# The Impact of Automation on Inequality Across Europe*

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**Abstract**

Existing research suggests that automation has the potential to impact inequality through two channels, either by changing the relative wage returns for different sets of tasks or by changing the composition of employment. This paper measures the relative importance of these two channels for a sample of European countries by decomposing the effects of a set of characteristics along these two dimensions using the structure of earnings survey (SES) and data for 2002 and 2014 Firpo et al. (2018). The approach isolates changes in the earnings distribution to identify the component that is due to changes in composition and to changes in the wage structure. We find that the risk of automation has the largest impact on inequality in our sample of European countries. The composition effect explains a large part of automation related inequality in all of the countries, but the wage effect is also relevant in half of the countries. These results confirm that the way in which technology is increasing inequality is largely due to the fact that there is a growing wage dispersion between jobs that are resilient to automation and those that are not.

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# 1 Introduction

Over the past 30 years, and since the new millennium in particular, inequality has increased across Europe. Countries that have experienced this rise vary in geographic region and include new member states of the European Union (EU), Nordic countries, Mediterranean countries and countries in western Europe. Table 1 reflects these trends by showing Gini coefficients for a cross-section of EU countries in 2007 and 2015. Research has shown that much of the observed rise in inequality is due to increases at the very top of the distribution Jaumotte & Osorio (2015), and that while the rate of increase in inequality slowed around the time of the global economic crisis, it began to resume its increasing trend shortly after the economic disruption Cingano (2014). Given Europe's historically low rate of inequality, these rising rates are alarming and raise questions regarding the major driving force behind the recent rise in inequality.

Existing analyses seeking to identify the causes of rising inequality have highlighted a broad set of factors that include changing labor institutions Malerba & Spreafico (2014), the decline of union participation N. M. Fortin & Lemieux (1997), increased financialization Karabarbounis & Neiman (2013), and more recently, technological change. In this paper we examine a wide array of causes that include individual, technological, firm, industry and national (labor market institutions) characteristics to understand the main drivers of rising inequality. When measuring technological change, we focus on the most recent wave of innovation.

Recent advances in computer science have made it possible to automate a variety of tasks that include routine and non-routine cognitive tasks. In particular, the ability to automate tasks related to non-routine cognitive tasks is relatively new, and largely driven by fast-paced advancement in artificial intelligence, machine learning and mobile robotics. Some jobs have been greatly transformed, such as help desk services that largely troubleshoot complex problems rather than redirecting calls to specialists, and cashiers at grocery stores who may solve self-checkout problems rather than checking out each customer individually. Other jobs have seen specific complex tasks automated within their occupation, such as doctors who can monitor patients through software remotely or lawyers who utilize text analysis for pre-trial analysis. Recent work including that of Frey and Osborne (2017) and Nedelkoska and Quintini (2018) suggest that a large share of current jobs will be automatable in the relatively near future. Frey and Osborne (2017) find that 47% of employment could potentially be disrupted with jobs in logistics and transportation, office and administrative support, and production occupations being most at risk. Overall, recent evidence has found that new technologies that have progressed substantially in the past decade offer the potential for increased and rapid automation within and across a wide variety of jobs.

**Table 1:** Gini Coefficients across Europe in 2007 & 2015

| Country | 2007 | 2015 | Change | % Change |
|---|---|---|---|---|
| Luxembourg | 0.277 | 0.306 | 0.029 | 10.29 |
| Lithuania | 0.338 | 0.372 | 0.034 | 10.00 |
| Sweden | 0.259 | 0.282 | 0.023 | 8.92 |
| Spain | 0.324 | 0.345 | 0.021 | 6.50 |
| Hungary | 0.272 | 0.289 | 0.018 | 6.48 |
| Italy | 0.313 | 0.333 | 0.020 | 6.48 |
| Estonia | 0.313 | 0.330 | 0.017 | 5.42 |
| Denmark | 0.244 | 0.256 | 0.012 | 5.02 |
| Norway | 0.250 | 0.262 | 0.012 | 4.83 |
| Slovenia | 0.239 | 0.250 | 0.011 | 4.61 |
| Greece | 0.329 | 0.340 | 0.012 | 3.55 |
| Germany | 0.285 | 0.293 | 0.008 | 2.97 |
| Slovak Republic | 0.245 | 0.251 | 0.006 | 2.27 |
| France | 0.292 | 0.295 | 0.003 | 1.01 |
| Czech Republic | 0.256 | 0.258 | 0.002 | 0.77 |
| Ireland | 0.304 | 0.298 | -0.006 | -1.83 |
| Turkey | 0.409 | 0.398 | -0.011 | -2.69 |
| Austria | 0.284 | 0.276 | -0.009 | -3.12 |
| Belgium | 0.277 | 0.268 | -0.009 | -3.19 |
| United Kingdom | 0.373 | 0.360 | -0.013 | -3.49 |
| Finland | 0.269 | 0.259 | -0.010 | -3.83 |
| Switzerland | 0.312 | 0.297 | -0.014 | -4.62 |
| Netherlands | 0.308 | 0.288 | -0.020 | -6.42 |
| Portugal | 0.361 | 0.336 | -0.025 | -6.87 |
| Latvia | 0.374 | 0.347 | -0.028 | -7.35 |
| Poland | 0.316 | 0.292 | -0.023 | -7.40 |
| Iceland | 0.286 | 0.246 | -0.039 | -13.78 |

Source: OECD Income Distribution Database (2018)

Tasks that are automated will decrease in demand over time. For example, automotive workers previously worked on assembly lines that repetitively fit parts to bolt holes, but today, this task is largely done by robotic machines. The demand for workers who work along assembly lines doing similar routine tasks has drastically decreased. However, there still remains some tasks that are unaffected by automation, and there are also tasks that work alongside new technologies. These types of tasks that can work alongside new technologies are increasing in demand. For example, computer programming to develop online platforms for services is a fast growing skill that requires non-routine cognitive skills and complex problem solving. Previous research has found that tasks that are experiencing higher rates of demand are related to skills that require higher levels of education and use non-routine cognitive tasks, while there is a decline in demand for skills associated with routine tasks that require lower levels of education D. H. Autor et al. (2003). As a consequence of changes in the demand for these skills, the relative wage of non-routine cognitive skills has risen compared to routine tasks, resulting in an increase in inequality. We can identify one part of this effect as the wage effect, which is how inequality may increase due to changes in relative wage returns. The other effect is a composition effect, which represents changes in the demand of tasks that may lead to some jobs disappearing, while other jobs growing.

This paper contributes to the literature by measuring the effect that automation has on inequality in terms of the wage effect and the composition effect across a broad set of 10 European countries. Using data from the Structure of Earnings Survey (SES), we examine the determinants of inequality for workers between 2002 and 2014. The dataset allows us to observe detailed information about an individual, such as gender and education, information about the firm for which they work, such as the industry and size of the company, and specific information about their earnings such as the type of contract they have and number of hours they work. We use a measure that estimates the risk of automation of each occupation to proxy automation levels of an occupation, and henceforth we use the terms risk of automation and automation interchangeably throughout this paper. Using this information, we decompose the relative importance that various characteristics have on income inequality. Although our data is observed cross-sectionally for two time periods (2002, 2014), we can identify whether observed changes in the wage distribution for each characteristic is due to changes in endowments (i.e. an increase in the share of automated jobs) or due to changes in the returns to endowments (i.e. a higher return to automation resilient jobs). As a result, we can identify the relative impact that automation has compared to other variables, and further, whether automation is impacting inequality more through the wage effect or the composition effect.

We find that the risk of automation, and in particular, new disruptive technologies that automate jobs via machine learning (such as text analysis, computer vision, speech recognition, and data mining), artificial intelligence, and mobile robotics, has had a substantial impact on increasing inequality in all of the countries in our analysis. Previous work has highlighted that technological change impacts the distribution of wages through two effects - changing relative wage differences between high and low skills (skill biased technological change) and the changing composition of jobs. We find that the changing composition of jobs explains a larger portion of inequality compared to changing relative wage premiums. This is present in all 10 countries in our analysis, whereas the skill-biased technological change effect is present in six countries. Workers are moving away from low-paying high and medium automation risk jobs towards higher paying low automation risk jobs, but this shift is increasing inequality. Jobs that are at high risk of being automated tend to have relatively similarly wage levels, while jobs that are less likely to be automated have a much higher dispersion of wages. Thus, as workers move into jobs that are less likely to be automated, inequality rises. Further evidence of this effect is seen when we decompose these changes by comparing changes that are occurring at the bottom half of the distribution with changes at the top half of the distribution. Increases in automation related inequality impact the top half more, partly because the relative difference between medium earners and top earners is increasing. These composition changes reveal that the main driver of increasing inequality is due to the fact that automation is pushing the share of workers towards more unequally paid jobs.

The remainder of this paper is organized as follows: Section 2 discusses relevant literature; Section 3 details our decomposition method and provides an overview of the variables that we include in our decomposition; Section 4 describes our data; Section 5 discusses the results; and Section 6 concludes.

# 2 Literature Review

The literature relating technology to labor market outcomes has grown rapidly in recent decades. One reason for this has been the observed increase in the returns to skilled labor - i.e. the skilled wage premium. This has occurred despite a rapid rise in the supply of skilled workers, suggesting a simultaneous increase in the demand for skills. One explanation put forward for this increased demand for skilled labor is technological progress, which is considered to be skill biased.

## 2.1 Theoretical Explanations

Acemoglu and Autor (2011) among others, however, have extended the focus on skills in the discussion on wage developments by arguing that a greater focus should be placed on tasks. Tasks are particular activities that produce output, and while related to skills it is unlikely that there is a one to one match between the two Acemoglu & Autor (2011). The distinction between the two becomes relevant because workers with particular skill levels are able to perform a variety of tasks and change the set of tasks that they can perform over time. This task-based framework is better able to explain recent developments in the labor market, such as the relative decline in labor demand for middle skill workers, which may be explained by ICT developments that have allowed for certain tasks performed by middle skilled workers to be offshored D. H. Autor et al. (2003).

In response to these kinds of arguments, a number of authors have developed task-based models, including D. H. Autor et al. (2003), Goos & Manning (2007), D. Autor & Dorn (2010), Acemoglu & Zilibotti (2001), Costinot & Vogel (2010), Deming (2017) and Acemoglu & Autor (2011). In the model of Acemoglu and Autor (2011) it is assumed that there is a continuum of tasks, which together produce a unique final good. Each of three different kinds of skilled workers - low, medium and high skilled - are endowed with certain types of skills, which gives them different comparative advantages. Given the prices of different tasks and the wages of different skill types, firms choose the optimal allocation of skills to tasks. Technical change plays a dual role in their model, changing the productivity of different worker types and also the productivity of different tasks. Technology can also substitute for labor in accomplishing various tasks, with the extent of substitution depending upon cost and comparative advantage. An important advantage over the canonical model (i.e. the Katz-Murphy model that models the skill wage differential due to relative demand changes Katz & Murphy (1992)) is that while factor-augmenting technical progress always increases all wages in the canonical model, in this more general model technical progress can reduce the wages of certain groups.

In a recent contribution, Caselli and Manning (2019) model theoretically the relationship between new technologies and wages. In their constant returns to scale and perfectly competitive setting, there are many types of labor, goods (for capital and consumption use) and technologies. Their model suggests that new technologies cause the wage to rise if the price of capital goods falls relative to consumption goods, as would be expected. The results further show that if the supply of the different types of labor is perfectly elastic, then wages of all kinds of workers will rise.

Acemoglu & Restrepo (2017) also theoretically model the relationship between AI and the demand for labor, wages and employment. Their model highlights the role of a displacement effect of these new technologies, with AI and robotics replacing workers in tasks that they previously performed. This displacement effect can reduce the demand for labor, have negative implications for wages and employment, and lead to a decoupling of output and wages per worker. In addition to this displacement effect, Acemoglu and Restrepo (2017) also highlight a number of offsetting effects, including: (i) a productivity effect due to the substitution of labor with cheaper machines, which can raise overall demand, including the demand for labor in non-automated tasks; (ii) a capital accumulation effect that is encouraged by automation, which raises the demand for both capital and labor; (iii) a deepening of automation, with tasks already automated being further automated, generating productivity and in turn demand effects that can raise labor demand; and (iv) the creation of new tasks, functions and activities in which labor has a comparative advantage relative to machines. The impact of AI and robotization then depends upon the relative strength of these countervailing forces. An important consideration for our purposes is the conclusion that a strong displacement effect that leads to both higher productivity and lower labor demand can actually reduce the wage of all workers.

## 2.2 Empirical evidence

Autor et al (2006) consider the evolution of the wage and employment distribution for the US. They show that the upper tail income distribution (90-50 spread) has continued to increase from the 1970s onwards, while the lower tail income distribution (10-50 spread) stopped increasing in the late 1980s. Wage growth is found to have polarized since the late 1980s, with wage growth in the bottom quartile growing faster than in the middle two quartiles, and with the most rapid growth occurring in the highest quartile. Employment growth was also found to differ significantly between the 1980s and 1990s, with a more rapid growth of jobs at the bottom and top of the skill distribution (relative to the middle) in the latter period. The skill distribution is defined by ordering occupations in order of years of schooling. They conclude that employment has polarized into low-wage and high-wage jobs at the expense of mid-wage jobs. They further develop a simple model in which computerization complements non-routine cognitive tasks, substitutes for routine tasks, and has little impact on non-routine manual tasks. In related work, Autor et al (2003) conduct a similar exercise but use data on task content. They show that employment growth since the 1990s was most rapid in jobs intensive in non-routine cognitive tasks (i.e. tasks most complementary with computerization), was declining at an increasing rate for jobs intensive in routine cognitive and manual tasks (i.e. those most substitutable by computers), and ceased declining in the 1990s for typically low-wage jobs intensive in non-routine manual tasks.

Firpo, Fortin and Lemieux (2011) sought to understand how much of these wage changes can be explained by the changing task content in occupations in the United States by creating a more extensive index of occupational characteristics. Inspired by Blinder et.

al (2007), Jensen et. al. (2010) and Autor et. al. (2003) they create five indexes from the O*NET database related to tasks, namely: (i) the information content of jobs; (ii) the degree of automation (routinization); (iii) the importance of face-to-face contact; (iv) the need for on-site work; and (v) the importance of decision making at work. Using a RIF regression decomposition technique, they find that technological change and de-unionization both had large roles in explaining wage changes in the 1980s and 1990s, but much less of an effect in the 2000s. Furthermore, offshorability played an increasingly important role in the 1990s and 2000s. They conclude that the return to skills vary by occupation and suggest moving to a task based metric which may better identify why wage distributions have changed so much over the past few decades.

While previous works focus on defined tasks and skills, Frey & Osborne (2017) created a new metric to estimate the probability that a job may be automated. Many non-routine tasks have been defined in the existing previous literature as resilient to automation, but Frey & Osborne rightly suggest that computerization has expanded and is increasingly competing in cognitive and non-routine tasks. To measure automation risk, they survey experts in machine learning and automation, asking for predictions on whether an occupation is likely be automated by new technologies. Rather than characterizing occupations on the likelihood that the job will be automated given a set of automatable tasks, Frey & Osborne characterize occupations as a function of the probability that a computer will be unable to automate certain tasks (automation bottlenecks), namely perception and manipulation, creative intelligence, and social intelligence, in the next ten years. They do this by applying machine learning classification methods on a database that details the tasks and skill components for every job (O*NET) to understand the relative concentration of tasks related to these automation bottlenecks. They distinguish these automation risks by defining three categories - low, medium, and high - and find that 47% of US employment is in the high-risk category, and that the probability of computerization is negatively correlated with wages and education levels.

Goos and Manning (2003) compare the Skill Biased Technological Change hypothesis - predicting a rising demand for skilled jobs relative to unskilled jobs - and the hypothesis of Autor et. al. (2003) that technology impacts the demand for different skills in more nuanced ways. In particular, that demand would be expected to fall for routine jobs in which technology can substitute for human labor, but not for non-routine tasks that are complementary to technology. These jobs would include skilled professional and managerial jobs, as well as many unskilled jobs. The paper thus considers whether there is evidence of job polarization and uses data from the UK over the period 1975-1999 to examine whether this is the case.

Goos and Manning (2003) begin by using the classification of Autor et. al. (2003) that splits occupations into five particular types of task: non-routine cognitive, non-routine interactive, routine cognitive, routine manual, and non-routine manual. Using this classification, they show that non-routine manual jobs are concentrated in the lower percentiles of the wage distribution, while non-routine cognitive and interactive jobs are concentrated in the top end of the wage range, with routine jobs thus concentrated in the middle of the wage distribution. Since non-routine jobs are concentrated in the middle of the wage distribution the hypothesis of Autor et. al. (2003) would predict a polarization of the workforce into 'lousy' and 'lovely' jobs. Using data for the UK the authors then show that there has been employment growth in jobs at the top and bottom end of the wage distribution, and a significant decline in jobs in the middle of the distribution. The authors further note that a number of papers (e.g. Berman et al. (1994); (1998); Machin & Van Reenen (1998) have presented evidence (i.e. shift-share analysis) suggesting that employment has shifted towards non-manual jobs, with this shift being more important within than between manufacturing industries. This is taken as evidence that technical change is a major driver of the changes, with the trend being pervasive across the economy. Extending this approach for the economy as a whole (not just manufacturing) and for a broader set of occupations Goos and Manning (2003) find a large increase in the employment shares of managerial and professional workers that is mostly within industries, consistent with earlier results. They also show that craft workers and machine operatives have large negative within and between components reflecting both the impact of technical change and the shift towards services. Routine clerical occupations have large negative employment effects within industries, and a positive between component reflecting the shift to services. A large within and between component is further found for low-paid personal and protective services and sales occupations, suggesting that technology has not managed to replace these jobs. Moving on to consider developments in lower and upper tail wage inequality, the authors find that inequality has been rising at both ends of the distribution, albeit to a larger extent at the upper tail. In other words, despite the relative rise in demand for low-wage labor (relative to middle-wage labor), there has been no corresponding increase in relative wages.

Goos et. al. (2011) look to do three things: (i) to document that job polarization is widespread across Europe; (ii) to consider the reasons for job polarization - concentrating on technological progress and offshoring; and (iii) to develop a conceptual framework to provide a more complete explanation for polarization. The paper uses data from the European Labor Force Survey (ELFS) for the period 1993-2006. While there are data for 28 countries, the authors rely on data for 15 European countries (Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom). Descriptive statistics indicate that high-paying occupations (e.g. managerial, professional) experienced the fastest increases in their employment shares, while employment shares for occupations that pay around the median occupational wage (e.g. office clerks, plant and machine operators) have declined. For low-paid occupations - particularly certain low-paid service occupations as well as low-educated laborers in manufacturing - employment shares have increased.

To explain these results, the authors develop a model in which output in all industries is produced by combining certain common building blocks - i.e. tasks - with some industries more intensive users of certain tasks than others. Output of individual tasks are produced using labor of one occupation and some other input, which is referred to as capital. This other input can be considered to be machinery - capturing task-biased technological progress - or offshored overseas employment to capture offshoring.

Graetz and Michaels (2018) estimate directly the impact of robot use on sectoral productivity, employment and wages for a panel of 14 industries and 17 countries over the period of 1993-2007. Using data from the International Federation of Robotics (IFR) on the deliveries of multipurpose manipulating industrial robots, the authors estimate robot density (i.e. the stock of robots per million hours worked) and relate this to labor productivity, employment and wages. Results suggest that robot density has increased relatively rapidly over time - by around 150% between 1993 and 2007 - with this rise being particularly strong in Germany, Denmark and Italy, and in the transport equipment, chemicals and metal sectors. Those sectors and countries that witnessed the most rapid increase in robot density were also the ones to experience the largest gains in labor productivity, albeit with the evidence suggesting diminishing marginal returns to increased robot use. While raising labor productivity, increased robot density was not found to be associated with significant changes in employment levels, though some evidence of a negative effect on low-skilled workers was observed, suggesting a skill-bias of robots. Despite this, however, the overall effect of robot use on wages was found to be positive.

In a related paper, Acemoglu & Restrepo (2017) consider the impact of robot usage in 19 industries on local labor market outcomes for the US. The focus on local labor market outcomes is justified by the fact that their definition of local - i.e. commuting zones - vary in their distribution of industrial employment, and thus their exposure to the use of robots. In contrast to the results of Graetz and Michaels (2018), Acemoglu & Restrepo (2017) find evidence of a robust and significant negative effect of robot usage on both employment and wages between 1990 and 2007. In their preferred specification, the results imply that one more robot per thousand workers reduces the ratio of aggregate employment to population by 0.34 percentage points and wages by around 0.5 percent.

