From Micro to Macro:

Essays on Technological Change and Income Divergence

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DISSERTATION

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Dedicated to my grandparents, my parents and Lucas.
Through their love I found strength.

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Chapter 1

Introduction

The history of capitalism is also the history of rapid technological transformation. These two forces have promoted productivity and economic growth resulting in increased income and improved livelihoods. However, these benefits have not been disseminated equally. Although inequality between countries is decreasing over the past few decades, income differences between developed and developing countries remain stubbornly large. Over the past few decades, inequality within countries is steadily increasing in most nations. Arguably, one of the reasons that income differences between nations persist, and inequality within nations is rising is due to technological change - who gains and loses motivates this thesis to understand the role that technological change has on income from micro to macro.

The most recent wave of innovation has been anointed with a few names, "Industry 4.0", "The Second Machine Age", and "The Fourth Industrial Revolution," and is marked by the rise of computers and the internet. With faster processing power and declining prices of silicon chips, computers are everywhere, from our desks to our pockets. Consequently, they are changing the way that we work. Its impact is a double edged sword where new technologies provide high productivity gains, but also displace workers. Its negative impacts have been more pronounced in popular media which damn the disruptive employment effects of automation, particularly because of more recent technologies that include mobile robotics, artificial intelligence, and machine learning. While we applaud smart phones for their capacity to summon a taxi within minutes and communicate with colleagues across the globe in seconds, we simultaneously fear the power that technology may have in replacing jobs and the possibility of making humans redundant. These fears are not new - the luddites in the early 19th century threw shoes to disrupt the belts of early manufacturing plants as a form of protest against machines for replacing their work. This paradox of progress was coined by Schumpeter as creative destruction in his book, *Capitalism, Socialism* *and Democracy*, and is a central tenet to his understanding of how capitalism works (Schumpeter, 1924). Technology improves the productivity and efficiency of production, which also creates new jobs, industries and firms to meet operation needs. At the same time, older and less efficient methods are replaced resulting in technological unemployment and the decline of some industries. One example of this is digital cameras. Color photography was previously done with cameras that refracted light and imprinted the image on film, which would later be developed through a chemical process resulting in a photograph. Digital technologies changed much of this process. Digital cameras capture light, turns this into electronic signals and captures these signals in an image sensor chip, which can then be transferred to a computer or other device to be printed. Developing film with chemical processes was no longer important in the process, and consequently firms that provided these services declined immensely. The film developer at the local photography shop or department store disappeared. However, jobs that created the sensor chip or provided print services increased substantially.

The impact of technology is not only through creation and destruction of jobs, but also at the intensive margin, the type of tasks that are done within jobs. What are the type of tasks that complement new technologies, and which ones are substituted? Zvi Griliches showed a broad relationship in that skilled labor, or those who have educational training, is more complementary to capital than unskilled labor (1969). For example, during the post world war years, factory workers often did routine, physical and manual tasks along assembly lines. These type of skills were in high demand to meet the production of a variety of technologically complex goods, like cars, televisions, or fans, and could be done by those with a high school degree. However, recent technologies have automated the production of many of these routine tasks that were traditionally done by people, and much of the production process of these goods are now done by robotic machinery (D. H. Autor, Levy, & Murnane, 2003). While routine tasks declined, non-routine cognitive types of skills increased in demand, and skills that include critical thinking, negotiation, creativity, and communication rose. ((David & Dorn, 2013), (Frey & Osborne, 2017)). These type of skills complement working with computers, and further, specializing in skills that computers can't automate. The relationship between the fall of some skills and the rise of others is central to understanding how technology can increase inequality. As routine tasks are automated, the relative return of these tasks decrease as compared to cognitive tasks, and thus, result in polarizing income effects.

