Accounting for the role of occupational change on earnings in Europe and Central Asia

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This paper analyzes the process of occupational changes in seven countries from Europe, the former Soviet bloc and Turkey (Georgia, Germany, Kyrgyz Republic, Poland, Russia, Spain and Turkey) using harmonized household surveys in the last twenty years. As for the existing literature, this paper starts by providing an assessment of labor market polarization across these economies. It broadly confirms results from earlier studies: occupations polarization is clearer and stronger for richer, Western European countries, than for the emerging Eastern economies. The paper main original contribution, however, is to link the occupational shifts to the changes in the earnings distribution. Not having a panel data which would allow to 'follow' individuals before and after the occupational shock, the paper has to rely on decomposition techniques based on micro-simulated counterfactuals (Bourguignon and Ferreira, 2005, and Inchauste et al., 2014). Using cross-sectional surveys, the method estimates models of occupational outcomes and wages for an initial and final (before and after) period. Results of our analysis show that changes in rewards linking individual characteristics to occupational choices explain growth in non-routine, manual task intensive jobs in EU countries. This change appears to hurt particularly those with less than higher education, whose probability of working in routine task intensive occupations decrease and end up being up displaced to the growing but lower paid non-routine, manual task intensive occupations. In former Soviet countries and Turkey, changes in rewards linking characteristics to occupational choices explain the growth in routine task intensive jobs, which affects relatively more women and the high skilled, who end up working in occupations for which they are over-skilled. Changes in individuals' characteristics -notably the increase in education levels- account for the growth in non-routine, cognitive task intensive occupations across the whole region and have a somewhat progressive impact overall. Changes in wage returns to individuals' characteristics are roughly similar across the sample countries and imply a decrease in wage returns to higher education in routine, task intensive occupations and an increase of those same returns in non-routine, cognitive task intensive occupations. However, their distributional impact is different: they hurt the bottom deciles in part of the EU countries and the top deciles in former Soviet countries and Turkey. This heterogeneous pattern results from differences in the distribution of skills across the earning distribution between the EU and former Soviet countries and Turkey. Our results illustrate the complex reality of occupational change across Europe and Central Asia: whilst the patterns of EU countries show that routine task intensive occupations and the bottom deciles of the earnings distribution are particularly affected, in the Eastern part of the region the reverse is true – the top deciles of the distribution are negatively impacted by occupational change, which affects relatively more non-routine, cognitive task intensive occupations.

JEL Codes D31, J21, J24, J31

1. Introduction

Globalization, technological change, and education upgrading have transformed labor markets across the world and Europe and Central Asia was no exception. In particular, one can mention three developments in these markets. The first one is an increasing polarization of the labor market. Across most of the developed and developing world, the share of workers in middle-skilled occupations is shrinking, while the share of workers in low- and high- skilled jobs is expanding (World Development Report, 2016). The second one is the rise of non-standard employment. In many Europe and Central Asia countries, the share of workers in traditional jobs (i.e. permanent full-time salaried jobs) is declining, as the fraction of workers in temporary, part-time and online freelancing jobs is increasing . Third, across most countries, the labor share of GDP declined dramatically, which means that workers are getting a smaller share of total income than before (WDR, 2016).

In this paper, we examine the first one of these developments, i.e. the occupational change linked to the phenomenon of labor market polarization. There is a large body of literature documenting this issue for developed countries (Acemoglu and Autor, 2011; Goos, Manning and Salomons, 2014). Empirical evidence for developed economies suggests that the rise of digital technologies contributes to this phenomenon (Autor and Dorn, 2013; Goos and Manning, 2007; Goos, Manning and Salomons, 2009). Digital technologies tend to substitute middle-skilled routine jobs, and tend to complement high-skilled workers. This also tends to increase the share of low-skilled workers, because displaced middle-skilled workers are more likely to compete for low-skilled than for high-skilled jobs.

Empirical evidence on the labor market polarization of developing countries is very scarce. While the World Bank WDR (2016) shows that labor market polarization is pervasive in the developing world, studies that use detailed data on skills show a more nuanced picture. Hardy, Keister and Lewandowski (2016) find that in contrast to the US, jobs intensive in middle-skill routine cognitive tasks increased in most Central and Eastern European countries. They also find that educational upgrading and the declining share of agricultural jobs, rather than technology, were the main driver of these changes. Accordingly, Apella and Zunino (2017) find that the evolution of the skill content of jobs in Argentina and Uruguay was more similar to that of Central and Eastern European countries than to that of rich countries. Maloney and Molina (2016) used the same aggregate classification of the World Bank WDR (2016) and data from Population Censuses (as opposed to household surveys) and find that only in two out of twenty-one developing countries there is evidence of labor market polarization.

This paper analyzes the evolution of labor market earnings and the role accounted by occupational change in seven countries from Europe, the former Soviet bloc and Turkey (Georgia, Germany, Kyrgyz Republic, Poland, Russia, Spain and Turkey) using harmonized household surveys. As for the existing literature, this paper starts by providing an assessment of labor market polarization across these economies. It broadly confirms results from earlier studies: occupations polarization is clearer and stronger for richer, Western European countries, than for the emerging Eastern economies. The paper main original contribution, however, is to link the occupational shifts to the changes in the earnings distribution. The aim is to identify winners and losers from occupational changes and, more generally, to isolate its contribution to increases or decreases of inequality of earnings.

Not having a panel data which would allow to 'follow' individuals before and after the occupational shock, the paper has to rely on decomposition techniques based on micro-simulated counterfactuals (Bourguignon and Ferreira, 2005, and Inchauste et al., 2014). The methodology uses cross-sectional surveys on two different time periods and estimates models of occupational outcomes and wages for each period. Using the estimated models, it first simulates the occupational structure in the second period, under the assumption that the parameters of the model linking individual characteristics to labor market outcomes are identical to those of the initial year. This experiment tries to account for occupational changes driven by unobserved labor demand and supply factors. Second, it simulates the occupational structure in the second period under the assumption that the characteristics of the labor force (in terms of age, gender and education) did not change over time. This exercise tries to account for the share of occupational changes driven by factors such as changing age and gender composition of the labor force or educational upgrading. Using the simulated occupational structure, it creates a counterfactual earnings' distribution, assigning to each individual the predicted earnings of their simulated occupation. Finally, the model allows to simulate changes in earnings driven by changes in the earnings' returns to individual characteristics.

It is important to mention the caveat that the methodology does not allow to estimate the causal impacts of different factors on occupational choices or wages. Instead, the simulation provides an accounting exercise where the relative weights of different factors driving changes in occupations and earnings are evaluated.

This paper makes four important contributions. First, it provides evidence on the extent of labor market polarization for countries at different levels of economic development in Europe and Central Asia. It shows that while richer countries exhibited patterns of labor market polarization more similar to those of the United States, the picture is more mixed among middle- and low-income economies. These results are robust to using more detailed data on the skill content of occupations. Second, it provides new evidence on the drivers of such occupational changes. While the dynamics observed in richer countries are consistent with the hypothesis of digital technologies being the main driver, other factors seem more important for developing economies. For example, increasing labor force participation played a crucial role behind the changes in their occupational structure of Georgia and Turkey. Moreover, it finds that while changes in the characteristics of the labor force in developing countries account for most of the growth in high-skilled jobs, other supply and demand factors account for the rise in the share of low-skill jobs. Third, it investigates who are the winners and losers of the process of labor market polarization among richer countries, and who are the winners and losers of the process of occupational changes among developing economies. It finds that in the richer countries, educational attainment is an important determinant of occupational mobility. In contrast while education is also important for occupational upgrading in the Eastern part of the region, workers who move into non-routine manual occupations seem to be over-skilled with respect to incumbents in those occupations. Finally, to our knowledge, it is the first paper to show how occupational changes account for changes in earnings. Growth-incidence curves for Germany, Poland and Spain show that changes in earnings have been regressive, and the paper finds that labor market polarization helps explain an important share of this phenomenon. In contrast, occupational changes do not seem to explain the progressive changes in earnings experienced by Russia, Turkey, Kyrgyz and Georgia.

These results suggest that the process of labor market polarization experienced by countries in the west of ECA, and the process of occupational changes experienced by countries in the east, could be good candidates to explain negative perceptions of economic well-being that are prevalent in the region. At the same time, even though educational upgrading seemed to have been an important force behind the rise of high-skilled jobs across most countries, other unobservable factors outweighed this force. As a result, the overall increase in the share of high-skilled (low-skilled) jobs was lower (higher) than predicted by the increasing levels of educational attainment. Aspirations attached to a college degree may result in frustration if the link between educational attainment and job quality is weak.

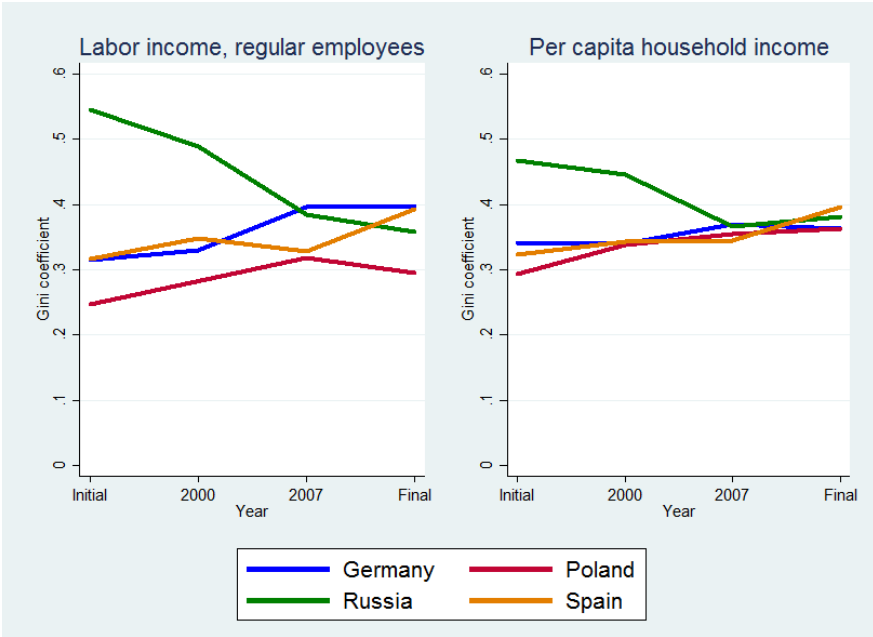
The rest of the paper is structured as follows. Section 2 illustrates the evolution of earnings inequality in the same period. Section 3 presents an overview of the changes in the occupational structure in Europe and Central Asia in the last twenty years. Section 4 presents the methodology used to decompose the changes in earnings in three components – occupational choice, individual characteristics and returns to characteristics. Section 5 details the evolution of the main variables explaining those components and section 6 presents the results of the decomposition analysis, making emphasis on the role of occupational change. Lastly, Section 7 concludes.

2. The evolution of earnings inequality in Europe and Central Asia

One of the characteristics of the changes in labor market inequality in the United States, and which has set the tone in public debate, is that of increasing wage polarization, by which we mean a growth in wages in both the lowest and highest quantiles of the earnings distribution. Ultimately, this results in a compression of earnings at the bottom of the distribution -since low quantiles gradually get close to the median- and an increasing dispersion at the top -since the highest quantiles gradually increase their difference with respect to the median. Autor and Acemoglu (2011) have linked this process of wage polarization to one of job polarization, which we will analyze more in detail in section 3. In any case, existing studies on this issue in Western Europe find limited evidence of a process of wage polarization (Ragusa et al., 2014). In this section we intend to analyze further this issue in the context of the seven countries of our study.

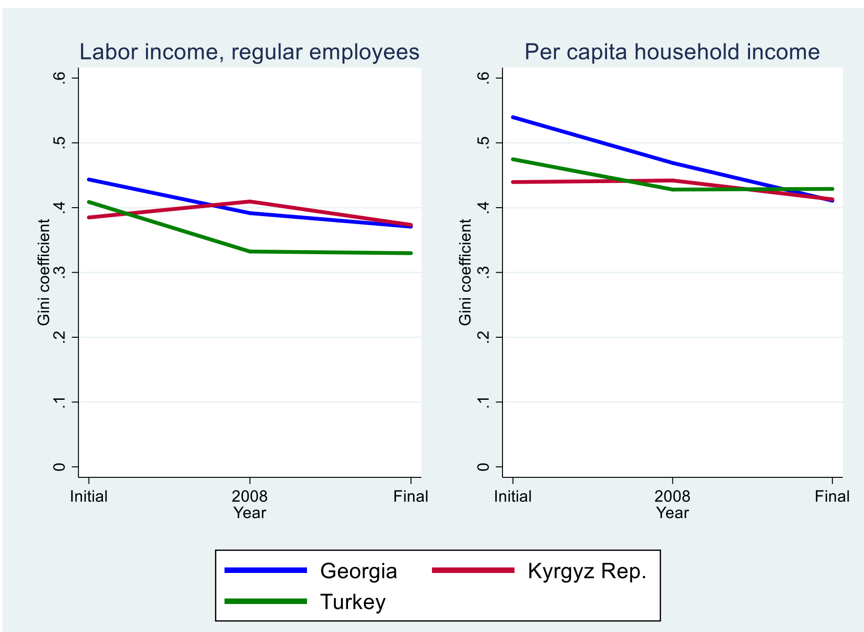
Figures 1.a and 1.b present the evolution of the Gini coefficient for labor income of regular employees and for per capita household income in the seven countries of our study. As in the previous section, we can distinguish two broad patterns: on the one hand, Germany, Poland and Spain see an increase in labor income inequality over the time frame under analysis – about 8 points in the Gini coefficient for Germany and Spain and 5 points in Poland. This is increase also present in household income inequality, albeit of a slightly smaller magnitude – 7 points in Poland and Spain and 3 points in Germany. On the other hand, Russia, Georgia, the Kyrgyz Republic and Turkey witness a decrease in both labor income and household income inequality.

Figure 1.a – Evolution of inequality



Source: own elaboration based on LIS and RLMS. This figure shows the evolution of the Gini coefficient of labor income (only regular employees, excluding self-employed) and of per capita household income (monetary) for four countries. Initial year is 1994 for Germany and Russia, 1992 for Poland and 1990 for Spain. Final year is 2013 for Germany, Poland and Spain and 2014 for Russia.

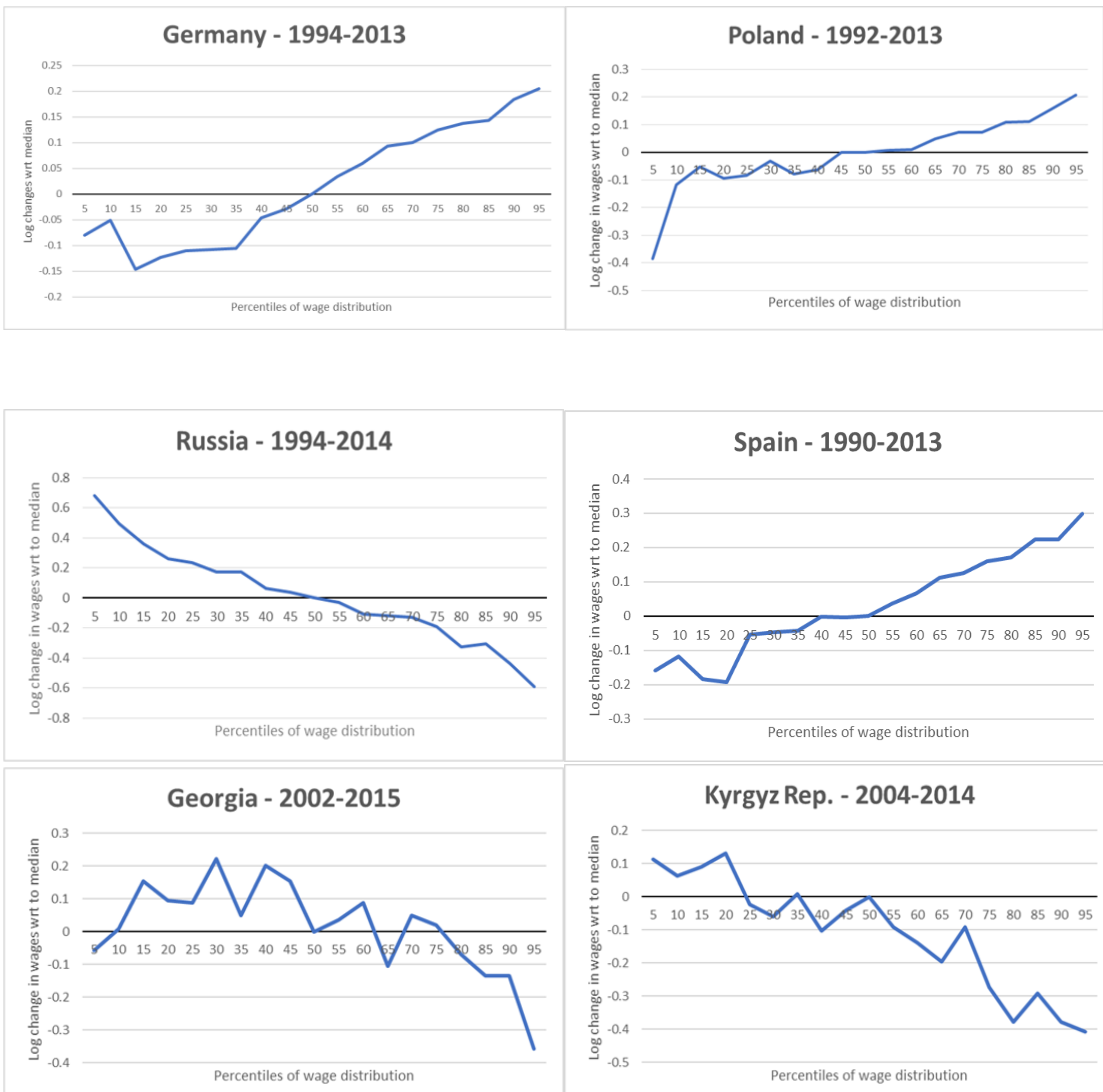
Figure 1.b – Evolution of inequality

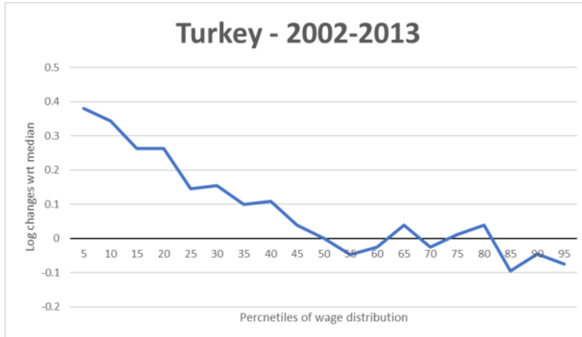


Source: own elaboration based on GIS, KHIZ and Turkey LFS/HICES. This figure shows the evolution of the Gini coefficient of labor income (only regular employees, excluding self-employed) and of per capita household income (monetary) for three countries. Initial year is 2002 for Georgia, 2004 for the Kyrgyz Republic and 2002 for Turkey (2003 for household income). Final year is 2015 for Georgia, 2014 for the Kyrgyz Republic and 2013 for Turkey.

The Gini coefficient is a summary measure of the inequality and its evolution may hide some dynamics happening in different points of the earnings distribution. In this sense, it is relevant to analyze how actual earnings changed in each quantile of the distribution over the time frame under study. In the different panels of Figure 2 we present the log change in wages from the initial to the final period for the countries in our study; we normalize the change to zero for the median so as to better capture the specific dynamics of different parts of the distribution.

<u>Figure 2 – Change in wages by quantiles of wage distribution</u>





These set of figures plot the log change in wages for the different ventiles of the wage distribution from the initial period to the final period. Changes are expressed with respect to the median, whose change is normalized to zero. Only the wage of regular employees is considered in this analysis. The irregular pattern of the figures of Georgia and the Kyrgyz Republic result from the limited sample size in those countries.