# 3 Decomposition Method

The approach that we adopt closely follows the methodology of Firpo, Fortin and Lemieux (2018) (henceforth FFL), which combines an approach from the treatment effect literature with the Oaxaca-Blinder (OB) decomposition for distributional statistics (2018). In this section we describe in detail their approach and how we implement it in our context.

The starting point for our discussion is the Oaxaca-Blinder decomposition (Blinder (1973), R. Oaxaca (1973)), which is used to divide the difference in mean wages between two groups into a composition effect and a wage structure effect, the former is due to differences in explanatory variables between two groups and the latter is due to differences in the returns to those explanatory variables between the two groups. These two groups commonly refer to two separate groups at a point in time, such as males versus females, but can also represent two similar groups at two different points in time. It is this latter approach that we follow in this paper. Adopting much of the terminology from FFL we denote the outcome variable - i.e. the wage of an individual - as $Y$, and we denote the two groups as $t = 0, 1$. In addition, we have a vector of covariates, $X$, that are observed for each individual and which are related to wages through the following linear model for each group:

$$Y_{0i} = X_{0i}\beta_0 + \epsilon_{oi} \tag{1}$$

$$Y_{1i} = X_{1i}\beta_1 + \epsilon_{1i} \tag{2}$$

Denoting the estimated coefficients as $\hat{\beta}_t$ and with a bar over a variable indicating the mean of that variable, we can write the difference in mean wages as:

$$\bar{Y}_1 - \bar{Y}_0 = \bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 \tag{3}$$

Where the error terms drop out because the mean of these terms is zero. This equation can be rewritten as:

$$\bar{Y}_1 - \bar{Y}_0 = (\bar{X}_1 - \bar{X}_0)\hat{\beta}_1 + \bar{X}_0(\hat{\beta}_1 - \hat{\beta}_0) \tag{4}$$

The first term on the RHS of this equation is the composition term and reflects the impact of differences in (average) characteristics (i.e. the explanatory variables) on average mean wages. The second term on the RHS is the wage structure effect and captures the impact of differences in the returns to the explanatory variables in the two groups.

An important limitation of this approach is that it only considers differences in average wages between the two groups. Since the original contributions of Blinder and Oaxaca, however, a number of papers have proposed extensions to allow the consideration of other distributional statistics (see N. Fortin et al. (2011) for a comprehensive review of this literature). In our analysis we follow the approach of FFL (2018), which undertakes a Oaxaca-Blinder type decomposition by combining RIF regressions with a reweighting strategy to decompose differences in distributional statistics beyond the mean. In our analysis we focus on the Gini coefficient and various quantiles of the distribution of wages. There are a number of advantages of this method. First, the method allows us to decompose the impact of particular variables, such as automation risk, on inequality in terms of both the wage and compositional effects for a wide variety of distributional measures. Most other decomposition methods are unable to decompose the contribution of particular variables beyond the general case of the mean, while this method allows us to observe these contributions for a variety of distribution measures, as well as providing a computationally efficient way to calculate these decompositions at each percentile of the distribution (Firpo et al. (2018)). Secondly, the method is able to get to the heart of our question of understanding the contribution of a particular variable to inequality (either a reduction or increase) and the extent to which this is due to changes in the wages structure or due to compositional changes.

In order to implement the decomposition for distributional statistics beyond the mean, we need to follow three steps, namely: (i) create a counterfactual distribution through a reweighting procedure that uses propensity scores; (ii) use Recentered Influence Function (RIF) regressions where the dependent variable is the RIF of the distributional statistic of interest; and (iii) implement a Oaxaca-Blinder decomposition using the RIF regression estimates. We will now discuss each of these steps in turn and how they allow us to decompose distributional statistics beyond the mean. In discussing this methodology we follow closely the description provided by Rios-Avila (2019).

FFL (2018) do not impose any distributional assumptions of functional form in their analysis, but do make the assumption that there is a joint distribution function between the dependent variable ($Y$), the explanatory variables ($X$) and the variable defining the groups ($t$), which following Rios-Avila (2019) we denote as ($f_{Y,X,t}(y_i, x_i, t)$. The categorical variable $t$ defines the two groups, with the joint probability distribution function and the cumulative distribution of $Y$ given $t$ being written as:

$$f^k_{Y,X}(y, x) = f^k_{Y|X}(Y|X)f^k_X(X) \tag{5}$$

$$F^k_Y(Y) = \int F^k_{Y|K}(Y|X)dF^k_X(X) \tag{6}$$

Where the subscript $k$ denotes that the density is conditional on $t = k$ with $k \in [0, 1]$. As described by Rios Avila (2019) the differences between the two groups for a given distributional statistic, $\upsilon$, can be calculated using the cumulative conditional distribution of $Y$:

$$\Delta\upsilon = \upsilon_1 - \upsilon_0 = \upsilon(F^1_Y - \upsilon(F^0_Y) \tag{7}$$

$$\Delta\upsilon = \upsilon(\int F^1_{Y|X}(Y|X)dF^1_X(X)) - \upsilon(\int F^0_{Y|X}(Y|X)dF^0_X(X)) \tag{8}$$

This latter equation has certain analogies with the standard OB decomposition, most notably by indicating that differences in the distributional statistic between the two groups will exist if there are differences in the distributions of the $Xs$ ($dF^1_X(X) \neq dF^0_X(X)$) or if there are differences in the relationships between $Y$ and $X$ between the two groups ($F^1_{Y|X}(Y|X) \neq F^0_{Y|X}(Y|X)$).

Given data at hand (i.e. on $Y$, $X$ and $t$) it is possible to estimate the distributions needed to construct the difference in the distributional statistic of interest, $\Delta\upsilon$. It would not be possible, however, to undertake a decomposition based on this data, since we would not be able to distinguish between the wage structure and composition effect. In order to do this, we need to define a counterfactual distribution that would have prevailed under the wage structure for group 0, but with the distribution of explanatory variables for group 1, i.e. $\upsilon_c = F^c_Y = \upsilon(\int F^0_{Y|X}(Y|X)dF^1_X(X))$. With this in hand, we can write:

$$\begin{aligned}\Delta\upsilon = &[\upsilon(\int F^1_{Y|X}(Y|X)dF^1_X(X))] - \upsilon(\int F^0_{Y|X}(Y|X)dF^1_X(X))] \\ &+[\upsilon(\int F^0_{Y|X}(Y|X)dF^1_X(X)) - \upsilon(\int F^0_{Y|X}(Y|X)dF^0_X(X))]\end{aligned} \tag{9}$$

Or,

$$\Delta\upsilon = (\upsilon_1 - \upsilon_c) + (\upsilon_c - \upsilon_o) \tag{10}$$

Note that the two terms in the first bracket on the RHS will differ because of differences in the relationship between $Y$ and $X$ between the two groups only, while the two terms in the second bracket on the RHS will differ because of differences in the distributions of the two groups only. As such, the first term corresponds to the wage structure effect in the standard OB decomposition, while the latter corresponds to the composition effect. The challenge is to construct this counterfactual distribution. Under the assumptions of ignorability or unconfoundedness and overlapping support, FFL (2018) show that a reweighting procedure can be used to construct this counterfactual distribution. As described by Rios Avila (2019) this approach allows us to approximate the counterfactual distribution by multiplying the observed distribution of characteristics, $dF_X^o(X)$, by a weighting term, $\omega(X)$, such that it resembles the distribution $dF_X^1(X)$, i.e.

$$F_Y^c = \int F_{Y|X}^0(Y|X) dF_X^1(X) \cong \int F_{Y|X}^0 dF_X^0(X)\omega(X) \tag{11}$$

Again following the description of the approach of Rios Avila (2019) the reweighting factor can be obtained using Bayes rule as:

$$\begin{aligned}\omega(X) = \frac{dF_X^1(X)}{dF_X^0(X)} = \frac{dF_{X|t}(X|t=1)}{dF_{X|t}(X|t=0} = \frac{dF_{t|X}(t=1|X)}{dF_t(t=1)} = \frac{dF_t(t=0)}{dF_{t|X}(t=0|X)} \\ = \frac{1-P}{P}\frac{Pr(t=1|X)}{1-Pr(t=1|X)}\end{aligned} \tag{12}$$

Where $P$ is the proportion of workers in group $t = 1$ and $Pr(t = 1|vertX)$ is the conditional probability of somebody with characteristics $X$ being in group $t = 1$. To estimate the weighting factor, therefore, involves estimating the conditional probability of being in group 1.

In practice, we obtain this reweighting by estimating a logit regression, with the dependent variable being whether an individual is in group 0 or 1 and a set of explanatory variables that capture worker characteristics:

$$\begin{aligned}Pr(t_i = 1|X) = \Phi(\beta_1 age_i + \beta_2 edu_i + \beta_3 gender_i + \beta_4 ar_i \\ +\beta_5 entyrs_i + \beta_6 enttype_i + \beta_7 entsize_i \\ +\beta_8 emptype_i + \beta_9 union_i + \beta_{10} ind_i + \tau_i)\end{aligned} \tag{13}$$

Where $t$ is a binary variable with $t = 1$ when that observation is in 2014 and $t = 0$ if it is in 2002, $\tau$ is an error term, and $\phi$ refers to the cumulative distribution function for a standard logistic random variable [1]. We include four categories of explanatory variables: individual; firm; industry; and labor institution characteristics. Individual characteristics include age (brackets), level of education defined by ISCED-2011, automation risk categories (low, middle or high, where low is the reference group), years at enterprise, and gender. Firm level characteristics include enterprise type (public or private) and the enterprise size (band sizes). Labor institution characteristics include union types, which can be national, regional or local, employment type, which include, full-time permanent contract, part-time permanent contract, fixed contract, apprentice, other contract and 85% part-time contract. Last, we include industry dummies, which capture industry characteristics[2] It should be noted that the choice of base group may be important in the decomposition

[1] Not all variables are consistently used across countries as some sub-measures either do not exist or are not measured within the country. In the case of the Netherlands, union type didn't have much variation and Sweden had little variation in terms of employment contract type, and thus, for these countries, those covariates were dropped.

[2] The bases for the categorical variables are as follows: Ages 40-49 as it is the modal for most countries and typically peak marginal earnings in a lifetime, union is no payment agreement, education is completed

as some argue that the decomposition can change depending on the base group of choice R. L. Oaxaca & Ransom (1999). For more details about the data, please see the appendix. Using the predicted probabilities from this model we are able to obtain estimates for the reweighting factor and in turn, obtain an estimate for the counterfactual distribution, $F_Y^c$ , using equation 11.

We use Frey & Osborne's risk of automation index for the underlying data of our automation risk categories Frey & Osborne (2017). Low risk is the probability of an occupation being automated that is below 25%, which is our baseline category in the decomposition regressions, mid-risk involves an automation risk of 25% - 74%, while high-risk has an automation risk above 75%. In their own work, they also distinguished occupations according to these three categories when discussing overall impacts on employment. We, too, find this distinction useful in our analysis and follow in their footsteps. Frey & Osborne's (2017) risk assessment covers 702 occupations using the SOC (US) classification system. Our data uses ISCO-08 categories for 2014, and ISCO-88 for 2002. To crosswalk between the SOC and ISCO classifications, we use the Bureau of Labor Statistics crosswalk. We then crosswalk ISCO-08 to ISCO-88 using the International Labor Organization's crosswalk. We aggregate occupational categories by averaging the automation risk by 2-digit occupational group. In some cases, we are unable to identify the automation risk for some occupations due to our crosswalks. As such, we create a separate category, unknown, to account for these cases. Keep in mind that these are exceptional case that impact only a few occupations in some countries. Finally, we categorize automation into our three categories based on these averages. Please see appendix 7.3 for the calculated automation risk by occupation group.

The second stage in the decomposition involves the use of RIF regressions. As discussed by Rios-Avila (2019) influence functions have long been used to analyze the robustness of distributional statistics to small disturbances in data (e.g. F. A. Cowell & Flachaire (2007)). The contribution of Firpo et. al. (2009) was to propose the use of recentered influence functions (RIFs) to analyze the impact of changes in the distribution of explanatory variables on the unconditional distribution of $Y$. Their initial approach focused on the case of unconditional quantiles of $Y$, but the approach extends to other distributional statistics including the Gini, which is used in this paper. An influence function (IF) is similar to sensitivity analysis. The influence function is the effect of taking one individual from our data, and seeing how the Gini changes from the exclusion of that individual. This allows us to see how an individual contributes to a distributional statistic. A recentered influence function is similar to an influence function, but uses a linear approximation for the distributional statistic of interest. An important characteristic of a RIF is that the estimated IF can be aggregated back to the statistic of interest as the definition is $RIF(y; v) = v(F) + IF(y; v)$ N. Fortin et al. (2011). The linear approximation allows us to see how a particular individual impacts the Gini, and allows us to aggregate all of these impacts to the overall Gini. Given that this is a linear

secondary school, which is also the modal for most countries, the type of employee contract is permanent as we are interested in the relative return of part-time earnings compared to full-time and its change over time, industry is wholesale trade, and enterprise size is firms employing between 250 and 500 people, which is also the modal, and finally, automation risk is low-risk, as we want to understand the contribution that mid and high-risk automation poses on wages and inequality. For reasons of brevity, we don't report the RIF regression results for the counterfactuals or for every quantile, but we do provide the counterfactual distribution in the appendix. Please feel free to contact the authors for these results.

combination, we can easily estimate the recentered influence function with OLS.

In practice a RIF regression involves replacing the dependent variable - i.e. in our case, replacing the log of the wage level of individuals with the recentered influence function of the relevant statistic of logged wages (e.g. the Gini or unconditional quantiles), and running an OLS regression of the recentered influence function on the same set of explanatory variables as in Equation 13. In particular, the RIF regression is estimated for the years 2002 and 2014, as well as for the counterfactual distribution, i.e.

$$\upsilon_1 = E(RIF(y_i; \upsilon(F_Y^1))) = \bar{X}^1 \hat{\beta}^1 \tag{14}$$

$$\upsilon_0 = E(RIF(y_i; \upsilon(F_Y^0))) = \bar{X}^0 \hat{\beta}^0 \tag{15}$$

$$\upsilon_c = E(RIF(y_i; \upsilon(F_Y^c))) = \bar{X}^c \hat{\beta}^c \tag{16}$$

While these models can be estimated using OLS, there is a somewhat different interpretation of the regression coefficients from the more standard interpretation. In particular, the coefficients can be interpreted as follows: $\beta_j$ provides an estimate of the change in the distributional statistic of interest (e.g. the Gini) in response to a change in the distribution of a variable $x_j$ that changes the unconditional average of the variable by one unit (i.e. $\Delta \hat{X}_j = 1$). Based upon the results from these regressions the decomposition can be defined as:

$$\Delta\upsilon = \bar{X}^1(\hat{\beta}^1 - \hat{\beta}^c) + (\bar{X}^1 - \bar{X}^c)\hat{\beta}^c + (\bar{X}^c - \bar{X}^0)\hat{\beta}^0 + \bar{X}^c(\hat{beta}^c - \hat{beta}^0) \tag{17}$$

$$\Delta\upsilon = \Delta\upsilon_s^p + \Delta\upsilon_s^e + \Delta\upsilon_x^p + \Delta\upsilon_x^e \tag{18}$$

The first two terms on the RHS of this latter equation (i.e. $\upsilon_s^p$ and $\upsilon_s^e$) correspond to the wage structure effect, while the latter two terms (i.e. $\upsilon_x^p$ and $\upsilon_x^e$) correspond to the aggregate composition effect. The two terms $\upsilon_s^e$ and $\upsilon_x^s$ can be used to assess the overall fitness of the model, with the first term being the reweighting error and the second term assessing the importance of departures from linearity. If these two terms are unimportant (and in the extreme if they tend to zero) we are left with $\Delta\upsilon = \Delta\upsilon_s^p + \Delta\upsilon_x^p = \bar{X}^1(\hat{\beta}^1 - \hat{\beta}^c) + (\bar{X}^c - \bar{X}^0)\hat{\beta}^0$, which mimics the standard OB decomposition. In our analysis we calculate the wage and composition effect for a variety of distributional measures including the Gini and the difference between the 50-10 and 90-50 percentiles [3].

These three steps - logistic regression to calculate propensity scores, RIF regressions, and a Oaxaca-Blinder decomposition - allow us to dig deeper into understanding how our covariates played a role in shaping inequality developments between 2002 and 2014. The decomposition allows us to see how our covariates play a role, where the composition effect is a quantity effect, and the wage effect is similar to a price effect or the returns to wages for specific characteristics. Each of these covariates can be aggregated up since the total is the sum of the parts. For example, individual characteristics include the estimates of education, gender and age. We present results at an aggregated level highlighting the 5 main factors (i.e. individual, technology, firms, industry and national) for ease of presentation, but the contribution of each specific covariate can be found in the appendix.

[3] In order to calculate the 90-50 percentiles, we take the unconditional quantile regressions for each of the deciles and then take the differences of the 90th percentile Oaxaca-Blinder coefficients and the 50th percentile Oaxaca-Blinder coefficients, with a similar approach adopted for the 50-10 differences.

## 3.1 Choice of Covariates

Our choice of explanatory variables for the logistic regression is informed by the literature on the determinants to wages and wage inequality. We can think of these variables as operating at five different levels - the level of the individual, of technology, of the firm, of the sector and of the country. We have reviewed the literature of technology on wages and inequality in a previous section and now turn to the remaining factors.

At the individual level, there is a large literature examining the impact of individual characteristics on wages. These characteristics include variables such as a person's race, gender, marital status and geographic location, as well as variables capturing a person's education, experience and skills (Altonji & Blank (1999), Antonovics & Town (2004), Weichselbaumer & Winter-Ebmer (2005), Cotton (1988), Florida & Mellander (2016), Card et al. (1994)). Age is another important characteristic because demographic changes are becoming increasingly important in Europe as the workforce composition is changing. During our observed time period baby boomers began to retire and younger workers entered the labor market (R. Lee (2003), Muenz et al. (2007)). Baby boomers are the largest group in the working age population, with the fertility rate continually declining since their generation was born. As they begin to retire, the workforce will begin to decrease and the higher wage positions will move to the next generation. How these composition changes may impact wages is still unclear.

At the level of the firm, it has been noted that the size of the enterprise that one works within influences earnings. This may be important as the concentration of larger firms has been increasing (Barth et al. (2016), Brown & Medoff (1989)). Additionally, firm differences can arise when a worker is more productive in a particular firm because of firm level compensation policies (Mortensen (2005), Fairris & Jonasson (2008), Oi & Idson (1999)). Firm ownership type, whether public or private, is another consideration, with Lucifora and Meurs finding that private companies pay higher (lower) wages for high- (low-) skilled workers when compared with public (majority government owned) companies (2006). Other firm-specific factors that have been shown to be positively correlated with wages include whether the firm is foreign-owned and whether it is engaged in trading activities (i.e. whether it is an exporter or importer). Existing research also provides some evidence to suggest that firm-specific effects contribute significantly to rising inequality in the case of Germany (Antonczyk et al. (2010)).

Evidence further suggests that across countries and time, workers with similar characteristics earn different wages across industries (W. Dickens & Katz (1987), Krueger & Summers (1988), Abowd et al. (2000), Barth & Zweimüller (1992)). Statistical models that decompose inter-industry wage premiums find that most of the person or firm effects in the United States can be explained by educational and occupational capital that are specific to the industry (Abowd et al. (2012)). In other words, the knowledge a person accumulates is valued differently across industries. A further source of intra-industry wage differentials are intra-industry productivity differentials, with more productive sectors paying higher wages (Thaler (1989)).