There are two effects that technology has on impacting inequality. One effect is through wage changes, where the relative wages of some tasks are higher than others depending on the needs of new technologies. The other effect is an employment effect, where some jobs are automated, and no longer employed. The two effects are inter-related in that tasks that are facing competitive pressure from automation pay less, and are likely to be automated. Chapter two of this thesis evaluates how much of the impact of automation on inequality is due to wage returns or changing composition in 10 countries within Europe. The chapter decomposes the contribution that a variety of characteristics, including individual, firm, institutional, and automation, have on inequality by using detailed individual level data, and finds that automation has lead to a rise in inequality in all of the countries observed. In half of the countries, automation increased inequality through the wage effect and the relative wages of low automation jobs were paid more compared to high automation jobs. However, the primary way in which automation increased inequality was through the composition effect. The share of low risk automation jobs is increasing, suggesting that high automation jobs are disappearing suggesting negative effects of creative destruction. High automation jobs are more equally paid, despite being lower paid, however, low automation jobs that pay better are more unequally paid. The increase in inequality due to the composition effect is due to the fact that as the share of low automation jobs increase, inequality increases because inequality within low automation jobs is higher. While there were many high automation jobs that were paid less, they were paid relatively more equally to each other, and therefore contributed to a decrease in inequality. As their prominence fades in the workforce, inequality rises with jobs that have a higher dispersion of income between them.

Chapter two focuses on rising inequality between individuals within countries, but chapter three addresses inequality between industries. Previous studies that looked at the inter-industry wage premium suggested that wage differences were do to the size of the industry as larger industries are likely to pay higher wages so that they could hire efficient and higher quality workers, reduce shirking, and better pay would motivate employees to be more productive ((Oi & Idson, 1999), (Brown & Medoff, 1989)). Chapter three shows that inter-industry wage premiums are not only due to size effects, but also due to the knowledge diversity in an industry. The chapter introduces a novel way to measure knowledge diversity through a network based approach. The measure captures the specialization of knowledge, relative knowledge differences, and can weight more common specializations less than more unique specializations. Using this measure, the chapter theorizes that when new technology is adopted in an industry, new specializations are also created to work alongside the new technology. However, in order for an industry to adopt a new technology, they must be able to coordinate these new specializations with all of their existing specializations, thus, industries must balance coordination costs with increasing specialization. Industries reduce coordination costs by hiring individuals who have communication and interpersonal skills, and thus, industries who have more knowledge diversity pay a wage premium to individuals who have more communication and interpersonal skills. In this view, the inequality of earnings between industries is explained by varying adoption rates of technology, and the ability of industries to reduce coordination costs.

The previous chapters focused on how technology polarized wages of individuals, but this effect can be seen at an aggregated level, as well. Chapter 4 addresses how technology, or rather, the capabilities needed for technology to be adopted, determines economic growth. The ability of what a nation can make is an important part of growth, but requires the orchestration of a society to put together varying parts of economic activity to produce one good. Of course, not all goods are alike and the complexity required to grow an apple is quite different than the production of a computer. Measuring the societal requirements to produce a variety of goods (both simple and complex) is quite difficult precisely because there are so many different parts of the system that must come together. There are two broad methods to measure the capabilities a country, aggregate capability indices and export based algorithms. This chapter provides an overview of these methods, and then compares three different types of export based algorithms to rigorously analyze their relationship to economic development measured in terms of economic growth. The chapter provides empirical evidence of the process of 'catching-up', where poorer nations can increase their economic growth rates through investing in technological capabilities to eventually catch up with wealthy nations. The trade patterns of the variety and difficulty in producing products are related to the aggregate income growth of nations, and this is particularly important for poorer nations. In other words, the products that firms produce can be aggregated as a reflection of the overall wealth of a nation. However, the process that promotes growth for poorer nations to catch up is not seen for wealthier nations, suggesting that there are other processes that may be more important for wealthier nations.

