The Impact of Automation on Inequality Across Europe*

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Abstract

Existing research suggests that automation has the potential to impact employment and wage earnings. This paper focuses on the latter dimension and finds that the risk of automation has impacted wage earnings, and as a consequence has contributed to rising inequality in Europe. Using the structure of earnings survey (SES) we apply a RIF decomposition technique from Firpo, et. al., (2018) to uncover the drivers of the change in inequality between 2002 and 2014. The approach allows one to isolate the composition and the wage return effects of a variety of factors on the earnings distribution. We find that the characteristic that has the largest impact on inequality across all countries in our sample of European countries is the risk of automation. The impact of automation on inequality is found to be due largely to the composition effect, suggesting that workers are moving towards better paying low automation risk jobs, but the degree of wage dispersion between these jobs is higher than that for high automation risk jobs. These results point to evidence that the polarization effect of automation on worker earnings is occuring in many countries within Europe.

JEL classifications:
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1 Introduction

Over the past 30 years, inequality has increased across Europe with many countries recording historically high rates of inequality in the past few years. Recent experiences across European countries have been mixed, but what remains consistent is that inequality has risen in a majority of countries, with the increases in some countries being relatively large. The countries for which inequality has risen also cover a broad geographical region, including new member states of the EU, Nordic countries, Mediterranean countries and countries in western Europe. Table ?? 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 has been due to increases at the very top of the distribution Jaumotte & Osorio (2015), and that while the rate of increase in inequality slowed during the early years of the crisis, it began to resume its increasing trend shortly after this economic disruption Cingano (2014). Given Europe's historically low rate of inequality these rising rates are alarming and raise the question of what is the major driving force behind the recent rise in inequality within Europe countries.

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 include a wide array of variables that cover individual, technological, firm, industry and national (labor institutions) characteristics to understand the main drivers of rising inequality, but focus on the impact on the role of the most recent wave of technological change - artificial intelligence, machine learning and mobile robotics.

Recent advances in computer science have made it possible to automate non-routine, cognitive tasks, examples including the automation of helpdesk services, cashiers at grocery stores and even analysts who compile weekly business reports. This new wave of technology is automating tasks within a wide variety of occupations, including lawyers, waitresses, *and* automotive workers, and offers the potential for increased and rapid automation in the future. Indeed, 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 at a relatively high risk of automation.

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

Table 1: Gini Coefficients across Europe in 2007 & 2015

With the rise of these new technologies, some tasks are automated, and leading for the demand for these types of skills to decrease. At the same time, some tasks that can't be automated or are necessary to work alongside these new technologies see their demand rise. As these technologies develop, tasks that are in higher demand will see a rise in relative wages as compared to those in lower demand. Thus, the impact of automation on inequality is twofold. Firstly, the change in the relative wage in response to automation may impact the income distribution, and secondly, the replacement of workers with machines, particularly workers who perform tasks that are highly automatable, can ultimately change the composition of the workforce.

To provide an in depth understanding of which factors have played an important role in the observed increase in inequality, we decompose changes in wage inequality across a broad set of 10 European countries. In our analysis, we pay particular attention to understanding the role of automation. Using data from the Structure of Earnings Survey (SES), which is collected by Eurostat and provides detailed earnings data for individuals across European countries, we examine the determinants of the change in wage inequality between 2002 and 2014. We use a decomposition method to identify the importance of a broad set of inequality drivers, including a measure of automation risk at the level of the individual's occupation. We further examine how automation risk has impacted inequality, and in particular whether the observed effects are due to changes in endowments (i.e. an increase in the level of automation risk for certain workers) or a change in the returns to the endowments (i.e. a higher return to automation risk). Finally, we analyze how automation risk has changed the wage distribution within countries.

We find that 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 increased inequality across all countries in our analysis. Historically, labor displacing technology has impacted the composition and wages of the workforce by automating tasks or streamlining jobs related to routine physical work. Our results suggest that automation has contributed to rising inequality across all ten European countries in our analysis and is the largest contributor to inequality. Given our finding on the importance of automation as a driver of rising inequality, we consider the components of our decomposition and find that for six countries automation increases inequality through its effect on wage composition. More interestingly, we find that automation is increasing inequality via the composition effect for all of the countries observed. We believe that this is due to the fact that over time there are more workers in low automation risk jobs. Workers are moving away from low-paying high and medium automation risk jobs towards higher paying low automation risk jobs. This composition effect of automation increases inequality since it involves a shift of workers away from low but relatively equal wages associated with high and medium automation risk towards higher paying but more unequal wages associated with low automation risk jobs. These composition changes provide further evidence that the polarization effect, the decline of that share of middle income jobs over the past few decade, is due to automation.