At the national level, policies associated with unionization levels, contract regulation, and minimum wage laws are typically at the heart of policies that shape wages. Most analysis on labor institutions tend to focus on cross-country changes, showing that decreasing unionization is associated with higher rates of income at the top end of the distribution that further increases inequality (Jaumotte & Osorio (2015)). When looking at changes within a country, rising inequality is partly explained by employment protection legislation (length and amount) (Koeniger et al. (2007)). Employment protection legislation includes changes in contract or collective bargaining regulations, unemployment benefits, activation programs, employment conditional incentives and early retirement plans. Evidence further suggests that there is a wage premium associated with permanent contracts, though the effect differs across countries, with fixed term workers getting paid less on average (Boeri et al. (2011)). Some of this literature further suggests that in cross-country analysis, temporary contracts have the effect of raising inequality, though it is not a large contributor (Cazes & de Laiglesia (2014)). Research at the country level indicates that lower union strength is associated with rising inequality, while minimum wage laws are associated with lower inequality in the US (Card (2001), DiNardo et al. (1996), D. S. Lee (1999), Card (1996)), Britain (Machin (1997), R. Dickens et al. (1999)), Italy (Erickson & Ichino (1995)), and Sweden (Edin & Holmlund (1993)). In one recent empirical analysis, Massari et. al. (2013) found that institutions rather than technology was the largest contributor to inequality in Europe.

# 4 Data

We use two waves (2002, 2014) of the structure of earnings survey (SES) which are cross-sectional harmonized data across the EU and include detailed information about enterprise and worker characteristics and are reported every 4 years (Eurostat (2014)). Each country is responsible for reporting a set of required questions that can be aggregated via surveys or the country's administration data. Descriptive characteristics of the dataset are provided in the appendix.

The survey is sampled in two stages with the first aimed to be representative of paid employees at the industry level and according to enterprise size, and the second aimed to be representative of contract type and occupation. Thus, our sample consists of a representative population of employed workers across 10 countries, Czech Republic, Spain, Finland, France, Hungary, Italy, Luxembourg, Netherlands, Romania, and the United Kingdom. We include the grossing-up factor, a type of survey weight, by multiplying our weights described in Section 3. The focus of attention on 10 EU countries is dictated by the data at hand, with a country included in our analysis if we have complete information on all of the variables of interest described earlier.

We use gross monthly earnings with the reference month as October, which also includes overtime and special shift work, and calculate real wages using the consumer price indices from Eurostat as a deflator. As a robustness test we repeated our analysis using gross annual earnings, including in-kind payments, and find the results are consistent with those presented in this paper. It is worth noting that we do not gross-up part-time earnings.

This is because we want to have an understanding of how part-time work contributes to inequality as a whole, which wouldn't be possible if we grossed-up part-time earnings. Instead, the estimated effects would capture the relative difference in wages between part-time and full-time workers *as if* part-time workers worked the same number of hours.

Over time industry codes change, while industry groupings differ between countries and over time. To create a time consistent dataset across the two waves, we update the 2002 waves from the NACE 1.1 version to the NACE 2.0 version using a crosswalk provided by SES and aggregate up any industries that were combined for some countries but not others. See Table 6 in the appendix for the industry classifications. Additionally, the education classification changed during our observed time period. For our analysis we update ISCED-97 codes applied in the 2002 data set to ISCED-08.

# 5 Results

## 5.1 Descriptive Statistics

The overall changes in the Gini coefficient along with changes in the 90-10, 50-10 and 90-50 (log) wage quantiles between 2002 and 2014 are reported in Table 2. There are a variety of country experiences in terms of developments in inequality across Europe, and we observe that half of the countries experienced an increase in inequality among workers. The extent of such changes varies across countries. The Netherlands and Italy saw inequality rise substantially, while there was a decrease in inequality for six countries, Finland, France, Hungary, Luxembourg, Romania and the United Kingdom.[4]

We consider changes in the 50-10 and 90-50 wage quantiles to understand where changes in the distribution occur. Declines in inequality in Romania, Hungary, Luxembourg and the UK were driven by declines in the bottom half of the distribution, while in France this was due to declining inequality in the top half of the distribution. In countries that experienced an increase in inequality, this was driven mostly by rising inequality in the bottom half of the distribution.

[4] These results only include employed individuals, thus these results differ substantially from those reported in Table 1, which report indicators of overall inequality for all individuals, employed or otherwise.

**Table 2:** Overview of Inequality Measures

| country | Initial Gini | Change in Gini | % Change Gini | 90-10 | 50-10 | 90-50 |
|---|---|---|---|---|---|---|
| CZ | 0.029 | 0.000 | 0.33% | 0.135 | 0.075 | 0.060 |
| ES | 0.050 | 0.001 | 1.27% | 0.221 | 0.272 | -0.051 |
| FI | 0.032 | -0.002 | -4.76% | 0.086 | 0.026 | 0.060 |
| FR | 0.047 | -0.008 | -17.16% | -0.042 | 0.007 | -0.049 |
| HU | 0.026 | -0.003 | -9.74% | 0.025 | -0.011 | 0.035 |
| IT | 0.022 | 0.001 | 5.07% | 0.113 | 0.122 | -0.009 |
| LU | 0.042 | -0.002 | -5.91% | 0.021 | -0.061 | 0.082 |
| NL | 0.067 | 0.007 | 10.99% | 0.427 | 0.322 | 0.105 |
| RO | 0.068 | -0.020 | -29.76% | -0.212 | -0.275 | 0.063 |
| UK | 0.066 | -0.005 | -7.70% | -0.047 | -0.042 | -0.005 |

## 5.2 Decomposition Results

### 5.2.1 Overall Decomposition Changes

We consider five broad factors - firm, individual, industry, labor institutions and risk of automation - that summarize our results by aggregating the effects of individual variables to create broader categories. The estimated decomposition for each individual characteristic is provided in the appendix. Firm characteristics include firm size and ownership type (public or private); individual characteristics include education level, gender, and age; industry characteristics are the industry in which the individual works in; labor institutions include Union Type (national, regional, and local) and employment contract/hours (full time permanent contract, part time permanent contract, fixed contract, apprentice, other contract and 85% part-time); and risk of automation is broken into 4 categories (low, medium, high and unknown).

Figure 1 presents the results of our decomposition method, displaying the contribution that each variable has on influencing the Gini during our observed time period [5]. Strikingly, we find that in all countries, automation contributes to rising inequality. However, the range of its contribution can be as little as 8.6% in the Czech Republic to as much as 77% of the overall inequality increase in Italy. In Spain, Finland, France, Hungary, Italy, Luxembourg and Romania, automation is the largest contributor to overall inequality.

[5]Inequality is measured using the Gini because it is a widely used measure that provides an overall snapshot of distributional changes. It is worth noting, however, that it does have some general limitations. Let's suppose there is a transfer of income between two individuals, $i$ and $j$. The impact of the transfer between these two individuals depends on the distance between the two individuals, meaning how far apart they are from each other in terms of where they are each located in the distribution of income. A transfer of 1 euro to incomes that are relatively similar to each other in the middle of the distribution will have a larger reduction on the Gini than a transfer of 1 euro between two individuals who have similar incomes at the top end of the distribution. More formally, this is called the "transfer effect" of the Gini and is defined as $\frac{2F(y_j)-F(y_i)}{n\bar{y}}$ (F. Cowell (2011)). Despite this limitation, we use the Gini to capture overall dispersion within a country.

The importance of other factors on inequality is largely country dependent, both in terms of size and direction. This reflects that each country has a unique wage structure. We will briefly summarize these initial results, because the effects of individual, firm, industry and national (i.e. labor institution) variables vary substantially. Labor institutions play a large role in only six countries. They tend to decrease inequality in the Netherlands, France and Finland, but increase inequality in Spain, Italy, and Romania. These results align with previous held beliefs on the role of labor market institutions in different countries - France, the Netherlands and Finland are well known for having strong labor institutions designed to reduce inequality, while Spain, Italy and Romania tend to have weaker ones (Boeri et al. (2011)). Industry is also an important contributor to inequality for the United Kingdom and Luxembourg. Previous research suggests that countries that have large financial sectors also have higher rates of inequality, which is true for both Luxembourg and the United Kingdom (Stockhammer (2013)). In the Czech Republic, Spain, Italy, the Netherlands and Romania, industry contributes to declining inequality. Individual and firm effects on inequality tend to play a relatively small role across countries with the only exception being the Netherlands where individual effects play a large role in increasing inequality. Most strikingly, automation risk is consistently associated with rising inequality. Given automation's important role in shaping inequality, the remainder of the paper will focus solely on automation's effect on inequality.

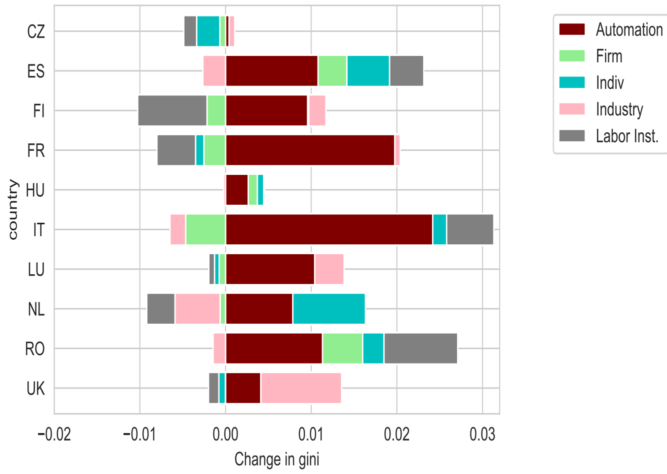
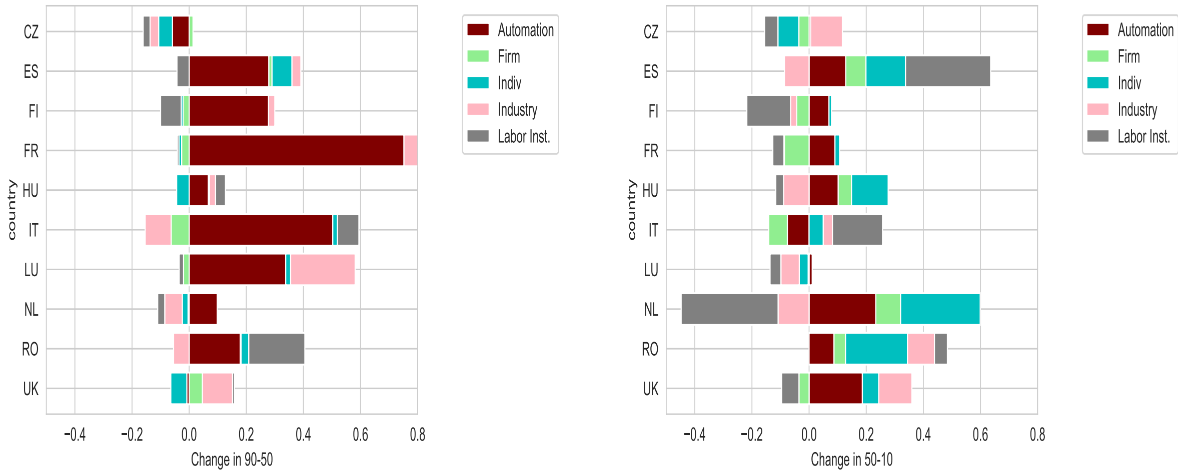



**Figure 1:** Overall Decomposition Change in Gini

While the Gini provides a general overview, we can also look at how factors contribute to other distributional changes. In other words, we can compare big earners to average earners (the top half of the distribution), and compare average earners to minimum wage workers (the bottom half of the distribution). Figures 2a and 2b visualize the decomposition of the distributional effects. Again, automation risk plays a prominent role, but its impact tends to be felt most strongly in the top half of the distribution as 8 out of 10 countries have large positive changes, ranging from .09 percentage points to .75 percentage points. In two countries, the United Kingdom and the Czech Republic, automation risk has a small negative impact on inequality in the upper part of the wage distribution. Automation risk also tends to increase inequality in the bottom half of the wage distribution (with the exception of Italy), but its effect tends to be much more muted (exceptions being the Netherlands and the United Kingdom where it has a relatively large impact). In most cases, therefore, automation risk is not the major driver of inequality in the lower half of the wage distribution, but it is a major driver of inequality at the upper end of the wage distribution. Given automation risk's prominent role in inequality, we delve deeper into understanding how automation risk is impacting wage inequality in the following sub-section.




**(a)** Top Distributional Half (90-50) Change  **(b)** Bottom Distributional Half (50-10) Change

**Figure 2:** Distributional Decomposition by Country

### 5.2.2 Impact of Automation

We focus our discussion on two aspects of our results, the RIF regressions, which show the impact of automation on inequality for each time period, and whether the observed impacts of automation are due to composition changes and/or to changes in wage returns.

**RIF Regressions** Recall that RIF regressions estimate the impact of a characteristic on the Gini. We present these detailed RIF regression estimates for 2002 and 2014 in Tables 9-12, and find that across countries, coefficients on high and mid-automation risk estimates are negative, with the only exception being the Netherlands in 2014. A negative coefficient on automation risk suggests that an increase in high automation risk would lead to a decrease in inequality. This may seem contradictory given that we've just detailed how automation has contributed to rising inequality. The RIF regressions decompose each covariate's contribution to inequality. Our interest is to see how much these coefficients change over time. The wage effect is the change of the covariate's contribution to inequality overtime. The composition effect is the change in the share of workers while taking into account the initial contribution that covariate has on inequality.

The RIF regressions look at levels for a particular year so that we can compare the relative magnitude of the effect that each variable has on inequality. For example, an increase in the share of high risk automation jobs in Italy would be associated with a decrease of .029 Gini points in 2002, while in 2014 this would be associated with a decrease of .010 Gini points. The negative coefficient suggests that inequality would decrease as the share of high automation risk jobs increase. This is partly due to the fact that the high automation risk group has a more equal distribution of income as compared to low risk occupations. Even though high risk automation wages are, on average, lower than low automation risk groups, the distribution of wages within this group is what contributes to rising or falling inequality. If we look at changes between time periods rather than levels alone, we can see that moving from an economy that has all low automation risk occupations, which have more unequal wages, to an economy of high automation risk occupations, with more equal wages, would result in a decrease in inequality (the Gini), ceteris paribus. Table 3 displays the Gini coefficient for each automation risk group by country and year, and shows that in most countries, the dispersion of income within high automation risk groups tends to be lower than in the low automation risk group. There are only two countries, Finland and the Netherlands, in which this is not true[6]. In the case of the Netherlands, the RIF regression coefficient for automation risk is positive for 2014, while Finland is an exception, with both low Gini coefficients, and a general decline in inequality during the time period.

[6]There are some years in which this is also not true. For the United Kingdom in 2014, the dispersion of high automation risk is higher than low automation risk, however the RIF regression of high automation risk is approximately zero, meaning that it had no impact on the Gini that year. In the case of Hungary for 2014, the Gini for high automation risk is slightly higher than the low automation risk group, but the two groups have relatively similar Gini coefficients, and as they are relatively low, one may expect automation risk, holding everything else constant, could reduce inequality in this country

**Table 3:** Gini Coefficient by Automation Risk, Country and Year

| Country | AR | 2002 | 2014 |
|---|---|---|---|
| Spain | Low AR | .050 | .047 |
| | Mid AR | .046 | .049 |
| | High AR | .050 | .041 |
| Finland | Low AR | .023 | .026 |
| | Mid AR | .026 | .027 |
| | High AR | .037 | .032 |
| France | Low AR | .034 | .039 |
| | Mid AR | .040 | .044 |
| | High AR | .047 | .033 |
| Hungary | Low AR | .021 | .016 |
| | Mid AR | .021 | .019 |
| | High AR | .020 | .019 |
| Italy | Low AR | .043 | .047 |
| | Mid AR | .031 | .045 |
| | High AR | .035 | .035 |
| Luxembourg | Low AR | .032 | .037 |
| | Mid AR | .040 | .039 |
| | High AR | .032 | .031 |
| The Netherlands | Low AR | .040 | .046 |
| | Mid AR | .053 | .069 |
| | High AR | .068 | .082 |
| Romania | Low AR | .025 | .048 |
| | Mid AR | .024 | .046 |
| | High AR | .021 | .035 |
| United Kingdom | Low AR | .049 | .053 |
| | Mid AR | .072 | .061 |
| | High AR | .047 | .065 |
| Czech Republic | Low AR | .031 | .026 |
| | Mid AR | .028 | .029 |
| | High AR | .025 | .022 |

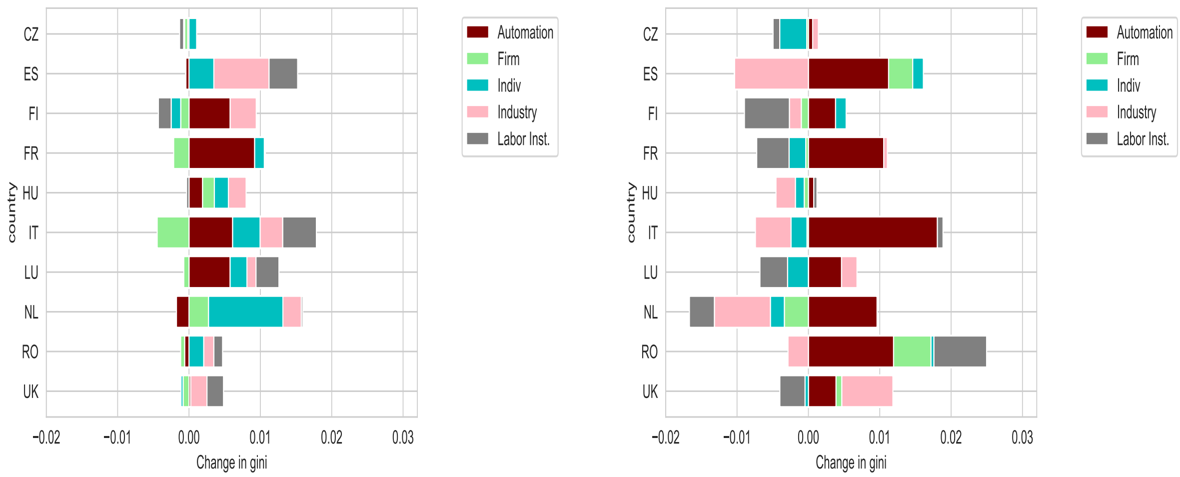
Another interesting finding from the RIF regression estimates is that the effect of automation on inequality decreases in absolute terms. While the impact of automation is negative effect in both years, the magnitude of this effect declined in 2014. Table 4 shows the difference in the Gini between the 2002 and 2014 RIF regression estimates for the mid and high automation risk group, as well as the percentage change in the coefficients. The table reveals that the contribution of inequality from high automation risk decreased inequality more in 2002 than it did in 2014. The negative coefficient declines over time in absolute value, so that all else being equal the decline in the negative coefficient increases inequality. The relative differences in the percentage change of the coefficients reflect that the change in the size of the coefficients were rather large, ranging from around 40% to as high as 160%. Analyzing the wage and composition effect help explain these changes.

**Table 4:** Difference and Percent Change of the Impact of Automation Risk on the Gini between 2002 - 2014

| Country | Mid-AR | | High-AR | |
|---|---|---|---|---|
| | Diff | % Change | Diff | % Change |
| FR | -0.024 | 82.66% | -0.020 | 71.32% |
| FI | -0.012 | 78.85% | -0.008 | 80.02% |
| ES | -0.015 | 75.15% | -0.006 | 38.00% |
| CZ | -0.001 | 43.71% | 0.000 | -7.47% |
| LU | -0.009 | 45.70% | -0.013 | 48.47% |
| NL | -0.013 | 110.25% | -0.007 | 159.76% |
| IT | -0.028 | 94.69% | -0.020 | 66.55% |
| HU | -0.003 | 56.17% | -0.006 | 77.52% |
| UK | -0.002 | 52.63% | -0.016 | 99.94% |
| RO | -0.013 | 65.74% | -0.011 | 47.83% |

Skill biased technological change would suggest that inequality is rising due to changes in the relative wage of non-routine cognitive skills that complement technology (computers, AI, robotics) compared to wages for skills that are at risk of being automated (manual and/or routine skills). Our results suggest that rising inequality is driven not only by wage differences between these two groups, but also because the type of jobs that are more resilient to automation have higher levels of inequality. Jobs that are less likely to be automated have higher inequality than jobs that are at high risk of automation. As the share of low automation jobs that are highly unequal increases, inequality will also rise. Furthermore, jobs that are resilient to automation have also seen inequality rise within this job category. The composition effect shows that the share of employment of low risk automation jobs is increasing, and these type of jobs have higher inequality. This observation confirms that automation is pushing jobs that are either very lucrative or poorly paid. Goos et. al. (2011) coins this shift as a push towards 'lousy or lovely jobs'. Our results confirm that automation is shifting the composition of jobs, and this effect has a large impact on inequality across Europe.