The evidence suggests that in none of the countries in our study -except, slightly, for Germany- there is a process of wage polarization, by which wages in the extremes of the distribution increase more than those of the middle. In almost all the cases the change is monotonous, either in a regressive direction, where bottom quantiles lose relative to the median and top quantiles gain (like in Germany, Poland and Spain), or in a progressive direction, where bottom quantiles gain relative to the median and top quantiles lose (like in Georgia, the Kyrgyz Republic, Russia and Turkey).

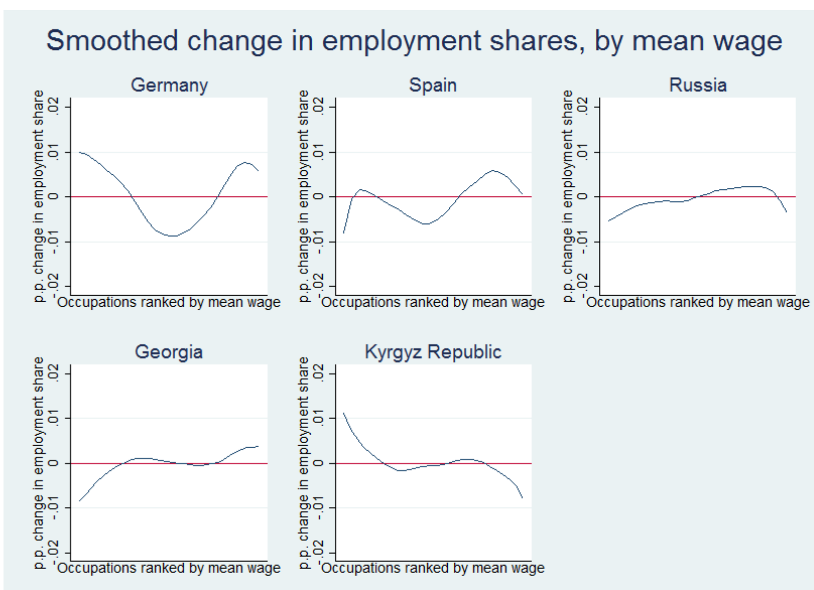
To the point that wage polarization in the US has been linked to job polarization, one could then expect that given the absence of the former in the countries under analysis, then the latter will also be absent. However, as we will see, some countries did actually see a certain degree of job polarization. In order to better understand this, the next section will analyze the changes that the occupational structure has undergone in the seven countries under study.

3. Changes in occupational structure in Europe and Central Asia: Job polarization?

One of the main features of the changes in occupational structure in the United States and Western Europe in the last three decades has been the growth of both “lousy” and “lovely” jobs (Goos and Manning, 2007), a phenomenon more commonly called job polarization. For the purpose of our study, we are interested in understanding to which extent is this phenomenon also present in the wider region of Europe and Central Asia. To do so, we will analyze seven countries that are representative of the different levels of development that are present in the region: Georgia, Germany, the Kyrgyz Republic, Poland, Russia, Spain and Turkey. Due to data limitations, the time frame covered by our study is different for every country. For Germany, Poland, Russia and Spain, we will cover the roughly twenty years between the first half of the 1990s and the first half of the 2010s. For Georgia, the Kyrgyz Republic and Turkey, our analysis will cover the ten years between the first half of the 2000s and the first half of the 2010s. In the Appendix section 1 we describe in detail the data sources and variable definitions of our analysis.

Job polarization has typically been defined as the simultaneous growth of the share of employment in high skill, high wage occupations and low skill, low wage occupations (Acemoglu and Autor, 2011). This definitions entails, first of all, establishing an ordering of the occupations according to their wage or skill level. Since at any given moment in time the correlation between wages and years of schooling (a proxy of skill level) is ordinally stable, some authors have used mean wages as the ranking variable of occupations when analyzing changes in the occupational structure (Goos, Manning and Salomons, 2014). We apply this definition to five of the seven countries in our study for which we are able to obtain occupation data disaggregated at the 2-digit level of the ISCO 88 classification[1]. We order occupations according to their mean wage in the initial year and plot their change in the employment share in the time period that followed.

Figure 3



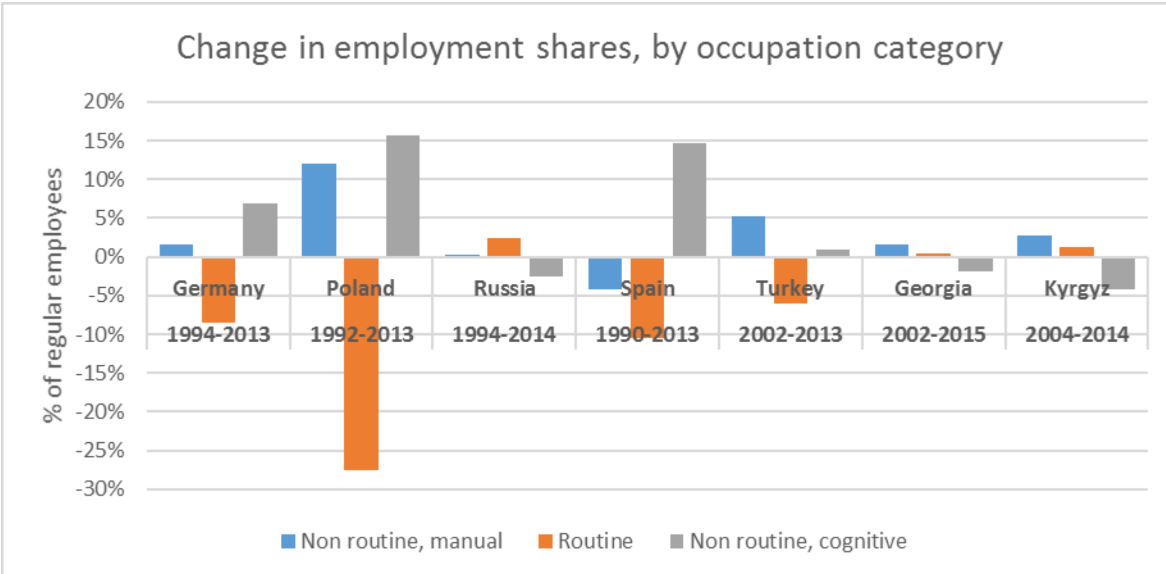
[1] In the case of Poland we don’t have occupation data at the ISCO 2-digit level for the initial year (1992) but we do have it for the final year (2013). In the case of Turkey, the survey which we use as main data source only records occupation data at the 1-digit level.

This figure plots the percentage point change in employment shares from the initial year (1990 for Spain, 1994 for Germany and Russia, 2002 for Georgia and 2004 for the Kyrgyz Republic) to the final year (2013 for Germany and Spain, 2014 for the Kyrgyz Republic and Russia, 2015 for Georgia) by occupations ranked according to their mean wage in the initial year. The changes are plotted by a locally weighted smoothing regression. Occupations are aggregated to the 2-digit level of the ISCO 88 classification.

As Figure 3 shows, there is evidence of job polarization under this definition only for Germany and somewhat for Spain. The rest of the countries show relatively heterogeneous patterns: in Georgia low paid jobs see a decrease in their share of employment, whilst high paid jobs witness an increase. Russia has a similar pattern albeit with changes of a smaller magnitude, with top paid jobs even decreasing. The reverse situation is happening in the Kyrgyz Republic, where low paid jobs have seen an increase in their share of employment and high paid jobs a decrease.

As wages vary across countries, this ordering of occupations is, thus, country-specific: an occupation may be highly paid in a given country but low paid in another and vice versa. In this sense, the plots of Figure 1 are not informative of what type of occupations are increasing or decreasing in relative importance from a cross-country point of view. A different way of looking at changes in occupational structure that allows for a cross-country comparison is to group occupations according to their task content. Following Acemoglu and Autor (2011)'s conceptual framework, we classify occupations into three categories: occupations relatively intensive in routine tasks, occupations relatively intensive in non-routine cognitive tasks and occupations relatively intensive in non-routine manual tasks. Note that any occupation implies carrying out both routine and non-routine tasks and both cognitive and manual tasks since they are not mutually exclusive: as described more in detail in the Appendix section 2, we group occupations according to the relative intensity of these tasks. To the point that occupations intensive in routine tasks are understood to be mid-skill occupations, job polarization has also been defined as the decline in the employment share of these occupations vis-à-vis an increase in the employment share of occupations intense in non-routine, cognitive tasks -high skill jobs- and in non-routine, manual tasks -low skill jobs-. The 2016 edition of the World Development Report uses this definition of labor market polarization in order to show evidence of the phenomenon across high income and developing countries. In Figure 4 we present the changes in the employment share of each of the three occupation categories for the countries in our study.

<u>Figure 4</u>

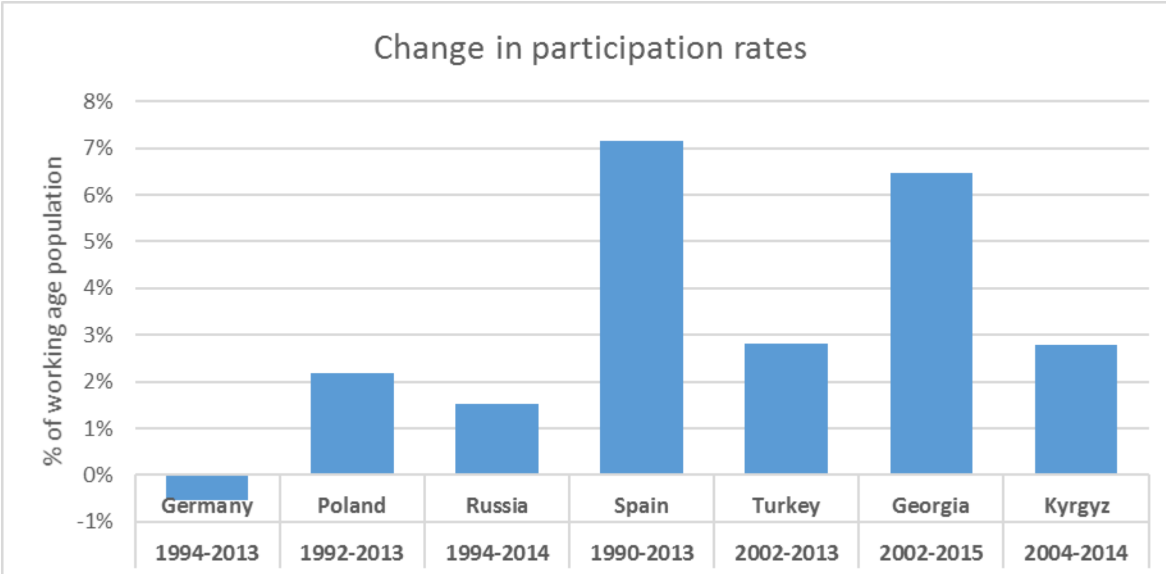


This figure shows the change, in percentage points, of the share of employment (regular employees, excluding self-employed) over a period of ten or twenty years of the three occupations categories: in blue, occupations relatively intensive in non-routine, manual tasks; in orange, occupations relatively intensive in routine tasks; in grey, occupations relatively intensive in non-routine, cognitive tasks. The time period depends on data availability. For more details on the construction of the occupation categories please see the appendix.

The evidence shows that, under this definition, job polarization is present in Germany, Poland, Turkey and up to a certain degree also in Spain, where occupations intense in non-routine, manual tasks decline in their share of employment but in a smaller magnitude than routine task intensive occupations. In these three countries de-routinization seems to be a common trend, a pattern that is shared with the United States – although in Turkey the growth in non-routine employment has been stronger in jobs intensive in manual tasks rather than in cognitive tasks. For the remaining countries the common factor is the opposite: jobs intensive in routine tasks are actually growing in their employment share, whilst jobs intensive in non-routine, cognitive tasks are declining. Jobs intensive in non-routine, manual occupations are increasing their employment share in Georgia and the Kyrgyz Republic, whilst they see almost no change in Russia.

The change in employment shares is nuanced if we take into account the fact that the labor force participation rate has actually increased in six out of the seven countries in our sample, as figure 5 shows.

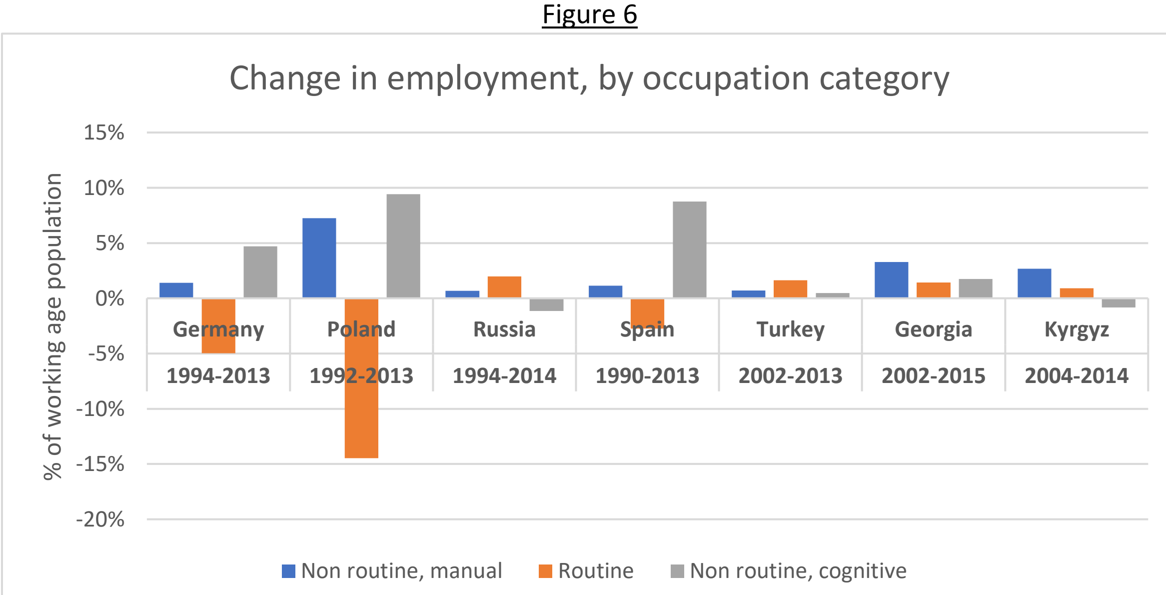
Figure 5



This figure shows the change, in percentage points of the working age population, of the share of employed people over a period of ten or twenty years.

In Figure 6 we express the changes in the employment of the three occupation categories as percentage points of the working age population. The picture remains mostly unchanged for Germany and Poland, whilst in Spain the great increase in the participation rate actually results in an increase in the share of people employed in non-routine, manual task intensive jobs. In Georgia and Turkey all the three occupation categories witness an increase in the share of people employed, and in the Kyrgyz Republic the decrease in employment in non-routine, cognitive task intensive jobs is much smaller. In any case, the main stylized facts hold: evidence of job polarization in Germany, Poland and Spain, whilst a different kind of occupational change taking place in the post-Soviet countries and Turkey – increase in participation rates and employment growth concentrated in non-routine, manual task intensive and routine task intensive occupations.

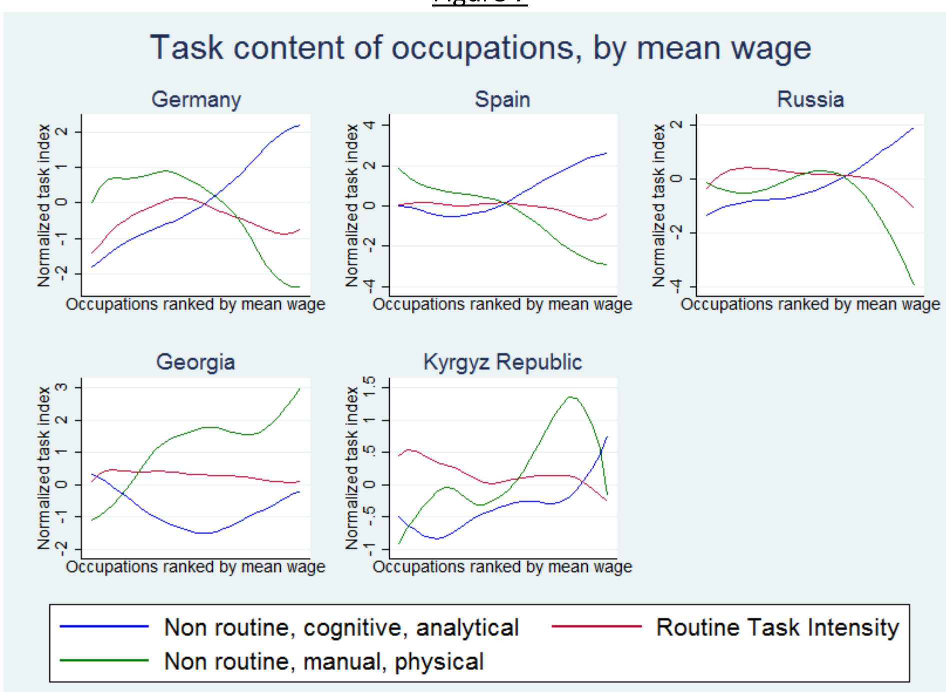
Figure 6



This figure shows the change, in percentage points, of the share of working age people employed in three occupations categories over a period of ten or twenty years: in blue, occupations relatively intensive in non-routine, manual tasks; in orange, occupations relatively intensive in routine tasks; in grey, occupations relatively intensive in non-routine, cognitive tasks. The time period depends on data availability. For more details on the construction of the occupation categories please see the appendix.

The contrasting results between both definitions of job polarization suggest strong differences in the correlation between the task content of jobs and their wages across countries. In order to further explore this relationship we plot in Figure 7 the task content indices underlying our three-group categorization and rank occupations according to their mean wage as in Figure 3. The difference between countries is striking. For Germany, Russia and Spain non-routine, cognitive task intensity is higher for jobs at the top of the wage distribution whilst routine task intensity is higher in the middle and the bottom of the distribution. This correlation explains why the evidence for Germany and Spain in Figures 1 and 2 is coincidental: the jobs in the middle of the wage distribution are routine task intensive jobs and are the ones that are losing an important share of employment. It also reflects the decrease in non-routine, cognitive intensive jobs in Russia that is seen in Figure 4. For Georgia and the Kyrgyz Republic we see a particularly interesting reversion of this pattern: non-routine, manual task intensity is particularly high in the top of the wage distribution, routine task intensity is high at the bottom and non-routine, cognitive task intensity show a "U" shaped like pattern.

Figure 7



This figure plots three task content indices of occupations ranked by their mean wage in the initial period as in Figure 1. The three task content indices (intensity in non-routine, cognitive, analytical tasks; intensity in non-routine, manual, physical tasks; routine task intensity) are normalized to their economy-wide means. The indices are plotted by a locally weighted smoothing regression. Occupations are aggregated to the 2-digit level of the ISCO 88 classification

The evidence of Figure 6 is mirrored in Table 1, where we present the mean wages for each of the three task-based occupation categories, expressing them as the ratio over the mean wage of routine intensive jobs. In Georgia, the Kyrgyz Republic and Russia the mean wages are of the three categories are very close to each other and in the initial period, jobs intensive in non-routine, cognitive tasks are actually paid on average less than routine intensive jobs in Georgia and the Kyrgyz Republic[2]. In Germany, Spain and Turkey wages are more dispersed across categories: wages in non-routine, cognitive task intensive jobs are paid up to three times the amount of those intensive in non-routine, manual tasks, whilst routine intensive jobs are in the middle. The pattern of Poland is similar to the one of Germany and Spain in 2013 but is similar to that of post-Soviet countries in 1992, suggesting a move between two different wage structures as a result of transition to market economy. In this sense, the evidence points to a different task-wage structure across the region: on the one hand, a very compressed wage structure in the post-Soviet countries, where non-routine, cognitive intensive jobs are paid only slightly more than the other two occupation categories. On the other hand, in Germany, Poland, Spain and Turkey the wage structure is more dispersed, and non-routine, cognitive intensive jobs are paid considerably higher than the rest of the jobs..

