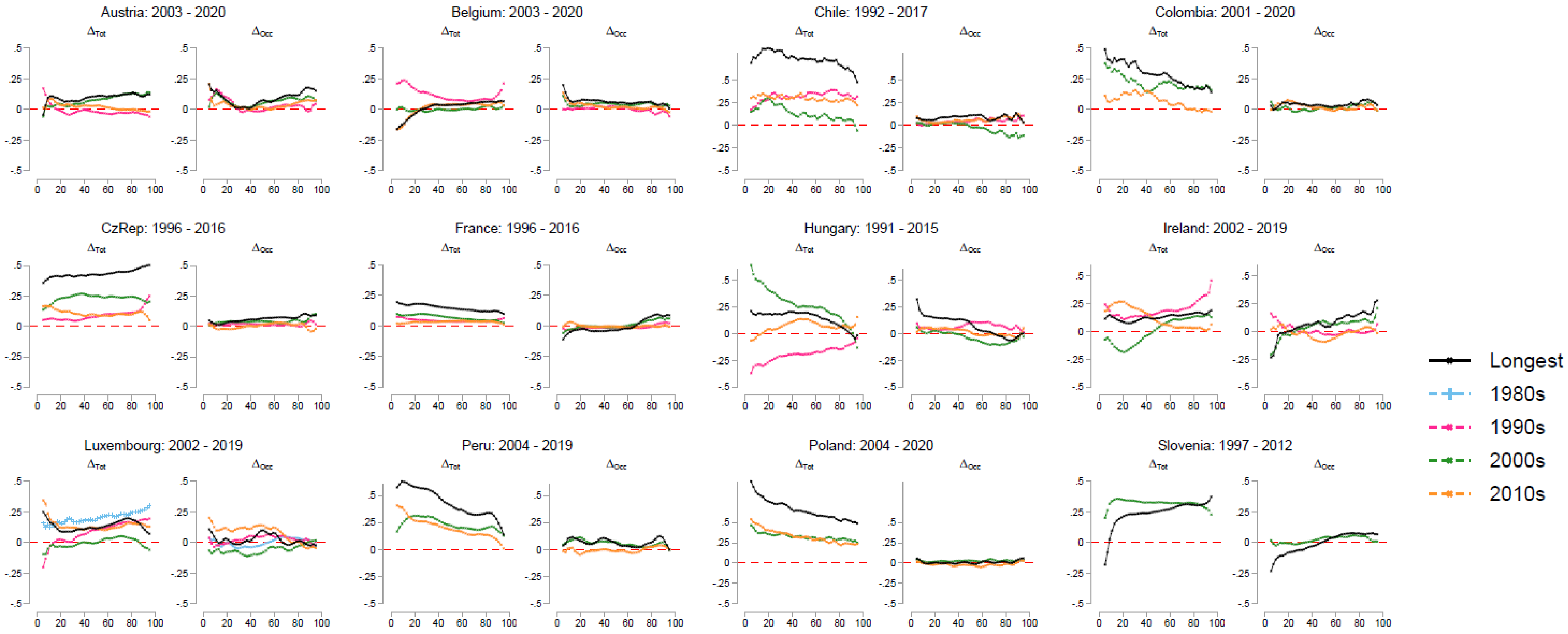
Result 5:

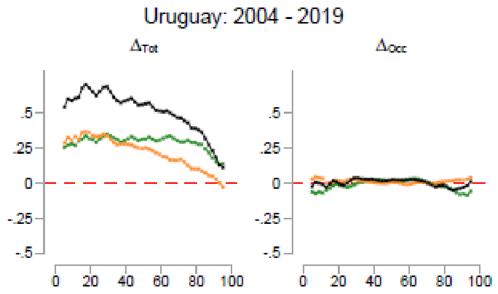
Job de-routinization does not explain the overall earnings growth (flat occupational effect), despite overall Earnings polarization (U-shaped total change)



Notes: Compiled by authors based on LIS data for the prime-age, employed population. For each country, the left panel shows the total percentile Earnings Growth (Δ^P) on the y-axis the left panel provides the counterfactual Occupational Effect (Δ^P_{Occ}) on the y-axis. Both panels show results, if available, for the longest time span, the 1980s, 1990s, 2000s, and 2010s, based on RIF quantiles decomposition explained in Section 4.2. The x-axis provides the percentiles of the earning distribution. Estimates are provided as rolling averages based on three percentiles, spanning from the 5th to the 95th percentile.