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 developments in 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.

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 upon 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. These results provide some support for the polarization hypothesis therefore.

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 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.

While much of the previous literature showed that automation can be directly linked to declines in wages, 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. Inspired by Blinder (2007), Jensen & Kletzer (2010) and D. H. 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, or on the impact of robotic usage, 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 being 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.

3 Decomposition Method

The approach that we adopt follows closely 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 due to differences in explanatory variables between two groups and the latter 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 or blacks versus whites, 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) using 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. 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, υ, can be calculated using the cumulative conditional distribution of Y:

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

$$\Delta\upsilon = \upsilon(\int F_{Y|X}^1(Y|X)dF_X^1(X)) - \upsilon(\int F_{Y|X}^0(Y|X)dF_X^0(X)) \tag{8}$$

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 ($dF_X^1(X) \neq dF_X^0(X)$) or if there are differences in the relationships between Y and X between the two groups ($F_{Y|X}^1(Y|X) \neq F_{Y|X}^0(Y|X)$).

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. $\upsilon_c = F_Y^c = \upsilon(\int F_{Y|X}^0(Y|X)dF_X^1(X))$. With this in hand, we can write:

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

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 zero if it is in 2002, τ is an error term, and ϕ 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-timer. 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 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

[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 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. Please feel free to contact the authors for these results.

to obtain estimates for the reweighting factor and in turn can obtain an estimate for the counterfactual distribution, F_Y^c , using equation (11).

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 $RIF(y;\upsilon) = \upsilon(F) + IF(y;\upsilon)$ N. Fortin et al. (2011). The linear approximation allows us to see how a particular individual impacts upon the Gini, and allows us to aggregate all of these impacts to the overall Gini. Given that this is a linear combination, we can easily estimate the recentered influence function with OLS.

In practice a RIF regression involves replacing the dependent variable - i.e. the log of the wage level of individuals in our case 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: β_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. υ_s^p and υ_s^e) correspond to the wage structure effect, while the latter two terms (i.e. υ_x^p and υ_x^e) correspond to the aggregate composition effect. The two terms υ_s^e and υ_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 decomposition - allow us to dig deeper into understanding how our covariates played a role in shaping inequality developments between 2002 and 2004. 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.

3.1 Choice of Covariates

Our choice of explanatory variables for the logistic regression is informed by the literature on the determinants of 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

[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.

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 within country inequality, 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, with the results being consistent with those presented below. 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 data set 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.

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 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. 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, though it should be kept 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.

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 between 2002 and 2014 as measured by the Gini coefficient. The extent of such changes varies across countries, with the increase largest for the Netherlands and Italy, and six countries (Finland, France, Hungary, Luxembourg, Romania and the United Kingdom) experience a decline in inequality[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 the decline 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 increasing inequality in the bottom half of the distribution.

[4] These results only include employed individuals, thus these results will dramatically differ as compared to Table ??, which is overall inequality for all individuals, employed or otherwise.

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

Table 2: Overview of Inequality Measures

5.2 Decomposition Results

5.2.1 Overall Decomposition Changes

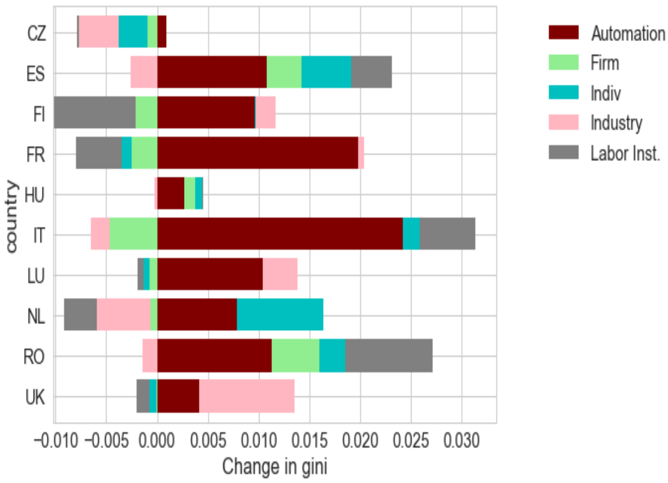
To summarize the characteristics that we analyze, we consider five broad factors - firm, individual, industry, labor institutions and risk of automation - aggregating the effects of the individual variables that comprise these broader categories. Firm characteristics include firm size and ownership type (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).