Table 1 – Mean wage by occupation category

	Germany		Poland		Spain		Georgia		Kyrgyz Republic		Russia		Turkey	
	1994	2013	1992	2013	1990	2013	2002	2015	2004	2014	1994	2014	2002	2013
Non routine, manual	0.697	0.569	0.727	0.719	0.746	0.651	1.033	0.771	0.859	0.997	0.882	0.880	0.811	0.835
Routine	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Non routine, cognitive	1.450	1.530	1.021	1.408	1.502	1.508	0.850	1.194	0.980	1.083	1.178	1.234	1.941	1.857

This table presents the mean wage of each occupation category expressed as a ratio over routine task intensive jobs. Wages are recorded in annual terms. See data appendix for more details on variable definition.

In conclusion, the combination of the evidence presented in Figures 3, 4 and 7 suggests that there are broadly two types of changes in occupational structure undergoing in Europe and Central Asia. On the one hand, countries in the Western end of the region, including an Eastern Europe, are clearly witnessing a process of de-routinization and consequent job polarization, where low paid, low skill jobs are increasing simultaneously with high paid, high skill jobs, whilst routine intensive, middling jobs are gradually disappearing. On the other hand, post-Soviet countries are seeing a growth in the employment share of routine intensive jobs, whilst jobs intensive in non-routine, cognitive jobs are actually decreasing. Moreover, another important difference between these two broad groups of countries is that, whilst in EU countries the correlation between task content of jobs and wages is similar to the one seen in the United States -where routine task intensity is higher for middle wage jobs-, in post-Soviet countries routine task intensive jobs are in some cases paid higher wages than jobs intensive in non-routine, cognitive tasks. This configures a situation in which distributional tensions stemming from occupational change may emerge in completely different ways across Europe and Central Asia.

[2]In these countries, for instance, teaching professionals are located in lower deciles of the wage distribution than drivers and mobile plant operators. See Appendix section 3 for a more detailed illustration of this phenomenon.

4. Methodology for decomposing changes in the earnings distribution[3]

The starting point of our analysis is the observed change in the distribution of earnings between t and t'. Let $f^t(y)$ and $f^{t'}(y)$ the density functions of the distribution of earnings y in both moments of time. Our focus is to identify the factors that account for the change between the first and the second distribution.

We can define $f^\tau(y)$ (where τ is alternatively t and t') as the marginal distribution of the joint distribution $\varphi^\tau(y, X)$ where X is a vector of observed individual or household characteristics (like the occupation, education, age, gender)n and, denoting $g^\tau(y|X)$ the distribution of earnings conditional on X, we obtain the following expression

$$f^\tau(y) = \iint_{C(X)} g^\tau(y|X)\ \chi^\tau(X)\, dX \quad (1)$$

Where the summation is over the domain $C(X)$ on which X is defined and $\chi^\tau(X)$ is the joint distribution of all elements of X at time τ. We can then express the change from $f^t(y)$ to $f^{t'}(y)$ as a function of the change in the two distributions appearing in equation (1) – the distribution of earnings conditional on characteristics X, $g^\tau(y|X)$, and the distribution of these characteristics, $\chi^\tau(X)$. To do so, we define the following counterfactual experiment:

$$f_g^{\,t\to t'}(y) = \iint_{C(X)} g^{t'}(y|X)\ \chi^t(X)\, dX \quad (2)$$

This distribution represents what would have been observed at time t if the distribution of earnings conditional on characteristics, $g^\tau(y|X)$, had been that observed in time t'. Similarly, we can define the following counterfactual experiment:

$$f_\chi^{\,t\to t'}(y) = \iint_{C(X)} g^{t}(y|X)\ \chi^{t'}(X)\, dX \quad (3)$$

This distribution represents what would have been observed at time t if the distribution of characteristics, $\chi^\tau(X)$, had been that observed in time t'. Note that this distribution could also have been obtained starting from period t' and replacing the conditional earnings distribution of that period by the one observed in period t. In this sense, the following identities can be defined:

$$f_g^{\,t\to t'}(y) \equiv f_\chi^{\,t'\to t}(y) \ \text{ and } \ f_\chi^{\,t\to t'}(y) \equiv f_g^{\,t'\to t}(y) \quad (4)$$

We can thus decompose the observed distributional change $f^t(y) - f^{t'}(y)$ into

$$f^t(y) - f^{t'}(y) = [\, f_g^{\,t\to t'}(y) - f^t(y)] + [f^{t'}(y) - f_g^{\,t\to t'}(y)] \quad (5)$$

The first term on the right hand side of equation (5) describes the way in which the distribution of earnings has changed over time because of the change in the distribution conditional on characteristics X. It shows how the same distribution of characteristics -that of period t- would have resulted in a different earnings distribution has the conditional distribution $g^\tau(y|X)$ been that of period t'. To see that the second term is indeed the effect of the change in the distribution of characteristics X that took place between times t and t', we can use equation (4) and rewrite the decomposition as:

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[3] This section draws heavily from Bourguignon and Ferreira (2005)

$$f^t(y) - f^{t'}(y) = [\, f_g^{\,t \to t'}(y) \; - f^t(y)] \; + [f^{t'}(y) - f_X^{\,t' \to t}(y)] \quad (6)$$

We can thus decompose the change in the distribution of earnings over time in a *rewards* component - the first term on the right hand side of equation (6) – and an *characteristics* component -the second term on the right hand side of equation (6). This is similar to a standard Oaxaca-Blinder decomposition but, instead of referring just to the means of the distributions, this decomposition refers to the full distributions. The only restrictive property of this decomposition method is its path dependence: changing the conditional income distribution from the one observed in *t* to the one observed in *t'* does not have the same effect on the distribution when this is done with the distribution of characteristics *X* observed in *t*, as when *X* is observed in *t'*.

For the purpose of our study we will rely on a parametric representation of the distributions used for defining counterfactuals. Moreover, in order to better understand the role played by changes in occupational structure, we will model occupational choice rather than treating occupations as a simple individual characteristic. Suppose we can partition the vector of individual characteristics in *(O, W)*, where *O* is the occupation of the individual and *W* are other exogenous individual and household characteristics. A general parametric representation of the conditional functions $g^\tau(y|O,W)$ and $h^\tau(O|W)$ relate the earnings *y* to occupation *O* and characteristics W, on the one hand, and relates occupations *O* to characteristics *W*, on the other hand, according to some predetermined functional form. These relationships may be denoted as follows:

$$y = G[O, W, \varepsilon;\ \Omega_\tau]$$

$$O = H[W, \eta;\ \Phi_\tau]$$

Where Ω_τ and ϕ_τ are sets of parameters: we will call Ω_τ the set of *returns to characteristics* and ϕ_τ the set of *occupation structural parameters* that link individual characteristics *W* to occupation *O* – they represent the conditional correlations of characteristics to occupational choice and can reflect, for instance, the technological equilibrium matching skills to occupations. Also ε and η are random variables and play a role similar to the residual term in standard regressions as they represent the dispersion of earnings *y* and occupations *O* for given values of *(O,W)* and *W* respectively. They are also assumed to be distributed independently of these characteristics according to density functions $\pi^\tau(\ )$ and $\mu^\tau(\ )$. With this parametrization, the marginal distribution of earnings in period τ may be written as follows:

$$f^\tau(y) = \int_{G(O,W,\varepsilon;\,\Omega_\tau)=y} \pi^\tau(\varepsilon)\, d\varepsilon \;\times\; \left[\int_{H(W,\eta,\Phi_\tau)=O} \mu^\tau(\eta)\, d\eta\right] \Psi^\tau(W)\, dO\, dW \qquad (7)$$

Counterfactuals may be generated by modifying some or all of the parameters in sets Ω_τ and ϕ_τ the distributions $\pi^\tau(\ )$ and $\mu^\tau(\ )$, or the joint distribution of exogenous characteristics $\Psi^\tau(W)$. These counterfactuals may be defined as follows:

$$D[\Psi, \pi, \eta; \Omega, \Phi] = \int_{G(O,W,\varepsilon;\,\Omega)=y} \pi(\varepsilon)\, d\varepsilon \;\times\; \left[\int_{H(W,\eta,\Phi)=O} \mu(\eta)\, d\eta\right] \Psi(W)\, dO\, dW \qquad (8)$$

Where any of the three distributions π( ), μ( ), Ψ( ) and the two sets of parameters Ω and ϕ can be observed at time *t* or *t'*. For instance $D[\Psi_t, \pi_t, \mu_t; \Omega_{t'}, \phi_t]$ refers to the distribution of earnings obtained by applying to the population observed at time *t* the set of returns to characteristics of time *t'* while keeping constant the distribution of the random residual term ε and all that is concerned with the variables *O* and *W*. Thus, the contribution of the change in parameters from Ω_t to $\Omega_{t'}$ may be measured by the difference between

$D[\Psi_t, \pi_t, \mu_t; \Omega_{t'}, \phi_t]$ and $D[\Psi_t, \pi_t, \mu_t; \Omega_t, \phi_t]$, which is $f^t(y)$. But, of course, other decomposition paths may be used. For instance the comparison may be performed using the population at time *t'* as reference, in which case the contribution of the change in parameters Ω would be given by $D[\Psi_{t'}, \pi_{t'}, \mu_{t'}; \Omega_{t'}, \phi_{t'}] - D[\Psi_{t'}, \pi_{t'}, \mu_{t'}; \Omega_t, \phi_{t'}]$. In order to address this problem, our strategy will be to consider both paths and estimate the "average" contribution of – referred to as a Shapley-value approach.

In our study, the decomposition path of the changes between $f^t(y)$ and $f^{t'}(y)$ we will use will be the following:

$$f^{t'}(y) - f^t(y) = \{D[\Psi_{t'}, \pi_{t'}, \eta_{t'}; \Omega_{t'}, \Phi_t] - f^{t'}(y)\} +$$
$$\{D[\Psi_t, \pi_{t'}, \eta_{t'}; \Omega_{t'}, \Phi_t] - D[\Psi_{t'}, \pi_{t'}, \eta_{t'}; \Omega_{t'}, \Phi_t]\} +$$
$$\{ D[\Psi_t, \pi_{t'}, \eta_{t'}; \Omega_t, \Phi_t] - D[\Psi_t, \pi_{t'}, \eta_{t'}; \Omega_{t'}, \Phi_t]\} +$$
$$\{f^t(y) - D[\Psi_t, \pi_{t'}, \eta_{t'}; \Omega_t, \Phi_t]\} \quad (9)$$

Where the first term in braces represents the contribution of changes in occupational choice as represented by occupation structural parameters ϕ, the second term in braces represents the contribution of exogenous characteristics *W*, the third term in braces represents the contribution of returns to characteristics Ω and the remaining term is the residual. In the appendix section 4 we detail the exact functional forms we use to carry out this decomposition analysis.

Note that when carrying out the counterfactual analysis for ϕ and *W* we are also simulating counterfactual distribution of occupations. In fact, we can define

$$f^\tau(O) = \iint_{C(W)} h^\tau(O|W) \ \Psi^\tau(W) \, dW \quad (10)$$

In a similar way as we defined the earnings distribution in equations (1). Thus, we can simulate the following two occupations distributions:

$$f_h{}^{t'\to t}(O) = \iint_{C(W)} h^t(O|W) \ \Psi^{t'}(W) \, dW \quad (11)$$

$$f_W{}^{t'\to t}(O) = \iint_{C(W)} h^{t'}(O|W) \ \Psi^t(W) \, dW \quad (12)$$

Where (11) represents the distribution of occupations that would have been observed at time *t'* if the distribution of occupations conditional on characteristics *W* had been that observed in time *t*. Note also that this is the distribution of occupations underlying the counterfactual earnings distribution in the first term in brace in equation (9). On the other hand (12) represents the distribution of occupations that would have been observed at time *t'* if the distribution of exogenous characteristics *W* had been that observed in time *t*.

5. Changes in occupational choice, characteristics and returns to characteristics

One of the features of our decomposition methodology is the fact that we model explicitly occupational choice. That is, rather than treating occupations as an exogenous characteristic, we take it as the result of a discrete choice model in which individuals select into occupations based on their characteristics. In this way, we are able to distinguish the role played by changes in exogenous characteristics from the one played by changes in occupational choice. This is particularly relevant in a context where it is understood that changes in characteristics -notably, a general increase in years of schooling- account for an important part of changes in occupational structure (Hardy et al., 2016). By parsing out that effect, we are able to capture the role that structural changes in occupational choice have on the overall evolution of earnings.

In Tables 2.a and 2.b we illustrate the change in structural parameters linking individuals' characteristics to occupations – that is, structural changes in occupational choice. For brevity, we present the marginal probabilities of being employed in any of the four occupation categories (not employed and the three occupations in employment) by education level for household heads and spouses. An extended table with the marginal probabilities for other variables and household members can be found in the appendix (tables A.2-A.4).

Table 2.a - Marginal change in the probability of being in each occupation category, by education level, household heads

		Initial year				Final year				Difference			
		NE	NR,M	R	NR,C	NE	NR,M	R	NR,C	NE	NR,M	R	NR,C
Germany	Tertiary	-0.092	-0.132	-0.116	0.340	-0.203	-0.157	-0.065	0.425	-0.111	-0.025	0.051	0.085
	Secondary	-0.042	-0.026	0.046	0.022	-0.189	-0.035	0.109	0.115	-0.147	-0.009	0.063	0.093
Poland	Tertiary	-0.153	-0.124	-0.064	0.341	-0.124	-0.197	-0.225	0.546	0.029	-0.073	-0.161	0.205
	Secondary	-0.105	-0.103	0.113	0.095	-0.148	-0.119	-0.004	0.271	-0.043	-0.016	-0.117	0.176
Spain	Tertiary	-0.090	-0.248	0.043	0.296	-0.205	-0.162	-0.024	0.392	-0.115	0.086	-0.067	0.096
	Secondary	-0.071	-0.138	0.180	0.029	-0.121	-0.017	0.099	0.039	-0.050	0.121	-0.081	0.010
Georgia	Tertiary	-0.121	-0.077	-0.029	0.227	-0.150	-0.069	-0.026	0.245	-0.029	0.007	0.003	0.019
	Secondary	-0.101	0.020	0.047	0.034	-0.156	0.013	0.099	0.044	-0.055	-0.007	0.052	0.010
Kyrgyz Rep.	Tertiary	-0.077	-0.198	0.016	0.259	-0.139	-0.069	-0.018	0.226	-0.062	0.129	-0.034	-0.034
	Secondary	-0.091	-0.045	0.089	0.047	0.002	-0.085	0.044	0.039	0.093	-0.040	-0.045	-0.008
Russia	Tertiary	-0.028	-0.302	-0.102	0.432	-0.188	-0.212	0.015	0.385	-0.160	0.090	0.117	-0.047
	Secondary	-0.075	-0.045	-0.007	0.127	-0.127	-0.022	0.040	0.109	-0.052	0.023	0.047	-0.018
Turkey	Tertiary	-0.464	-0.199	-0.257	0.920	-0.307	-0.112	-0.145	0.563	0.157	0.088	0.112	-0.357
	Secondary	-0.180	-0.054	0.096	0.138	-0.116	-0.056	0.073	0.099	0.064	-0.002	-0.023	-0.039

This table presents the marginal change in probabilities of being out of employment (NE), in a Non-routine, Manual task intensive occupation (NR, M), in a Routine task intensive occupation (R) or in a Non-routine, Cognitive task intensive occupation (NR,C) for household heads holders of tertiary education diploma or secondary education diploma. The marginal change in probabilities for tertiary education is calculated with respect to those that hold a secondary education diploma, whilst the marginal change in probabilities for secondary education is calculated with respect to those that hold a primary education diploma or have no formal education.

Table 2.b - Marginal change in the probability of being in each occupation category, by education level, spouses

		Initial year				Final year				Difference			
		NE	NR,M	R	NR,C	NE	NR,M	R	NR,C	NE	NR,M	R	NR,C
Germany	Tertiary	-0.104	-0.082	-0.035	0.220	-0.439	-0.050	0.089	0.399	-0.335	0.032	0.124	0.180
	Secondary	-0.073	-0.073	0.135	0.012	-0.431	0.114	0.217	0.100	-0.357	0.187	0.082	0.088
Poland	Tertiary	-0.235	-0.094	-0.055	0.384	-0.149	-0.129	-0.094	0.372	0.086	-0.035	-0.038	-0.012
	Secondary	-0.156	-0.139	0.179	0.117	-0.165	0.015	0.071	0.079	-0.009	0.154	-0.107	-0.038
Spain	Tertiary	-0.190	-0.041	0.084	0.147	-0.221	-0.157	0.017	0.361	-0.031	-0.116	-0.068	0.214
	Secondary	-0.051	-0.011	0.054	0.008	-0.115	0.006	0.072	0.037	-0.064	0.017	0.018	0.029
Georgia	Tertiary	-0.190	-0.003	-0.014	0.208	-0.187	-0.067	0.018	0.236	0.003	-0.064	0.033	0.029
	Secondary	-0.096	0.022	0.029	0.045	-0.193	0.132	0.039	0.022	-0.098	0.110	0.010	-0.023
Kyrgyz Rep.	Tertiary	-0.145	-0.060	-0.041	0.245	-0.251	-0.003	-0.005	0.259	-0.106	0.057	0.036	0.013
	Secondary	-0.149	0.054	0.057	0.038	-0.109	0.000	0.064	0.045	0.040	-0.054	0.007	0.007
Russia	Tertiary	-0.132	-0.347	-0.052	0.532	-0.175	-0.310	0.023	0.462	-0.042	0.037	0.075	-0.070
	Secondary	-0.140	-0.134	0.038	0.236	-0.112	-0.091	0.053	0.150	0.028	0.043	0.015	-0.086
Turkey	Tertiary	-0.558	-0.003	0.147	0.414	-0.479	-0.050	0.066	0.462	0.079	-0.046	-0.081	0.048
	Secondary	-0.082	0.009	0.042	0.031	-0.093	0.021	0.036	0.036	-0.010	0.012	-0.006	0.005

This table presents the marginal change in probabilities of being out of employment (NE), in a Non-routine, Manual task intensive occupation (NR, M), in a Routine task intensive occupation (R) or in a Non-routine, Cognitive task intensive occupation (NR,C) for household heads holders of tertiary education diploma or secondary education diploma. The marginal change in probabilities for tertiary education is calculated with respect to those that hold a secondary education diploma, whilst the marginal change in probabilities for secondary education is calculated with respect to those that hold a primary education diploma or have no formal education.

In all the countries and periods a common, expected pattern is present: having a tertiary education diploma increases considerably the probability in being in a Non-routine, Cognitive task intensive occupation by as much as 60 percentage points and as low as 22 percentage points. However, for household heads this probability has changed differently over time: in EU countries it has increased in the period under analysis, whilst in the former Soviet countries and Turkey it has remained stable or even decreased. Having a tertiary education diploma also decreases considerably the probabilities of being in a Non-routine, Manual task intensive occupation by as much as 30 percentage points and as low as 7 percentage points for household heads – for spouses, the magnitudes are relatively smaller. The evolution of this probability over time was also heterogeneous for household heads: it decreased in Germany and Poland, whilst it increased in the remaining countries in the sample. For tertiary education holders, the marginal change in probabilities of being in a Routine task intensive occupation doesn't show a common pattern across countries or sub-regions. It has increased for both household heads and spouses in Germany, Georgia, Russia and Turkey, whilst it has decreased in Poland, Spain. In the Kyrgyz Republic it has decreased for household heads but increased for spouses.

The picture for secondary education holders has some differences with respect to the one of tertiary education holders. Whilst having a secondary education diploma increased the probability of being in a Non-routine, Cognitive task intensive occupation, it also increased the probability of being in a Routine task intensive occupation in almost every country in both the initial and final period. The marginal probability of being in a Non-Routine Manual task intensive occupation for holders of a secondary education diploma has shown an interesting pattern for spouses, who are mostly female. In the EU countries in the initial period this marginal probability was negative: finalizing secondary education implied a decrease in the probability of being in a Non-routine, Manual task intensive occupation by 1 to 14 percentage points in the early 1990s. In the early 2010s this probability had turned positive, between 1 and 11 percentage points. This happened simultaneously with an increase in the participation rate of spouses, suggesting a strong entry of spouses (mostly female), holders of a secondary education diploma, into Non-routine, manual task intensive occupations. A similar pattern is also seen in former Soviet countries and Turkey.