Figure 8: RIF Decomposition: Increasing Earnings Inequality





Notes: Compiled by authors based on LIS data for the prime-age, employed population. For each country, the left panel shows the total percentile Earnings Growth (Δ^P) on the y-axis the left panel provides the counterfactual Occupational Effect (Δ^P_{Occ}) on the y-axis. Both panels show results, if available, for the longest time span, the 1980s, 1990s, 2000s, and 2010s, based on RIF quantiles decomposition explained in Section 4.2. The x-axis provides the percentiles of the earning distribution. Estimates are provided as rolling averages based on three percentiles, spanning from the 5th to the 95th percentile.

Figure 9: RIF Decomposition: Constant and Decreasing Earnings Inequality

Conclusions:

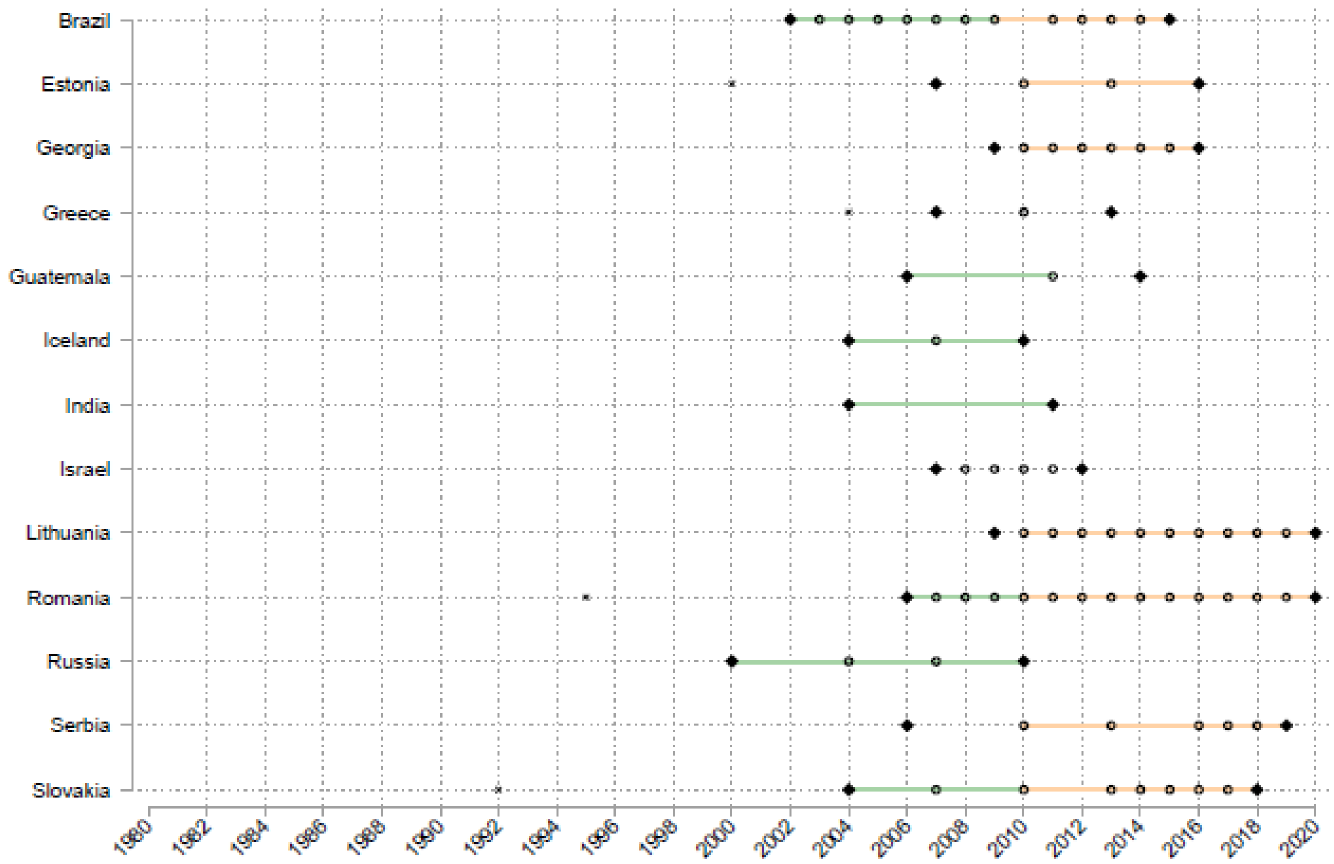
We find that de-routinization of jobs:

- is an international phenomenon **well explaining the observed shifts in employment shares** in the workforce.