**Gini: Wage & Composition Effects** We now consider our decomposition results and consider whether the increase in the Gini is because of composition changes, i.e. more jobs moving towards more/less automatable jobs, or due to changing wage returns for high/low automatable jobs. Figure 3a shows the wage effect, and 3b shows the composition effect.




**(a)** Wage Effect: Change in Gini

**(b)** Composition Effect: Change in Gini

**Figure 3:** Wage and Composition Effect in Gini

These figures illustrate that the composition effect explains a larger portion of changes to the Gini than the wage effect. We observe that automation risk contributes very little in the Czech Republic as inequality is falling, but in Italy the composition effect accounts for over 95% of the rise in inequality. The wage effect of automation risk generally contributes to higher inequality, but the strength of its contribution varies. Automation is a driver of inequality via the wage structure effect in Finland, France, Hungary, Italy and Luxembourg, which further bolsters automation's impact on inequality as these countries also see automation increasing inequality via the composition effect.

The composition effect is the change in the effect of high automation jobs on inequality multiplied by the share of employment in high risk automation jobs. In technical terms it is the coefficient of the 2002 RIF regressions (Tables 9-12) multiplied by the change in the share of the automation risk category (Section 10). Thus, the composition effect is positive because there is a lower share of high risk automation workers (i.e. the change in high risk is negative), and when combined with the negative coefficient in 2002, this results in an increase in inequality. In other words, the increase in inequality due to composition changes occurs because there is a higher share of low risk automation jobs. Inequality within low risk automation jobs is higher than inequality in high and medium automation risk jobs as detailed in Table 3, which explains why the coefficient on high automation risk is negative. Wages for jobs in high automation risk categories remain low during the time period as they face competition not only from automation technologies that may threaten to displace them, but also a large workforce with similar skills that can fill these positions quickly.

We find evidence that relative wage returns between high and low automation workers are causing rising inequality, as predicted by Skill Biased Technological Change, in Finland, France, Hungary, Italy, Luxembourg, and to a lesser extent, the United Kingdom. However, this effect is not prevalent in all countries, and is not the largest contributor to inequality in European countries - a conclusion that is also found by Goos et. al. (2011). However, what is driving inequality across countries is a shift in the composition of jobs, a rising share of low automation jobs, and a declining presence of high automation jobs. As the share of low automation jobs increases, and will likely continue to increase given the current trend found in our results and others, inequality will rise. It's not only the difference of relative wage returns between jobs that require manual tasks compared to cognitive tasks that contributes to inequality, but polarization is also rising within jobs that require similar skill sets. For example, childcare workers and teachers are jobs that are more resilient to automation and both jobs require cognitive thinking and social skills. However, there is a large wage disparity between these two jobs. Even though these jobs are less likely to be automated, inequality remains relatively high. The lowest and highest paid occupations are both resilient to automation, while jobs that are being automated are those that tend to be near the median wage - a fact also confirmed by Goos et. al. (2011). The composition of the workforce is driving inequality towards jobs that are more resilient to automation, which tend to be either low or high paying. Jobs that are more likely to be automated tend to earn similar wages, and these jobs are disappearing as a share of employment.

# 6 Conclusion

Wage inequality has increased in recent years and can be attributed to a variety factors including individual, firm, and industry characteristics, labor institutions, and the impact of automation. Using a large number of characteristics from the Structure of Earnings Survey we decompose the major drivers of wage inequality between 2002 and 2014 for 10 European Countries. We applied a RIF regression to identify the effect that each characteristic has on the Gini by year, and using a reweighing procedure, we identify whether the changes to inequality were due to the wage effect and/or composition effect with a Oaxaca-Blinder decomposition. This method allows us to evaluate the effect that each characteristic has on inequality - whether that is the overall contribution, the wage effect, or the composition effect. The wage effect isolates changes in inequality that are due to the relative return of wages allowing us to identify if inequality is due to wage return differences between high and low automation jobs, while holding the composition effect constant. This effectively tests which countries experienced Skill Biased Technological Change. The composition effect identifies if changes in inequality are due to shifts in the structure of employment, while holding wage returns constant.

Our results show that rising inequality within European countries is largely explained by automation with the top half of the distribution impacted the most. The composition effect has a consistently large impact across all countries, however some countries also see a rise in inequality due to the wage effect (Finland, the Czech Republic, France, Hungary, Italy, the United Kingdom and Luxembourg). The composition effect is due to the fact that low automation risk jobs have more unequal wages, and the share of these jobs are rising over time, which is also seen in the descriptive statistics in the appendix in Table 10. As the share of low automation risk increases and the dispersion within that group grows, inequality increases.

These results reveal that automation is changing the composition of jobs and this is driving rising inequality across Europe. The share of high risk automation jobs has been steadily declining, and these types of jobs are paid relatively similar to each other. In place of these jobs, low-risk automation jobs have risen, but these jobs are paid much more unequally to one another. This effect is mostly occurring at the top half of the distribution, which is that the relative earning differences between middle income earners and high income earners are increasing due to automation. As middle income jobs disappear, the difference of earnings between middle income and high income earners increase. These results further support evidence that the upper tail of the wage distribution continue to increase while low wages stagnate (David et al. (2006)). Changing composition driven by automation is present in a variety of European countries. However, the effect of skill biased technical change is present in only six European countries, and further, its effect on inequality is not as strong as the composition effect.

Automation is contributing to inequality, and our decomposition shows that this is partly due to dynamic structural shifts - the composition effect. Individuals are moving towards low automation risk jobs, but leaving some behind. Our results show that the impact of automation on wages is changing, and that it is important to consider the structural, as well as wage effects in order to understand the varied ways through which automation impacts inequality. Many fear the employment and displacement effects of automation, but even if we assume that employment levels remain high and workers will be sorted to new jobs without long lasting unemployment effects, our results suggest that inequality will continue to grow.

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# 7 Data Appendix

Enterprises that are below 10 people may not be assigned, but in some cases are noted. The categories of enterprise size bands are, 10 -49, 50 -249, 250-499, and 500-999. Age brackets are as follows, 14-19, 20-29, 30-39, 40-49, 50-59, 60+. In the case of Romania, we divided 2002 wages by 10000 to make the currency equivalent to 2014 Leu. This is done because of a currency change in 2005 which redenominated its currency by 10000 Leu.

## 7.1 Education

We converted the 2002 education variables from ISCED - 97 to ISCED - 2011 using the cross walk provided by Eurostat shown in Table 5. The category represents the level of education the individual has successfully completed which are categorized into four groups below.

**Table 5:** ISCED Crosswalk

| Category | ISCED Code | Description |
|---|---|---|
| 1 | 0 | Early childhood education ('less than primary' ) |
| | 1 | Primary education |
| 2 | 2 | Lower secondary education |
| | 3 | Upper secondary education |
| | 4 | Post-secondary non-tertiary education |
| 3 | 5 | Short-cycle tertiary education |
| | 6 | Bachelor's or equivalent level |
| | 7 | Master's or equivalent level |
| 4 | 8 | Doctoral or equivalent level |

## 7.2 Industry

While the SES data is harmonized across the member states of the European Union there remained a few consistency issues across the waves and countries. For this analysis the most notable concern was the industry classification changes which were grouped inconsistently depending on the country and year. In cases where two sectors were combined, we aggregated the information. Thus, our final industry classification groups is in Table 6.

**Table 6:** Industry Groups, NACE 2.0

| No. | Industry Group | Name |
|---|---|---|
| 1 | B, 35, 36 | Mining and quarrying, Electricity, gas, steam and air conditioning supply, Water collection, treatment and supply |
| 2 | 10-15 | Manufacture of food products, beverages and tobacco products, Manufacture of textiles, wearing apparel and leather products |
| 3 | 16-18, 58-60 | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials, Manufacture of paper and paper products, Printing and reproduction of recorded media, Publishing activities Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities |

| No. | Industry Group | Name |
|---|---|---|
| 4 | 19-23, 26, 27, 29-33 | Manufacture of coke and refined petroleum products, Manufacture of chemicals and chemical products, Manufacture of basic pharmaceutical products and pharmaceutical preparations, Manufacture of rubber and plastic products, Manufacture of other non-metallic mineral products, Manufacture of computer, electronic and optical products, Manufacture of electrical equipment, Manufacture of motor vehicles, trailers and semi-trailers, Manufacture of other transport equipment, Manufacture of furniture; other manufacturing, Repair and installation of machinery and equipment |
| 5 | 24, 25, 28 | Manufacture of basic metals, Manufacture of fabricated metal products, except machinery and equipment, Manufacture of machinery and equipment n.e.c. |
| 6 | 37-39 | Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services |
| 7 | F | Construction |
| 8 | 45, 46 | Wholesale and retail trade and repair of motor vehicles and motorcycles, Wholesale trade, except of motor vehicles and motorcycles |
| 9 | 47 | Retail trade, except of motor vehicles and motorcycles |
| 10 | 49-52 | Land transport and transport via pipelines, Water transport, Air transport, Warehousing and support activities for transportation |
| 11 | 53, 61-63,79 | Postal and courier activities, Telecommunications, Computer programming, consultancy and related activities; information service activities, Travel agency, tour operator, and other reservation service and related activities |
| 12 | I | Accommodation and food service activities |
| 13 | 64-66, 68-75, 77, 78, 80-82, 86-88, 90-93, 95, 96 | Financial service activities, except insurance and pension funding, Insurance, reinsurance and pension funding, except compulsory social security, Activities auxiliary to financial services and insurance activities , Real estate activities, Legal and accounting activities; activities of head offices; management consultancy activities, Architectural and engineering activities; technical testing and analysis, Scientific research and development, Advertising and market research, Other professional, scientific and technical activities; veterinary activities, Other service activities, Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, Activities of extraterritorial organizations and bodies, Administrative and support service activities |
| 14 | O | Public administration and defence; compulsory social security |
| 15 | P | Education |
| 16 | Q | Human health and social work activities |
| unknown | ZZZ | not specified |

## 7.3 Automation Risk

Frey & Osborne's risk assessment is done with 702 occupations using the SOC (US) classification system. Our data uses ISCO-08 categories for 2014, and ISCO-88 for 2002. To crosswalk between the SOC and ISCO classifications, we use the Bureau of Labor Statistics crosswalk. We then crosswalk ISCO-08 to ISCO-88 using the International Labor Organization's crosswalk. Since our occupation categories are at the 2-digit or 3-digit level (depending on the year and country), we aggregate them by taking the average automation risk for that occupational group. Below is the occupation by automation risk by 2 and 3 digit codes for ISCO-88 and ISCO-08.

**Table 7:** 2-digit Occupation Code Automation Risk

| ISCO-88 | Auto. Risk | Occupation Title | ISCO-08 | Auto. Risk | Occupation Title |
|---|---|---|---|---|---|
| 11 | 0.113 | Legislators and senior officials | 11 | 0.110 | Chief Exec., Senior Officials and Legisla... |
| 12 | 0.210 | Corporate Mngr | 12 | 0.259 | Admin and Commercial Mngr |
| 13 | 0.352 | General Mngr | 13 | 0.112 | Production and Specialized Services Mngr |
| 21 | 0.146 | Physical, mathematical and engineering science... | 14 | 0.133 | Hospitality, Retail and Other Services profs. |
| 22 | 0.057 | Life science and health profs. | 21 | 0.118 | Science and Engineering profs. |
| 23 | 0.065 | Teaching profs. | 22 | 0.038 | Health profs. |
| 24 | 0.285 | Other profs. | 23 | 0.074 | Teaching profs. |
| 31 | 0.456 | Physical and engineering science associate pro... | 24 | 0.417 | Business and Admin profs. |
| 32 | 0.264 | Life science and health associate profs. | 25 | 0.105 | Information and Comms. Technology Prof... |
| 33 | 0.151 | Teaching associate profs. | 26 | 0.179 | Legal, Social and Cultural profs. |
| 34 | 0.422 | Other associate profs. | 31 | 0.537 | Science and Engineering Associate profs. |
| 41 | 0.922 | Office clerks | 32 | 0.316 | Health Associate profs. |
| 42 | 0.685 | Customer services clerks | 33 | 0.491 | Business and Administration Associate profsi... |
| 51 | 0.476 | Personal and protective services wrkrs | 34 | 0.438 | Legal, Social, Cultural and Related Associate ... |
| 52 | 0.771 | Models, salespersons and demonstrators | 35 | 0.536 | Information and Comms. Techn. |
| 61 | 0.732 | Market-oriented skilled agricultural and fishe... | 41 | 0.923 | General and Keyboard Clerks |
| 62 | 0.800 | Subsistence agricultural and fishery wrkrs | 42 | 0.626 | Customer Services Clerks |
| 71 | 0.662 | Extraction and building trades wrkrs | 43 | 0.971 | Numerical and Material Recording Clerks |
| 72 | 0.614 | Metal, machinery and related trades wrkrs | 44 | 0.893 | Other Clerical Support wrkrs |
| 73 | 0.789 | Precision, handicraft, craft printing and rela... | 51 | 0.525 | Personal Services wrkrs |
| 74 | 0.725 | Other craft and related trades wrkrs | 52 | 0.777 | Sales wrkrs |
| 81 | 0.801 | Stationary plant and related operators | 53 | 0.396 | Personal Care wrkrs |
| 82 | 0.860 | Machine operators and assemblers | 54 | 0.476 | Protective Services wrkrs |
| 83 | 0.621 | Drivers and mobile plant operators | 61 | 0.709 | Market-oriented Skilled Agricultural wrkrs |
| 91 | 0.801 | Sales and services elementary occupations | 62 | 0.754 | Market-oriented Skilled Forestry, Fishery and ... |
| 92 | 0.890 | Agricultural, fishery and related labourers | 63 | 0.800 | Subsistence Farmers, Fishers, Hunters and Gath... |
| 93 | 0.735 | Labourers in mining, construction, manufacturi... | 71 | 0.675 | Building and Related Trades wrkrs (excluding... |
| | | | 72 | 0.738 | Metal, Machinery and Related Trades wrkrs |
| | | | 73 | 0.768 | Handicraft and Printing wrkrs |
| | | | 74 | 0.560 | Electrical and Electronic Trades wrkrs |
| | | | 75 | 0.698 | Food proc., Woodworking, Garment and Othe... |
| | | | 81 | 0.827 | Stationary Plant and Machine Operators |
| | | | 82 | 0.946 | Assemblers |
| | | | 83 | 0.621 | Drivers and Mobile Plant Operators |
| | | | 91 | 0.631 | Cleaners and Helpers |
| | | | 92 | 0.910 | Agricultural, Forestry and Fishery Labourers |
| | | | 93 | 0.727 | Labourers in Mining, Construction, Manufacturi... |
| | | | 94 | 0.848 | Food Preparation Assistants |
| | | | 95 | 0.940 | Street and Related Sales and Services wrkrs |
| | | | 96 | 0.839 | Refuse wrkrs and Other Elementary wrkrs |

**Table 8:** 3-digit Occupation Code Automation Risk

| 88 | AR | Occupation Title | 08 | AR | Occupation Title |
|---|---|---|---|---|---|
| 111 | 0.113 | Legislators & Senior Officials | 111 | 0.113 | Legislators |
| 112 | 0.087 | Managing Directors & Chief Exec. | 112 | 0.059 | Senior government officials |
| 121 | 0.331 | Business Services & Admin Mngr | 113 | 0.015 | Traditional chiefs & heads of villages |
| 122 | 0.019 | Sales, Marketing & Development Mngr | 114 | 0.142 | Senior officials of special-interest organisat... |
| 131 | 0.047 | Production Mngr in Agriculture, Forestry a... | 121 | 0.087 | Directors & chief Exec. |
| 132 | 0.275 | Manuf, Mining, Construction & Distri... | 122 | 0.216 | Production & operations department Mngr |
| 133 | 0.035 | Information & Comms. Technology Serv... | 123 | 0.211 | Other specialist Mngr |

**Table 8:** 3-digit Occupation Code Automation Risk

| 88 | AR | Occupation Title | 08 | AR | Occupation Title |
|---|---|---|---|---|---|
| 134 | 0.068 | profsional Services Mngr | 131 | 0.352 | General Mngr |
| 141 | 0.043 | Hotel & Restaurant Mngr | 211 | 0.199 | Physicists, chemists & related profs. |
| 142 | 0.160 | Retail & Wholesale Trade Mngr | 212 | 0.148 | Mathematicians, statisticians & related prof... |
| 143 | 0.210 | Other Services Mngr | 213 | 0.105 | Computing profs. |
| 211 | 0.225 | Physical & Earth Science profs. | 214 | 0.138 | Architects, engineers & related profs. |
| 212 | 0.148 | Math., Actuaries & Statisticians | 221 | 0.069 | Life science profs. |
| 213 | 0.063 | Life Science profs. | 222 | 0.023 | Health profs. (except nursing) |
| 214 | 0.086 | Engineering profs. (excluding Electrote... | 223 | 0.058 | Nursing & midwifery profs. |
| 215 | 0.062 | Electrotechnology Engineers | 231 | 0.009 | College, university & higher education teach... |
| 216 | 0.225 | Architects, Planners, Surveyors & Designers | 232 | 0.008 | Secondary education teaching profs. |
| 221 | | Medical Doctors | 233 | 0.083 | Primary & pre-primary education teaching pro... |
| 222 | | Nursing & Midwifery profs. | 234 | 0.012 | Special education teaching profs. |
| 223 | | Traditional & Complementary Medicine profs... | 235 | 0.098 | Other teaching profs. |
| 224 | 0.140 | Paramedical Practitioners | 241 | 0.428 | Business profs. |
| 225 | 0.038 | Veterinarians | 242 | 0.284 | Legal profs. |
| 226 | 0.032 | Other Health profs. | 243 | 0.452 | Archivists, librarians & related information... |
| 231 | | University & Higher Education Tchrs. | 244 | 0.130 | Social science & related profs. |
| 232 | 0.009 | Vocational Education Tchrs. | 245 | 0.195 | Writers & creative or performing artists |
| 233 | 0.008 | Secondary Education Tchrs. | 246 | 0.008 | Religious profs. |
| 234 | 0.083 | Primary School & Early Childhood Tchrs. | 311 | 0.534 | Physical & engineering science Techn. |
| 235 | 0.084 | Other Teaching profs. | 312 | 0.300 | Computer Assoc. profs. |
| 241 | 0.586 | Finance profs. | 313 | 0.442 | Optical & electronic equipment oprts. |
| 242 | 0.210 | Admin profs. | 314 | 0.211 | Ship & aircraft controllers & Techn. |
| 243 | 0.268 | Sales, Marketing & Public Relations profsi... | 315 | 0.508 | Safety & quality inspectors |
| 251 | 0.135 | Software & Apps. Developers & Analysts | 321 | 0.446 | Life science Techn. & related Assoc.... |
| 252 | 0.030 | Database & Network profs. | 322 | 0.226 | Health Assoc. profs. (except nursing) |
| 261 | 0.284 | Legal profs. | 323 | 0.058 | Nursing & midwifery Assoc. profs. |
| 262 | 0.452 | Librarians, Archivists & Curators | 324 | | Traditional medicine practitioners & faith h... |
| 263 | 0.105 | Social & Religious profs. | 331 | 0.087 | Primary education teaching Assoc. profs |
| 264 | 0.306 | Authors, Journalists & Linguists | 332 | 0.079 | Pre-primary education teaching Assoc. profs |
| 265 | 0.114 | Creative & Performing Artists | 333 | 0.012 | Special education teaching Assoc. profs |