These three chapters show how technology impacts inequality and earnings at the micro-, meso- and macro-levels of analysis. The second chapter uses microlevel data to decompose inequality changes. Using detailed individual information reveals distributional changes for each characteristic rather than looking at mean differences. The third chapter analyzes industry level data to explain how industry specific differences can determine earnings. Industries have different adoption rates of new technology, and consequently varying rates of knowledge specialization, which impacts wages between industries. Finally, the fourth chapter takes a macro-level approach, and measures technological capabilities with detailed trade data. At the most aggregated level, the technological capability of a country impact economic growth rates. By using a variety of data sources and unit of analysis, the thesis shows that technology impacts earnings at each level - from micro to macro.

1 Approach to Thesis

Unlike our economist predecessors, we are now swimming in a sea of data, some more easily accessible than others, some more reliable than others, and many new sources originating from unofficial sources like crowdsourcing or mobile data. We are living in the *age of big data* and are in the early phase of learning how to manage and analyze large swarms of data to help us answer our research questions. In the past, statistical problems were usually associated with small samples - the limits of inference and statistical significance. The discovery of the T-distribution was one of the most important statistical discoveries because it helped guide us on the properties of small sample distributions. Today, we are now overcoming how to efficiently calculate entire cumulative distribution functions, understand biasedness arising from our data sources and methods, and how to quality check our data where one can't review every observation. What was once the dominance of the frequentist approach to statistics is now confronted with the resurgence of Bayesian approaches, and this is no coincidence. In the past, we had no ability to know the true distribution of any variable, and with the central limit theorem, the frequentists could derive many interesting statistical properties that could hold for multiple randomly drawn small samples. This often came at the cost of limiting our ability to predict as out of sample estimation was prone to error. We were focused on the estimation of the average marginal effect of a particular variable. However, today, we can reasonably understand the true distribution with a superfluous amount of observations for the population under evaluation. It is fair to say that we actually know the entire distribution of income in countries like Sweden or the Netherlands, where the informal sector is small and the entire nation's income is tracked. We are now discovering what are the limits to big data and how our approaches to analysis must change as we analyze larger datasets. As economists, we are at the intersection of large data sets that answer old, but dynamic questions. This requires the profession to become open minded in approaches to quantitative techniques by learning from computer scientists, physicists, and other social scientists. That is why this thesis takes a data-driven quantitative analysis approach with datasets that range from the hundreds of thousands to the millions of observations using traditional econometric techniques within panel data, but also utilizes network statistics inspired from physicists, modeling methods from psychology, and decomposition methods.

2 Structure of Thesis

This thesis is composed of three levels of observational units, individual, industry and country, and evaluates the impact that technological change has on income using large datasets at each level. It reveals the interconnectedness of each level to one another, where industry characteristics can impact individual earnings, automation can impact income distribution, and the products that firms trade across countries impact national earnings.

Starting at the microlevel (individual) level, Chapter 2 seeks to understand the impact of automation on workers. Using data from 10 European countries from Eurostat, the analysis applies a recentered influence function (RIF) regression decomposition methodology to compare 2002 earnings distribution to 2014 earnings distribution with a number of individual and firm level characteristics ranging from education, risk of automation, age, gender, experience, industry, firm size to contract type, among others. Rising inequality is found to be caused by automation across all of the countries, and the impact of inequality on automation has been increasing during this time period. Across the countries studied, rising inequality is due to composition changes as the share of high automation risk jobs are decreasing as compared to low automation risk jobs. High automation risk jobs tend to be paid less on average, but are more equitable, whereas low automation risk jobs are paid more on average, but are more unequal.

Chapter 3 moves to the mesolevel (industry) to analyze the impact of increasing knowledge on earnings. Using the Bureau of Labor Statistics from the United States, the study develops a novel way to measure knowledge diversity using an industry-occupation network, and then estimates the returns to earnings for occupations who work in knowledge diverse industries. By connecting this with data on skills, tasks and activities from data by O*NET, the results reveal that jobs that have high levels of social, communication and interpersonal skills are paid more in knowledge diverse industries compared to the same occupation in a less knowledge diverse industry.