- Has **weak distributional consequences**. This is due to:
  - Great heterogeneity **within** occupational classes. Despite a clear hierarchy in the returns of service, routine and abstract jobs, occupational classes are scattered along the whole distribution.
  - **Routine jobs are replaced along the entire distribution of jobs, and not just at the middle.**
  - 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, apriori, **ambiguous**.

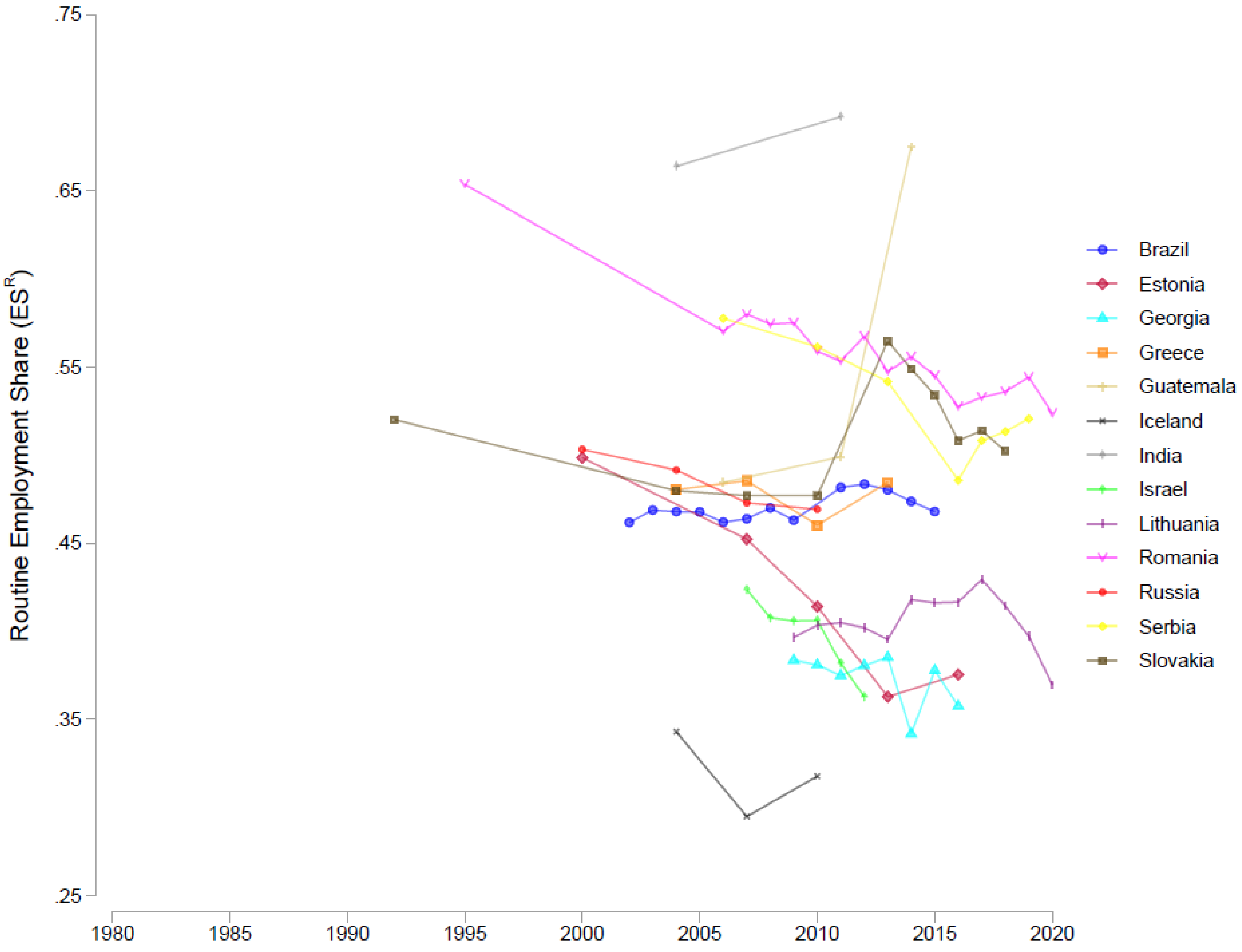
Thank You!