As mentioned before, an individual's allocation into an occupation depends not only on the structural parameters driving that occupational choice, but also on the individual's characteristics. In Table 3 we present the evolution of the main characteristics of individuals in our sample. The patterns are roughly common across countries: a wide increase in tertiary education attainment, particularly in Poland (increase of 13 percentage points) and Spain (almost twenty percentage points). Depending on the country, secondary education attainment may have also increased. Aging is present in the countries in our sample, with Georgia being the strongest case – an increase of 4 years in the average age of individuals. As expected, the share of women in the samples don't change in most countries – except for Germany, where they increase in three percentage points, and Turkey, where they decrease in two percentage points.

Table 3 – Evolution of working age individuals' characteristics in sample

	Initial year					Final year					Difference				
	Max education level			Age	Share of women	Max education level			Age	Share of women	Max education level			Age	Share of women
	1ry or less	2ndry	3ry			1ry or less	2ndry	3ry			1ry or less	2ndry	3ry		
German	0.256	0.526	0.218	39.72	0.492	0.171	0.563	0.267	42.23	0.523	-0.085	0.037	0.048	2.51	0.031
Poland	0.303	0.631	0.067	38.11	0.533	0.183	0.616	0.201	39.45	0.515	-0.120	-0.014	0.134	1.34	-0.017
Spain	0.709	0.170	0.120	37.67	0.506	0.428	0.226	0.317	40.54	0.498	-0.281	0.056	0.197	2.86	-0.008
Georgia	0.103	0.635	0.262	37.45	0.531	0.013	0.675	0.311	41.77	0.523	-0.090	0.040	0.050	4.32	-0.008
Kyrgyz Rep.	0.111	0.769	0.120	32.61	0.511	0.102	0.742	0.156	35.18	0.511	-0.008	-0.027	0.036	2.57	0.000
Russia	0.254	0.575	0.172	37.69	0.518	0.160	0.591	0.246	39.16	0.524	-0.093	0.017	0.074	1.48	0.006
Turkey	0.619	0.314	0.067	34.27	0.500	0.467	0.399	0.134	36.76	0.501	-0.152	0.085	0.067	2.49	0.000

This table shows the average characteristics of working age (15-64) individuals in the country-year samples used in our analysis. Initial year for Germany and Russia is 1994, for Poland is 1992, for Spain is 1990, for Georgia is 2002, for the Kyrgyz Republic is 2004 and for Turkey is 2002. Final year is 2013 for Germany, Poland, Spain and Turkey, 2014 for the Kyrgyz Republic and Russia and 2015 for Georgia.

And additional factor relevant in our analysis is the evolution of returns to individuals' characteristics in each occupation category. In Tables 3.a and 3.b we present the point estimates of the tertiary-secondary education wage premium in the different countries and years under analysis, both for household heads and spouses. Point estimates for other variables and household members are shown in the appendix.

Table 3.a – Point estimates of tertiary-secondary education wage premium, household heads

	Initial year			Final year			Difference year		
	NR, M	R	NR, C	NR, M	R	NR, C	NR, M	R	NR, C
Germany	0.239	0.196	0.080	0.187	0.151	0.315	-0.052	-0.045	0.236
Poland	-0.050	0.336	0.382	0.202	0.181	0.277	0.252	-0.155	-0.105
Spain	0.248	0.090	0.152	0.275	0.057	0.261	0.027	-0.033	0.109
Georgia	0.254	0.021	0.295	0.257	0.224	0.301	0.003	0.203	0.006
Kyrgyz Rep.	0.187	0.117	0.215	0.098	0.180	0.164	-0.089	0.063	-0.051
Russia	0.194	0.304	0.178	0.135	0.214	0.291	-0.059	-0.090	0.113
Turkey	0.305	0.367	0.352	0.634	0.332	0.448	0.329	-0.035	0.096

This table shows the point estimate of the tertiary-secondary education wage premium (i.e. the log difference of the return to tertiary education and the return to secondary education) for household heads in each occupation category: Non-routine, Manual task intensive occupations (NR, M), Routine task intensive occupations (R) and Non-routine, Cognitive task intensive occupations (NR, C). Estimates come from a standard Mincer equation. For more details on the methodology see the appendix.

Table 3.b – Point estimates of tertiary-secondary education wage premium, spouses

	Initial year			Final year			Difference year		
	NR, M	R	NR, C	NR, M	R	NR, C	NR, M	R	NR, C
Germany	0.212	0.021	0.318	0.103	0.235	0.479	-0.110	0.214	0.161
Poland	-0.166	0.320	0.250	0.144	0.142	0.253	0.310	-0.178	0.003
Spain	0.004	0.017	0.439	0.159	0.275	0.523	0.155	0.258	0.084
Georgia	0.149	0.026	0.275		0.496	0.584		0.470	0.309
Kyrgyz Rep.	0.207	0.450	0.440	0.251	0.066	0.191	0.044	-0.384	-0.249
Russia	0.576	0.356	0.307	0.289	0.183	0.338	-0.287	-0.173	0.031
Turkey	0.605	0.426	0.401	0.483	0.379	0.411	-0.122	-0.047	0.010

This table shows the point estimate of the tertiary-secondary education wage premium (i.e. the log difference of the return to tertiary education and the return to secondary education) for spouses in each occupation category: Non-routine, Manual task intensive occupations (NR, M), Routine task intensive occupations (R) and Non-routine, Cognitive task intensive occupations (NR, C). Estimates come from a standard Mincer equation. For the case of spouses in Non-routine, Manual occupations in Georgia in year 2015, limited sample variability doesn't allow for a correct estimation of returns to education. the For more details on the methodology see the appendix.

There evidence shows that some common pattern exists across countries: returns to tertiary education have increased in Non-routine, Cognitive task intensive occupations in all countries except Poland and the Kyrgyz Republic for household heads, and in all countries except the Kyrgyz Republic for spouses. In Routine task intensive occupations returns to tertiary education have decreased in all countries except Georgia and the Kyrgyz Republic for household heads, whilst the picture is mixed for spouses – Germany, Spain, Georgia see big increases in returns to tertiary education and Poland, the Kyrgyz Republic and Russia see strong decreases. In Non-routine, manual occupations returns to tertiary education haven't seen big changes with the exception of Poland and Turkey for household heads -where there has been an increase. In the case of spouses the pattern is very mixed, with returns to tertiary education strongly decreasing in Germany and Russia, and strongly increasing in Poland and Spain.

6. Decomposition results

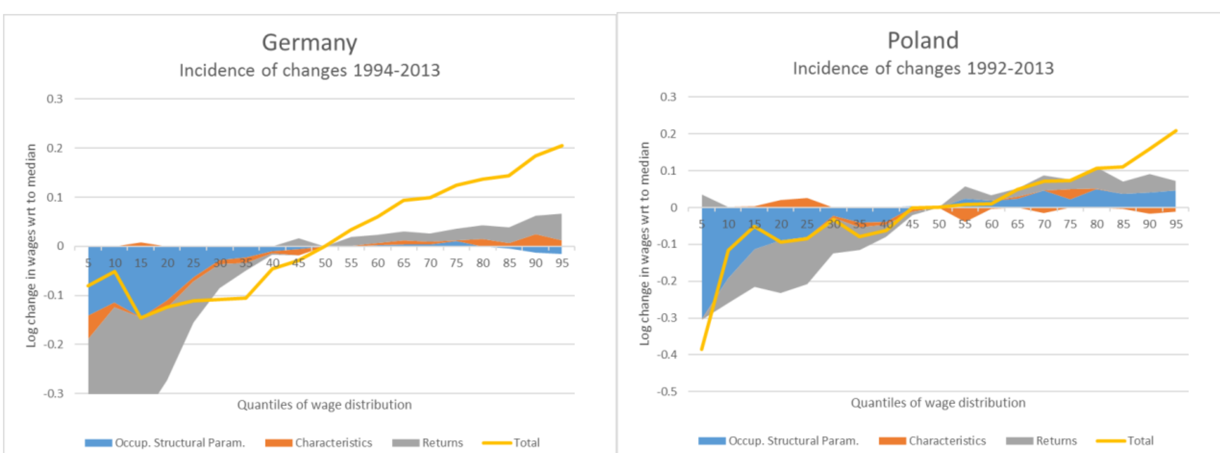
In previous sections 2 and 3 we have shown that the evolution of earnings inequality has had two correlated patterns: a monotonically regressive change in the EU countries and a monotonically progressive change in post-Soviet economies. At the same time, two broad types of occupational change that have taken place in Europe and Central Asia in the last two decades. In the Western part of the region there has been a de-routinization process, whilst in the post-Soviet countries there has been an increase in both routine and non-routine, manual task intensive occupations. In this section we intend to decompose the changes in earnings according to the methodology detailed in section 4 in order to understand the role that occupational change has had in explaining the evolution of earnings inequality in the region.

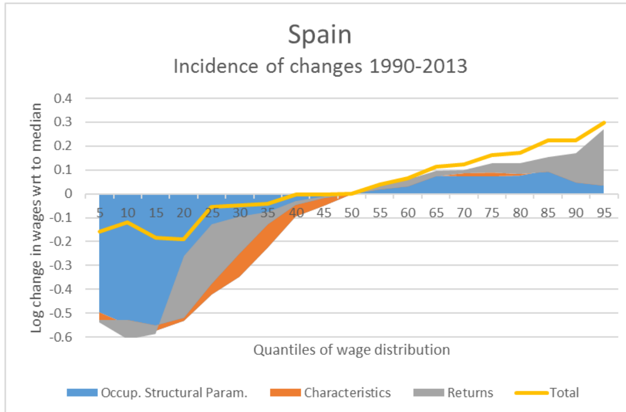
6.1 Decomposing the evolution of earnings

Occupational change can have an impact on earnings: as individuals move across occupations or show some change in their characteristics, their labor market earnings will also vary. Moreover, changes in returns to characteristics will also have an impact. In this section we carry out a counterfactual analysis that will allows us to understand how each of these factors contributed to changes in earnings. As detailed in section 4, our methodology does not intend to provide causal estimates but to quantify the contribution of each factor (occupation structural parameters, individual characteristics and returns to characteristics) to the change in earnings. In the different panels of Figure 8 we present the result of the decomposition.

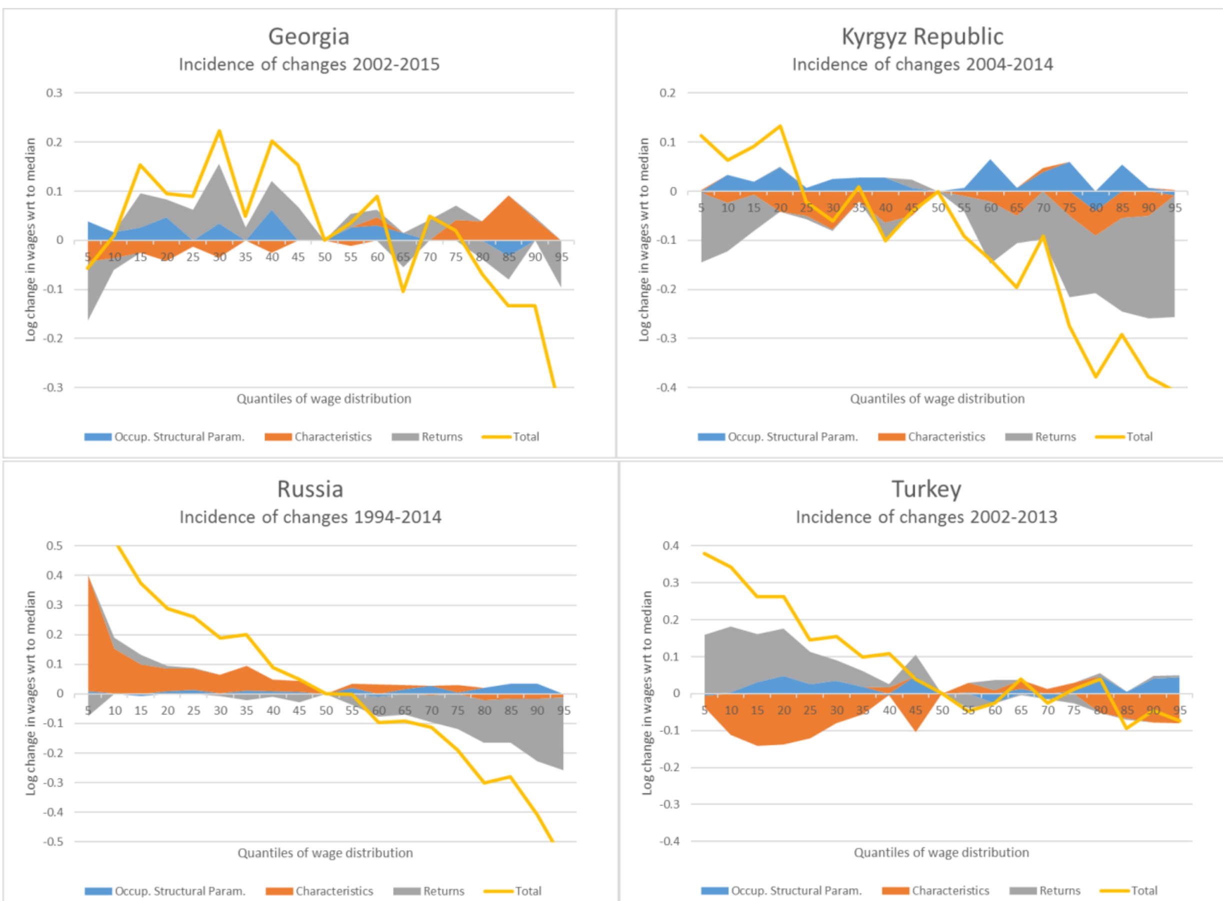
Figure 8 – Decomposition of changes in earnings

a. European Union countries





b. Former Soviet countries and Turkey



These set of figures plot the log change in wages for the different ventiles of the wage distribution from the initial period to the final period in the observed data (yellow line) and the contribution of each component: changes in occupational choice (blue), changes in characteristics (orange) and changes in returns (grey).. Changes are expressed with respect to the median, whose change is normalized to zero. Only the wage of regular employees is considered in this analysis. For more details on the methodology for estimating the counterfactual scenario see the appendix.

The results depict two different type of changes. On the one hand, the EU countries in our sample - Germany, Poland and Spain- show a pattern where changes in occupational choice are particularly negative for the lowest quantiles of the earnings distribution and slightly positive for the top quantiles. Thereby, structural change in occupational choice appears to be particularly regressive, hitting the bottom quantiles the most. As seen in section 5, this is consistent with a structural change in occupational choice raising the share of employment in non-routine, manual task intensive occupations, where wages are lowest. The shift out of routine task intensive jobs and into non-routine, manual task intensive jobs appears to account for a particularly strong decline in the earnings of individuals in the bottom of the distribution. On the other hand, in the former Soviet countries and Turkey the change in occupation structural parameters doesn't account for significant changes in the earnings distribution. This is not completely unexpected as the magnitude of overall occupational change in these countries has been smaller than in the EU countries in our sample.

With respect to the contribution of changes in individuals' characteristics, among the EU countries in our sample Spain is the only one where changes in characteristics account for a significant change in earnings – particularly progressive since it benefits mostly the middle-lower quantiles of the earnings distribution. In Germany and Poland, change in characteristics doesn't appear to have a significant distributional impact on earnings. This is surprising for Poland, where educational upgrading was significant during the period under analysis. The results point out that this change in educational characteristics in Poland was spread across the whole earnings distribution in an equal way, having thus a neutral the distributional impact.

The results for the former Soviet countries and Turkey show that in Georgia changes in characteristics were positive for the top deciles, in Russia they were positive for the bottom deciles. In the Kyrgyz Republic and Turkey, as in Poland, the effects were neutral in distributional terms. Given that in all the cases the direction of the change in characteristics was roughly the same -slight aging and increase in education levels-, the difference in its impact on earnings reflects the heterogeneity of the different countries' labor markets.

The last component of our analysis captures the distributional impact of changes in returns to characteristics. In the EU countries of our sample top deciles benefit from the change in returns to characteristics, as expected from the rather broad increase in returns to education in Non-routine, Cognitive task intensive occupations, particularly in Germany and Spain – however, the situation is mixed for the bottom deciles: in particular in Germany and slightly so in Poland, changes in returns to characteristics hit negatively the bottom quantiles of the earnings distribution, whilst in Spain the impact is mostly positive. In fact, as seen in Tables 3.a and 3.b, returns to education in Non-routine, manual task intensive occupations, the most prevalent in the bottom deciles, mirror the pattern shown in Germany and Spain: in Germany returns to education in those occupations decreased whilst in Spain they increased.

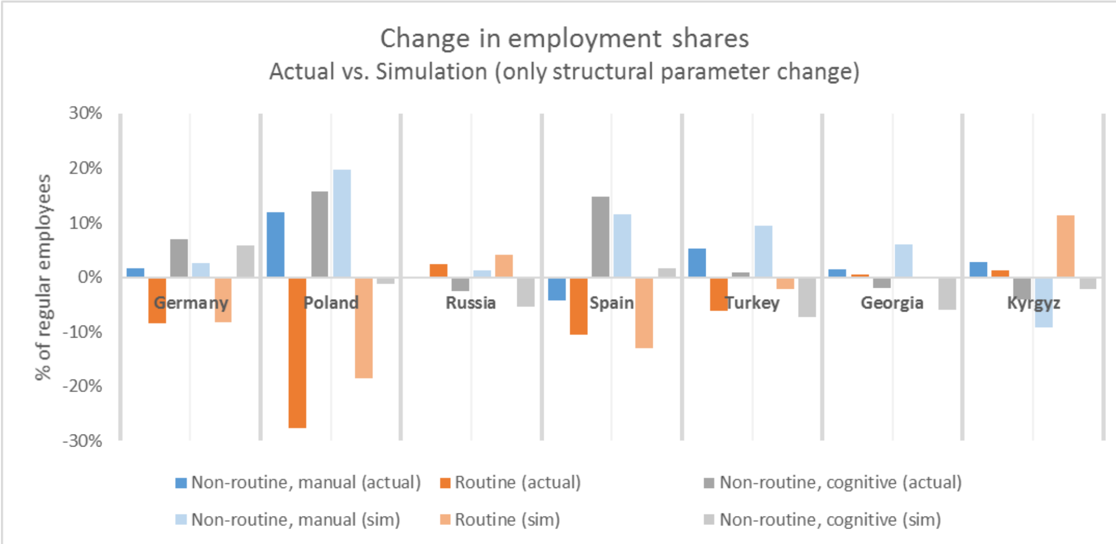
There is a common pattern among the former Soviet countries and Turkey, which is the opposite to that of EU countries with respect to top deciles: changes in returns to characteristics had a negative distributional impact in the earnings of those deciles. The effect was particularly strong in the Kyrgyz Republic and Russia: in these countries returns to tertiary education decreased for Routine, task intensive occupations – jobs which grew during the period under analysis. This effect was not present in Georgia and Turkey, where the negative impact on top deciles was present in a smaller magnitude.

6.2 Decomposing occupational change

Underlying the decomposition of changes in earnings is a similar decomposition of changes in occupations which, as mentioned before, we don't treat as simple characteristics but, rather, as the result of a discrete choice model. Our model allows us to decompose the change in the share of employment of each occupational category into two parts: on the one hand, structural changes in occupational choice, represented by changes in the conditional correlations between individuals' characteristics and the occupation where they are employed. For instance, the probability of being employed in a non-routine, cognitive job by having a secondary education diploma can change. Even if the characteristics of individuals are not modified, any change in that probability will alter the occupational structure of the economy. If, for instance, the probability of being employed in a non-routine, cognitive job by having a tertiary education is higher today than it was twenty years ago -which is actually the case in four of the seven countries of this study, as shown in table 2.a- and the education profile of the population hasn't changed, then one would expect a higher share of non-routine, cognitive jobs in the economy. The change in the structural parameters driving occupational choiceis a first source of variability. On the other hand, even if these parameters don't change, the individuals' characteristics can change. If, for instance, the probability of being employed in a non-routine, cognitive job for tertiary education holders is higher than the one of being employed in a routine task intensive job and, at the same time, the share of tertiary education holders increases in the economy, then one would expect to see an increase in the share of people employed in non-routine, cognitive jobs. This would reflect the change that educational upgrading entails for occupational change.