Chapter 4 analyzes macreconomic (country) growth patterns to compare the effect of three different measures of technological capability by using fixed effects, random effects, generalized method of moments and Hausman-Taylor growth regressions. The growth of GDP per capita is influenced by technological capabilities (the capability of a nation to make complex products) for the poorest nations, but this effect is no longer significant for wealthier nations, where other forces may be more important determinants to growth.

Chapter 5 draws conclusions and reflects on the findings from this thesis.

Chapter 2

The Impact of Automation on Inequality Across Europe

Existing research suggests that automation has the potential to impact inequality through two channels. One explanation is that differences in relative wage returns for particular sets of tasks are diverging, while another explanation is that the composition of jobs is changing. This paper measures the strength of these two effects by decomposing a set of characteristics using the structure of earnings survey (SES) between 2002 and 2014 (Firpo, Fortin, & Lemieux, 2018). The approach isolates changes in the earnings distribution to identify the component that is due to changes in the composition or changes in the wage structure. We find that the risk of automation has the largest impact on inequality in our sample of European countries. The composition effect explains a large part of automation related inequality across all of the countries we observe, but the wage effect is also present in half of the countries. These results confirm that the way in which technology is increasing inequality is largely due to jobs becoming more polarized in that there is growing wage dispersion between jobs that are resilient to automation.

JEL classifications: 03, J3, J31, D63

Keywords: Inequality, Technological Change, Labor Markets, Wage Structure

1 Introduction

Over the past 30 years, inequality has increased across Europe with many countries experiencing an increase in inequality since the new millennium. The countries for which inequality has risen cover a broad geographical region, including new member states of the European Union (EU), Nordic countries, Mediterranean countries and countries in western Europe. Table 2.1.1 reflects these trends by showing Gini coefficients for a cross-section of EU countries in 2007 and 2015. Research has shown that much of the observed rise in inequality is due to increases at the very top of the distribution (Jaumotte & Osorio, 2015), and that while the rate of increase in inequality slowed during the early years of the 2009 economic crisis, it began to resume its increasing trend shortly the 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.

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

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

Table 2.1.1: Gini Coefficients across Europe in 2007 & 2015

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

Source: OECD Income Distribution Database (2018)

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

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

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

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

2 Literature Review

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

2.1 Theoretical Explanations

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

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

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

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

2.2 Empirical evidence

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

Firpo, Fortin and Lemieux (2011) sought to understand how much of these wage changes can be explained by the changing task content in occupations in the United States by creating a more extensive index of occupational characteristics. Inspired by Blinder et. al (2007), Jensen et. al. (2010) and Autor et. al. (2003) they create five indexes from the O*NET database related to tasks, namely: (i) the information content of jobs; (ii) the degree of automation (routinization); (iii) the importance of face-to-face contact; (iv) the need for on-site work; and (v) the importance of decision making at work. Using a RIF regression decomposition technique, they find that technological change and de-unionization both had large roles in explaining wage changes in the 1980s and 1990s, but much less of an effect in the 2000s. Furthermore, offshorability played an increasingly important role in the 1990s and 2000s. They conclude that the return to skills vary by occupation and suggest moving to a task based metric which may better identify why wage distributions have changed so much over the past few decades.

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

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

Goos and Manning (2003) begin by using the classification of Autor et al

(2003) that splits occupations into five particular types of task: non-routine cognitive, non-routine interactive, routine cognitive, routine manual, and non-routine manual. Using this classification, they show that non-routine manual jobs are concentrated in the lower percentiles of the wage distribution, while non-routine cognitive and interactive jobs are concentrated in the top end of the wage range, with routine jobs thus concentrated in the middle of the wage distribution. Since non-routine jobs are concentrated in the middle of the wage distribution the hypothesis of Autor et al (2003) would predict a polarization of the workforce into 'lousy' and 'lovely' jobs. Using data for the UK the authors then show that there has been employment growth in jobs at the top and bottom end of the wage distribution, and a significant decline in jobs in the middle of the distribution. The authors further note that a number of papers (e.g. (Berman, Bound, & Griliches, 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.