**Table 8:** 3-digit Occupation Code Automation Risk

| 88 | AR | Occupation Title | 08 | AR | Occupation Title |
|---|---|---|---|---|---|
| 311 | 0.538 | Physical & Engineering Science Techn. | 334 | 0.212 | Other teaching Assoc. profs. |
| 312 | 0.170 | Mining, Manuf & Construction Supervi... | 341 | 0.430 | Finance & sales Assoc. profs. |
| 313 | 0.730 | Process Control Techn. | 342 | 0.242 | Business services agents & trade brokers |
| 314 | 0.720 | Life Science Techn. & Related Assoc.... | 343 | 0.739 | Admin Assoc. profs. |
| 315 | 0.220 | Ship & Aircraft Controllers & Techn. | 344 | 0.304 | Customs, tax & related government Assoc. ... |
| 321 | 0.518 | Medical & Pharmaceutical Techn. | 345 | 0.563 | Police inspectors & detectives |
| 322 | 0.058 | Nursing & Midwifery Assoc. profs. | 346 | 0.130 | Social work Assoc. profs. |
| 323 | | Trad. & Comp. Medicine Associa... | 347 | 0.186 | Artistic, entertainment & sports Assoc. p... |
| 324 | 0.444 | Veterinary Techn. & Assistants | 348 | | Religious Assoc. profs. |
| 325 | 0.275 | Other Health Assoc. profs. | 411 | 0.905 | Secretaries & keyboard-operating clerks |
| 331 | 0.721 | Financial & Math. Assoc. profs. | 412 | 0.978 | Numerical clerks |
| 332 | 0.453 | Sales & Purchasing Agents & Brokers | 413 | 0.955 | Material-recording & transport clerks |
| 333 | 0.360 | Business Services Agents | 414 | 0.882 | Library, mail & related clerks |
| 334 | 0.808 | Admin & Specialized Secretaries | 419 | 0.980 | Other office clerks |
| 335 | 0.278 | Government Regulatory Assoc. profs. | 421 | 0.707 | Cashiers, tellers & related clerks |
| 341 | 0.666 | Legal, Social & Religious Assoc. profsi.wrkrs | 422 | 0.646 | Client information clerks |
| 342 | 0.208 | Sports & Fitness wrkrs | 511 | 0.411 | Travel attendants & related wrkrs |
| 343 | 0.326 | Artistic, Cultural & Culinary Assoc. Prof... | 512 | 0.691 | Housekeeping & restaurant services wrkrs |
| 351 | 0.280 | Information & Comms. Technology Oper... | 513 | 0.454 | Personal care & related wrkrs |
| 352 | 0.663 | Telecom & Broadcasting Techn. | 514 | 0.418 | Other personal services wrkrs |
| 411 | 0.980 | General Office Clerks | 515 | | Astrologers, fortune-tellers & related wrkrs |
| 412 | 0.960 | Secretaries (general) | 516 | 0.416 | Protective services wrkrs |
| 413 | 0.900 | Keyboard oprts. | 521 | 0.980 | Fashion & other models |
| 421 | 0.698 | Tellers, Money Collectors & Related Clerks | 522 | 0.683 | Shop, stall & market salespersons & demons... |
| 422 | 0.541 | Client Information wrkrs | 523 | 0.930 | Stall & market salespersons |
| 431 | 0.978 | Numerical Clerks | 611 | 0.646 | Market gardeners & crop growers |
| 432 | 0.955 | Material Recording & Transport Clerks | 612 | 0.767 | Market-oriented animal producers & related w... |
| 441 | 0.893 | Other Clerical Support wrkrs | 613 | 0.760 | Market-oriented crop & animal producers |
| 511 | 0.411 | Travel Attendants, Conductors & Guides | 614 | 0.792 | Forestry & related wrkrs |
| 512 | 0.732 | Cooks | 615 | 0.649 | Fishery wrkrs, hunters & trappers |
| 513 | 0.770 | Waiters & Bartenders | 621 | 0.800 | Subsistence agricultural & fishery wrkrs |

**Table 8:** 3-digit Occupation Code Automation Risk

| 88 | AR | Occupation Title | 08 | AR | Occupation Title |
|---|---|---|---|---|---|
| 514 | 0.437 | Hairdressers, Beauticians & Related wrkrs | 711 | 0.693 | Miners, shotfirers, stone cutters & carvers |
| 515 | 0.660 | Building & Housekeeping Supervisors | 712 | 0.603 | Building frame & related trades wrkrs |
| 516 | 0.524 | Other Personal Services wrkrs | 713 | 0.681 | Building finishers & related trades wrkrs |
| 521 | 0.913 | Street & Market Salespersons | 714 | 0.720 | Painters, building structure cleaners & rela... |
| 522 | 0.585 | Shop Salespersons | 721 | 0.716 | Metal moulders, welders, sheet-metal wrkrs, ... |
| 523 | 0.830 | Cashiers & Ticket Clerks | 722 | 0.838 | Blacksmiths, tool-makers & related trades wo... |
| 524 | 0.821 | Other Sales wrkrs | 723 | 0.490 | Machinery mechanics & fitters |
| 531 | 0.084 | Child Care wrkrs & Tchrs.-Aides | 724 | 0.567 | Electrical & electronic equipment mechanics ... |
| 532 | 0.448 | Personal Care wrkrs in Health Services | 731 | 0.521 | Precision wrkrs in metal & related materials |
| 541 | 0.476 | Protective Services wrkrs | 732 | 0.901 | Potters, glass-makers & related trades wrkrs |
| 611 | 0.570 | Market Gardeners & Crop Growers | 733 | 0.520 | Handicraft wrkrs in wood, textile, leather a... |
| 612 | 0.760 | Animal Producers | 734 | 0.930 | Printing & related trades wrkrs |
| 613 | 0.760 | Mixed Crop & Animal Producers | 741 | 0.751 | Food Procs. & related trades wrkrs |
| 621 | 0.792 | Mixed Crop & Animal Producers | 742 | 0.934 | Wood treaters, cabinet-makers & related trad... |
| 622 | 0.713 | Fishery wrkrs, Hunters & Trappers | 743 | 0.659 | Textile, garment & related trades wrkrs |
| 631 | | Subsistence Crop Farmers | 744 | 0.465 | Pelt, leather & shoemaking trades wrkrs |
| 632 | | Subsistence Crop Farmers | 811 | 0.748 | Mining & mineral-Procs.-plant oprts. |
| 633 | | Subsistence Crop Farmers | 812 | 0.882 | Metal-Procs. plant oprts. |
| 634 | 0.800 | Subs. Fishers, Hunters, Trappers & Gat... | 813 | 0.915 | Glass, ceramics & related plant oprts. |
| 711 | 0.659 | Building Frame & Rel. Trades wrkrs | 814 | 0.649 | Wood & paper plant oprts. |
| 712 | 0.669 | Building Finishers & Rel. Trades wrkrs | 815 | 0.829 | Chemical-Procs.-plant oprts. |
| 713 | 0.770 | Painters, Bld. Struct. Cleaners & Rela... | 816 | 0.814 | Power-production & related plant oprts. |
| 721 | 0.776 | Sheet & Struct. Metal wrkrs, Moulders a... | 817 | 0.360 | Automated-assembly-line & industrial-robot o... |
| 722 | 0.851 | Blcksmth Toolmakers & Rel. Trades Wor... | 821 | 0.867 | Metal- & mineral-products machine oprts. |
| 723 | 0.520 | Machinery Mechanics & Repairers | 822 | 0.860 | Chemical-products machine oprts. |
| 731 | 0.700 | Handicraft wrkrs | 823 | 0.862 | Rubber- & plastic-products machine oprts. |
| 732 | 0.913 | Printing Trades wrkrs | 824 | 0.970 | Wood-products machine oprts. |
| 741 | 0.539 | Electrical Equipment Installers & Repairers | 825 | 0.910 | Printing-, binding- & paper-products machine... |
| 742 | 0.568 | Electronics & Telecom Installers ... | 826 | 0.868 | Textile-, fur- & leather-products machine op... |

**Table 8:** 3-digit Occupation Code Automation Risk

| 88 | AR | Occupation Title | 08 | AR | Occupation Title |
|---|---|---|---|---|---|
| 751 | 0.751 | Food proc. & Related Trades wrkrs | 827 | 0.816 | Food & related products machine oprts. |
| 752 | 0.940 | Wood Treaters, Cabinet-makers & Related Trad... | 828 | 0.945 | Assemblers |
| 753 | 0.642 | Garment & Related Trades wrkrs | 829 | 0.940 | Other machine oprts. & assemblers |
| 754 | 0.352 | Other Craft & Related wrkrs | 831 | 0.639 | Locomotive engine drivers & related wrkrs |
| 811 | 0.740 | Mining & Mineral proc. Plant oprts. | 832 | 0.508 | Motor-vehicle drivers |
| 812 | 0.886 | Metal proc. & Finishing Plant oprts. | 833 | 0.712 | Agricultural & other mobile-plant oprts. |
| 813 | 0.837 | Chemical & Photographic Products Plant & M... | 834 | 0.725 | Ships' deck crews & related wrkrs |
| 814 | 0.870 | Rubber, Plastic & Paper Products Machine Ope... | 911 | 0.934 | Street vendors & related wrkrs |
| 815 | 0.845 | Textile, Fur & Leather Products Machine Oper... | 912 | | Shoe cleaning & other street services elemen... |
| 816 | 0.816 | Food & Related Products Machine oprts. | 913 | 0.694 | Domestic & related helpers, cleaners & lau... |
| 817 | 0.764 | Wood proc. & Papermaking Plant oprts. | 914 | 0.620 | Building caretakers, window & related cleaners |
| 818 | 0.922 | Other Stationary Plant & Machine oprts. | 915 | 0.902 | Messengers, porters, doorkeepers & related w... |
| 821 | 0.946 | Assemblers | 916 | 0.706 | Garbage collectors & related wrkrs |
| 831 | 0.639 | Locomotive Engine Drivers & Related wrkrs | 921 | 0.890 | Agricultural, fishery & related wrkrs |
| 832 | 0.471 | Car, Van & Motorcycle Drivers | 931 | 0.773 | Mining & construction wrkrs |
| 833 | 0.545 | Heavy Truck & Bus Drivers | 932 | 0.774 | Manuf wrkrs |
| 834 | 0.712 | Mobile Plant oprts. | 933 | 0.599 | Transport wrkrs & freight handlers |
| 835 | 0.725 | Ships Deck Crews & Related wrkrs | | | |
| 911 | 0.603 | Domestic, Hotel & Office Cleaners & Helpers | | | |
| 912 | 0.670 | Vehicle, Window, Laundry & Other Hand Cleani... | | | |
| 921 | 0.910 | Agricultural, Forestry & Fishery wrkrs | | | |
| 931 | 0.773 | Mining & Construction wrkrs | | | |
| 932 | 0.751 | Manuf wrkrs | | | |
| 933 | 0.599 | Transport & Storage wrkrs | | | |
| 941 | 0.848 | Food Preparation Assistants | | | |
| 951 | | Street & Related Services wrkrs | | | |
| 952 | 0.940 | Street Vendors (excluding Food) | | | |
| 961 | 0.705 | Refuse wrkrs | | | |
| 962 | 0.888 | Other Elementary wrkrs | | | |

# 8 RIF Regressions Results

**Table 9:** RIF Regressions on Gini - Mediterranean Countries

| | (1)<br>ES 2014 | (2)<br>ES 2002 | (3)<br>IT 2014 | (4)<br>IT 2002 |
|---|---|---|---|---|
| Female | -0.000422** | 0.00112*** | -0.00473*** | -0.000303 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Mid AR | -0.00492*** | -0.0198*** | -0.00155*** | -0.0292*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| High AR | -0.00961*** | -0.0155*** | -0.00980*** | -0.0293*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Unk. AR | 0.00515 | | 0.0155*** | |
| | (0.004) | | (0.001) | |
| Private | -0.00869*** | -0.0149*** | -0.00991*** | -0.00114** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| PT Cont. | 0.0603*** | 0.0764*** | 0.0485*** | 0.0473*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Fixed Cont. | 0.0276*** | 0.0159*** | 0.0157*** | 0.00866*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Apprentice | | 0.0513*** | 0.00949*** | 0.0273*** |
| | | (0.002) | (0.001) | (0.001) |
| Oth. Cont. | -0.00308*** | 0.00104 | | 0.00259 |
| | (0.001) | (0.001) | | (0.002) |
| 85% PT Cont. | | | 0.00234*** | 0.00640*** |
| | | | (0.001) | (0.002) |
| Firm size <50 | 0.00227*** | -0.00476*** | -0.00146*** | 0.000683** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Firm size 50-250 | -0.00171*** | -0.00518*** | -0.000995*** | 0.000595** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Firm size all | -0.00107*** | -0.00476*** | | |
| | (0.000) | (0.001) | | |
| Age 14-19 | 0.0471*** | 0.0112*** | 0.0200*** | 0.0159*** |
| | (0.002) | (0.001) | (0.002) | (0.001) |
| Age 20-29 | -0.00117*** | -0.0112*** | -0.00129*** | -0.00329*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Age 30-39 | -0.00677*** | -0.00749*** | -0.00460*** | -0.00488*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |

| | (1) ES 2014 | (2) ES 2002 | (3) IT 2014 | (4) IT 2002 |
|---|---|---|---|---|
| Age 50-59 | 0.00424*** | 0.00476*** | 0.00454*** | 0.00478*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Age 60+ | 0.0142*** | 0.00741*** | 0.0107*** | 0.00901*** |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| Primary Edu | 0.00225*** | 0.00187*** | 0.000684*** | -0.000758*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Uni Edu | 0.00127*** | 0.00229*** | -0.00412*** | 0.00898*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Doctoral Edu | 0.0141*** | 0.0139*** | 0.0121*** | 0.0201*** |
| | (0.000) | (0.002) | (0.000) | (0.001) |
| Nat. Union | -0.00329*** | -0.00253*** | | -0.00473*** |
| | (0.000) | (0.000) | | (0.000) |
| Mining & Util | -0.00283*** | 0.000811 | -0.000789 | 0.00598*** |
| | (0.001) | (0.000) | (0.001) | (0.001) |
| Textile | -0.0000472 | 0.00268*** | 0.00116* | 0.00113 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Manuf wood | 0.00101** | 0.000533 | -0.00328*** | -0.000900** |
| | (0.001) | (0.000) | (0.000) | (0.000) |
| Manuf. | -0.00399*** | -0.00419*** | -0.00284*** | -0.000120 |
| | (0.001) | (0.001) | (0.000) | (0.001) |
| Metal Manuf. | -0.00785*** | 0.000253 | -0.00697*** | -0.00208 |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Util. | -0.00221*** | 0.00256*** | -0.00267*** | -0.00115** |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Constru. | -0.00128*** | 0.00368*** | -0.00817*** | -0.00247*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Retail | 0.00123* | 0.00969*** | -0.00390*** | 0.00252*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Transport | 0.00417*** | 0.0132*** | 0.00848*** | 0.00892*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Comms. | 0.0127*** | 0.0111*** | 0.00601*** | 0.000654 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Food & Hotels | -0.0136*** | -0.0115*** | -0.00652*** | -0.00161*** |

| | (1) ES 2014 | (2) ES 2002 | (3) IT 2014 | (4) IT 2002 |
|---|---|---|---|---|
| | (0.001) | (0.000) | (0.001) | (0.001) |
| Finance | 0.00696*** | | 0.0110*** | 0.00953*** |
| | (0.000) | | (0.001) | (0.001) |
| Public Admin. | | | 0.00276*** | |
| | | | (0.000) | |
| Educ. Ind. | | | -0.00871*** | |
| | | | (0.001) | |
| Cons. | 0.0432*** | 0.0633*** | 0.0366*** | 0.0611*** |
| | (0.001) | (0.001) | (0.000) | (0.001) |
| N | 209436 | 217147 | 189221 | 81975 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 10:** RIF Regressions of Gini on Log Wages - Eastern European Countries

| | (1) CZ 2014 | (2) CZ 2002 | (3) HU 2014 | (4) HU 2002 | (5) RO 2014 | (6) RO 2002 |
|---|---|---|---|---|---|---|
| Female | -0.00393*** | -0.000918*** | -0.00399*** | -0.00423*** | -0.00381*** | -0.00291*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Mid AR | -0.00170*** | -0.00302*** | -0.00213*** | -0.00486*** | -0.00699*** | -0.0204*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| High AR | -0.00475*** | -0.00442*** | -0.00165*** | -0.00734*** | -0.0120*** | -0.0230*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Unk. AR | 0.00889*** | 0.00774*** | -0.00524*** | -0.00181*** | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | | |
| Private | -0.00649*** | -0.00364*** | -0.00615*** | -0.00994*** | -0.0140*** | -0.0107*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| PT Cont. | 0.0328*** | 0.0404*** | -0.0000934 | 0.000701*** | 0.0782*** | 0.0548*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Fixed Cont. | 0.00216*** | 0.00802*** | -0.00249*** | -0.00246*** | 0.00688*** | 0.00940*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Apprentice | | 0.00891*** | | -0.00751 | | |
| | | (0.000) | | (0.009) | | |
| Oth. Cont. | 0.00655*** | 0.00387*** | | -0.00181*** | -0.00108 | |
| | (0.000) | (0.000) | | (0.000) | (0.004) | |
| Firm size <50 | 0.000878*** | 0.00144*** | -0.00406*** | -0.00306*** | 0.00371*** | 0.0175*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Firm size 50-250 | -0.000802*** | 0.000538*** | 0.000288*** | -0.00229*** | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | | |
| Age 14-19 | -0.00111*** | 0.00685*** | -0.000832** | -0.00230*** | 0.00199* | 0.0135*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Age 20-29 | -0.00657*** | -0.00298*** | -0.00436*** | -0.00261*** | -0.00479*** | 0.000749** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Age 30-39 | -0.00163*** | 0.000136* | -0.000929*** | -0.000242*** | -0.000558*** | 0.0000167 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Age 50-59 | -0.000901*** | 0.000575*** | -0.000211*** | 0.00144*** | -0.000286* | 0.00210*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Age 60+ | 0.000378*** | 0.00883*** | -0.000535*** | 0.00329*** | 0.00310*** | 0.0231*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Primary Edu | 0.00498*** | 0.00600*** | 0.00464*** | -0.000124 | 0.00161*** | 0.00711*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Uni Edu | 0.00352*** | 0.0120*** | 0.0108*** | 0.0169*** | 0.0129*** | 0.0110*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Doctoral Edu | 0.0127*** | 0.0195*** | 0.0209*** | | 0.0276*** | 0.0500*** |
| | (0.000) | (0.000) | (0.000) | | (0.000) | (0.001) |
| Nat. Union | -0.00353*** | -0.000543*** | 0.00342*** | 0.00230*** | -0.00385*** | -0.00863*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Firm Yrs. | -0.00000266 | -0.0000775*** | | | 0.000172*** | -0.000189*** |
| | (0.000) | (0.000) | | | (0.000) | (0.000) |
| Mining & Util | -0.000770*** | 0.00313*** | -0.00310*** | -0.000460*** | -0.00898*** | -0.00272*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Textile | 0.000767*** | 0.00151*** | 0.000380** | 0.00174*** | -0.00170*** | 0.000256 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Manuf wood | -0.00307*** | -0.00220*** | -0.0000747 | 0.00109*** | -0.00938*** | -0.00934*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

| | (1) CZ 2014 | (2) CZ 2002 | (3) HU 2014 | (4) HU 2002 | (5) RO 2014 | (6) RO 2002 |
|---|---|---|---|---|---|---|
| Manuf. | -0.00583*** | -0.00315*** | -0.000712*** | -0.00120*** | -0.0140*** | -0.0117*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Metal Manuf. | -0.00419*** | -0.00378*** | -0.00145*** | 0.00139*** | -0.00903*** | -0.00980*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Util. | -0.000842*** | 0.00140*** | 0.000987*** | 0.00266*** | -0.00469*** | 0.000538 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Constru. | 0.000501*** | 0.00613*** | -0.00266*** | -0.000888*** | -0.00831*** | 0.0103*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Retail | 0.00691*** | -0.000263 | 0.00328*** | 0.00681*** | 0.00437*** | 0.0177*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Transport | 0.00132*** | -0.000454*** | -0.000370*** | 0.00305*** | -0.00263*** | 0.00262*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Comms. | 0.000244* | -0.00104*** | 0.00222*** | 0.00209*** | 0.0116*** | 0.00892*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Food & Hotels | -0.00427*** | -0.00379*** | -0.00142*** | -0.00108*** | -0.00886*** | -0.0133*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Finance | 0.0135*** | | -0.000546*** | | -0.000919* | |
| | (0.000) | | (0.000) | | (0.000) | |
| Public Admin. | 0.00152*** | -0.00485*** | 0.00888*** | | 0.00897*** | 0.00550*** |
| | (0.000) | (0.000) | (0.000) | | (0.000) | (0.001) |
| Educ. Ind. | -0.00506*** | -0.00578*** | -0.00488*** | -0.00383*** | -0.0119*** | -0.0192*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| 85% PT Cont. | | | -0.00145*** | -0.00127*** | | |
| | | | (0.000) | (0.000) | | |
| Ind. Union | | | 0.00384*** | 0.00148*** | -0.00496*** | -0.0119*** |
| | | | (0.000) | (0.000) | (0.000) | (0.001) |
| Firm size >250 | | | | | 0.00254*** | -0.00737*** |
| | | | | | (0.000) | (0.000) |
| Reg. Union | | | | | -0.00322*** | -0.00900*** |
| | | | | | (0.000) | (0.001) |
| Mining & Util6 | | | | | | -0.00821*** |
| | | | | | | (0.001) |
| Cons. | 0.0345*** | 0.0308*** | 0.0274*** | 0.0349*** | 0.0584*** | 0.105*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| N | 2202636 | 1030982 | 882373 | 479009 | 286718 | 230161 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 11:** RIF Regressions on Gini - Scandinavian Countries