Appendix



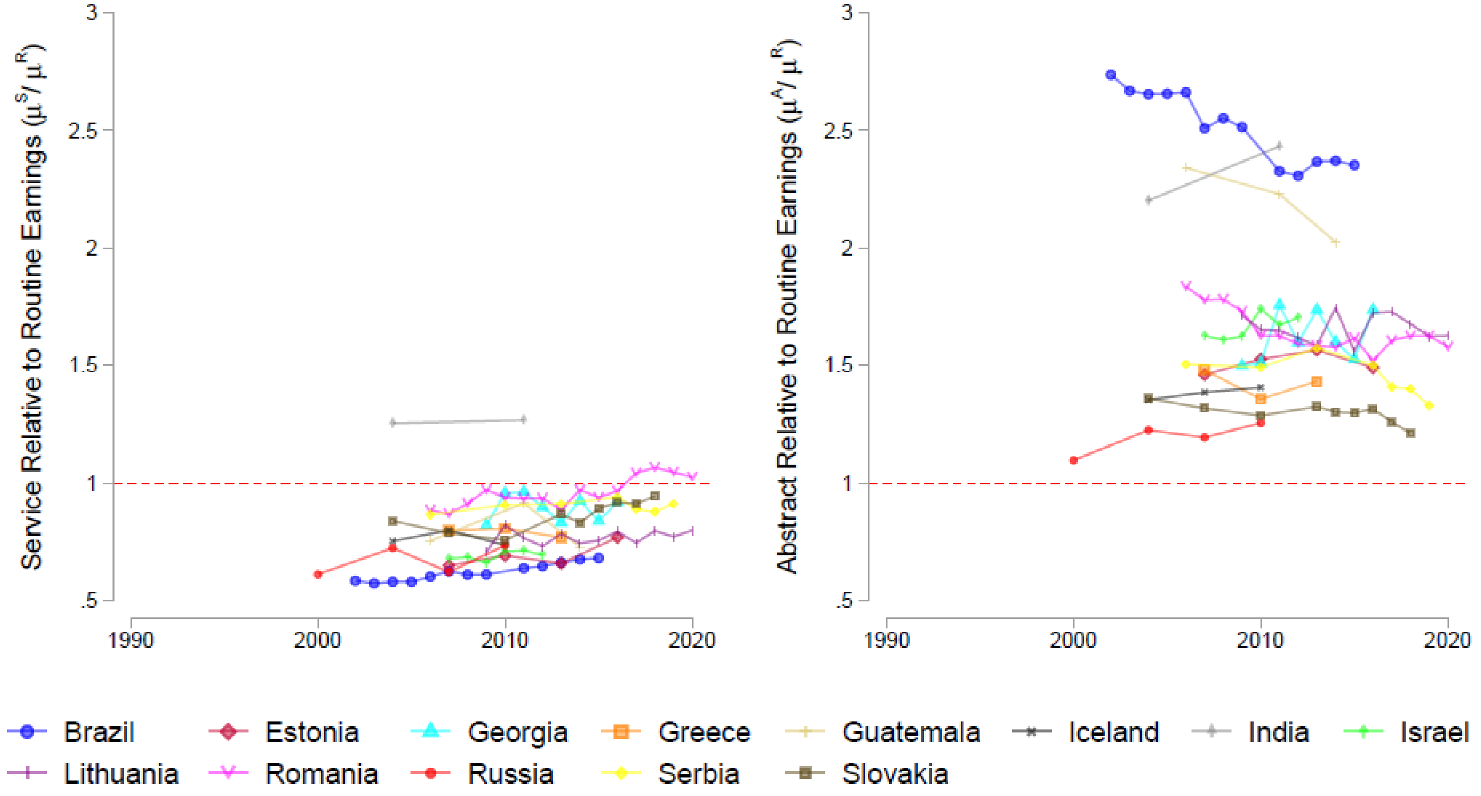
Notes: The figure shows a detailed overview of the country-specific waves used for the analysis. Dots represent waves with consistent earnings definitions (gross/net). Crosses mark those years in the country series that deviate from the core earnings definition and, therefore, cannot be directly compared with the former. Diamonds define the earliest and latest waves comparable for each country. Colored bars link survey waves used for the decade-specific RIF decomposition estimations. The 2000s are in green, and the 2010s are in orange. The figure depicts the 13 extended countries with a time frame of less than 15 years.