The Gini 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, its usefulness to capture overall dispersion within a country is why we continue to include it among our other measures.

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. Strikingly, we find that in all countries automation contributes to rising inequality, with the range of its contribution to explaining increasing inequality being as little as 8.6% in the

Czech Republic to as much as 77% in Italy. In Spain, Finland, France, Hungary, Italy, Luxembourg and Romania, automation is the largest contributor to overall inequality.

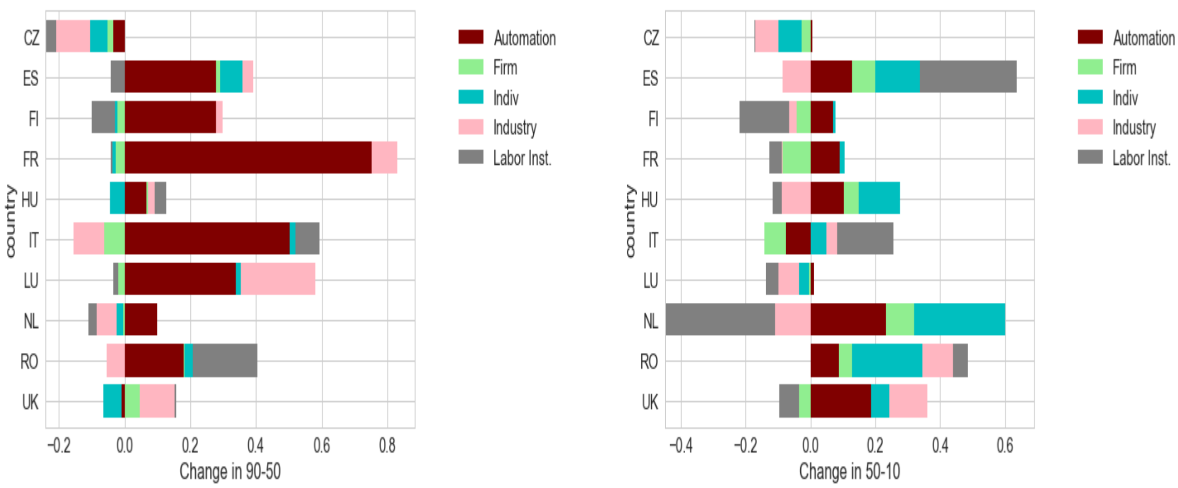
The importance of other factors on inequality is largely country dependent, both in terms of size and direction. This reflects that each country has a unique wage structure, and the importance of each factor is largely country dependent. To summarize these initial results, we find that the effects of individual, firm, industry and national (i.e. labor institution) variables impact countries in different ways and to different extents. However, automation risk is consistently associated with rising inequality, as measured by the Gini coefficient, although the strength of its impact is country dependent.



(a) Overall Decomposition Change in Gini

Figure 1: Gini Decomposition by Country

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).



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

Figures 2a and 2b visualize the decomposition of the distributional effects. Again, automation risk plays a prominent role, but mostly on its impact on the top half of the distribution as 8 out of 10 countries have large positive changes, ranging from .09 percentage point to .75 percentage point. 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 which 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 is a major driver of inequality at the upper end of the wage distribution. Given automation risks' prominent role in inequality, we delve deeper into understanding how automation risk is impacting wage inequality in the following sub-section.

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, 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, which is that an increase in the share of high automation risk workers is associated with a decrease in inequality. For example, if all jobs are transformed into high risk automation in Italy this would be associated with a decrease in .029 Gini points in 2002, while in 2014 this would be associated with a decrease in .010 Gini points. The negative coefficient suggests that inequality would decrease as the share of high automation risk occupations increases. 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, although their wages are much lower than low automation risk groups (as evidenced in our descriptive statistics in the appendix). Inequality decreases in this scenario because all workers would earn similar low wages. Low automation risk workers may earn more on average, but their wages are more dispersed. Thus, moving from an economy of all low automation risk occupations that have higher, but more unequal wages to an economy of high automation risk occupations with lower, but more equal wages would result in a decrease in inequality (the Gini). 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 tend to be lower than low automation risk. There are only two countries, Finland and The Netherlands, in which this is not true[5]. In the case of the Netherlands, the RIF regression coefficient for

[5] 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

automation risk are positive for 2014, while Finland is an exception that already has low Gini coefficients, and experienced a general decline in inequality during the time period.