| | (1)<br>FI 2014 | (2)<br>FI 2002 | (3)<br>NL 2014 | (4)<br>NL 2002 |
|---|---|---|---|---|
| Mid AR | -0.00330*** | -0.0156*** | 0.00122*** | -0.0119*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| High AR | -0.00192*** | -0.00961*** | 0.00254*** | -0.00425*** |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Unk. AR | | | -0.0109*** | 0.00572*** |
| | | | (0.003) | (0.001) |
| Private | -0.00488*** | 0.00433*** | -0.0189*** | -0.00852*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Female | -0.00475*** | -0.00138*** | 0.0000176 | -0.00411*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| PT Cont. | 0.0403*** | 0.0689*** | 0.0251*** | 0.0434*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Fixed Cont. | 0.00907*** | 0.0148*** | 0.0289*** | 0.0402*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Apprentice | 0.00630*** | 0.0371*** | 0.0353*** | |
| | (0.002) | (0.001) | (0.005) | |
| Oth. Cont. | | 0.0883*** | -0.0154*** | -0.00724*** |
| | | (0.004) | (0.001) | (0.001) |
| Firm size <50 | -0.00122*** | -0.00101*** | 0.00697*** | 0.00235*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Firm size 50-250 | -0.00103*** | -0.00199*** | | |
| | (0.000) | (0.000) | | |
| Age 14-19 | 0.0480*** | 0.0559*** | 0.162*** | 0.133*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Age 20-29 | 0.00266*** | 0.000446 | 0.00815*** | 0.000724 |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Age 30-39 | -0.00463*** | -0.00238*** | -0.0120*** | -0.00737*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Age 50-59 | 0.00182*** | 0.000846*** | 0.00575*** | 0.00226*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Age 60+ | 0.00323*** | 0.00108 | 0.0138*** | 0.0240*** |
| | (0.000) | (0.001) | (0.001) | (0.001) |

| | (1) FI 2014 | (2) FI 2002 | (3) NL 2014 | (4) NL 2002 |
|---|---|---|---|---|
| Primary Edu | 0.00136*** | -0.000642** | 0.00218*** | 0.00425*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Uni Edu | -0.00205*** | -0.000216 | 0.0116*** | 0.00610*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Doctoral Edu | 0.00840*** | 0.0186*** | 0.0192*** | 0.0304*** |
| | (0.000) | (0.002) | (0.001) | (0.003) |
| Nat. Union | -0.00937*** | -0.00237*** | | |
| | (0.000) | (0.001) | | |
| Ind. Union | -0.0109*** | -0.0286*** | | |
| | (0.001) | (0.003) | | |
| Firm Yrs. | -0.000114*** | -0.000252*** | -0.000226*** | -0.000269*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Mining & Util | -0.00372*** | -0.00490*** | -0.00338*** | 0.00334** |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| Textile | -0.00106*** | -0.00164*** | -0.00487*** | 0.0000845 |
| | (0.000) | (0.001) | (0.001) | (0.002) |
| Manuf wood | -0.00162*** | -0.00554*** | | |
| | (0.000) | (0.000) | | |
| Manuf. | -0.00475*** | -0.00633*** | -0.00892*** | -0.00778*** |
| | (0.000) | (0.000) | (0.001) | (0.002) |
| Metal Manuf. | -0.00476*** | | -0.00904*** | 0.00254 |
| | (0.001) | | (0.003) | (0.003) |
| Util. | -0.000377 | 0.00392*** | -0.00594*** | 0.00264*** |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| Constru. | 0.00473*** | -0.000229 | 0.0112*** | 0.0242*** |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| Retail | 0.00159*** | -0.00504*** | 0.0101*** | 0.0116*** |
| | (0.000) | (0.001) | (0.001) | (0.002) |
| Transport | 0.000875*** | 0.00423*** | 0.00723*** | 0.0142*** |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Comms. | 0.00250*** | -0.00509*** | 0.00635*** | 0.0144*** |
| | (0.000) | (0.001) | (0.002) | (0.003) |
| Food & Hotels | -0.00739*** | -0.00871*** | -0.00852*** | -0.00312*** |

| | (1) FI 2014 | (2) FI 2002 | (3) NL 2014 | (4) NL 2002 |
|---|---|---|---|---|
| | (0.000) | (0.001) | (0.001) | (0.001) |
| Firm size >250 | | | 0.00311*** | 0.000818 |
| | | | (0.000) | (0.001) |
| Wholesale | | | -0.00281*** | 0.00830*** |
| | | | (0.001) | (0.001) |
| Finance | | | 0.0345*** | 0.0471*** |
| | | | (0.001) | (0.001) |
| Public Admin. | | | 0.00858*** | 0.00868*** |
| | | | (0.001) | (0.001) |
| Cons. | 0.0423*** | 0.0458*** | 0.0411*** | 0.0411*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| N | 315187 | 125169 | 155625 | 83217 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 12:** RIF Regressions on Gini - Western European Countries

| | (1)<br>FR 2014 | (2)<br>FR 2002 | (3)<br>LU 2014 | (4)<br>LU 2002 | (5)<br>UK 2014 | (6)<br>UK 2002 |
|---|---|---|---|---|---|---|
| Female | -0.00457*** | 0.0000973 | -0.00315*** | 0.00187*** | -0.00452*** | -0.00596*** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) |
| Mid AR | -0.00503*** | -0.0290*** | -0.0101*** | -0.0186*** | -0.00135*** | -0.00285*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| High AR | -0.00806*** | -0.0281*** | -0.0135*** | -0.0262*** | -0.00000895 | -0.0159*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Unk. AR | 0.00488*** | | 0.00663** | 0.0258*** | -0.00136** | 0.0137*** |
| | (0.000) | | (0.003) | (0.006) | (0.001) | (0.003) |
| Private | -0.00901*** | -0.00556*** | -0.00397*** | 0.00141 | -0.00355*** | -0.00555*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| PT Cont. | 0.0381*** | 0.0755*** | 0.0300*** | 0.0501*** | 0.0526*** | 0.0697*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Fixed Cont. | 0.0266*** | 0.0402*** | 0.0235*** | 0.0177*** | 0.0511*** | 0.0464*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Apprentice | 0.0415*** | 0.0601*** | 0.0667*** | 0.0800*** | -0.00465*** | 0.0623*** |
| | (0.001) | (0.002) | (0.003) | (0.003) | (0.001) | (0.002) |
| Oth. Cont. | | 0.0426*** | | 0.0523*** | | 0.00884*** |
| | | (0.001) | | (0.002) | | (0.002) |
| 85% PT Cont. | 0.00215*** | 0.00677*** | 0.00142 | 0.0170*** | | |
| | (0.000) | (0.001) | (0.002) | (0.003) | | |
| Firm size <50 | 0.00323*** | 0.00253*** | | | 0.00203*** | 0.00000300 |
| | (0.000) | (0.000) | | | (0.000) | (0.000) |
| Firm size 50-250 | 0.00141*** | 0.000846* | | | | |
| | (0.000) | (0.001) | | | | |
| Age 14-19 | 0.0548*** | 0.0463*** | 0.0634*** | 0.0378*** | 0.0702*** | 0.0447*** |
| | (0.001) | (0.002) | (0.003) | (0.002) | (0.001) | (0.001) |
| Age 20-29 | -0.00386*** | -0.00407*** | -0.00374*** | -0.00390*** | -0.00784*** | -0.00632*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Age 30-39 | -0.00525*** | -0.00425*** | -0.00704*** | -0.00448*** | -0.00558*** | -0.00289*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Age 50-59 | 0.00294*** | 0.00407*** | 0.00465*** | 0.00406*** | -0.000492 | -0.000489 |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Age 60+ | 0.0102*** | 0.0255*** | 0.0248*** | 0.0256*** | 0.00600*** | 0.00835*** |
| | (0.000) | (0.002) | (0.002) | (0.003) | (0.001) | (0.001) |
| Primary Edu | 0.00743*** | 0.00567*** | 0.00886*** | 0.00964*** | 0.00215*** | 0.00389*** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) |
| Uni Edu | 0.00106*** | 0.00583*** | -0.000105 | -0.000342 | -0.000799** | -0.000678* |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Doctoral Edu | 0.0177*** | 0.0320*** | 0.00861*** | 0.0167*** | -0.00155*** | 0.00596*** |
| | (0.000) | (0.002) | (0.001) | (0.003) | (0.000) | (0.001) |
| Mining & Util | -0.00470*** | 0.00108 | 0.00129 | 0.00120 | -0.00340*** | -0.00916*** |
| | (0.000) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) |
| Textile | -0.000256 | -0.000563 | -0.00340 | -0.00309 | 0.00358*** | -0.00837*** |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) |
| Manuf wood | 0.000264 | -0.00287*** | -0.00389** | -0.00409*** | 0.0000244 | -0.00779*** |
| | (0.000) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |
| Manuf. | -0.00565*** | -0.00702*** | 0.000149 | -0.00486*** | -0.00437*** | -0.0115*** |
| | (0.000) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |

| | (1) FR 2014 | (2) FR 2002 | (3) LU 2014 | (4) LU 2002 | (5) UK 2014 | (6) UK 2002 |
|---|---|---|---|---|---|---|
| Metal Manuf. | -0.00633*** | | -0.00405 | | -0.00105 | -0.0142*** |
| | (0.001) | | (0.004) | | (0.002) | (0.003) |
| Util. | -0.00138*** | 0.000511 | 0.00143 | -0.00363*** | -0.00487*** | -0.0126*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constru. | 0.00184*** | 0.000858 | 0.00833*** | 0.00309*** | 0.00373*** | -0.00116* |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Retail | -0.00263*** | -0.00986*** | 0.000126 | -0.00603*** | 0.00261*** | -0.0113*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Transport | 0.00137*** | 0.00427*** | 0.00628*** | 0.00342*** | 0.00365*** | -0.00746*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Comms. | 0.0114*** | 0.00379*** | 0.0100*** | 0.0109*** | 0.00875*** | -0.00240 |
| | (0.001) | (0.001) | (0.003) | (0.003) | (0.001) | (0.002) |
| Food & Hotels | -0.00693*** | -0.00708*** | -0.00575*** | -0.00826*** | -0.00275*** | -0.0122*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Finance | -0.00183*** | | 0.0103*** | | 0.0167*** | |
| | (0.000) | | (0.001) | | (0.001) | |
| Nat. Union | | | 0.00259 | 0.00116** | -0.00772*** | -0.00630*** |
| | | | (0.002) | (0.001) | (0.000) | (0.001) |
| Ind. Union | | | -0.00173*** | -0.0101 | -0.00314*** | -0.00481*** |
| | | | (0.001) | (0.009) | (0.000) | (0.000) |
| Public Admin. | | | 0.00585*** | | 0.00178* | -0.00482*** |
| | | | (0.002) | | (0.001) | (0.001) |
| Firm size >250 | | | | | 0.0000497 | 0.00166*** |
| | | | | | (0.000) | (0.000) |
| Firm Yrs. | | | | | -0.0000692*** | -0.000149*** |
| | | | | | (0.000) | (0.000) |
| Educ. Ind. | | | | | 0.00869*** | 0.000967 |
| | | | | | (0.001) | (0.001) |
| Cons. | 0.0364*** | 0.0579*** | 0.0380*** | 0.0515*** | 0.0472*** | 0.0641*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| N | 267383 | 121178 | 23017 | 27613 | 175477 | 150653 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 9 Detailed Tables of Decompositions

Note that the total effect in Tables 9-12 are the simple RIF regression decompositions (ie no counterfactual) between the two time periods, and thus, will not be the total composition effect of the wage structure and composition effects. Below we provide the detailed decomposition for our covariates.

**Table 13:** Detailed Gini Decomposition, Overall

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0013 | 0.0037 | 0.0011 | 0.0002 | -0.0007 | 0.0021 | 0.0004 | 0.0035 | 0.0015 | 0 |
| Education | -0.0003 | 0.0019 | 0.001 | 0.0011 | 0.0013 | 0.0014 | 0.0009 | 0.0031 | 0.0015 | -0.0015 |
| Firm | -0.001 | 0.0034 | -0.0022 | -0.0025 | 0.0011 | -0.0047 | -0.0007 | -0.0006 | 0.0047 | -0 |
| Gender | -0.0012 | -0.0006 | -0.0021 | -0.0023 | 0.0001 | -0.0019 | -0.0018 | 0.0018 | -0.0004 | 0.0007 |
| High-risk Automation | -0.0001 | 0.0027 | 0.003 | 0.0077 | 0.0011 | 0.0142 | 0.0047 | 0.0015 | 0.0036 | 0.0035 |
| Mid-risk Automation | 0.001 | 0.0081 | 0.0066 | 0.012 | 0.0017 | 0.0099 | 0.0057 | 0.0069 | 0.0078 | 0.0007 |
| Unknown-risk Automation | 0 | 0 | 0 | 0.0001 | -0.0001 | 0.0002 | 0 | -0.0005 | 0 | -0.0001 |
| Manuf | -0.0016 | -0 | 0.0014 | 0.0008 | -0.0002 | -0.0004 | 0.0003 | -0.0002 | 0.0002 | 0.0011 |
| Retail | 0.0001 | -0.0002 | 0.0004 | 0.0004 | -0.0002 | -0.0002 | 0.0002 | -0.0003 | -0.0003 | 0.0005 |
| Services | -0.0009 | 0.0008 | 0.0007 | 0.0002 | 0.001 | -0.0009 | 0.0013 | -0.0016 | 0.0001 | 0.0033 |
| Utilities & Mining | -0.0015 | -0.0032 | -0.0006 | -0.0008 | -0.0009 | -0.0003 | 0.0016 | -0.0031 | -0.0017 | 0.0045 |
| Other Industry | - | - | - | - | - | - | - | - | 0.0003 | - |
| National Union | -0.0002 | -0.0004 | -0.0069 | - | 0 | 0.0044 | -0.0003 | - | 0.0002 | -0.0004 |
| Regional Union | 0.0013 | - | -0 | - | 0.0001 | 0 | -0.0007 | - | 0.0015 | 0.0012 |
| Local Union | - | - | - | - | - | - | - | - | 0.0044 | - |
| Fixed Contract | -0.0005 | 0.0014 | 0.0002 | 0.0012 | 0.0001 | 0.0012 | 0.0011 | 0.0007 | 0 | 0.0018 |
| Part-time | -0.0001 | 0.0032 | -0.0009 | -0.0045 | -0 | 0.0001 | 0.0002 | -0.0033 | 0.0025 | -0.0035 |
| 85% Part-time | -0.0002 | -0.0001 | - | -0 | 0 | 0 | -0.0001 | -0.0007 | -0 | -0 |
| Apprentice | - | - | -0.0004 | -0.0003 | 0 | -0.0001 | -0 | - | - | - |
| Other Contract | -0.0005 | -0.0002 | -0.0001 | -0.0009 | 0 | -0 | -0.0008 | 0 | 0 | -0.0003 |

**Table 14:** Detailed Gini Decomposition, Wage Composition

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0014 | 0.0036 | 0.0016 | -0.0001 | -0.0007 | 0.0007 | 0.0007 | -0.0047 | 0.001 | -0.0005 |
| Education | -0.0017 | -0.0028 | 0.0003 | -0.0008 | -0.0012 | -0.0025 | -0.0014 | 0.0013 | 0.0001 | -0.0015 |
| Firm | 0.0007 | 0.0034 | -0.001 | -0.0004 | -0.0006 | -0.0002 | -0 | -0.0034 | 0.0052 | 0.0008 |
| Gender | -0.0003 | 0.0007 | -0.0004 | -0.0014 | 0.0007 | -0.0004 | -0.0023 | 0.0014 | -0.0007 | 0.0016 |
| High-risk Automation | -0.0001 | 0.0022 | 0.0003 | 0.0027 | 0 | 0.0089 | 0.0041 | 0.0017 | 0.0032 | 0.0033 |
| Mid-risk Automation | 0.0009 | 0.009 | 0.0035 | 0.0079 | 0.0006 | 0.0092 | 0.0006 | 0.0089 | 0.0087 | 0.0006 |
| Unknown-risk Automation | -0.0002 | 0 | 0 | 0 | 0.0001 | 0 | -0 | -0.0009 | 0 | -0 |
| Manuf | -0.0013 | -0.0017 | -0.0001 | 0.0006 | -0.0002 | -0.0024 | 0.0001 | -0.0001 | 0.0001 | 0.0009 |
| Retail | -0 | -0.0004 | 0.0002 | 0.0004 | -0.0003 | -0.0001 | 0.0001 | -0.0002 | -0.0004 | 0.0004 |
| Services | -0.0006 | -0.0011 | -0 | 0.0005 | -0.0005 | -0.0003 | 0.0012 | -0.0038 | -0.0005 | 0.0018 |
| Utilities & Mining | -0.0011 | -0.0072 | -0.0017 | -0.001 | -0.0017 | -0.0022 | 0.0008 | -0.0038 | -0.0022 | 0.004 |
| Other Industry | - | - | - | - | - | - | - | - | 0.0003 | - |
| National Union | -0.0001 | -0.0032 | -0.005 | - | -0 | 0.0044 | -0.0023 | - | 0.0008 | -0.0008 |
| Regional Union | -0.0011 | - | 0 | - | 0.0003 | 0 | 0 | - | 0.0014 | 0.0004 |
| Local Union | - | - | - | - | - | - | - | - | 0.0052 | - |
| Fixed Contract | -0.0004 | 0.0028 | 0 | -0.0008 | 0.0002 | -0 | 0.0015 | -0.0018 | 0 | 0.0007 |
| Part-time | -0.0001 | 0.0005 | -0.0009 | -0.0031 | 0 | -0.0034 | -0.002 | -0.0014 | 0.0001 | -0.0036 |
| 85% Part-time | 0.0003 | -0 | - | 0 | 0 | -0 | -0.0001 | -0.0003 | 0 | -0 |
| Apprentice | - | - | -0.0004 | 0.0002 | 0 | -0.0002 | -0.0002 | - | - | - |
| Other Contract | -0.0005 | -0.0002 | -0.0001 | -0.0009 | 0 | -0 | -0.0008 | 0 | 0 | -0.0002 |