The changes in structural parameters we have just described represent the first factor that can account for occupational change. In Figure 9 we provide a first snapshot of our decomposition analysis. What occupational change would have occurred if only the structural parameters would have changed? That is, we simulate the share of employment of each occupational category in the counterfactual scenario in which we keep the individuals' characteristics (age, gender and education profile of the population) as they were in the initial period and let the structural parameters take the values they actually took by the early 2010s as shown in Tables 2.a and 2.b. Formally, this is the distribution of occupations defined in equation 11 of section 4. In Germany the simulation and the actual data look very similar – that is, changes in structural parameters seem to account for the bulk of the occupational change in that country. In the case of Poland, Spain and Turkey the simulation results seem to match the decline in routine intensive occupations but overestimate the growth in non-routine, manual task intensive jobs whilst they clearly underestimate the growth in non-routine, cognitive task intensive jobs. In the post-Soviet countries, the simulation seems to match the decline in non-routine, cognitive task intensive jobs. In sum, this simulation exercise suggests that structural change can explain most of the change in occupations in Germany and the growth in non-routine, manual task intensive jobs in Poland and Spain; in post-Soviet countries, similarly, structural change explains the decrease in non-routine, cognitive task intensive occupations.

Figure 9



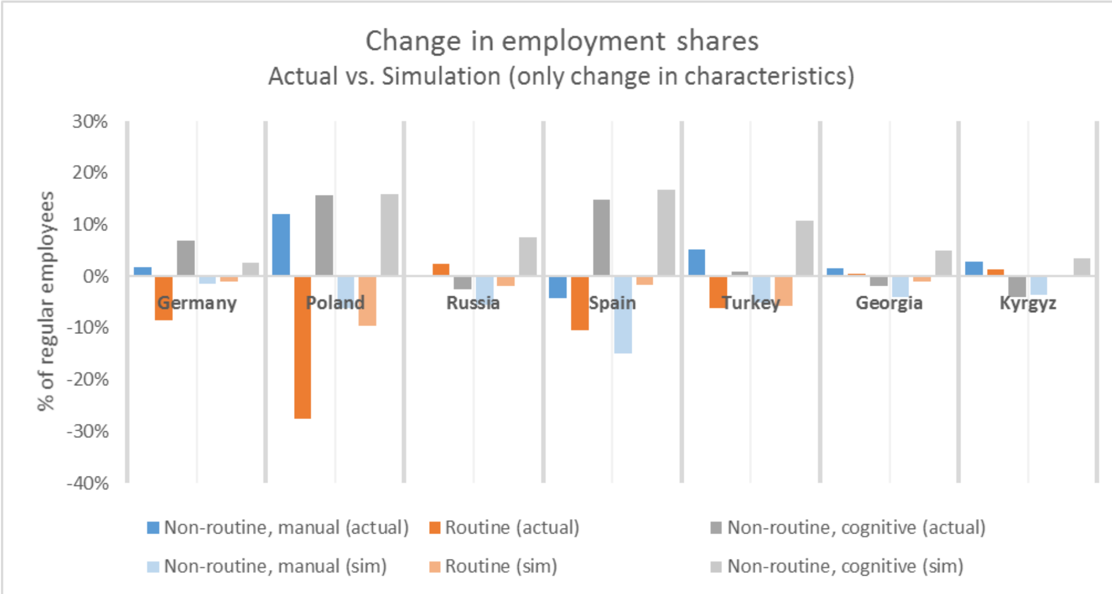
This figure shows the change, in percentage points, of the share of employment (regular employees, excluding self-employed) over a period of ten or twenty years of the three occupations categories in the actual data (dark colors) and in the counterfactual scenario where only occupation structural parameters change (light colors): in blue, occupations relatively intensive in non-routine, manual tasks; in orange, occupations relatively intensive in routine tasks; in grey, occupations relatively intensive in non-routine, cognitive tasks. The time period depends on data availability. For more details on the construction of the occupation categories and the methodology for estimating the counterfactual scenario see the appendix.

The other source of occupational change is the change in individuals' characteristics.

In Figure 10 we show the results of a simulation in which the structural parameters of the mid 1990s are left unchanged, with individuals' characteristics -in particular those shown in Table 3- being the only source of variation. Formally, this is the distribution of occupations defined in equation 12 of section 4. In the case of Germany, the simulated occupational change is very small, suggesting a limited explanatory power of changes in characteristics. In the case of Poland and Spain, the simulation matches quite well the increase in the share of non-routine, cognitive task intensive jobs but underestimates the growth in non-routine, manual task intensive skills (or they limited decrease in the case of Spain) and the decline in routine-task intensive jobs. This means that occupational change in Poland and Spain seems to have been the combination of a structural change -leading to a relative increase in non-routine, manual task intensive jobs- and a change in characteristics, most notably an increase in schooling, that has led to an increase in non-routine, cognitive task intensive jobs. The decline in routine task intensive jobs is accounted for by both factors -structural change and change in characteristics.

For the post-Soviet countries and Turkey, the change in individuals' characteristics would result in a strong increase in non-routine, cognitive task intensive occupations – the opposite of what actually happened. In these countries, then, the change in structural parameters that increased non-routine, manual and routine task intensive jobs seems to have more than compensated the change in characteristics which would have resulted in an opposite occupational change.

Figure 10



This figure shows the change, in percentage points, of the share of employment (regular employees, excluding self-employed) over a period of ten or twenty years of the three occupations categories in the actual data (dark colors) and in the counterfactual scenario where only individual's characteristics change (light colors): in blue, occupations relatively intensive in non-routine, manual tasks; in orange, occupations relatively intensive in routine tasks; in grey, occupations relatively intensive in non-routine, cognitive tasks. The time period depends on data availability. For more details on the construction of the occupation categories and the methodology for estimating the counterfactual scenario see the appendix.

6.3 Overall patterns

Two storylines emerge from this section. In Germany, Spain and Poland, structural changes in occupational choice contributed to a fall in routine employment and the increase in non-routine manual employment. This phenomenon contributes to account for the increase in wage inequality observed during this period. At the same time, the rise of non-routine cognitive jobs seems to be driven by two different forces among these three countries. In Germany, it was driven by changes in structural parameters, while educational upgrading played a bigger role in Spain and Poland. However, educational upgrading per se does not help explain changes in wage inequality during this period. Changes in the demand and supply for skills seem to affect wage inequality only through changes in the returns to education. In Germany and Spain the increasing returns to education in the growing job categories over time contributed to the rise in wage inequality.

In the post-soviet countries and Turkey, a different picture emerges. Changes in structural parameters help explain the rise in routine employment in all countries (except Georgia), while educational upgrading tends to over-predict the rise in non-routine cognitive occupations (which actually declined). Occupational changes and upskilling fail to account for the decline in wage inequality during this period. Changes in the supply and demand for skills seem to affect inequality only through changes in the returns to education. More specifically, the combined decline in returns to education in the growing Routine task intensive occupations and increase in the supply of skills suggest a disproportionate increase in the supply of workers (relative to their demand) during this period.

In the Annex we provide a more detailed description of the “losers” and “winners” of occupational change.

7. **Concluding remarks**

The evidence presented in this study describes to two types of occupational change happening in Europe and Central Asia. In Germany, Spain and Poland, changes in labor demand and supply contributed to a fall in routine employment and the increase in non-routine manual employment. Simulations show that skilled individuals previously employed in routine jobs would tend to move into non-routine, cognitive jobs, were they are paid salaries between 20% and 30% higher; routine workers with lower levels of education would move into non-routine, manual task intensive jobs where they can be paid up to 50% less. This phenomenon helps to account for the increase in wage inequality observed during this period. One common characteristic, however, is that women make up a bigger share of those who move out of routine jobs.

At the same time, the rise of non-routine cognitive jobs seems to be driven by two different forces among these three countries. In Germany, it was driven by changes in structural parameters, while educational upgrading played a bigger role in Spain and Poland. However, educational upgrading per se does not help explain changes in wage inequality during this period. Changes in the demand and supply for skills seem to affect wage inequality only through changes in the returns to education. In Germany and Spain the increasing returns to education in the growing job categories over time contributed to the rise in wage inequality.

In the post-soviet countries and Turkey, a different picture emerges. Changes in structural parameters help explain the rise in non-routine, manual and routine employment in all countries, while educational upgrading tends to over-predict the rise in non-routine cognitive occupations (which actually declined). As in the Western part of the region, it is women who are mostly moving between occupations and, particularly in Turkey, into the labor force. Young people are increasing their participation in wage employment in the poorest countries, whilst older men are staying longer in the labor force in Russia. Occupational changes and upskilling fail to account for the decline in wage inequality during this period. Changes in the supply and demand for skills seem to affect inequality only through changes in the returns to education.

More specifically, the combined decline in returns to education in the growing Routine task intensive occupations and increase in the supply of skills suggest a disproportionate increase in the supply of workers (relative to their demand) during this period. Despite the progressive changes observed in the wage distribution, the occupational change seen in post-Soviet countries and Turkey has a clear group of losers – those with a high level of education, who move into occupations where they are over-skilled and where returns to educations are lower.

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Appendix 1: Data and variable definition

A.1 Sources

	Baseline			Final		
	Year	Survey and observations	Harmonization	Year	Survey and observations	Harmonization
Georgia	2002	Household Integrated Survey *40050 obs.*	ECAPOV	2015	Household Integrated Survey *38130 obs.*	ECAPOV
Germany	1994	German Socio-Economic Panel *17812 obs.*	LIS	2013	German Socio-Economic Panel *41657 obs.*	LIS
Kyrgyz Republic	2004	Kyrgyz Household Integrated Survey *21176 obs.*	ECAPOV	2014	Kyrgyz Household Integrated Survey *20094 obs.*	ECAPOV
Poland	1992	Household Budget Survey *18807 obs.*	LIS	2013	EU-SILC *102780 obs.*	LIS
Russia	1994	Russia Longitudinal Monitoring Survey *11280 obs.*	None	2014	Russia Longitudinal Monitoring Survey *18365 obs.*	None
Spain	1990	Household Budget Survey *72119 obs.*	LIS	2013	EU-SILC *31622 obs.*	LIS
Turkey	2002	Household Labor Force Survey *300689 obs.*	None	2013	Household Labor Force Survey *502426 obs.*	None

A.2 Variables

Employment status: three categories: regular wage employment, self-employment, out of employment (out of labor force and unemployed)

Occupation: ISCO88 or ISCO08 occupation code for primary job grouped into three categories. Check Appendix section 2 for full description of occupation categories

Wage: annual labor market incomes expressed in local currency units, constant prices of the final year.

Education: maximum level of education attained, ISCED three categories (low for primary or no education; medium for secondary education; high for tertiary education or more)

Appendix 2: construction of occupation categories

Grouping occupations according to their task content implies making a decision on which task dimension to prioritize over others. As the potential number of tasks by which an occupation can be characterized is very large, we rely on pre-built task content indices by IBS (2015) which originate from O*NET[4] and follow Acemoglu and Autor (2011). There are six task content indices: i) non-routine, cognitive, analytical; ii) non-routine, cognitive, personal; iii) routine, cognitive; iv) routine, manual; v) non-routine, manual, physical; vi) non-routine, manual, personal. Additionally, indices iii) and iv) can be combined into a routine task intensity (RTI) index based on Autor, Levy and Murnane (2003). Each occupation at the ISCO 88 4-digit level (unit group titles) has a value in every task content index. For the purpose of this work we aggregate occupations at the ISCO 88 2-digit level (sub-major group titles) by taking a simple average of the indices of the unit groups included in the corresponding sub-major group. This is done in order to have a common aggregation level across countries since not all the surveys record occupations at the 4-digit level.

For the ISCO 88 classification we have in total 27 sub-major occupation groups and we will split them into three groups according to the following algorithm. First of all, we rank the 27 groups according to the RTI index and we create our first category -occupations intensive in routine tasks- by choosing the top third (9 groups) which have the highest value for the index. We are left with 18 sub-major occupation groups which we will split in two according to their value of the non-routine, cognitive, analytical index[5]. The top half which has the highest values of the non-routine, cognitive, analytical index are classified into our second category -occupations intensive in non-routine, cognitive tasks- and the remaining bottom half is classified into our third category -occupations intensive in non-routine, manual tasks. Table A.1 presents a statistical summary of the categories. Note that our categorization of occupations is based on the relative intensity of some tasks: non-routine, manual, physical task content is high in both the first and third groups, but the first group has also high routine task intensity whereas the third group has a low value for routine tasks. In this sense, the first group in relatively more routine-intensive than the third group, which is relatively more intensive in non-routine, manual, physical tasks.

Table A.1 – Summary statistics of occupation categories

	Occupations intensive in routine tasks	**Occupations intensive in non-routine, cognitive tasks**	**Occupations intensive in non-routine, manual tasks**
RTI index	1.930	0.188	0.079
O*NET task content indices (average)			
Routine, manual	9.308	6.336	8.191
Routine, cognitive	9.929	8.973	8.495
Non-routine, cognitive, personal	8.538	10.635	8.734
Non-routine, cognitive, analytical	8.651	11.105	8.120

[4] A caveat of using O*NET data is that we do the implicit assumption that the task content of each occupation is the same across all the countries – and, in particular, that is the one of each occupation in the United States, where O*NET was specifically constructed for. There is evidence that the type of tasks performed by the same occupation (e.g. an office clerk) differ across countries (Di Carlo et al., 2016).

[5] Results practically don't change if we use the non-routine, cognitive, personal index.

Non-routine, manual, physical	10.867	7.952	11.309
Non-routine, manual, personal	2.905	3.513	3.037
Examples (ISCO 88 sub-major groups)	Office clerks (41), Metal, machinery and related trades workers (72), Stationary-plan and related operators (81)	Corporate managers (12), Physical, mathematical and engineering science professionals (21), Life science and health associate professionals (32)	Personal and protective services workers (51), Sales and services elementary occupations (91), Drivers and mobile-plant operators (83)

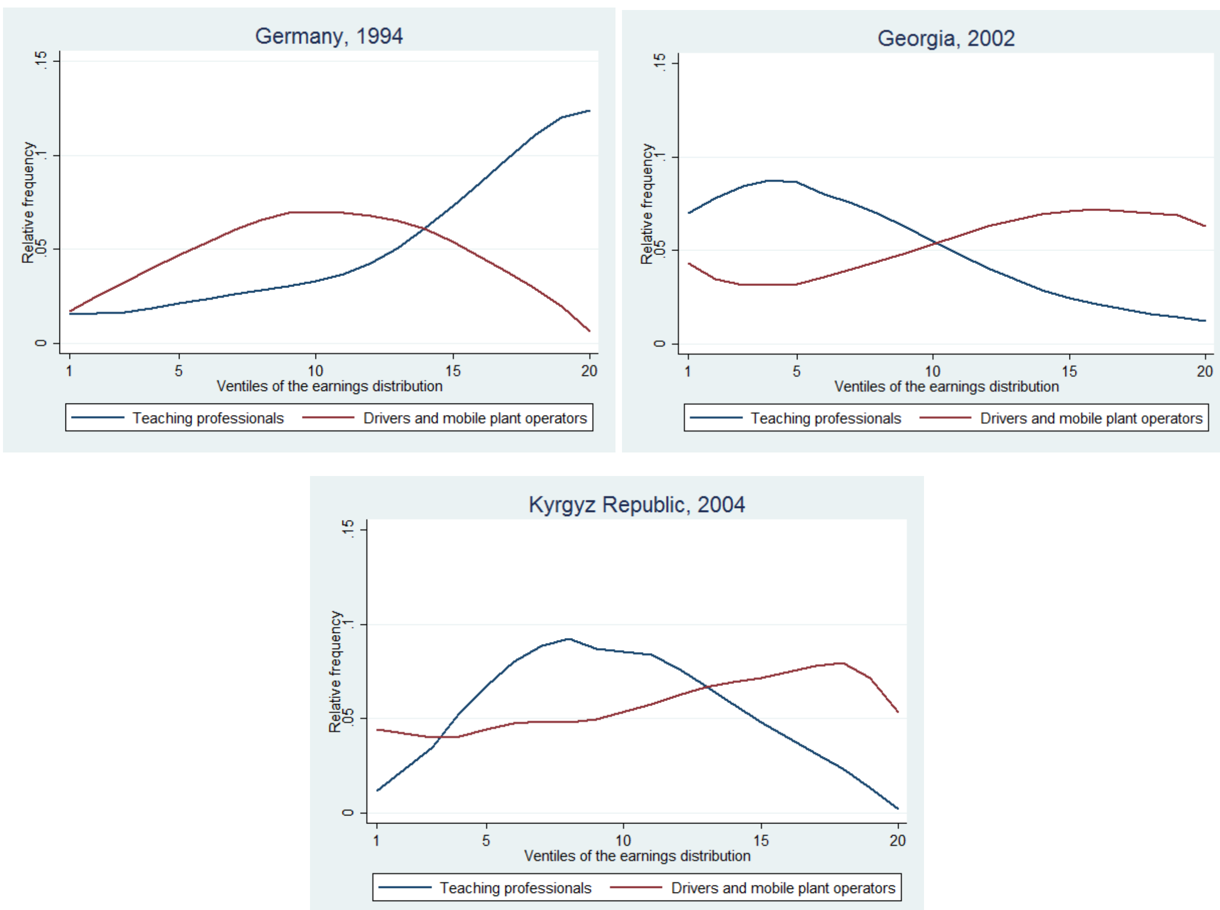
Source: own elaboration based on IBS (2015)

This classification is possible when occupation data is available at the ISCO 2-digit level. For Poland (1992 survey) and for Turkey (2003 and 2013 surveys) this data is only available at the ISCO 1-digit level (major groups). In this case the first occupation category (occupations intensive in routine tasks) comprises ISCO major groups 4, 7 and 8; the second occupation category (occupations intensive in non-routine, cognitive tasks) comprises ISCO major groups 1, 2 and 3; the third occupation category comprises ISCO major groups 5, 6 and 9.

Appendix 3: Heterogeneity in wage compensation of occupations across Europe and Central Asia

One of the findings of our analysis is the fact that the joint distribution of earnings and occupations is remarkably different across Europe and Central Asia. In particular, in former Soviet countries -the main examples in our study being Georgia and the Kyrgyz Republic- some occupations intensive in Non-routine, Cognitive tasks are paid on average less than Routine task intensive occupations, something that is not the case, for instance, in Germany. This difference is particularly strong in the earlier years of our analysis in Georgia and the Kyrgyz Republic (2002 and 2004 respectively). In Figure A.1 below we plot the distribution of teaching professionals (ISCO code 23, relatively intense in Non-routine, Cognitive tasks) and drivers and mobile plant operators (ISCO code 83, relatively intense in Routine tasks) by ventile of the overall wage distribution of the economy for the initial years of our analysis in Georgia, the Kyrgyz Republic and Germany.

Figure A.1 – Distribution of Teaching Professionals and Drivers and Mobile Plant Operators in the earnings distribution, initial year



This figure plots the relative distribution of teaching professionals (ISCO code 23) and drivers and mobile plant operators (ISCO code 83) on the overall earnings distribution in the initial year of the analysis. All curves are smoothed by a locally weighted regression. All values include self-employed. Similar patterns are observed when excluding self-employed.

The difference in the compensations is strong: whilst teaching professionals are concentrated in the upper part of the earnings distribution in Germany, in Georgia and the Kyrgyz Republic they are rather found in the bottom half. Conversely, drivers and mobile plant operators are found in the middle of the distribution in Germany, whilst in Georgia and the Kyrgyz Republic they are located in the upper part of the earnings distribution. This difference most probably owes to the fact that teaching professionals are prevalently employed by the public sector, differently to drivers which work relatively more in the private sector. Public sector employees are notably less well paid than private sector employees in these countries, particularly during the early transition years.

Figure A.2 – Distribution of Teaching Professionals and Drivers and Mobile Plant Operators in the earnings distribution, final year

This figure plots the relative distribution of teaching professionals (ISCO code 23) and drivers and mobile plant operators (ISCO code 83) on the overall earnings distribution in the final year of the analysis. All curves are smoothed by a locally weighted regression. All values include self-employed. Similar patterns are observed when excluding self-employed.