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

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

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

3 Decomposition Method

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

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

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

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

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

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

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

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

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

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

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

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

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

$$F_Y^k(Y) = \int F_{Y|K}^k(Y|X)dF_X^k(X) \tag{6}$$

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 $t = 0$ 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-time contract. Last, we include industry dummies, which capture industry characteristics[2] It should be noted that the choice of base group may be important in the decomposition as some argue that the decomposition can change depending on the base group of choice (R. L. Oaxaca & Ransom, 1999). For more details about the data, please see the appendix. Using the predicted probabilities from this model we are able to obtain estimates for the reweighting factor and in turn, obtain an estimate for the counterfactual distribution, F_Y^c , using equation 11.

[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, but we do provide the counterfactual distribution in the appendix. Please feel free to contact the authors for these results.

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

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

(N. Fortin et al., 2011). The linear approximation allows us to see how a particular individual impacts the Gini, and allows us to aggregate all of these impacts to the overall Gini. Given that this is a linear combination, we can easily estimate the recentered influence function with OLS.

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

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

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

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

While these models can be estimated using OLS, there is a somewhat different interpretation of the regression coefficients from the more standard interpretation. In particular, the coefficients can be interpreted as follows: 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-Blinder decomposition - allow us to dig deeper into understanding how our covariates played a role in shaping inequality developments between 2002 and 2014. The decomposition allows us to see how our covariates play a role, where the composition effect is a quantity effect, and the wage effect is similar to a price effect or the returns to wages for specific characteristics. Each of these covariates can be aggregated up since the total is the sum of the parts. For example, individual characteristics include the estimates of education, gender and age. We present results at an aggregated level highlighting the 5 main factors (i.e. individual, technology, firms, industry and national) for ease of presentation, but the contribution of each specific covariate can be found in the appendix.

3.1 Choice of Covariates

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

[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.

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, Krueger, 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, Bryson, Davis, & Freeman, 2016), (Brown & Medoff, 1989)). Additionally, firm differences can arise when a worker is more productive in a particular firm because of firm level compensation policies ((Mortensen, 2005), (Fairris & Jonasson, 2008), (Oi & Idson, 1999)). Firm ownership type, whether public or private, is another consideration, with Lucifora and Meurs finding that private companies pay higher (lower) wages for high- (low-) skilled workers when compared with public (majority government owned) companies (2006). Other firm-specific factors that have been shown to be positively correlated with wages include whether the firm is foreign-owned and whether it is engaged in trading activities (i.e. whether it is an exporter or importer). Existing research also provides some evidence to suggest that firm-specific effects contribute significantly to rising inequality in the case of Germany (Antonczyk, Fitzenberger, & Sommerfeld, 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, Kramarz, Lengermann, & Roux, 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, Kramarz, Lengermann, McKinney, & Roux, 2012). In other words, the knowledge a person accumulates is valued differently across industries. A further source of intra-industry wage differentials are intra-industry productivity differentials, with more productive sectors paying higher wages (Thaler, 1989).

At the national level, policies associated with unionization levels, contract regulation, and minimum wage laws are typically at the heart of policies that shape wages. Most analysis on labor institutions tend to focus on cross-country changes, showing that decreasing unionization is associated with higher rates of income at the top end of the distribution that further increases inequality (Jaumotte & Osorio, 2015). When looking at changes within a country, rising inequality is partly explained by employment protection legislation (length and amount) (Koeniger, Leonardi, & Nunziata, 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, Fortin, & Lemieux, 1996), (D. S. Lee, 1999), (Card, 1996)), Britain ((Machin, 1997), (R. Dickens, Machin, & Manning, 1999)), Italy (Erickson & Ichino, 1995), and Sweden (Edin & Holmlund, 1993). In one recent empirical analysis, Massari et. al (2013) found that institutions rather than technology was the largest contributor to inequality in Europe.