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

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

Another interesting finding from the RIF regression estimates shows that the effect of automation on inequality is decreasing in absolute terms. The effect of automation in 2002 and 2014 decreases inequality (a negative effect) in both years, however the magnitude of the negative effect declined in 2014. Table 4 shows the difference between the 2002 and 2014 RIF regression estimates of the mid and high automation risk group on the Gini, as

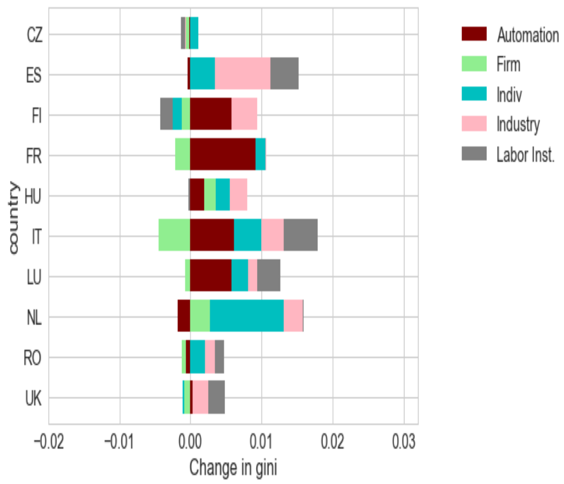
risk is approximately zero, meaning that it had no impact on the Gini that year. In the case of Hungary for 2014, the Gini for high automation risk is slightly higher than the low automation risk group, but the two groups have relatively similar Gini coefficients, and as they are relatively low, one may expect automation risk, holding everything else constant, could reduce inequality in this country well as the percent change differences in the coefficients. The table reveals that the impact of automation on inequality declined during our time period, as the estimated negative impact on inequality was higher in 2002 as compared to 2014. The relative differences as shown by the percentage change of the coefficients shows that these changes were rather large, ranging from around 40% to as high as 160% so that the impact of automation on inequality has increased with the exception of the Czech Republic which saw automation contribute to a moderate decrease in inequality during the time period. The impact of automation on inequality changed during this time period - high automation risk jobs decreased inequality more in 2002 as compared to 2014. The decomposition between wage and composition effect explains why we see this effect.

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

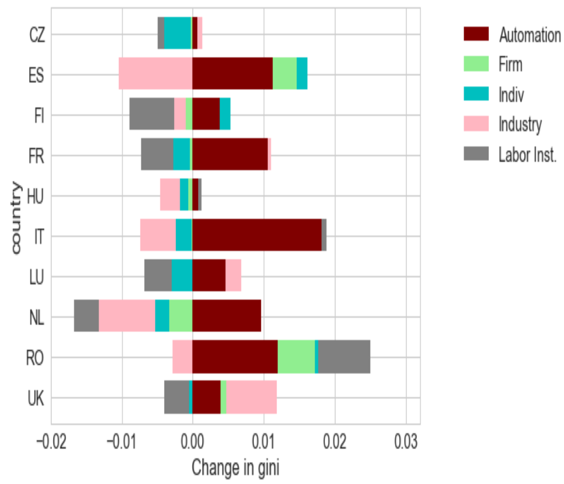
Country	Mid-AR		High-AR	height
	Diff	% Change	Diff	% Change
FR	-0.024	82.66%	-0.020	71.32%
FI	-0.012	78.85%	-0.008	80.02%
ES	-0.015	75.15%	-0.006	38.00%
CZ	-0.001	43.71%	0.000	-7.47%
LU	-0.009	45.70%	-0.013	48.47%
NL	-0.013	110.25%	-0.007	159.76%
IT	-0.028	94.69%	-0.020	66.55%
HU	-0.003	56.17%	-0.006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

Skill biased technological change argues that inequality is rising due to relative wage differences for skills that complement technology (computers, AI, robotics) as compared to skills that are at risk of being automated (manual and/or routine skills). Hence, the wage differences between lousy and lovely jobs drives polarization. Our results suggests that rising inequality is driven not only because of wage differences between these two groups, but also within job groups (automation categories). These results show that jobs that are less likely to be automated have high inequality. Hence, the relative share of each of these groups also determines inequality. As the share of low automation jobs increase, inequality rises not only because of the relative wage difference as compared to high automation jobs, but also because inequality is high within jobs that are resilient to automation, and further, we've seen that inequality within in low risk automation jobs is rising. In the following section we explore whether automation related inequality is driven by differences in relative wage returns, the rising share of high inequality automation groups, or both.