In Figure A.2 we plot the same distributions in the final year of our sample (2013 in Germany, 2014 in the Kyrgyz Republic and 2015 in Georgia). Whilst in Germany the pattern is roughly similar to one twenty years earlier, in Georgia and the Kyrgyz Republic there has been a slight convergence in the distribution of both teaching professionals and drivers and mobile plant operators. However, the distribution of teaching professionals is still skewed to the left with respect to drivers and mobile plant operators, which are comparatively more prevalent in the top half of the earnings distribution.

Appendix 4: parametric decomposition of changes in earnings

Our methodology draws heavily from Bourguignon, Ferreira and Leite (2008) and Inchauste et al. (2014). We adapt these methods to the particular question we want to address, i.e. how have occupational changes affected earnings inequality in Europe and Central Asia?

The main objective of our work is to understand the differences between the earnings distribution in two points in time – baseline year *s* and final year *t*. In particular, define a given earnings distribution as:

$$F(y_i, \dots, y_n) = F\left(\sum_{k=1}^{4} I_i^k\, y_i^k, \dots, \sum_{k=1}^{4} I_n^k\, y_n^k\right)$$

Where y_i are the earnings of individual *i*, which are made up of the earnings the individual gets in each occupation *k* (y_i^k) – there are four possible occupations (see Appendix section 2 below). $I_i^k$is an indicator function which takes a value of 1 if the individual is employed in occupation *k* and zero otherwise. We restrict individuals to be employed in only one occupation at the time.

a. Occupational choices

In our model, individuals first choose their occupation according to the following model:

$$I_i^k = 1\ if\ Z_i\Gamma^k + \varepsilon_i^k > Max(0, Z_i\Gamma^m + \varepsilon_i^m), k = 1, \dots, K, \forall m \neq k \qquad (1)$$

$$I_i^k = 0 \text{ for all } k = 1, \dots, K \text{ if } Z_i\Gamma^k + \varepsilon_i^k \leq 0 \text{ for all } k = 1, \dots, K$$

Where Z_i is a vector of individuals characteristics and Γ^k is a vector of coefficients for each occupation, k; and ε_i^k is a vector of random variables identically and independently distributed across individuals and activities according to the law of extreme values. The intuition behind this model is that individual i chooses occupation k if the utility associated from being in such occupation, $Z_i\Gamma^k + \varepsilon_i^k$, is greater than that associated from every other occupation. Without imposing more structure to the model and ignoring the dynamic aspect of occupational choices, this model fails to capture the actual process by which individuals choose an occupation as in the Roy model. Thereby, we argue that instead of estimating occupational choices, we model the conditional distributions of occupations based on individual characteristics such as education, age, gender, region and area. In other words, our model tries to *account* for occupational choices rather than estimating their causal determinants.

We estimate model (1) using a multinomial logit considering four mutually exclusive occupations:

1: Not working

2: Non-routine, manual task intensive occupation

3: Routine task intensive occupation

4: Non-routine, cognitive task intensive occupation

b. Earnings equations

In the next steps, we estimate earnings equations for each occupation k using a log-linear Mincerian model:

$$\ln\left(y_i^k\right) = X_i\Omega^k + \epsilon_i^k \qquad (2)$$

Where X_i is a vector of individual characteristics such as individual characteristics such as education, age, gender, region, area and sector of economic activity; Ω^k is a vector of coefficients and ϵ_i^k is a random variable assumed to be distributed identically and independently across individuals according to the standard normal distribution. We estimate equation (2) by ordinary least squares.

c. Decomposition approach

We estimate models (1) and (2) for two years, and simulate the impact of occupational changes by substituting the estimated parameters for one year with the parameters of the other year. We then use this hypothetical income to calculate a series of distributional statistics and compare them against those estimated using the actual income data.

- **C.1** Accounting for the impact of occupational changes

To carry out this simulation, we assign the estimated coefficients of equation (1) in year s to the household survey in year t. To allow individuals to change occupations in the simulation, we need the residual terms ε_i^k of the multinomial logit in equation (1), which are unobserved. Following Inchauste et al. (2014) and Train and Wilson (2008), we draw the residuals from an extreme value distribution in a way that is consistent with observed choices. The simulated earnings for individual i are given by:

$$\widetilde{y_i}^{s\to t,\Gamma} = \sum_{k=1}^{4} y_{i,t}^k \, \widetilde{I_{i,t}^k}(\, Z_{i,t}, \widetilde{\Gamma^{k,s}}, \varepsilon_i^k)$$

We argue that the difference between the Gini coefficient (or any distributional statistic) using the simulated income and the actual Gini coefficient in year t is accounted by the change in the occupational structure.

- **C.2** Accounting for the impact of changes in occupational wage premia

To perform this simulation, we carry out an experiment similar to the one above, but using the wage equation. More specifically, the simulated earnings for individual i are given by:

$$\widetilde{y_i}^{s\to t,\Omega} = \sum_{k=1}^{4} I_{i,t}^k \, \widetilde{y_{i,t}^k}(X_{i,t}, \widetilde{\Omega^{k,s}}, \epsilon_{i,t}^k)$$

Since the results of these simulations (C.1 and C.2) will depend on the year chosen as the baseline, we also run them in reverse order, that is assigning the coefficients of year t to the characteristics of year s.

- **C.3** Accounting for the impact of changes in relevant exogenous characteristics

Lastly, in order to study the role played by changes in individual and household characteristics which are exogenous to the occupational choice model (such as education, gender and age structure of the population) we perform a reweighting exercise as the one proposed by Bourguignon et al. (2008). First of all, we will split exogenous characteristics (Z_i for the occupational choice model and X_i for the earnings equation) into a group of relevant, common characteristics (W_i: education, gender and age), which will be the focus of our exercise, and remaining specific characteristics (R_i^Z for the occupational choice model and R_i^X for the earnings equation) (Any sample distributional statistic *G* is a function of the individuals' income ($y_{i,t}$) and their corresponding sample weight ($\omega_{i,t}$). Our exercise consists in modifying the weights of year *t* so the joint distribution of the relevant exogenous characteristics (W_i) match that of year *s*. In other words, if in year *s* the average years of schooling are lower than in year *t*, we then modify the weights of year *t* so the sample of that year has the same average years of schooling than that of year *s*. To do this simultaneously for all the set of relevant exogenous characteristics we use the cross-entropy approach (Wittenberg, 2010). The simulated earnings of individual *i* are given by:

$$\widetilde{y_i}^{s\to t,W} = \sum_{k=1}^{4} \widetilde{I_{i,t}^k}(R_{i,t}^Z, \widetilde{W_{i,s}}, \Gamma^{k,t}, \varepsilon_{i,t}^k)\, \widetilde{y_{i,t}^k}(R_{i,t}^X, \widetilde{W_{i,s}}, \Omega^{k,t}\, \epsilon_{i,t}^k)$$

As for the parametric simulations mentioned above, this reweighting method is path dependent. We take this into account by also performing the exercise in reverse order – choosing year *s* as baseline and reweighting the sample of that year by weights that simulate the joint distribution of year *t*. We then report the average difference in the distributional statistics between year *t* and year *s* using both reweighting orders. Note that, differently to cases C.1-C.3 above, this exercise does not take place at the individual level - individual characteristics and variables don't change, but only their sample weight changes.

- Decomposition order

One of the caveats of our methodology is its path dependency on the decomposition order. That is, the results change whether one performs first the simulation on occupational changes, on wage premia or on the exogenous characteristics. Since the main focus of our analysis are occupational changes, the first counterfactual simulation we carry out is the one corresponding to occupations (**C.1**). That is, we will attribute to changes in occupations the difference in earnings between the counterfactual simulation and the actual earnings distribution:

$$\Delta^{occ} = y_{i,t} - \widetilde{y_i}^{s\to t,\Gamma}$$

$$\Delta^{occ} = y_{i,t} - \sum_{k=1}^{4} y_{i,t}^k\, \widetilde{I_{i,t}^k}(Z_{i,t}, \widetilde{\Gamma^{k,s}}, \varepsilon_i^k)$$

Preserving the changes resulting from this first simulation, we then move on to the reweighting of exogenous characteristics (**C.3**). We will attribute to the changes in these characteristics the difference between the previous counterfactual simulation and the one corresponding to the reweighting exercise. That is:

$$\Delta^{exc} = \widetilde{y_i}^{s\to t,\Gamma} - \widetilde{y_i}^{s\to t,\Gamma,\mathrm{W}}$$

$$\Delta^{exc} = \sum_{k=1}^{4} y_{i,t}^k\, \widetilde{I_{i,t}^k}(Z_{i,t}, \widetilde{\Gamma^{k,s}}, \varepsilon_i^k) - \sum_{k=1}^{4} \widetilde{I_{i,t}^k}(R_{i,t}^Z, \widetilde{W_{i,s}},, \widetilde{\Gamma^{k,s}}, \varepsilon_{i,t}^k)\, \widetilde{y_{i,t}^k}(R_{i,t}^X, \widetilde{W_{i,s}}, \Omega^{k,t}\, \epsilon_{i,t}^k)$$

We then move to the wage premia simulation (**C.2**). We will attribute to the changes in these premia the difference between the simulation in the previous step and the one corresponding to the wage premia simulation. That is:

$$\Delta^{wpr} = \widetilde{y}_{\iota}^{s\to t,\Gamma,\mathrm{W}} - \widetilde{y}_{\iota}^{s\to t,\Gamma,\mathrm{W},\Omega}$$

$$\Delta^{wpr} = \sum_{k=1}^{4} \widetilde{I_{\iota,t}^{k}}\left(R_{i,t}^{Z}, \widetilde{\mathrm{W}_{\iota,s}}, \widetilde{\Gamma^{k,s}}, \varepsilon_{i,t}^{k}\right) \widetilde{y_{\iota,t}^{k}}\left(R_{i,t}^{X}, \widetilde{\mathrm{W}_{\iota,s}}, \Omega^{k,t}\, \epsilon_{i,t}^{k}\right)$$
$$- \sum_{k=1}^{4} \widetilde{I_{\iota,t}^{k}}\left(R_{i,t}^{Z}, \widetilde{\mathrm{W}_{\iota,s}}, \widetilde{\Gamma^{k,s}}, \varepsilon_{i,t}^{k}\right) \widetilde{y_{\iota,t}^{k}}\left(R_{i,t}^{X}, \widetilde{\mathrm{W}_{\iota,s}}, \widetilde{\Omega^{k,s}}\, \epsilon_{i,t}^{k}\right)$$

Lastly, the unexplained part, which can be attributed to changes in the non-common exogenous characteristics (R_i^Z, R_i^X) and unobserved variables (ε_i^k, ϵ_i^k) corresponds to the difference between the last simulation and the actual earnings in the baseline year:

$$\Delta^{unx} = \widetilde{y}_{\iota}^{s\to t,\Gamma,\mathrm{W},\Omega} - y_{i,s}$$

Note that, in a repeated cross-section setting, $y_{i,s}$ is unobserved because individuals are not followed across years. Thus, the unexplained part of changes in earnings will only be possible to estimate for aggregate, anonymous quantiles of the distribution.

Annex. **“Movers” and “stayers”: describing occupational structure change.**

The evidence presented in previous sections illustrates the two broad patterns of occupational change that Europe and Central Asia has been facing in the last twenty years. Whilst the Western part of the region has been going through a process of de-routinization coupled with a regressive change in the earnings distribution, the post-Soviet countries have seen an increase in routine-intensive and non-routine manual intensive jobs and a reduction in earnings inequality. Our analytical model allows us to dig into the characteristics of the flows between occupations. It simulates a counterfactual scenario in which the occupational structure parameters don’t change – a scenario in which part of the occupational change is frozen in time: by comparing the occupation in this counterfactual scenario to the occupation they actually work in we can classify individuals into “movers” -that is, those whose occupation in the counterfactual scenario is different from their actual occupation- and “stayers” -those whose occupation is the same in the counterfactual scenario as in the actual data. We then look at some specific characteristics of the “movers” and “stayers” in different occupations to better characterize occupational change.

1.1 De-routinization of jobs: the case of Germany Poland and Spain

In section 2 we have seen that the main pattern of occupational change in Germany, Poland and Spain is that of a decrease in the share of routine-intensive jobs and a particularly high increase in non-routine, cognitive task intensive jobs, with some times also a slight growth in the share of non-routine, manual task intensive jobs. This describes a process of de-routinization of jobs. But where would individuals have been employed if this process had not happened? In table 4 we present the distribution of the individuals who in the counterfactual scenario -assuming no change in occupational structure parameters since the mid 1990s- are employed in routine task intensive occupations according to their actual occupation observed in 2013. Between 30% and 40% are actually in occupations different from routine task intensive jobs, meaning they “moved” out of those jobs. In Germany and Spain most of those who moved out did it out of employment, whilst in Poland they moved into non-routine, manual intensive occupations. If we restrict to those who move into other occupation categories, in all the cases the movement into non-routine, manual task intensive jobs is bigger than the movement into non-routine, cognitive task intensive jobs.

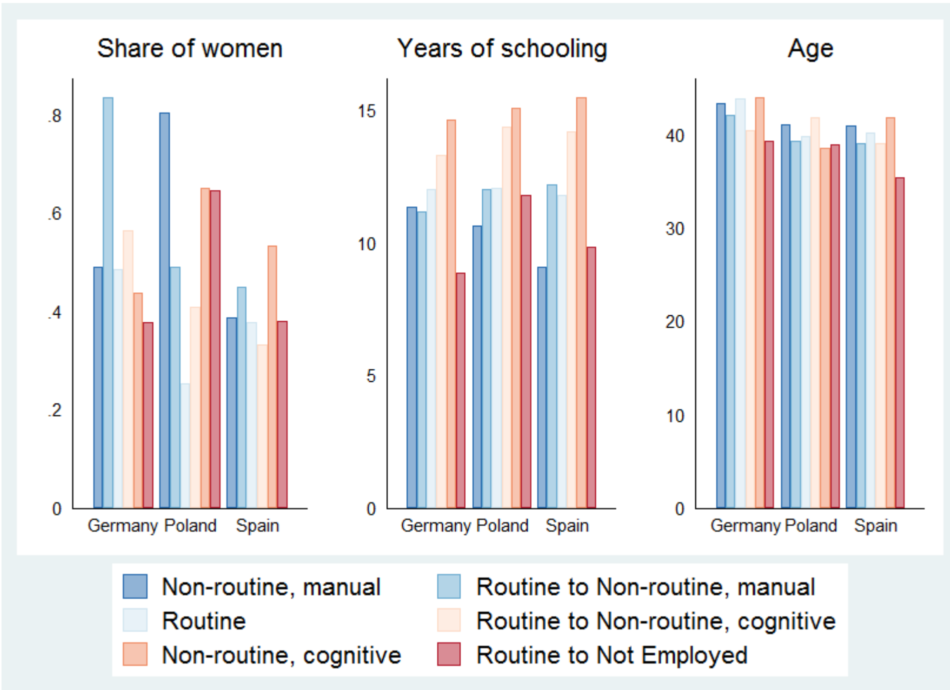
Table 4 – Flows out of routine-task intensive occupations

	Actual occupation observed in 2013 for individuals employed in routine task intensive occupations in the counterfactual scenario (assuming occupational structure parameters as in the mid 1990s)			
	Not employed	Non-routine, manual	Non-routine, cognitive	Routine
	“Movers”			“Stayers”
Germany	15.0%	8.2%	6.2%	70.7%
Poland	9.5%	15.4%	9.2%	65.9%
Spain	23.9%	11.0%	3.3%	61.8%

This table presents the distribution of individuals employed in routine task intensive occupations in the counterfactual scenario according to their actual employment observed in the data. The first column shows those individuals who are not employed but, according to our analytical model, would have been employed in routine task intensive occupations had the occupational structure parameters been the same as in the mid 1990s.The second column shows those individuals who are employed in non-routine, manual task intensive occupations but would have been employed in routine task intensive occupations in the counterfactual scenario simulated by our model. The third column shows those individuals who are employed in non routine, cognitive task intensive occupations but would have been employed in routine task intensive occupations in the counterfactual scenario. The fourth column shows those individuals who are employed in routine task intensive occupations both in the actual and in the counterfactual simulation.

In Figure 14 we present the main characteristics in terms of gender, schooling and age of the "stayers" (in the three occupation categories" and the "movers" (from routine to non-routine, manual task intensive jobs, from routine to non-routine, cognitive task intensive jobs and from routine occupations out of employment).

Figure 14 – Characteristics of "stayers" and "movers": Germany, Poland and Spain



This figure shows a set of descriptive characteristics of the individuals in the final year sample. The dark blue bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, manual task intensive occupations. The light blue bars show the average characteristics of individuals who in the actual data are employed in non-routine, manual task intensive occupations but in the counterfactual scenario are employed in routine-task intensive occupations ("movers" from routine to non-routine, manual task intensive occupations). The lightest blue bars show the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in routine task intensive occupations ("stayers" in routine task intensive occupations). The light orange bars show the average characteristics of individuals who in the actual data are employed in non-routine, cognitive task intensive occupations but in the counterfactual scenario are employed in routine task intensive occupations ("movers" from routine to non-routine, cognitive task intensive occupations). The dark orange bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, cognitive task intensive occupations. The red bar shows the average characteristic of individuals who in the actual data are not employed but in the counterfactual scenario are employed in routine intensive occupations.

In terms of gender, routine task intensive jobs are mostly male occupations. In no case does the share of women among "stayers" of routine task intensive jobs exceed 50%. However, among "movers" out of those occupations the share of women is always equal or greater than that of "stayers", except for the movement out of employment in Germany where it is more male dominated. The comparison between the share of women among "movers" and that of the "stayers" in the occupations where they move to does not have a clear pattern: in Poland and Spain, for instance, the share of women in non-routine, cognitive task intensive jobs is higher than that of the movers into those jobs from routine task intensive occupations, whilst in Germany it's the opposite. On the other hand, the share of women among the "movers" to non-routine, manual task intensive occupations is higher than that of those already in those occupations in Germany and Spain – but not in Poland.

With respect to schooling, there is a clear, common pattern across the three countries. Within "stayers", individuals in non-routine, manual task intensive occupations have the lowest number of years of schooling and individuals in non-routine, cognitive task intensive occupations have the highest number of years of schooling – the individuals in routine task intensive occupations being in the middle. With respect to "movers", those that move into non-routine, manual task intensive jobs have a similar or slightly lower level of education than those that stay in routine intensive occupations, whilst those that move into non-routine, cognitive task intensive occupations. Those that move out of employment have the lowest education level among the three groups of "movers". In this sense, it is the most skilled within routine task-intensive occupations in the counterfactual scenario that are then found in non-routine, cognitive task intensive occupations in the actual data. Those with an average level of education either stay in routine jobs in both scenarios or move into non-routine, manual task intensive jobs, where in any case they have a similar or higher level of education than those already in those occupations. Those with a low level of education end up being out of employment in the actual scenario.

Age wise there are only little and non-significant differences across groups except for those that move out of employment, who in all cases have a lower age than the average of those staying in routine occupations or move into the other occupation categories. In sum, what appears to describe the movers out of routine jobs in Germany, Poland and Spain is their lower degree of masculinity and the difference in their skill level: those with higher levels of education move into non-routine, cognitive task intensive jobs, whilst those with average or lower levels of education move into non-routine, manual task intensive jobs and those with lowest level of education eventually move out of employment. Education, thus, appears to be a key determinant of the trajectories followed by those who move out of routine task intensive jobs.

Lastly, an important aspect of occupational change is its consequence on labor income. Our model allows us to do a quick analytical exercise that can provide an approximation of the actual change in earnings arising from the occupational change seen during the last two decades. We can compare the salary individuals have in the actual data to the one they would have had in the counterfactual scenario. In particular, we can estimate the difference for "movers" – between the wage they are paid in their actual occupation (either intensive in non-routine, manual tasks or in non-routine, cognitive tasks) and the wage they would have been paid in a routine task intensive occupation. We do this using the estimates of the Mincer wage equation for the final year of our analysis. Figure 15 presents the results of this simulated difference[6] for Germany, Poland and Spain.