**Table 15:** Detailed Gini Decomposition, Structural Composition

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0014 | 0.0036 | 0.0016 | -0.0001 | -0.0007 | 0.0007 | 0.0007 | -0.0047 | 0.001 | -0.0005 |
| Education | -0.0017 | -0.0028 | 0.0003 | -0.0008 | -0.0012 | -0.0025 | -0.0014 | 0.0013 | 0.0001 | -0.0015 |
| Firm | 0.0007 | 0.0034 | -0.001 | -0.0004 | -0.0006 | -0.0002 | -0 | -0.0034 | 0.0052 | 0.0008 |
| Gender | -0.0003 | 0.0007 | -0.0004 | -0.0014 | 0.0007 | -0.0004 | -0.0023 | 0.0014 | -0.0007 | 0.0016 |
| High-risk Automation | -0.0001 | 0.0022 | 0.0003 | 0.0027 | 0 | 0.0089 | 0.0041 | 0.0017 | 0.0032 | 0.0033 |
| Mid-risk Automation | 0.0009 | 0.009 | 0.0035 | 0.0079 | 0.0006 | 0.0092 | 0.0006 | 0.0089 | 0.0087 | 0.0006 |
| Unknown-risk Automation | -0.0002 | 0 | 0 | 0 | 0.0001 | 0 | -0 | -0.0009 | 0 | -0 |
| Manuf | -0.0013 | -0.0017 | -0.0001 | 0.0006 | -0.0002 | -0.0024 | 0.0001 | -0.0001 | 0.0001 | 0.0009 |
| Retail | -0 | -0.0004 | 0.0002 | 0.0004 | -0.0003 | -0.0001 | 0.0001 | -0.0002 | -0.0004 | 0.0004 |
| Services | -0.0006 | -0.0011 | -0 | 0.0005 | -0.0005 | -0.0003 | 0.0012 | -0.0038 | -0.0005 | 0.0018 |
| Utilities & Mining | -0.0011 | -0.0072 | -0.0017 | -0.001 | -0.0017 | -0.0022 | 0.0008 | -0.0038 | -0.0022 | 0.004 |
| Other Industry | - | - | - | - | - | - | - | - | 0.0003 | - |
| National Union | -0.0001 | -0.0032 | -0.005 | - | -0 | 0.0044 | -0.0023 | - | 0.0008 | -0.0008 |
| Regional Union | -0.0011 | - | 0 | - | 0.0003 | 0 | 0 | - | 0.0014 | 0.0004 |
| Local Union | - | - | - | - | - | - | - | - | 0.0052 | - |
| Fixed Contract | -0.0004 | 0.0028 | 0 | -0.0008 | 0.0002 | -0 | 0.0015 | -0.0018 | 0 | 0.0007 |
| Part-time | -0.0001 | 0.0005 | -0.0009 | -0.0031 | 0 | -0.0034 | -0.002 | -0.0014 | 0.0001 | -0.0036 |
| 85% Part-time | 0.0003 | -0 | - | 0 | 0 | -0 | -0.0001 | -0.0003 | 0 | -0 |
| Apprentice | - | - | -0.0004 | 0.0002 | 0 | -0.0002 | -0.0002 | - | - | - |
| Other Contract | -0.0005 | -0.0002 | -0.0001 | -0.0009 | 0 | -0 | -0.0008 | 0 | 0 | -0.0002 |

**Table 16:** Detailed 50-10 Decomposition, Overall

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0098 | 0.0872 | 0.0219 | 0.0307 | 0.0248 | 0.0555 | 0.002 | 0.1011 | 0.0991 | -0.0267 |
| Education | -0.0038 | 0.051 | 0.0169 | 0.0468 | 0.0719 | 0.0187 | -0.0045 | 0.1549 | 0.1275 | 0.0114 |
| Firm | -0.0256 | 0.0706 | -0.0431 | -0.0863 | 0.0466 | -0.0649 | -0.0033 | 0.0868 | 0.0405 | -0.0354 |
| Gender | -0.0576 | 0.0004 | -0.0299 | -0.0614 | 0.0315 | -0.0245 | -0.0285 | 0.0225 | -0.0099 | 0.0728 |
| High-risk Automation | 0.0015 | 0.0192 | 0.0251 | 0.0374 | 0.0249 | -0.0518 | 0.0161 | 0.0287 | 0.0559 | 0.1263 |
| Mid-risk Automation | 0.0044 | 0.1094 | 0.0444 | 0.0551 | 0.0711 | -0.0256 | -0.0047 | 0.2218 | 0.0314 | 0.0561 |
| Unknown-risk Automation | 0.0001 | -0.0001 | 0 | -0.0019 | 0.0061 | 0.0013 | -0.0006 | -0.0169 | 0 | 0.004 |
| Manuf | -0.0223 | -0.0019 | 0.0088 | 0.0339 | -0.0251 | 0.0077 | -0.0029 | 0.014 | 0.0526 | 0.0118 |
| Retail | 0.0018 | -0.0032 | 0.0057 | 0.006 | -0.0043 | -0.0002 | 0.0033 | 0.0017 | 0.0006 | 0.006 |
| Services | -0.0195 | -0.0017 | 0.004 | 0.0039 | -0.0338 | 0.0266 | -0.0232 | -0.0409 | -0.0195 | 0.0348 |
| Utilities & Mining | -0.0331 | -0.0793 | -0.0401 | -0.0455 | -0.0261 | -0.0018 | -0.0416 | -0.0833 | 0.0435 | 0.0633 |
| Other Industry | - | - | - | - | - | - | - | - | 0.0173 | - |
| National Union | -0.0092 | 0.0759 | -0.1895 | - | 0.0005 | 0.0629 | -0.0233 | - | -0.0027 | 0.0038 |
| Regional Union | 0.0439 | - | -0.0003 | - | -0.0286 | 0 | 0.029 | - | 0.0124 | 0.0224 |
| Local Union | - | - | - | - | - | - | - | - | 0.0371 | - |
| Fixed Contract | -0.0255 | 0.1113 | 0.0223 | 0.0996 | 0.0055 | 0.0402 | 0.0006 | -0.1131 | -0.0025 | 0.0382 |
| Part-time | -0.0045 | 0.1362 | 0.0215 | -0.0872 | -0.0078 | 0.0782 | -0.0185 | -0.226 | 0.0009 | -0.1194 |
| 85% Part-time | -0.0047 | -0.0203 | - | -0.0066 | 0.0023 | 0.0005 | -0.006 | -0.0022 | 0 | 0.0035 |
| Apprentice | - | - | -0.0064 | -0.0217 | -0 | -0.0064 | -0.0074 | - | - | - |
| Other Contract | -0.0022 | -0.0053 | -0.0007 | -0.0228 | 0.0008 | -0.0003 | -0.0124 | 0.002 | 0 | -0.009 |

**Table 17:** Detailed 50-10 Decomposition, Wage Composition

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | 0.0854 | -0.0109 | -0.0032 | -0.051 | 0.0126 | 0.0873 | -0.0654 | 0.5304 | -0.0443 | 0.0644 |
| Education | -0.0084 | 0.0711 | 0.0277 | -0.0484 | -0.012 | 0.0831 | -0.0353 | -0.1555 | -0.0009 | -0.0533 |
| Firm | 0.0488 | -0.0689 | 0.0322 | -0.0262 | 0.2194 | -0.01 | -0.0388 | 0.3346 | -0.1649 | -0.0411 |
| Gender | 0.0128 | -0.0725 | 0.0016 | 0.0928 | 0.0349 | 0.0092 | 0.0082 | -0.0553 | 0.0404 | 0.0847 |
| High-risk Automation | 0.0307 | 0.0427 | 0.1184 | 0.0628 | -0.0542 | 0.0368 | 0.035 | -0.0761 | 0.0788 | 0.0403 |
| Mid-risk Automation | -0.0789 | 0.0126 | 0.1242 | 0.0486 | -0.0189 | -0.0421 | 0.1492 | -0.2504 | 0.1143 | 0.0189 |
| Unknown-risk Automation | -0.0012 | -0.0001 | 0 | -0.0019 | 0.0009 | 0.0013 | -0.0028 | 0.0106 | 0 | 0.0038 |
| Manuf | 0.1306 | 0.088 | 0.0459 | 0.0744 | 0.0243 | 0.0048 | 0.0096 | 0.0042 | -0.0108 | 0.003 |
| Retail | 0.0214 | 0.0062 | 0.004 | -0.0028 | 0.0077 | -0.0057 | 0.0112 | -0.0287 | 0.002 | 0.0035 |
| Services | 0.0355 | 0.0833 | 0.0163 | 0.0587 | 0.0163 | 0.027 | -0.0283 | -0.1011 | 0.0993 | 0.0014 |
| Utilities & Mining | 0.047 | 0.166 | 0.0011 | 0.0093 | 0.0448 | 0.0118 | 0.019 | -0.2224 | 0.0707 | 0.0546 |
| Other Industry | - | - | - | - | - | - | - | - | 0 | - |
| National Union | 0.0222 | 0.1082 | 0.0028 | - | -0.0014 | 0 | 0.1274 | - | -0.0045 | 0.0453 |
| Regional Union | 0.2291 | - | -0.0004 | - | -0.0085 | 0 | 0.0288 | - | 0.0023 | 0.0299 |
| Local Union | - | - | - | - | - | - | - | - | 0.0459 | - |
| Fixed Contract | -0.03 | -0.3525 | -0.0189 | 0.0561 | -0.0067 | 0.037 | -0.0593 | -0.178 | 0.0006 | -0.0673 |
| Part-time | -0.0392 | -0.1452 | -0.0587 | -0.4205 | -0.019 | 0.1744 | 0.0143 | -0.6139 | 0.0034 | -0.5165 |
| 85% Part-time | -0.0453 | -0.0138 | - | -0.0134 | -0.0035 | 0.0007 | -0.0011 | 0.0748 | 0 | 0 |
| Apprentice | - | - | -0.0004 | -0.1134 | 0 | 0.0061 | -0.0048 | - | - | - |
| Other Contract | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0 | -0.0068 |

**Table 18:** Detailed 50-10 Decomposition, Structural Composition

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0952 | 0.0981 | 0.025 | 0.0817 | 0.0122 | -0.0318 | 0.0674 | -0.4293 | 0.1434 | -0.0911 |
| Education | 0.0046 | -0.02 | -0.0107 | 0.0953 | 0.0838 | -0.0644 | 0.0308 | 0.3104 | 0.1284 | 0.0647 |
| Firm | -0.0745 | 0.1395 | -0.0753 | -0.0602 | -0.1728 | -0.0549 | 0.0355 | -0.2479 | 0.2053 | 0.0057 |
| Gender | -0.0704 | 0.0729 | -0.0315 | -0.1542 | -0.0033 | -0.0337 | -0.0368 | 0.0779 | -0.0503 | -0.0118 |
| High-risk Automation | -0.0292 | -0.0235 | -0.0932 | -0.0254 | 0.0791 | -0.0886 | -0.0189 | 0.1049 | -0.0229 | 0.086 |
| Mid-risk Automation | 0.0834 | 0.0968 | -0.0797 | 0.0065 | 0.09 | 0.0164 | -0.1539 | 0.4722 | -0.083 | 0.0372 |
| Unknown-risk Automation | 0.0013 | 0 | 0 | 0 | 0.0052 | 0 | 0.0022 | -0.0275 | 0 | 0.0003 |
| Manuf | -0.1529 | -0.0899 | -0.0371 | -0.0405 | -0.0494 | 0.0029 | -0.0125 | 0.0098 | 0.0634 | 0.0088 |
| Retail | -0.0196 | -0.0094 | 0.0017 | 0.0087 | -0.0119 | 0.0055 | -0.0079 | 0.0304 | -0.0014 | 0.0025 |
| Services | -0.055 | -0.085 | -0.0123 | -0.0548 | -0.05 | -0.0004 | 0.0051 | 0.0602 | -0.1188 | 0.0334 |
| Utilities & Mining | -0.0801 | -0.2453 | -0.0412 | -0.0548 | -0.0709 | -0.0136 | -0.0606 | 0.1391 | -0.0272 | 0.0087 |
| Other Industry | - | - | - | - | - | - | - | - | 0.0173 | - |
| National Union | -0.0313 | -0.0323 | -0.1923 | - | 0.0019 | 0.0629 | -0.1507 | - | 0.0019 | -0.0415 |
| Regional Union | -0.1852 | - | 0.0001 | - | -0.02 | 0 | 0.0002 | - | 0.0101 | -0.0075 |
| Local Union | - | - | - | - | - | - | - | - | -0.0088 | - |
| Fixed Contract | 0.0045 | 0.4638 | 0.0412 | 0.0435 | 0.0122 | 0.0031 | 0.0599 | 0.0649 | -0.0031 | 0.1055 |
| Part-time | 0.0347 | 0.2814 | 0.0802 | 0.3333 | 0.0112 | -0.0961 | -0.0328 | 0.388 | -0.0025 | 0.3972 |
| 85% Part-time | 0.0406 | -0.0065 | - | 0.0068 | 0.0058 | -0.0002 | -0.0049 | -0.0769 | 0 | 0.0035 |
| Apprentice | - | - | -0.006 | 0.0917 | -0 | -0.0125 | -0.0026 | - | - | - |
| Other Contract | -0.0022 | -0.0053 | -0.0007 | -0.0228 | 0.0008 | -0.0003 | -0.0124 | 0 | 0 | -0.0022 |

**Table 19:** Detailed 90-50 Decomposition, Overall

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0364 | 0.0366 | 0.0124 | -0.0206 | -0.0579 | 0.025 | 0.0006 | -0.0353 | -0.0267 | 0.0035 |
| Education | 0.0057 | 0.0569 | 0.0255 | 0.0419 | 0.0505 | 0.0512 | 0.045 | -0.003 | 0.0622 | -0.0513 |
| Firm | -0.0176 | 0.0111 | -0.0213 | -0.0264 | 0.0038 | -0.063 | -0.0197 | -0.0039 | 0.0029 | 0.0465 |
| Gender | -0.0227 | -0.0236 | -0.0445 | -0.0306 | -0.0363 | -0.0596 | -0.0284 | 0.0182 | -0.0086 | -0.0083 |
| High-risk Automation | -0.026 | 0.1091 | 0.095 | 0.2848 | 0.0267 | 0.2946 | 0.1355 | 0.0208 | 0.0414 | -0.0014 |
| Mid-risk Automation | -0.001 | 0.1695 | 0.1829 | 0.4658 | 0.0515 | 0.2025 | 0.2018 | 0.0697 | 0.1375 | -0.0023 |
| Unknown-risk Automation | -0.006 | 0.0003 | 0 | 0.0014 | -0.0109 | 0.0056 | 0.0006 | 0.0077 | 0 | -0.0045 |
| Manuf | -0.053 | -0.0009 | -0.0017 | 0.0138 | -0.0008 | -0.0106 | 0.0183 | -0.0096 | -0.0187 | 0.0154 |
| Retail | 0.0058 | 0.0005 | 0.0031 | 0.0052 | -0.0054 | -0.0036 | 0.0089 | -0.0115 | -0.0028 | 0.0095 |
| Services | -0.0188 | 0.0266 | -0.0032 | 0.0056 | 0.0486 | -0.0716 | 0.0872 | -0.0079 | 0.0199 | 0.0378 |
| Utilities & Mining | -0.0372 | 0.0048 | 0.0237 | 0.0535 | -0.0212 | -0.0052 | 0.1114 | -0.0325 | -0.0485 | 0.0427 |
| Other Industry | - | - | - | - | - | - | - | - | -0.0045 | - |
| National Union | -0.0024 | -0.0684 | -0.0782 | - | -0.002 | 0.0667 | 0.0087 | - | 0.0292 | -0.0183 |
| Regional Union | -0.0056 | - | -0.0016 | - | 0.0231 | 0 | -0.0403 | - | 0.0437 | 0.0124 |
| Local Union | - | - | - | - | - | - | - | - | 0.1197 | - |
| Fixed Contract | -0.0014 | -0.0035 | 0.0039 | 0.0038 | 0.0002 | 0.0097 | 0.0149 | 0.0022 | -0.0023 | 0.0132 |
| Part-time | -0.0024 | 0.0244 | 0.0048 | -0.0079 | 0.014 | -0.0025 | 0.006 | -0.0064 | 0.006 | -0.002 |
| 85% Part-time | -0.005 | 0.0061 | - | 0.0003 | -0.0007 | 0.0005 | -0.0018 | -0.0208 | -0 | -0.0027 |
| Apprentice | - | - | -0.001 | -0 | 0 | 0.0005 | 0.0014 | - | - | - |
| Other Contract | -0.0172 | -0.0011 | -0.0001 | -0.0017 | 0.0001 | -0 | -0.004 | 0.0004 | 0 | 0.004 |

**Table 20:** Detailed 90-50 Decomposition, Wage Composition

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | 0.0258 | 0.0446 | 0.0422 | 0.0844 | 0.0063 | 0.0047 | 0.0665 | 0.0353 | 0.0263 | 0.0314 |
| Education | 0.023 | 0.1109 | 0.0327 | 0.0343 | 0.032 | 0.1685 | 0.0598 | -0.0412 | -0.058 | 0.0394 |
| Firm | -0.0686 | 0.0447 | -0.0167 | -0.001 | 0.1018 | -0.0652 | -0.0052 | 0.0924 | 0.0829 | -0.0517 |
| Gender | -0.0404 | -0.0072 | -0.0311 | -0.0142 | 0.0184 | -0.0565 | -0.0014 | 0.0543 | 0.0287 | -0.0377 |
| High-risk Automation | 0.014 | 0.0241 | 0.0903 | 0.3406 | 0.1431 | 0.2931 | 0.0755 | 0.0258 | 0.051 | -0.0149 |
| Mid-risk Automation | 0.0306 | -0.0184 | 0.1592 | 0.3309 | 0.1931 | 0.0621 | 0.1668 | -0.0032 | 0.0246 | -0.0019 |
| Unknown-risk Automation | 0.0064 | 0.0003 | 0 | 0.0014 | -0.0136 | 0.0056 | 0.0259 | -0.0057 | 0 | -0.0028 |
| Manuf | -0.0241 | -0.0117 | 0.0185 | -0.0399 | -0.0144 | 0.1091 | 0.0129 | 0.0004 | 0.0473 | 0.0155 |
| Retail | -0.0075 | 0.0012 | 0.0008 | 0.0015 | -0.0051 | 0.001 | -0.0033 | 0.0026 | 0.0037 | 0.0026 |
| Services | -0.0202 | 0.0239 | 0.0124 | -0.0538 | 0.1119 | -0.0516 | 0.0262 | 0.0954 | 0.0469 | 0.0573 |
| Utilities & Mining | -0.0224 | 0.0063 | 0.0374 | -0.0438 | 0.0373 | 0.0449 | -0.0614 | 0.0894 | 0.0478 | -0.0152 |
| Other Industry | - | - | - | - | - | - | - | - | 0 | - |
| National Union | -0.0022 | 0.1427 | 0.017 | - | 0.0003 | 0 | 0.0738 | - | -0.0153 | 0.0386 |
| Regional Union | 0.083 | - | -0.0016 | - | -0.047 | 0 | -0.0403 | - | 0.0081 | 0.0485 |
| Local Union | - | - | - | - | - | - | - | - | -0.0446 | - |
| Fixed Contract | -0.0217 | -0.0154 | -0.0056 | 0.0046 | -0.0032 | 0.0087 | 0.0063 | -0.0282 | -0.0005 | 0.0007 |
| Part-time | -0.0077 | 0.0008 | -0.0035 | -0.0166 | 0.0069 | 0.009 | 0.0112 | -0.037 | 0.0058 | -0.0436 |
| 85% Part-time | -0.015 | 0.0049 | - | -0.0028 | -0.0024 | 0.0011 | 0.0015 | -0.0256 | -0 | 0 |
| Apprentice | - | - | -0.0004 | -0.008 | 0 | 0.0004 | 0.001 | - | - | - |
| Other Contract | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0004 | 0 | 0.0028 |

**Table 21:** Detailed 90-50 Decomposition, Structural Composition

| var | CZ | ES | FI | FR | HU | IT | LU | NL | RO | UK |
|---|---|---|---|---|---|---|---|---|---|---|
| Demographic | -0.0623 | -0.008 | -0.0298 | -0.105 | -0.0643 | 0.0203 | -0.0659 | -0.0706 | -0.0531 | -0.0279 |
| Education | -0.0172 | -0.0541 | -0.0072 | 0.0076 | 0.0185 | -0.1173 | -0.0148 | 0.0382 | 0.1202 | -0.0907 |
| Firm | 0.051 | -0.0336 | -0.0045 | -0.0255 | -0.098 | 0.0021 | -0.0145 | -0.0963 | -0.08 | 0.0981 |
| Gender | 0.0177 | -0.0164 | -0.0135 | -0.0163 | -0.0547 | -0.0031 | -0.027 | -0.036 | -0.0373 | 0.0295 |
| High-risk Automation | -0.0399 | 0.085 | 0.0046 | -0.0558 | -0.1164 | 0.0015 | 0.06 | -0.005 | -0.0096 | 0.0135 |
| Mid-risk Automation | -0.0316 | 0.1879 | 0.0237 | 0.1349 | -0.1416 | 0.1404 | 0.035 | 0.0729 | 0.1128 | -0.0004 |
| Unknown-risk Automation | -0.0124 | 0 | 0 | 0 | 0.0028 | 0 | -0.0253 | 0.0134 | 0 | -0.0016 |
| Manuf | -0.0289 | 0.0108 | -0.0202 | 0.0537 | 0.0136 | -0.1197 | 0.0053 | -0.01 | -0.066 | -0.0002 |
| Retail | 0.0133 | -0.0007 | 0.0023 | 0.0037 | -0.0003 | -0.0045 | 0.0122 | -0.0141 | -0.0064 | 0.0069 |
| Services | 0.0014 | 0.0027 | -0.0156 | 0.0593 | -0.0633 | -0.02 | 0.061 | -0.1032 | -0.027 | -0.0195 |
| Utilities & Mining | -0.0149 | -0.0015 | -0.0137 | 0.0973 | -0.0585 | -0.0501 | 0.1728 | -0.1218 | -0.0963 | 0.058 |
| Other Industry | - | - | - | - | - | - | - | - | -0.0045 | - |
| National Union | -0.0002 | -0.2112 | -0.0952 | - | -0.0023 | 0.0667 | -0.065 | - | 0.0445 | -0.0569 |
| Regional Union | -0.0887 | - | 0 | - | 0.0701 | 0 | -0 | - | 0.0356 | -0.0361 |
| Local Union | - | - | - | - | - | - | - | - | 0.1643 | - |
| Fixed Contract | 0.0204 | 0.0119 | 0.0095 | -0.0009 | 0.0034 | 0.001 | 0.0086 | 0.0303 | -0.0018 | 0.0126 |
| Part-time | 0.0053 | 0.0235 | 0.0083 | 0.0088 | 0.007 | -0.0115 | -0.0052 | 0.0306 | 0.0002 | 0.0416 |
| 85% Part-time | 0.01 | 0.0011 | - | 0.0031 | 0.0017 | -0.0006 | -0.0032 | 0.0048 | 0 | -0.0027 |
| Apprentice | - | - | -0.0005 | 0.0079 | 0 | 0.0001 | 0.0004 | - | - | - |
| Other Contract | -0.0172 | -0.0011 | -0.0001 | -0.0017 | 0.0001 | -0 | -0.004 | 0 | 0 | 0.0012 |

# 10 Data Overview: Descriptive Statistics

Real Wages are in the currency of the country. Education, Firm Size, Union Type, Contract Type, and Age are categorical variables, the averages below are the averages of their assigned values. Below is a table to reference the categories to their assigned value.