Gini: Wage & Composition Effects We now consider our decomposition results and look at whether the increase in the Gini was due to composition changes, i.e. more jobs moving towards more/less automatable jobs, or whether the increase was due to changing wage returns for high/low automatable jobs. Figure 2a shows the wage effect, and 2b shows the composition effect.



(a) Wage Effect: Change in Gini



(b) Composition Effect: Change in Gini

These figures illustrate that the composition effect explains a larger portion of changes to the Gini than the wage effect, as the coefficients tend to be larger for automation in the composition 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 of inequality in the composition effect. The wage effect of automation risk generally contributes to higher inequality, but the strength of the contribution varies by factor. Automation is a driver of inequality via the wage structure in Finland, France, Hungary, Italy and Luxembourg, which further bolster automation's impact on inequality as these countries also see automation increasing inequality via the composition effect.

If we consider that the composition effects are all positive, this suggests that there is a shift of high and mid automation jobs towards low automation risk jobs. Note that the composition effect can be evaluated by multiplying the change in automation risk (Section 10) by the coefficient of the 2002 RIF regressions (Tables 9-12). In other words, the increase in inequality due to composition changes is occurring because there is a higher share of low risk automation jobs, which have higher initial Gini coefficients and are also growing as detailed in Table 3, as compared to high and medium automation risk jobs, which tend to pay less, but more equally. 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 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 not the largest contribution 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, which is that there is 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 skillsets. For example, childcare workers and teachers are jobs that are more resilient to automation and require similar skill sets (both 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 concentrated by the median wage - a fact also confirmed by Goos et al. (2011). The composition of the workforce is driving inequality jobs that are more resilient to automation tend to be either low or high paying, and jobs that are more likely to be automated tend to earn similar wages, and these jobs are disappearing as a share of employment. These results support the polarization hypothesis - there is a hollowing out of middle income jobs, which is largely caused by automation.

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 was due to changes in the wage structure and/or composition structure with a Oaxaca-Blinder decomposition. This method allows us to evaluate the effect 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 differences between high and low automation jobs while holding the composition effect constant. The composition effect identifies if inequality is due to changes in the structure of employment.

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 confirm the polarization effect of automation - the hollowing out of middle income jobs, which have high risks of being automated. The share of high risk automation jobs have been steadily declining, and these types of jobs are paid relatively similar to each other, and tend to earn median wages. In replace 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 increases. These results further support evidence that the upper tail of wages continue to increase while low wages stagnate in the United States David et al. (2006). Our results confirm that the polarization effect can be seen across a variety of European countries, and that this effect is largely caused by automation.

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 risks, but leaving some behind. Our results show that the impact of automation on wages is changing and considering the structural, as well as wage effects is important 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 are 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.

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

Table 5: ISCED Crosswalk

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

Table 6: Industry Groups, NACE 2.0

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

Table 6: Industry Groups, NACE 2.0

No.	Industry Group	Name
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	Mngr 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

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
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)

88	AR	Occupation Title	08	AR	Occupation Title
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
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
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...
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

88	AR	Occupation Title	08	AR	Occupation Title
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) ES 2014	(2) ES 2002	(3) IT 2014	(4) 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

Table 9: RIF Regressions on Gini - Mediterranean Countries

	(1) ES 2014	(2) ES 2002	(3) IT 2014	(4) IT 2002
	(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)
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)

Table 9: RIF Regressions on Gini - Mediterranean Countries

	(1) ES 2014	(2) ES 2002	(3) IT 2014	(4) IT 2002
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***
	(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)

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
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) FI 2014	(2) FI 2002	(3) NL 2014	(4) 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)

Table 11: RIF Regressions on Gini - Scandinavian Countries

	(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)

Table 11: RIF Regressions on Gini - Scandinavian Countries

	(1) FI 2014	(2) FI 2002	(3) NL 2014	(4) NL 2002
Food & Hotels	-0.00739***	-0.00871***	-0.00852***	-0.00312***
	(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) FR 2014	(2) FR 2002	(3) LU 2014	(4) LU 2002	(5) UK 2014	(6) 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)