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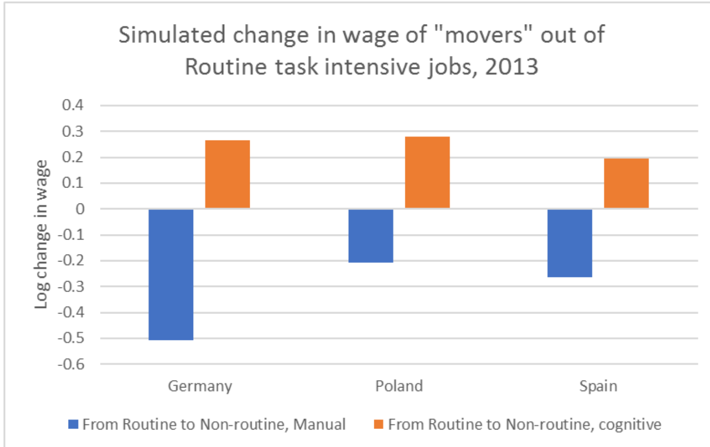
[6] Note that these figures are representative of the group of individuals that have a difference in their occupational category between the actual data and the counterfactual scenario. They do not represent the simulated difference for an average worker presently employed in a routine task intensive occupation.

Figure 15



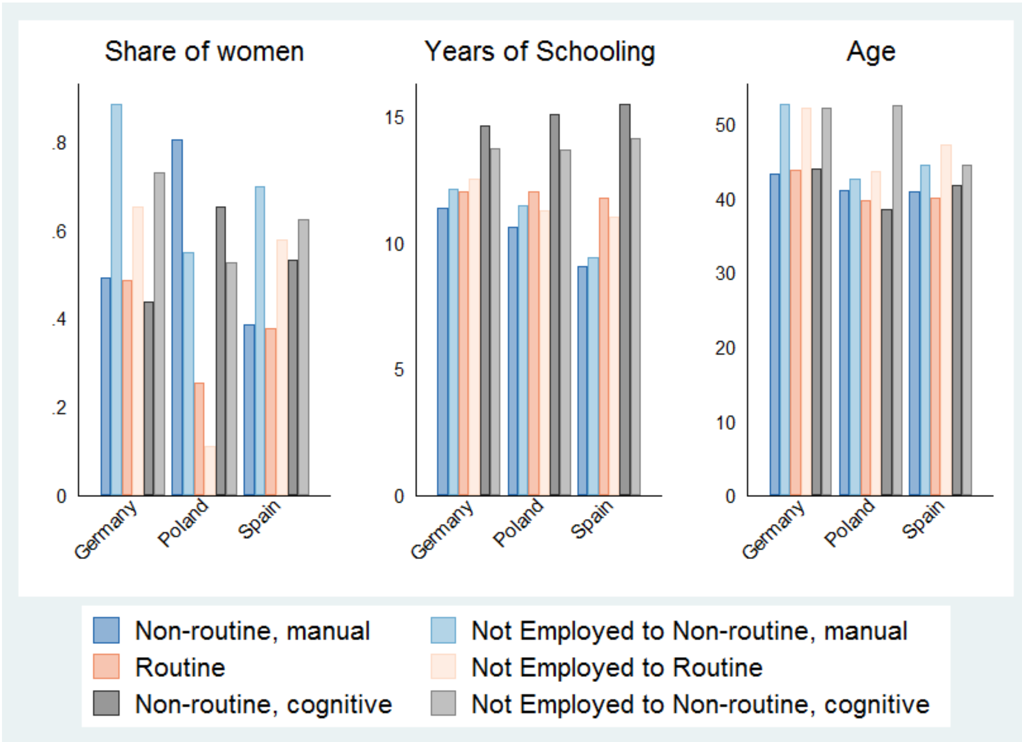
This figure shows the difference between the actual wage and the counterfactual wage for the group of “movers” in the final year sample. The blue bars show the difference between the wage “movers” in non-routine, manual task intensive jobs receive and the wage they would have received if they had been employed in a routine task intensive occupation. The orange bars show the difference between the wage “movers” in non-routine, cognitive task intensive jobs receive and the wage they would have received if they had been employed in a routine task intensive occupation. See the methodological appendix for more details about the estimation of counterfactual wages.

The difference of having moved out from a routine task intensive job to a non-routine, manual task intensive job is negative in all countries, ranging from -0.5 log points (about -40%) in the case of Germany to -0.2 log points in Poland (about -20%), whilst the difference of having moved into non-routine, cognitive task intensive occupations is positive, ranging from 0.2 log points in Spain (about 20%) to 0.27 log points in Poland (about 31%). These estimations show the powerful polarizing effect that de-routinization has had: it may have ultimately resulted in individuals moving into a job where their income is at least 20% higher -when they move to a non-routine, cognitive task intensive job- or moving into a job where their income is at least 20% lower -when they move to a non-routine, manual task intensive job. Note that, to the point that our simulation is retrospective -that is, we classify individuals into their counterfactual occupations had the occupational structure parameters of the mid 1990s been in place- our analysis provides information on the impact de-routinization has had until now. It remains to be seen what are the potential effects of future de-routinization or, more generally, of future occupational change.

In section 2 we have seen that one of the characteristics of occupational change was not only de-routinization but also an increase in participation rates. To analyze better this simultaneous process we provide in Figure 16 the average characteristics of the “new entrants” into the three occupational categories (i.e. those who with the occupational structure parameters of the mid 1990s would have been out of the labor force) and we compare them to those of the incumbents in the same categories. In terms of gender, the striking pattern of Germany and Spain is that, for all the three occupation categories -even for the declining routine, task intensive jobs- the new “entrants” are overwhelmingly more likely to be female than the incumbents. In particular, the share of women among “new entrants” into non-routine, manual task intensive jobs was above 80% in Germany and close to 70% in Spain. For the other two occupational categories, the percentages were around 60%. In the case of Poland the opposite is true: “new entrants” are considerably more masculine than incumbents in all categories.

With respect to education, the common pattern is that “new entrants” into non-routine, cognitive task intensive jobs have a lower number of years of schooling than incumbents, whilst they have a slightly higher level than incumbents in non-routine, manual task intensive jobs. And lastly, with respect to age, the common pattern is that “new entrants” are always older than incumbents, especially in Germany. This suggests that the overall aging process that these economies are facing may be spilling over into occupational change, as participation rates of older people increase – especially those of women in Germany and Spain, and those of men in Poland.

Figure 16 – Characteristics of “new entrants” and incumbents: Germany, Poland and Spain



This figure shows a set of descriptive characteristics of the individuals in the final year sample. The dark blue bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, manual task intensive occupations. The light blue bars show the average characteristics of individuals who in the actual data are employed in non-routine, manual task intensive occupations but in the counterfactual scenario are not employed (“new entrants” into non-routine, manual task intensive occupations). The dark orange bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in routine task intensive occupations. The light orange bars show the average characteristics of individuals who in the actual data are employed in routine task intensive occupations but in the counterfactual scenario are not employed (“new entrants” into to routine task intensive occupations). The dark gray bars show the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, cognitive task intensive occupations. The light grey bars show the average characteristics of individuals who in the actual data are employed in non-routine, cognitive task intensive occupations but in the counterfactual scenario are not employed (“new entrants” into non-routine, cognitive task intensive occupations).

1.2 Occupational change in post-Soviet countries and Turkey

Occupational change in post-Soviet countries and Turkey during the last decade has two distinctive features: on the one hand, an increase in participation rates, which have brought "new" workers into all occupational categories, and on the other hand a relative growth of routine task intensive and particularly non-routine, manual task intensive jobs at the expense of a decrease in the share of employment of non-routine, cognitive task intensive occupations. In table 5 we present the distribution of those employed in non-routine, manual task intensive jobs and routine task intensive jobs according to their occupational category in the counterfactual scenario where occupational structure parameters are the same as in the initial period. In this way, we are able to simulate the "occupation of origin" of those who are presently employed in those two occupation categories.

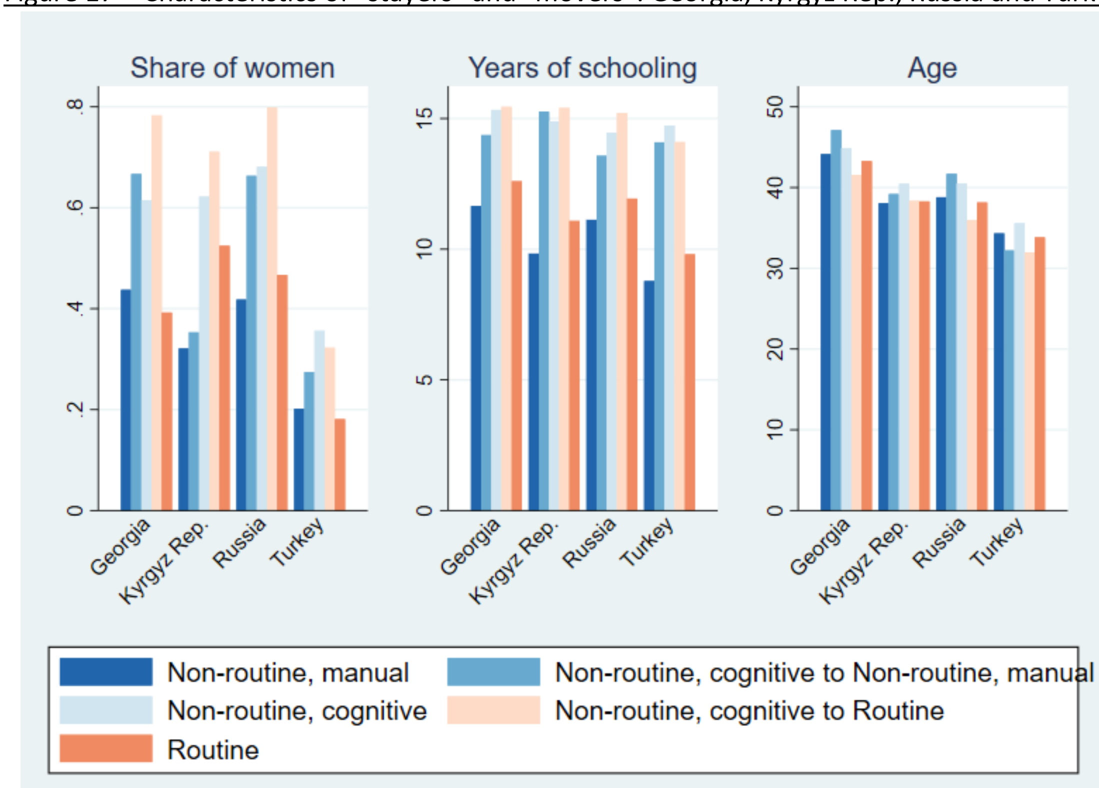
Table 5 – Flows into non-routine, manual and routine intensive occupations

	Occupation in counterfactual scenario (assuming occupational structure parameters as in the initial year)				Actual change in share of employment, p.p. of working age population
Actual occupation observed in final year	Not employed	Non-routine, manual	Routine	Non-routine, cognitive	
Non-routine, manual	"New Entrants"	"Stayers"	"Movers"		*Non-routine, manual*
Georgia	34.0%	57.4%	2.8%	5.8%	3.3%
Kyrgyz Rep.	21.0%	69.4%	2.2%	7.4%	2.7%
Russia	17.0%	69.5%	5.5%	8.0%	0.7%
Turkey	34.7%	43.9%	1.9%	5.1%	4.4%
Routine	"New Entrants"	"Movers"	"Stayers"	"Movers"	*Routine*
Georgia	28.8%	1.5%	63.6%	6.1%	1.4%
Kyrgyz Rep.	17.1%	4.1%	70.8%	7.9%	0.9%
Russia	14.0%	2.3%	68.3%	15.4%	2.0%
Turkey	18.8%	0.1%	53.1%	3.6%	2.3%

This table presents different statistics on the flows into non-routine, manual task intensive and routine task intensive occupations. The first four columns describe the distribution of the individuals presently employed in non-routine, manual task intensive occupations (first four rows) and in routine task intensive occupation (second four rows) according to their occupation in the counterfactual scenario that assumes structural parameters to be the same as those in the initial sample year. The first column shows those individuals who, according to our analytical model, would have been out of employment in the counterfactual scenario. The second column shows those individuals who would have been employed in non-routine, manual task intensive occupations had the occupational structural parameters been the same as in the initial year. The third column shows those individuals who would have been employed in routine task intensive occupations and the fourth column shows those who would have been employed in non-routine, cognitive task intensive occupations in the counterfactual scenario. Lastly, the fifth column shows the change in the share of employment (over the working age population, excluding self employed) between the initial year (2002 for Georgia, 2004 for the Kyrgyz Republic, 1994 for Russia and 2002 for Turkey) and the final year (2015 for Georgia, 2014 for the Kyrgyz Republic and Russia, 2013 for Turkey) of the corresponding occupation categories.

The first pattern that emerges from the figures presented in Table 5 is the relevance that have those who have moved from out of employment into both occupational categories – a reflection of the important increase in participation rates we have shown in section 2. Around a third of those that are presently working in non-routine, manual task intensive occupations in Georgia and Turkey -the countries where that occupational category presented the highest growth, more than three percentage points of the working population during the period under analysis- would have been out of the labor force had the occupational structure been the same as in the early 2000s. For the Kyrgyz Republic and Russia that same figure is around 20%. In the case of those presently employed in routine task intensive occupations, the percentage of individuals who would have been out of the labor force is lower in all the cases – below 20% in all countries except Georgia, where it is slightly lower than 30%. A second common pattern is that, considering those who moved from employed occupation categories, the share of "movers" from non-routine, cognitive task intensive jobs is the largest, even in Georgia and Turkey where the actual share of non-routine, cognitive jobs increased as percentage of the working age population. It appears that the growth of non-routine, manual task intensive jobs and routine intensive jobs has been fueled by individuals coming from out of the labor force or from non-routine, cognitive task intensive occupations, with limited movement between the two growing categories. In Figure 17 we present some descriptive statistics of the "movers" from non-routine, cognitive task intensive occupations in comparison to those of the "stayers" in that same category and in the two growing categories – non-routine, manual task intensive and routine task intensive occupations.

Figure 17 – Characteristics of "stayers" and "movers": Georgia, Kyrgyz Rep., Russia and Turkey



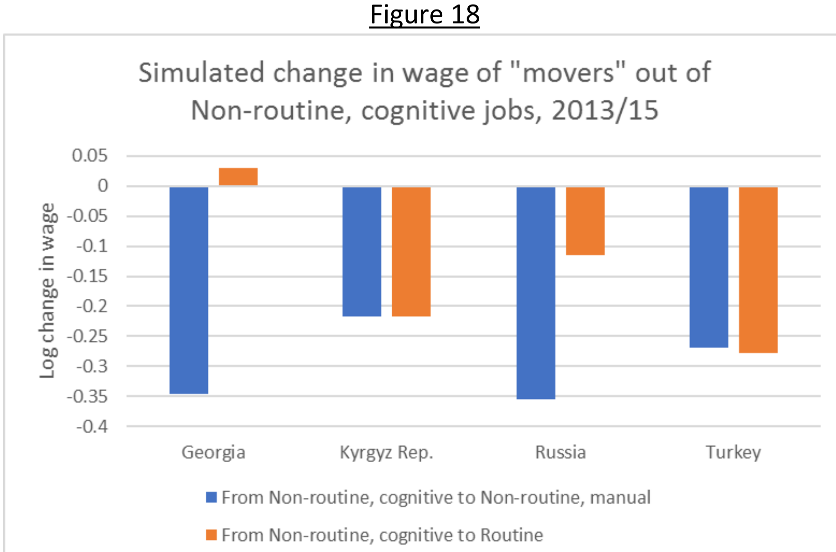
This figure shows a set of descriptive characteristics of the individuals in the final year sample. The dark blue bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, manual task intensive occupations. The light blue bars show the average characteristics of individuals who in the actual data are employed in non-routine, manual task intensive occupations but in the counterfactual scenario are employed in non-routine, cognitive task intensive jobs ("movers" from non-routine, cognitive task intensive to non-routine, manual task intensive occupations). The lightest blue bars show the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, cognitive task intensive occupations ("stayers" in non-routine, cognitive task intensive occupations). The light orange bars show the average characteristics of individuals who in the actual data are employed in routine task intensive occupations but in the counterfactual scenario are employed in non-routine, cognitive task intensive occupations ("movers" from non-routine, cognitive task intensive to routine task intensive occupations). The dark orange bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in routine task intensive occupations.

Non-routine, cognitive task intensive jobs have in all four countries a share of women higher than the two other occupation categories and, thus, the "movers" out of those jobs are made up of a higher share of women than those in non-routine, manual task intensive and routine task intensive jobs. The share of women in "movers" out of non-routine, cognitive task intensive jobs is above 50% in all the countries except Turkey, where it is between 20% and 30%. In this sense, within-employed occupational change appears to be predominantly female driven in these countries.

In terms of schooling, a similar pattern arises: as expected, the years of education of both "stayers" in non-routine, cognitive task intensive jobs and "movers" out of that category are higher than in the other two, growing occupational categories. In particular, this suggests that "movers" into non-routine, manual task intensive and routine task intensive jobs may be overskilled with respect to the incumbents in those occupations. Lastly, with respect to age all occupational categories appear to have a similar age profile, without significant differences between them.

The consequence in terms of labor income of the occupational change we have just described can be seen in the Figure 18, where we have simulated the difference in wages that "movers" have between the actual salary they receive in either non-routine, manual task intensive occupations or routine task intensive occupations and the salary they would have received in non-routine, cognitive task intensive jobs.

Figure 18



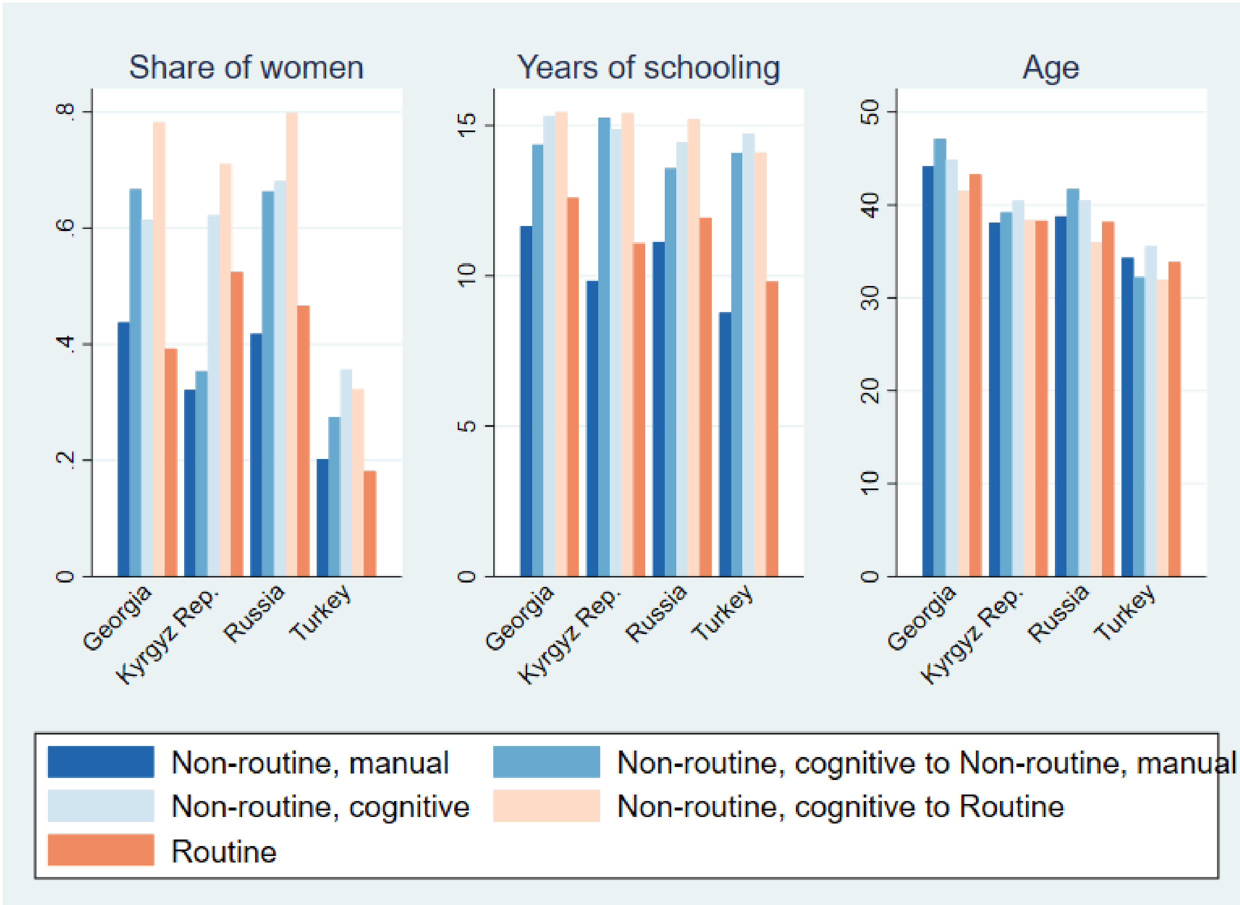
This figure shows the difference between the actual wage and the counterfactual wage for the group of "movers" out of non-routine, cognitive jobs in the final year sample. The blue bars show the difference between the wage "movers" in non-routine, manual task intensive jobs receive and the wage they would have received if they had been employed in a non-routine, cognitive task intensive occupation. The orange bars show the difference between the wage "movers" in routine task intensive jobs receive and the wage they would have received if they had been employed in a non-routine, cognitive task intensive occupation. See the methodological appendix for more details about the estimation of counterfactual wages.