4 Data

We use two waves (2002, 2014) of the structure of earnings survey (SES) which are cross-sectional harmonized data across the EU and include detailed information about enterprise and worker characteristics and are reported every 4 years

((Eurostat, 2014)). Each country is responsible for reporting a set of required questions that can be aggregated via surveys or the country's administration data. Descriptive characteristics of the dataset are provided in the appendix.

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

We use gross monthly earnings with the reference month as October, which also includes overtime and special shift work, and calculate real wages using the consumer price indices from Eurostat as a deflator. As a robustness test we repeated our analysis using gross annual earnings, including in-kind payments, and find the results are consistent with those presented in this paper. It is worth noting that we do not gross-up part-time earnings. This is because we want to have an understanding of how part-time work contributes to inequality as a whole, which wouldn't be possible if we grossed-up part-time earnings. Instead, the estimated effects would capture the relative difference in wages between part-time and full-time workers *as if* part-time workers worked the same number of hours.

Over time industry codes change, while industry groupings differ between countries and over time. To create a time consistent 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 2.7.6 in the appendix for the industry classifications. Additionally, the education classification changed during our observed time period. For our analysis we update ISCED-97 codes applied in the 2002 data set to ISCED-08.

5 Results

5.1 Descriptive Statistics

The overall changes in the Gini coefficient along with changes in the 90-10, 50-10 and 90-50 (log) wage quantiles between 2002 and 2014 are reported in Table 2.5.2. There are a variety of country experiences in terms of developments in inequality across Europe, and we observe that half of the countries experienced an increase in inequality among workers. The extent of such changes varies across countries. The Netherlands and Italy saw inequality rise substantially, while there was a decrease in inequality for six countries, Finland, France, Hungary, Luxembourg, Romania and the United Kingdom.[4]

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

Table 2.5.2: Overview of Inequality Measures

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

[4] These results only include employed individuals, thus these results will dramatically differ as compared to Table 2.1.1, which is overall inequality for all individuals, employed or otherwise.

5.2 Decomposition Results

5.2.1 Overall Decomposition Changes

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

Figure 2.1 presents the results of our decomposition method, displaying the contribution that each variable has on influencing the Gini during our observed time period [5]. Strikingly, we find that in all countries, automation contributes to rising inequality. However, the range of its contribution can be as little as 8.6% in the Czech Republic to as much as 77% of the overall inequality increase in Italy. In Spain, Finland, France, Hungary, Italy, Luxembourg and Romania, automation is the largest contributor to overall inequality.

The importance of other factors on inequality is largely country dependent, both in terms of size and direction. This reflects that each country has a unique wage structure. We will briefly summarize these initial results, because the effects of individual, firm, industry and national (i.e. labor institution) variables vary

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

substantially. Labor institutions play a large role in only six countries. They tend to decrease inequality in the Netherlands, France and Finland, but increase inequality in Spain, Italy, and Romania. These results align with previous held beliefs on the role of labor market institutions in different countries - France, the Netherlands and Finland are well known to have strong labor institutions designed to reduce inequality, while Spain, Italy and Romania tend to have weaker ones (Boeri et al., 2011). Industry is also an important contributor to inequality for the United Kingdom and Luxembourg. Previous research suggests that countries that have large financial sectors also have higher rates of inequality, which is true for both Luxembourg and the United Kingdom (Stockhammer, 2013). In the Czech Republic, Spain, Italy, the Netherlands and Romania, industry contributes to declining inequality. Individual and firm effects on inequality tend to play a relatively small role across countries with the only exception being the Netherlands where individual effects play a large role in increasing inequality. Most strikingly, automation risk is consistently associated with rising inequality. Given automation's important role in shaping inequality, the remainder of the paper will focus solely on automation's effect on inequality.