**Table 22:** Categorical Variables and Values

| Variable | Category Name | Value |
|---|---|---|
| Automation Risk | Low-risk | 1 |
| | Mid-risk | 2 |
| | High-risk | 3 |
| Education | Primary | 1 |
| | Secondary | 2 |
| | University & Masters | 3 |
| | Doctoral or Equivalent | 4 |
| Firm Size | $< 50$ | 1 |
| | 50-250 | 2 |
| | $> 250$ | 3 |
| | all | 4 |
| Union Type | National Level | 1 |
| | Industry Level | 2 |
| | Local Level | 3 |
| | None | 4 |
| Contract Type | Permanent Full-time | 1 |
| | Permanent Part-time | 2 |
| | Fixed Contract | 3 |
| | Apprentice | 4 |
| | Other Contract | 5 |
| | 85% Part-time | 6 |
| Age | 14-19 | 1 |
| | 20-29 | 2 |
| | 30-39 | 3 |
| | 40-49 | 4 |
| | 50-59 | 5 |
| | 60+ | 6 |

**Table 23:** Descriptive Statistics: Finland

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Diff |
| Real Wage | 1922.05 | 815.86 | 3272.43 | 1573.03 | 1350.38 |
| Low AR | 0.10 | 0.30 | 0.21 | 0.41 | 0.11 |
| Med AR | 0.54 | 0.50 | 0.60 | 0.49 | 0.06 |
| High AR | 0.36 | 0.48 | 0.19 | 0.39 | -0.17 |
| Unk. AR | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 |
| Edu | 2.09 | 0.75 | 2.58 | 0.88 | 0.49 |
| Priv. Owned | 0.12 | 0.32 | 0.49 | 0.50 | 0.37 |
| Gender(F) | 0.39 | 0.49 | 0.57 | 0.49 | 0.18 |
| Firm Size | 2.55 | 0.69 | 2.63 | 0.66 | 0.08 |
| Union Type | 1.12 | 0.83 | 1.06 | 0.53 | -0.06 |
| Contract Type | 1.30 | 0.78 | 1.46 | 0.95 | 0.16 |
| Age | 3.55 | 1.15 | 3.91 | 1.21 | 0.36 |
| Observations | 125287 | | 315318 | | |

**Table 24:** Descriptive Statistics: Czech Republic

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Diff |
| Real Wage | 13689.62 | 9071.59 | 28913.50 | 20252.20 | 15223.88 |
| Low AR | 0.17 | 0.37 | 0.19 | 0.40 | 0.03 |
| Med AR | 0.55 | 0.50 | 0.48 | 0.50 | -0.07 |
| High AR | 0.27 | 0.44 | 0.29 | 0.46 | 0.02 |
| Unk. AR | 0.02 | 0.14 | 0.03 | 0.18 | 0.01 |
| Edu | 2.07 | 0.56 | 2.35 | 0.87 | 0.28 |
| Priv. Owned | 0.40 | 0.49 | 0.43 | 0.50 | 0.03 |
| Gender(F) | 0.46 | 0.50 | 0.50 | 0.50 | 0.04 |
| Firm Size | 2.87 | 0.37 | 2.65 | 0.65 | -0.22 |
| Union Type | 4.29 | 1.10 | 4.91 | 1.51 | 0.62 |
| Contract Type | 1.77 | 1.51 | 1.50 | 0.90 | -0.27 |
| Age | 3.65 | 1.18 | 3.71 | 1.19 | 0.07 |
| Observations | 1031018 | | 2202680 | | |

**Table 25:** Descriptive Statistics: Spain

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Diff |
| Real Wage | 1127.63 | 821.84 | 1987.34 | 1517.50 | 859.71 |
| Low AR | 0.11 | 0.32 | 0.15 | 0.36 | 0.04 |
| Med AR | 0.55 | 0.50 | 0.61 | 0.49 | 0.06 |
| High AR | 0.34 | 0.47 | 0.24 | 0.42 | -0.10 |
| Unk. AR | 0.00 | 0.01 | 0.00 | 0.02 | 0.00 |
| Edu | 1.74 | 0.88 | 2.19 | 1.14 | 0.45 |
| Priv. Owned | 0.09 | 0.29 | 0.16 | 0.36 | 0.07 |
| Gender(F) | 0.35 | 0.48 | 0.43 | 0.49 | 0.07 |
| Firm Size | 2.21 | 0.91 | 2.63 | 1.01 | 0.42 |
| Union Type | 3.01 | 0.98 | 3.36 | 1.43 | 0.36 |
| Contract Type | 1.61 | 0.96 | 1.64 | 1.12 | 0.03 |
| Age | 3.30 | 1.12 | 3.76 | 1.06 | 0.46 |
| Observations | 217265 | | 209567 | | |

**Table 26:** Descriptive Statistics: France

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Diff |
| Real Wage | 2114.44 | 2672.75 | 3495.04 | 3417.69 | 1380.60 |
| Low AR | 0.31 | 0.46 | 0.35 | 0.48 | 0.04 |
| Med AR | 0.40 | 0.49 | 0.42 | 0.49 | 0.02 |
| High AR | 0.29 | 0.46 | 0.20 | 0.40 | - 0.10 |
| Unk. AR | 0.00 | 0.01 | 0.03 | 0.17 | 0.03 |
| Edu | 2.14 | 0.77 | 2.66 | 1.00 | 0.53 |
| Priv. Owned | 0.08 | 0.27 | 0.27 | 0.45 | 0.20 |
| Gender(F) | 0.35 | 0.48 | 0.45 | 0.50 | 0.10 |
| Firm Size | 2.32 | 0.81 | 2.47 | 0.73 | 0.15 |
| Union Type | 1.35 | 1.40 | 2.60 | 1.47 | 1.25 |
| Contract Type | 1.36 | 0.94 | 1.43 | 1.01 | 0.07 |
| Age | 3.51 | 1.09 | 3.91 | 1.13 | 0.40 |
| Observations | 121296 | | 267435 | | |

**Table 27:** Descriptive Statistics: Hungary

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Diff |
| Real Wage | 61262.80 | 45627.50 | 227769.75 | 156148.06 | 166506.95 |
| Low AR | 0.47 | 0.50 | 0.35 | 0.48 | -0.12 |
| Med AR | 0.41 | 0.49 | 0.42 | 0.49 | 0.01 |
| High AR | 0.12 | 0.32 | 0.17 | 0.38 | 0.05 |
| Unk. AR | 0.01 | 0.08 | 0.06 | 0.24 | 0.06 |
| Edu | 2.20 | 0.71 | 2.44 | 0.88 | 0.24 |
| Priv. Owned | 0.75 | 0.43 | 0.81 | 0.40 | 0.06 |
| Gender(F) | 0.69 | 0.46 | 0.61 | 0.49 | -0.08 |
| Firm Size | 1.96 | 0.79 | 2.36 | 0.82 | 0.40 |
| Union Type | 6.68 | 0.99 | 6.86 | 0.69 | 0.19 |
| Contract Type | 1.22 | 0.83 | 1.15 | 0.55 | -0.07 |
| Age | 3.75 | 1.11 | 3.86 | 1.10 | 0.11 |
| Observations | 479047 | | 882517 | | |

**Table 28:** Descriptive Statistics: Italy

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Diff |
| Real Wage | 1502.80 | 843.29 | 2948.41 | 7716.45 | 1445.61 |
| Low AR | 0.05 | 0.21 | 0.19 | 0.39 | 0.14 |
| Med AR | 0.36 | 0.48 | 0.45 | 0.50 | 0.09 |
| High AR | 0.59 | 0.49 | 0.34 | 0.47 | -0.25 |
| Unk. AR | 0.00 | 0.01 | 0.02 | 0.15 | 0.02 |
| Edu | 1.63 | 0.69 | 2.36 | 1.08 | 0.73 |
| Priv. Owned | 0.06 | 0.24 | 0.35 | 0.48 | 0.29 |
| Gender(F) | 0.32 | 0.47 | 0.46 | 0.50 | 0.14 |
| Firm Size | 2.21 | 0.87 | 2.20 | 0.85 | -0.01 |
| Union Type | 1.29 | 1.29 | 1.00 | 0.00 | -0.29 |
| Contract Type | 1.24 | 0.66 | 1.56 | 1.03 | 0.32 |
| Age | 3.46 | 1.02 | 3.94 | 1.07 | 0.48 |
| Observations | 82094 | | 189271 | | |

**Table 29:** Descriptive Statistics: Luxembourg

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Diff |
| Real Wage | 2164.33 | 1198.81 | 3916.46 | 2636.42 | 1752.13 |
| Low AR | 0.11 | 0.32 | 0.21 | 0.41 | 0.10 |
| Med AR | 0.57 | 0.50 | 0.54 | 0.50 | -0.03 |
| High AR | 0.32 | 0.46 | 0.24 | 0.43 | -0.07 |
| Unk. AR | 0.00 | 0.04 | 0.01 | 0.08 | 0.01 |
| Edu | 1.97 | 0.70 | 2.19 | 1.00 | 0.22 |
| Priv. Owned | 0.05 | 0.22 | 0.12 | 0.33 | 0.07 |
| Gender(F) | 0.31 | 0.46 | 0.39 | 0.49 | 0.08 |
| Firm Size | 4.00 | 0.00 | 4.00 | 0.00 | 0.00 |
| Union Type | 4.02 | 2.72 | 4.41 | 2.34 | 0.39 |
| Contract Type | 1.21 | 0.70 | 1.44 | 0.93 | 0.23 |
| Age | 3.24 | 0.99 | 3.49 | 1.07 | 0.25 |
| Observations | 28488 | | 23075 | | |

**Table 30:** Descriptive Statistics: The Netherlands

| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Diff |
| Real Wage | 1726.02 | 1175.31 | 2653.85 | 2008.87 | 927.83 |
| Low AR | 0.21 | 0.41 | 0.25 | 0.43 | 0.04 |
| Med AR | 0.49 | 0.50 | 0.55 | 0.50 | 0.07 |
| High AR | 0.21 | 0.41 | 0.19 | 0.40 | -0.01 |
| Unk. AR | 0.09 | 0.29 | 0.00 | 0.06 | 0.09 |
| Edu | 2.08 | 0.78 | 2.44 | 0.91 | 0.35 |
| Priv. Owned | 0.54 | 0.50 | 0.36 | 0.48 | -0.18 |
| Gender(F) | 0.50 | 0.50 | 0.49 | 0.50 | -0.01 |
| Firm Size | 2.73 | 0.56 | 2.24 | 0.87 | -0.48 |
| Union Type | 6.00 | 0.00 | 2.42 | 2.55 | -3.58 |
| Contract Type | 2.13 | 1.55 | 2.23 | 1.46 | 0.10 |
| Age | 3.49 | 1.17 | 3.77 | 1.35 | 0.28 |
| Observations | 83334 | | 155756 | | 239090 |

**Table 31:** Descriptive Statistics: Romania

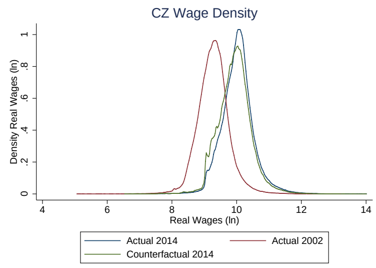
| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Diff |
| Real Wage | 2776.46 | 2981.95 | 2409.83 | 2413.89 | 366.63 |
| Low AR | 0.14 | 0.34 | 0.23 | 0.42 | 0.09 |
| Med AR | 0.60 | 0.49 | 0.58 | 0.49 | -0.02 |
| High AR | 0.27 | 0.44 | 0.19 | 0.39 | -0.08 |
| Unk. AR | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 |
| Edu | 2.15 | 0.60 | 2.38 | 0.73 | 0.23 |
| Priv. Owned | 0.35 | 0.48 | 0.34 | 0.48 | 0.00 |
| Gender(F) | 0.46 | 0.50 | 0.48 | 0.50 | 0.02 |
| Firm Size | 2.23 | 0.78 | 2.04 | 0.82 | -0.20 |
| Union Type | 3.47 | 1.13 | 3.51 | 1.46 | 0.04 |
| Contract Type | 1.04 | 0.28 | 1.09 | 0.38 | 0.05 |
| Age | 3.45 | 1.03 | 3.77 | 1.08 | 0.32 |
| Observations | 230278 | | 286849 | | |

**Table 32:** Descriptive Statistics: United Kingdom

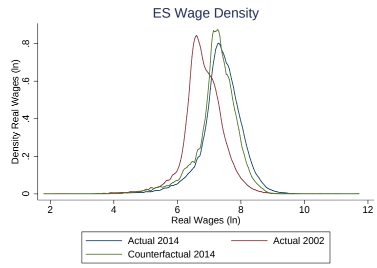
| | (2002) | | (2014) | | (Diff in Means) |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Diff |
| Real Wage | 1314.53 | 1220.48 | 2131.33 | 1775.09 | 816.80 |
| Low AR | 0.28 | 0.45 | 0.21 | 0.40 | -0.07 |
| Med AR | 0.47 | 0.50 | 0.52 | 0.50 | 0.05 |
| High AR | 0.25 | 0.43 | 0.23 | 0.42 | -0.02 |
| Unk. AR | 0.00 | 0.04 | 0.05 | 0.21 | 0.04 |
| Edu | 2.12 | 0.93 | 2.32 | 0.87 | 0.20 |
| Priv. Owned | 0.27 | 0.45 | 0.24 | 0.43 | -0.03 |
| Gender(F) | 0.49 | 0.50 | 0.52 | 0.50 | 0.03 |
| Firm Size | 2.49 | 0.80 | 2.44 | 0.82 | -0.05 |
| Union Type | 5.03 | 1.81 | 5.43 | 2.03 | 0.40 |
| Contract Type | 1.36 | 0.67 | 1.46 | 0.69 | 0.10 |
| Age | 3.53 | 1.24 | 3.62 | 1.33 | 0.09 |
| Observations | 150701 | | 175533 | | |

## 10.1 Weighted Wage Densities

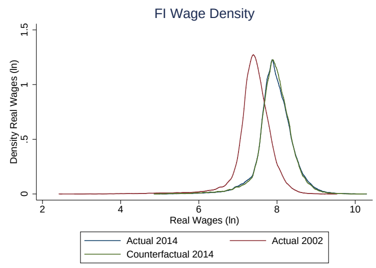
The decomposition RIF regressions consider three weighted distributions, the density of wages for the years 2002 and 2014 and the counterfactual distribution - 2014 wages with 2002 characteristics - which we display by country in Figure 4. While the weighted distributions closely follow the actual distribution in most cases, we do observe differences in some cases. In particular, there is an important role played by minimum wages in the cases of some East European countries - notably Hungary and Romania, with the peak of their distributions often at the lower end of the distribution. When the minimum wage law changes - that is, as we move from 2002 to 2014 - the floor shifts right suggesting an increase in minimum wages. For Western European nations the distributions are more Gaussian, though since our variable of interest is wages the natural distribution is longer tailed (results are presented in logs). Since we do not model minimum wages in our analysis, the initial density and the reweighted density are superimposed in those wage ranges. This implies that the wage setting variables are likely inadequate for modeling the distribution of wages when minimum wages matter. As such, we should be careful when interpreting results at the bottom of the distribution in those cases where minimum wages play a role. While minimum wages are found to play an important role in the distribution of wages in a number of countries, top-coding, where earnings is censored at a maximum threshold so that individuals who earn above a certain level appear to have the same income, does not appear to be an issue in any of the countries considered.



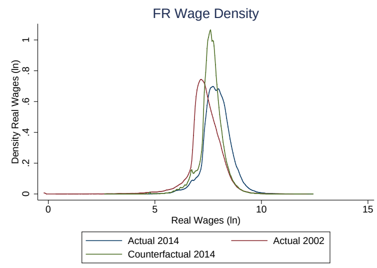

**(a)** Czech Republic



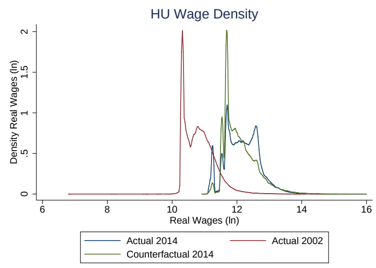

**(b)** Spain



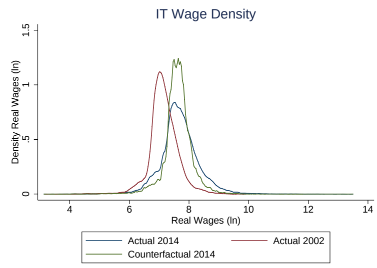

**(c)** Finland



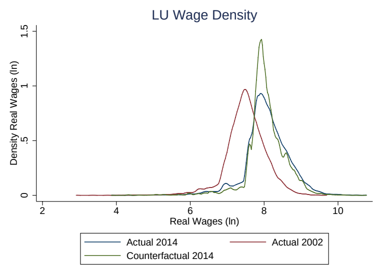

**(d)** France



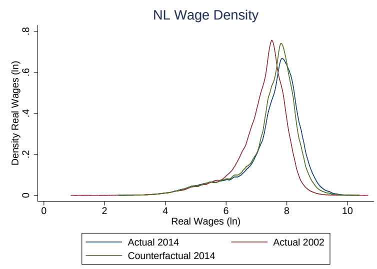

**(e)** Hungary



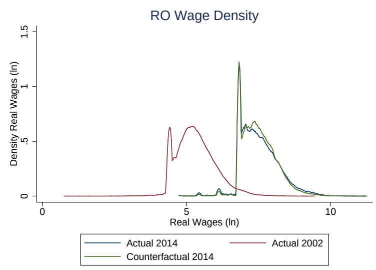

**(f)** Italy



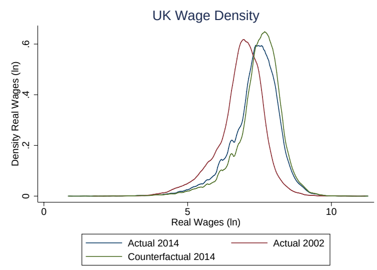

**(g)** Luxembourg




**(h)** Netherlands




**(i)** Romania




**(j)** United Kingdom

**Figure 4:** Wage Densities Across Europe: Actual and Counterfactual for 2002 & 2014