Figure A2: Working Sample: Extended Countries



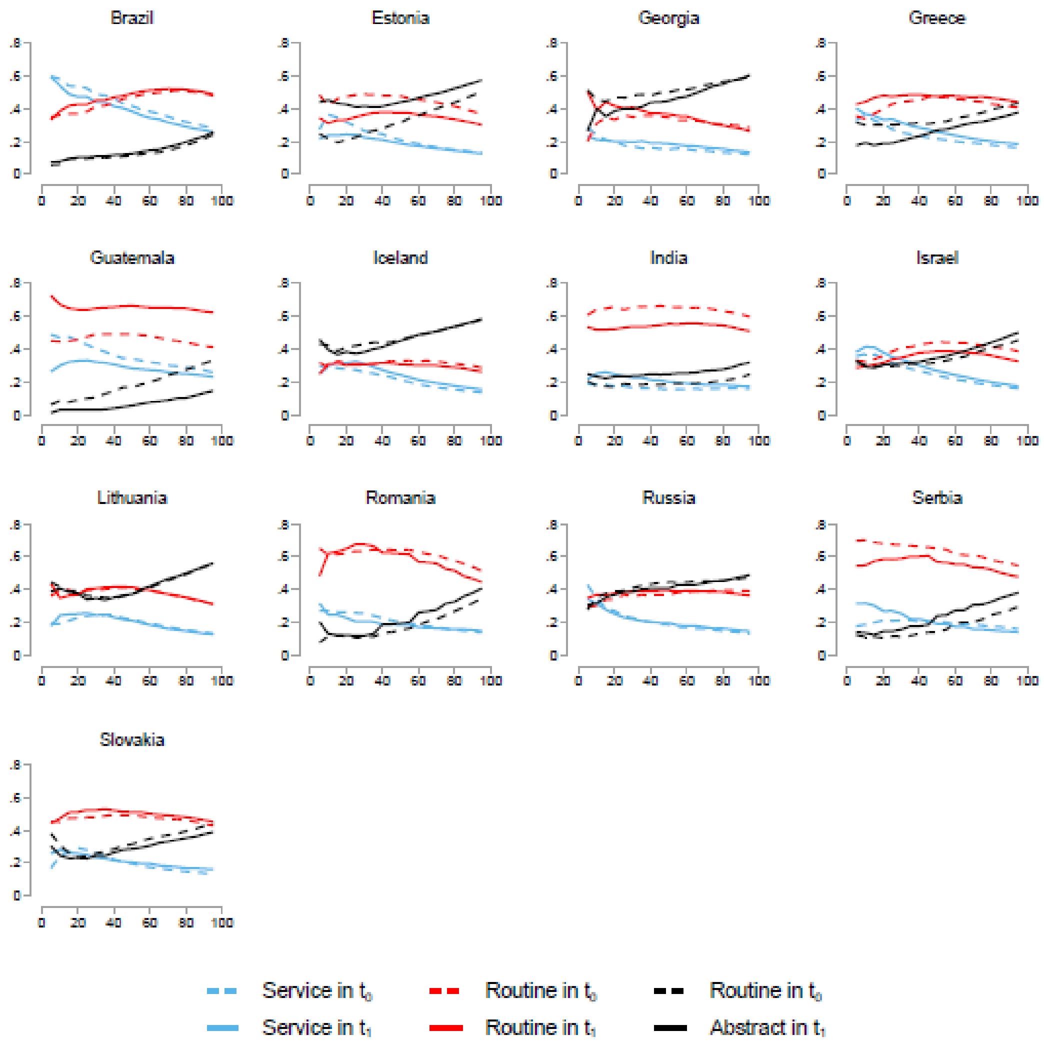
Notes: Compiled by authors based on LIS-ERF data for the prime-age, employed population. The y-axis shows the occupational share in routine occupation OS_t^R. The figure depicts the 13 extended countries with a time frame of less than 15 years.

Figure A3: Job De-routinization: Extended Countries



Notes: Compiled by authors based on LIS-ERF data for the prime-aged, employed population. The two plots provide the average earnings of occupational classes (left $\mu_t^{Service}$; right $\mu_t^{Abstract}$) divided by the average of routine occupations ($\mu_t^{Routine}$) in each year, respectively. Countries with a time frame of less than 15 years are depicted here.

Figure A4: Job Polarization: Extended Countries



Notes: Compiled by authors based on LIS-ERF data for the prime-aged, employed population. For each country, the figure depicts the occupational shares for service, routine, and abstract occupational classes. The dotted line presents the share at the fist year of observation, the line the most recent year. The x-axis provides the population ranked by the earnings quantiles.

Figure A6: Composition: Extended Countries

Notes: Compiled by authors based on LIS-ERF data for the prime-age, employed population. For each country, the left panel shows the total percentile Earnings Growth (Δ^P) on the y-axis the left panel provides the counterfactual Occupational Effect (Δ^P_{Occ}) on the y-axis. Both panels show results, if available, for the longest time span, the 1980s, 1990s, 2000s, and 2010s, based on RIF quantiles decomposition explained in Section 4.2. The x-axis provides the percentiles of the earning distribution.

Figure A8: RIF Decomposition: Extended Countries