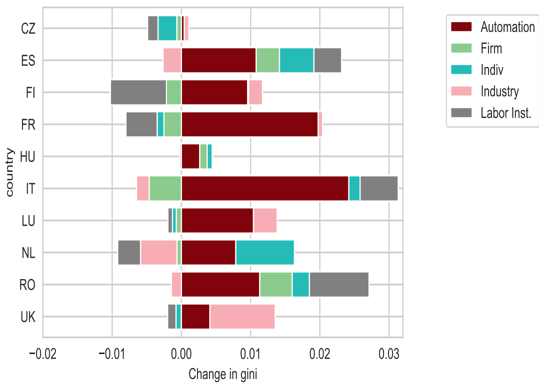
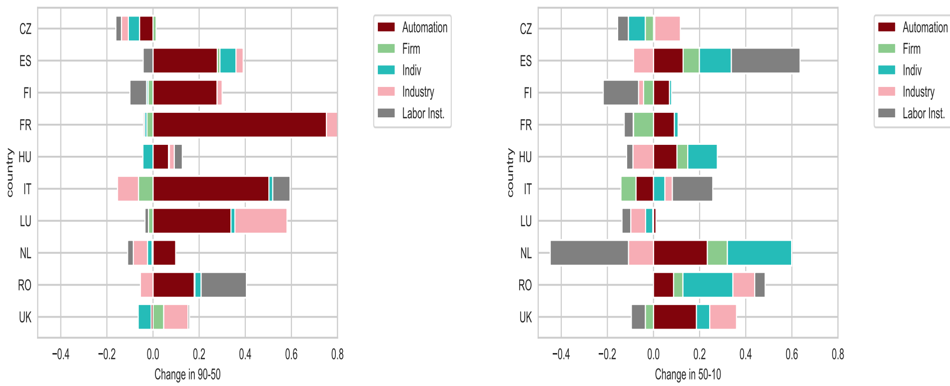


Figure 2.1: Overall Decomposition Change in Gini

While the Gini provides a general overview, we can also look at how factors contribute to other distributional changes. In other words, we can compare big earners to average earners (the top half of the distribution), and compare average earners to minimum wage workers (the bottom half of the distribution). Figures 2.2a and 2.2b visualize the decomposition of the distributional effects. Again, automation risk plays a prominent role, but its impact tends to be felt most strongly in the top half of the distribution as 8 out of 10 countries have large positive changes, ranging from .09 percentage points to .75 percentage points. In two countries, the United Kingdom and the Czech Republic, automation risk has a small negative impact on inequality in the upper part of the wage distribution. Automation risk also tends to increase inequality in the bottom half of the wage distribution (with the exception of Italy), but its effect tends to be much more muted (exceptions being the Netherlands and the United Kingdom where it has a relatively large impact). In most cases, therefore, automation risk is not the major driver of inequality in the lower half of the wage distribution, but it is a major driver of inequality at the upper end of the wage distribution. Given automation risk's prominent role in inequality, we delve deeper into understanding how automation risk is impacting wage inequality in the following sub-section.



(a) Top Distributional Half (90-50) Change

(b) Bottom Distributional Half (50-10) Change

Figure 2.2: Distributional Decomposition by Country

5.2.2 Impact of Automation

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

RIF Regressions Recall that RIF regressions estimate the impact of a characteristic on the Gini. We present these detailed RIF regression estimates for 2002 and 2014 in Tables 2.8.9-2.8.12, and find that across countries, coefficients on high and mid-automation risk estimates are negative, with the only exception being the Netherlands in 2014. A negative coefficient on automation risk suggests that an increase in high automation risk would lead to a decrease in inequality. This may seem contradictory given that we've just detailed how automation has contributed to rising inequality. The RIF regressions decompose each covariate's contribution to inequality. Our interest is to see how much these coefficients change over time. The wage effect is the change of the covariate's contribution to inequality overtime. The composition effect is the change in the share of workers while taking into account the initial contribution that covariate has on inequality.