Table 12: RIF Regressions on Gini - Western European Countries

	(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

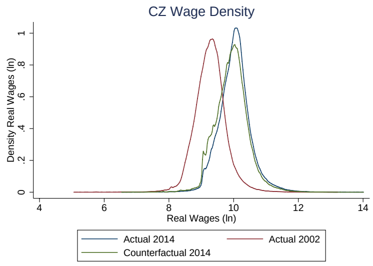
	(2002)		(2014)		(Diff in Means)
	Mean	SD	Mean	SD	Diff
Real Wage	1314.53	1220.48	2131.33	1775.09	816.80
Low AR	0.28	0.45	0.21	0.40	-0.07
Med AR	0.47	0.50	0.52	0.50	0.05
High AR	0.25	0.43	0.23	0.42	-0.02
Unk. AR	0.00	0.04	0.05	0.21	0.04
Edu	2.12	0.93	2.32	0.87	0.20
Priv. Owned	0.27	0.45	0.24	0.43	-0.03
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

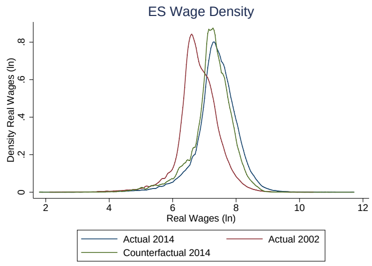
The decomposition RIF regressions consider three weighted distributions, the density of wages for the years 2002 and 2014 and the counterfactual distribution - 2014 wages with 2002 characteristics - which we display by country in Figure 2. While the weighted distributions closely follow the actual distribution 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.

Figure 2: Wage Densities Across Europe: Actual and Counterfactual for 2002 & 2014

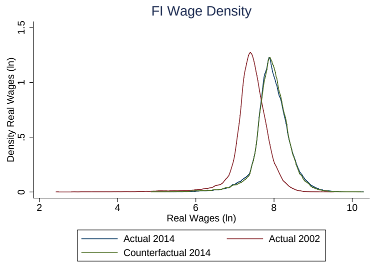
(a) Czech Republic



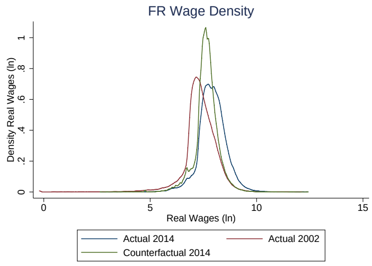
(b) Spain



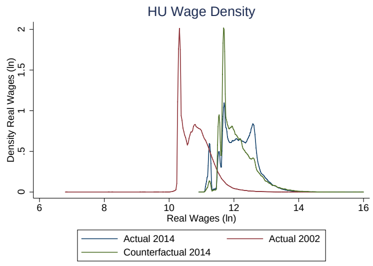
(c) Finland



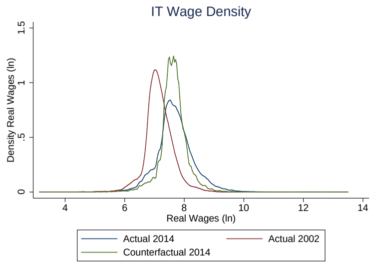
(d) France



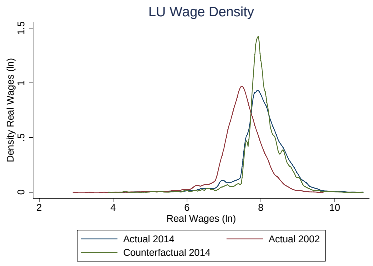
(e) Hungary



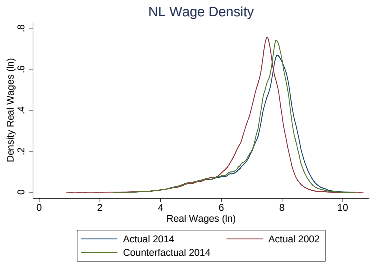
(f) Italy



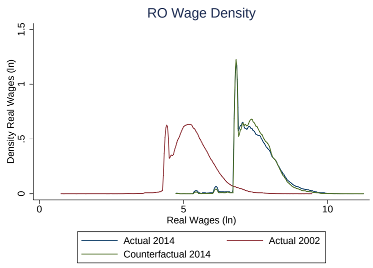
(g) Luxembourg



(h) Netherlands



(i) Romania



(j) United Kingdom