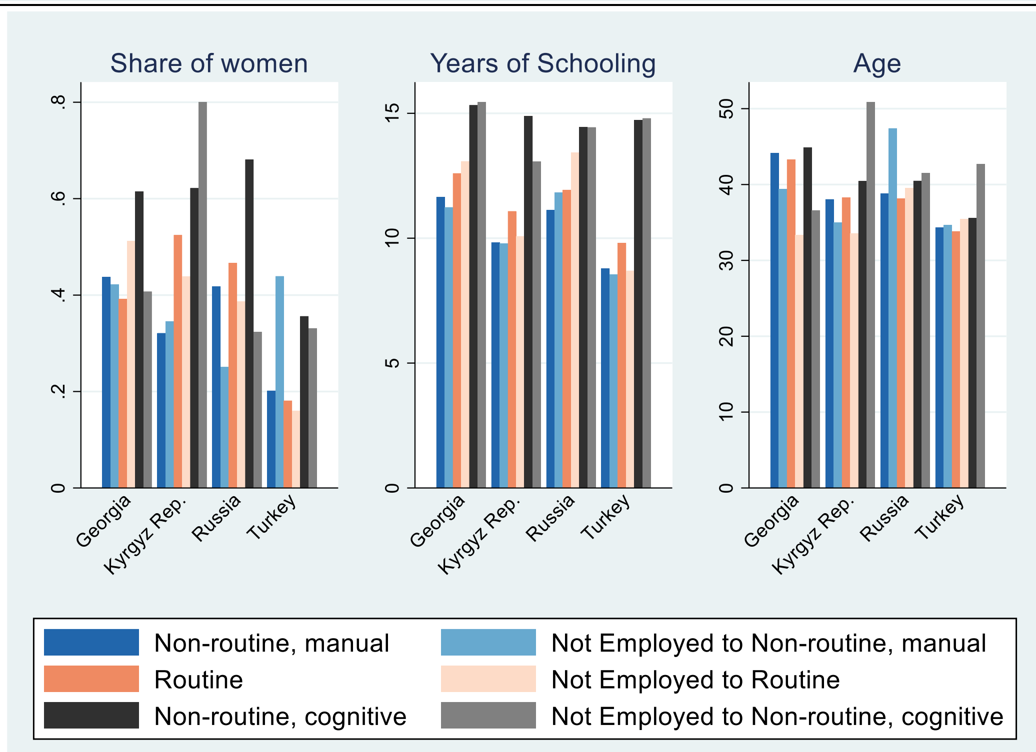
Differently to the case of Germany, Poland and Spain, were a part of the “movers” from de-routinization gained income and another part lost income, in post-Soviet countries and Turkey most of the “movers” actually lose income. Only in Georgia do “movers” from non-routine, cognitive task intensive jobs gain a slight amount of income by moving into routine, task intensive jobs. In the rest of the cases, the loses vary between about 10% of the wage to more than 30%. This is not surprising given the fact that, as we saw in the previous paragraph, “movers” from non-routine, cognitive task intensive jobs are 1) more educated than the “incumbents” in the categories they move to; 2) move into categories with lower returns to education[7]. This evidence suggests that the most educated in these four countries are the relative losers of occupational change.

As we saw in Table 5, the role of “new entrants” into the labor force is relevant in routine task intensive jobs and especially in non-routine, manual task intensive occupations. In Figure 19 we compare the average characteristics of “new entrants” into the three occupational categories with the same characteristics of the incumbents in those categories, i.e. the “stayers”.

[7] The log difference in wages between tertiary education and secondary education for household heads is highest in non-routine, cognitive occupations than in the other two categories in the four countries.

Figure 19 – Characteristics of "new entrants" and incumbents: Georgia, Kyrgyz Rep., Russia and Turkey





This figure shows a set of descriptive characteristics of the individuals in the final year sample. The dark blue bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, manual task intensive occupations. The light blue bars show the average characteristics of individuals who in the actual data are employed in non-routine, manual task intensive occupations but in the counterfactual scenario are not employed ("new entrants" into non-routine, manual task intensive occupations). The dark orange bar shows the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in routine task intensive occupations. The light orange bars show the average characteristics of individuals who in the actual data are employed in routine task intensive occupations but in the counterfactual scenario are not employed ("new entrants" into to routine task intensive occupations). The dark gray bars show the average characteristics of individuals who in the actual data and in the counterfactual scenario are employed in non-routine, cognitive task intensive occupations. The light grey bars show the average characteristics of individuals who in the actual data are employed in non-routine, cognitive task intensive occupations but in the counterfactual scenario are not employed ("new entrants" into non-routine, cognitive task intensive occupations).

First of all, with respect to gender, heterogeneous patterns emerge: the share of women among new entrants is considerably higher than that of incumbents in Turkey, suggesting a strong increase in female labor participation rate. In Russia, the opposite is true: the share of women is lower among "new entrants" in relation to incumbents in all three occupational categories: the increase in participation rates appears to be driven by men. In Georgia and the Kyrgyz Republic the gender profile is mixed, with no clear pattern. With respect to education, new entrants appear in all cases to match the level of education of incumbents, suggesting that new entrants select into occupations were people of the same schooling profile as them are employed. Lastly, with respect to age, new entrants appear to be younger than incumbents in Georgia and partly in the Kyrgyz Republic[8], whilst they appear to be older than incumbents in Russia, with no clear age pattern in Turkey. Summing up, the evidence suggests that the increase in participation rates appears to be driven by young men and women in Georgia and the Kyrgyz Republic, by older men in Russia and by women in general in Turkey.

Appendix Tables

Table A.2 - Marginal change in the probability of being in each occupation category, household heads

		Initial				Final				Difference			
		NE	NR, M	R	NR, C	NE	NR, M	R	NR, C	NE	NR, M	R	NR, C
Germany	Tertiary edu.	-0.092	-0.132	-0.116	0.340	-0.203	-0.157	-0.065	0.425	-0.111	-0.025	0.051	0.085
	Secondary edu.	-0.042	-0.026	0.046	0.022	-0.189	-0.035	0.109	0.115	-0.147	-0.009	0.063	0.093
	Female	0.019	-0.014	0.024	-0.028	-0.016	0.055	-0.010	-0.030	-0.034	0.069	-0.033	-0.001
Poland	Tertiary edu.	-0.153	-0.124	-0.064	0.341	-0.124	-0.197	-0.225	0.546	0.029	-0.073	-0.161	0.205
	Secondary edu.	-0.105	-0.103	0.113	0.095	-0.148	-0.119	-0.004	0.271	-0.043	-0.016	-0.117	0.176
	Female	0.089	0.078	-0.226	0.059	0.065	0.104	-0.238	0.069	-0.024	0.026	-0.012	0.010
Spain	Tertiary edu.	-0.090	-0.248	0.043	0.296	-0.205	-0.162	-0.024	0.392	-0.115	0.086	-0.067	0.096
	Secondary edu.	-0.071	-0.138	0.180	0.029	-0.121	-0.017	0.099	0.039	-0.050	0.121	-0.081	0.010
	Female	0.147	-0.069	-0.087	0.009	0.111	-0.017	-0.070	-0.023	-0.036	0.051	0.017	-0.033
Georgia	Tertiary edu.	-0.121	-0.077	-0.029	0.227	-0.150	-0.069	-0.026	0.245	-0.029	0.007	0.003	0.019
	Secondary edu.	-0.101	0.020	0.047	0.034	-0.156	0.013	0.099	0.044	-0.055	-0.007	0.052	0.010
	Female	-0.098	0.089	-0.032	0.041	-0.080	0.071	-0.035	0.044	0.018	-0.018	-0.003	0.003

[8] To the point that agricultural familiar or unpaid employment is classified as out of employment in our model, this may actually reflect a move of young people from that type of employment to actual wage employment.

Kyrgyz Rep.	Tertiary edu.	-0.077	-0.198	0.016	0.259	-0.139	-0.069	-0.018	0.226	-0.062	0.129	-0.034	-0.034
	Secondary edu.	-0.091	-0.045	0.089	0.047	0.002	-0.085	0.044	0.039	0.093	-0.040	-0.045	-0.008
	Female	0.085	-0.117	0.033	-0.001	0.078	-0.125	0.020	0.028	-0.008	-0.008	-0.013	0.028
Russia	Tertiary edu.	-0.028	-0.302	-0.102	0.432	-0.188	-0.212	0.015	0.385	-0.160	0.090	0.117	-0.047
	Secondary edu.	-0.075	-0.045	-0.007	0.127	-0.127	-0.022	0.040	0.109	-0.052	0.023	0.047	-0.018
	Female	-0.036	-0.061	-0.022	0.118	0.043	-0.106	0.002	0.060	0.079	-0.045	0.024	-0.058
Turkey	Tertiary edu.	-0.130	-0.207	-0.268	0.605	-0.158	-0.148	-0.230	0.536	-0.029	0.059	0.039	-0.069
	Secondary edu.	-0.057	-0.042	-0.021	0.119	-0.042	-0.058	-0.019	0.120	0.014	-0.017	0.002	0.001
	Female	0.173	-0.122	-0.081	0.030	0.109	-0.071	-0.087	0.049	-0.064	0.052	-0.007	0.019

This table presents the marginal change in probabilities of being out of employment (NE), in a Non-routine, Manual task intensive occupation (NR, M), in a Routine task intensive occupation (R) or in a Non-routine, Cognitive task intensive occupation (NR,C) for household heads holders of tertiary education diploma or secondary education diploma and females. The marginal change in probabilities for tertiary education is calculated with respect to those that hold a secondary education diploma, whilst the marginal change in probabilities for secondary education is calculated with respect to those that hold a primary education diploma or have no formal education. The marginal change in probabilities for females are calculated with respect to males.

Table A.3 - Marginal change in the probability of being in each occupation category, spouses

		Initial				Final				Difference			
		NE	NR, M	R	NR, C	NE	NR, M	R	NR, C	NE	NR, M	R	NR, C
Germany	Tertiary edu.	-0.104	-0.082	-0.035	0.220	-0.439	-0.050	0.089	0.399	-0.335	0.032	0.124	0.180
	Secondary edu.	-0.073	-0.073	0.135	0.012	-0.431	0.114	0.217	0.100	-0.357	0.187	0.082	0.088
	Employed head	-0.060	-0.010	0.026	0.044	-0.087	0.010	0.031	0.047	-0.028	0.019	0.005	0.003
Poland	Tertiary edu.	-0.235	-0.094	-0.055	0.384	-0.149	-0.129	-0.094	0.372	0.086	-0.035	-0.038	-0.012
	Secondary edu.	-0.156	-0.139	0.179	0.117	-0.165	0.015	0.071	0.079	-0.009	0.154	-0.107	-0.038
	Employed head	0.040	0.008	-0.036	-0.012	-0.220	0.071	0.103	0.047	-0.260	0.063	0.139	0.058
Spain	Tertiary edu.	-0.190	-0.041	0.084	0.147	-0.221	-0.157	0.017	0.361	-0.031	-0.116	-0.068	0.214
	Secondary edu.	-0.051	-0.011	0.054	0.008	-0.115	0.006	0.072	0.037	-0.064	0.017	0.018	0.029
	Employed head	0.050	-0.041	-0.004	-0.005	-0.032	0.013	-0.008	0.026	-0.082	0.054	-0.004	0.032
Georgia	Tertiary edu.	-0.190	-0.003	-0.014	0.208	-0.187	-0.067	0.018	0.236	0.003	-0.064	0.033	0.029
	Secondary edu.	-0.096	0.022	0.029	0.045	-0.193	0.132	0.039	0.022	-0.098	0.110	0.010	-0.023
	Employed head	-0.027	0.005	-0.007	0.028	0.009	0.012	-0.003	-0.018	0.036	0.007	0.004	-0.046
Kyrgyz Rep.	Tertiary edu.	-0.145	-0.060	-0.041	0.245	-0.251	-0.003	-0.005	0.259	-0.106	0.057	0.036	0.013
	Secondary edu.	-0.149	0.054	0.057	0.038	-0.109	0.000	0.064	0.045	0.040	-0.054	0.007	0.007
	Employed head	-0.062	0.040	0.016	0.005	-0.037	0.011	0.012	0.013	0.025	-0.029	-0.004	0.008
Russia	Tertiary edu.	-0.132	-0.347	-0.052	0.532	-0.175	-0.310	0.023	0.462	-0.042	0.037	0.075	-0.070
	Secondary edu.	-0.140	-0.134	0.038	0.236	-0.112	-0.091	0.053	0.150	0.028	0.043	0.015	-0.086
	Employed head	-0.106	-0.012	0.057	0.061	-0.055	0.026	0.053	-0.023	0.051	0.038	-0.004	-0.084
Turkey	Tertiary edu.	-0.356	-0.003	0.089	0.270	-0.322	0.022	0.088	0.212	0.034	0.025	-0.002	-0.057
	Secondary edu.	-0.072	0.012	0.024	0.035	-0.089	0.020	0.036	0.033	-0.017	0.008	0.011	-0.002
	Employed head	0.008	-0.004	-0.005	0.001	-0.003	-0.006	0.015	-0.006	-0.011	-0.002	0.019	-0.006

This table presents the marginal change in probabilities of being out of employment (NE), in a Non-routine, Manual task intensive occupation (NR, M), in a Routine task intensive occupation (R) or in a Non-routine, Cognitive task intensive occupation (NR,C) for spouses holders of tertiary education diploma or secondary education diploma and for those whose head of household is employed. The marginal change in probabilities for tertiary education is calculated with respect to those that hold a secondary education diploma, whilst the marginal change in probabilities for secondary education is calculated with respect to those that hold a primary education diploma or have no formal education. The marginal change in probabilities for females are calculated with respect to males.

Table A.4 - Marginal change in the probability of being in each occupation category, other household members

		Initial				Final				Difference			
		NE	NR, M	R	NR, C	NE	NR, M	R	NR, C	NE	NR, M	R	NR, C
Germany	Tertiary edu.	-0.132	0.039	-0.030	0.122	-0.537	0.105	0.238	0.193	-0.405	0.066	0.268	0.071
	Secondary edu.	-0.102	0.017	0.072	0.013	-0.286	0.092	0.152	0.042	-0.184	0.074	0.081	0.028
	Female	0.006	-0.029	-0.005	0.027	-0.025	0.050	-0.029	0.004	-0.031	0.079	-0.024	-0.023
	Employed head	-0.009	-0.013	0.023	-0.001	-0.016	0.011	0.006	-0.001	-0.007	0.024	-0.017	0.000
Poland	Tertiary edu.	-0.118	-0.048	-0.070	0.236	-0.291	0.021	0.128	0.142	-0.173	0.069	0.198	-0.094
	Secondary edu.	-0.129	-0.021	0.103	0.047	-0.235	0.068	0.108	0.059	-0.106	0.089	0.005	0.012
	Female	-0.059	0.105	-0.078	0.032	0.068	0.040	-0.112	0.004	0.126	-0.065	-0.034	-0.028
	Employed head												
Spain	Tertiary edu.	-0.043	-0.111	0.045	0.109	-0.231	-0.040	0.004	0.267	-0.188	0.071	-0.041	0.158
	Secondary edu.	0.087	-0.102	0.009	0.006	-0.065	0.018	0.024	0.022	-0.151	0.120	0.015	0.016
	Female	0.088	-0.060	-0.030	0.002	0.020	0.011	-0.039	0.009	-0.068	0.071	-0.010	0.007
	Employed head	-0.014	0.012	-0.005	0.007	-0.062	0.041	0.012	0.010	-0.049	0.029	0.017	0.002
Georgia	Tertiary edu.	-0.129	-0.023	0.009	0.142	-0.187	-0.028	0.022	0.193	-0.058	-0.006	0.013	0.051
	Secondary edu.	-0.067	0.024	0.019	0.025	-0.184	0.106	0.058	0.021	-0.117	0.082	0.039	-0.004
	Female	-0.036	-0.010	-0.008	0.054	-0.005	-0.035	0.017	0.023	0.031	-0.025	0.025	-0.031
	Employed head	-0.038	0.017	0.008	0.013	-0.033	0.020	-0.007	0.020	0.005	0.003	-0.015	0.007
Kyrgyz Rep.	Tertiary edu.	-0.100	-0.033	0.014	0.120	-0.112	-0.004	0.004	0.112	-0.011	0.029	-0.010	-0.008
	Secondary edu.	-0.088	0.040	0.026	0.022	-0.050	0.015	0.018	0.017	0.038	-0.025	-0.008	-0.005
	Female	0.051	-0.073	-0.004	0.026	0.136	-0.120	-0.037	0.021	0.085	-0.047	-0.033	-0.005
	Employed head	-0.066	0.046	0.016	0.003	-0.006	-0.015	0.009	0.012	0.059	-0.061	-0.007	0.009
Russia	Tertiary edu.	-0.159	-0.038	-0.046	0.243	-0.278	-0.082	0.108	0.253	-0.120	-0.044	0.154	0.010
	Secondary edu.	-0.106	0.002	0.011	0.093	-0.188	0.058	0.064	0.066	-0.082	0.056	0.053	-0.028
	Female	-0.017	-0.042	-0.009	0.068	0.054	-0.051	-0.026	0.023	0.071	-0.009	-0.017	-0.045
	Employed head	-0.056	0.018	0.034	0.004	-0.049	0.009	0.035	0.005	0.007	-0.008	0.001	0.001
Turkey	Tertiary edu.	-0.075	-0.050	-0.037	0.163	-0.126	-0.063	-0.023	0.211	-0.051	-0.012	0.015	0.049
	Secondary edu.	-0.014	-0.001	-0.014	0.029	-0.022	0.007	-0.023	0.037	-0.008	0.009	-0.009	0.008
	Female	0.121	-0.060	-0.067	0.006	0.146	-0.062	-0.090	0.006	0.025	-0.002	-0.023	0.000
	Employed head	-0.013	0.003	0.004	0.006	-0.073	0.032	0.027	0.014	-0.061	0.029	0.023	0.009

This table presents the marginal change in probabilities of being out of employment (NE), in a Non-routine, Manual task intensive occupation (NR, M), in a Routine task intensive occupation (R) or in a Non-routine, Cognitive task intensive occupation (NR,C) for other household members holders of tertiary education diploma or secondary education diploma, females and for those whose head of household is employed. The marginal change in probabilities for tertiary education is calculated with respect to those that hold a secondary education diploma, whilst the marginal change in probabilities for secondary education is calculated with respect to those that hold a primary education diploma or have no formal education. The marginal change in probabilities for females are calculated with respect to males. The marginal change in probabilities for females are calculated with respect to males.