The RIF regressions look at levels for a particular year so that we can compare the relative magnitude of effect that each variable has on inequality. For example, an increase in the share of high risk automation jobs in Italy would be associated with a decrease of .029 Gini points in 2002, while in 2014 this would be associated with a decrease of .010 Gini points. The negative coefficient suggests that inequality would decrease as the share of high automation risk jobs increase. This is partly due to the fact that the high automation risk group has a more equal distribution of income as compared to low risk occupations. Even though high risk automation wages are, on average, lower than low automation risk groups, the distribution of wages within this group is what contributes to rising or falling inequality. If we look at changes between time periods rather than the levels alone, we can see that moving from an economy that has all low automation risk occupations which have more unequal wages to an economy of high automation risk occupations with more equal wages would result in a decrease in inequality (the Gini), ceteris paribus. Table 2.5.3 displays the Gini coefficient for each automation risk group by country and year, and shows that in most countries, the dispersion of income within high automation risk groups tends to be lower than in the low automation risk group. There are only two countries, Finland and the Netherlands, in which this is not true[6]. In the case of the Netherlands, the RIF regression

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

coefficient for automation risk is positive for 2014, while Finland is an exception, with both low Gini coefficients, and a general decline in inequality during the time period.

Table 2.5.3: Gini Coefficient by Automation Risk, Country and Year

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

Another interesting finding from the RIF regression estimates shows that the effect of automation on inequality decreases in absolute terms. The impact of automation has a negative effect in both years, however the magnitude of this effect declined in 2014. Table 2.5.4 shows the difference between the 2002 and

else constant, could reduce inequality in this country

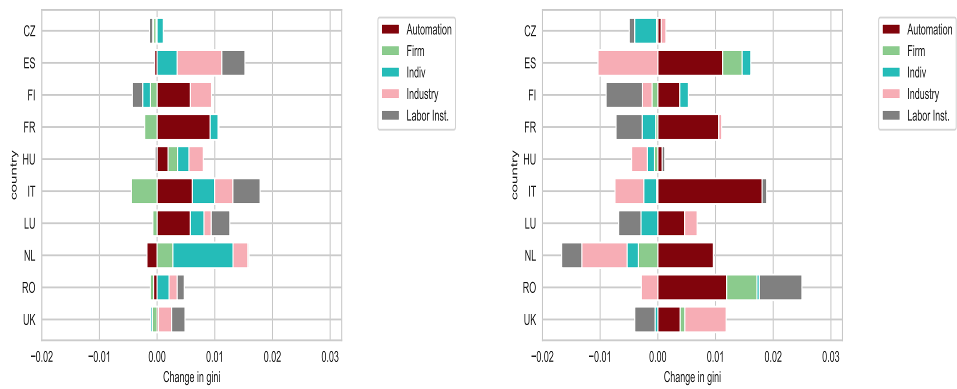
2014 RIF regression estimates for the mid and high automation risk group on the Gini, as well as the percentage change in the coefficients. The table reveals that the contribution of inequality from high automation risk decreased inequality more in 2002 than it did in 2014. The negative coefficient declines over time in absolute value, so that all else being equal the decline in the negative coefficient increases inequality. The relative differences in the percentage change of the coefficients reflect that the change in the size of the coefficients were rather large, ranging from around 40% to as high as 160%. Analyzing the wage and composition effect help explain these changes.

Table 2.5.4: Difference and Percent Change of the Impact of Automation Risk on the Gini between 2002 - 2014

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

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

Gini: Wage & Composition Effects We now consider our decomposition results and look at the relative importance of whether the increase in the Gini is because of 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 2.3a shows the wage effect, and 2.3b shows the composition effect.



(a) Wage Effect: Change in Gini (b) Composition Effect: Change in Gini

Figure 2.3: Wage and Composition Effect in Gini

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

The composition effect is the change of the effect of high automation jobs on inequality multiplied by the share of employment in high risk automation jobs. In technical terms it is the coefficient of the 2002 RIF regressions (Tables 2.8.9-2.8.12) multiplied by the change in the share of the automation risk category (Section 10). Thus, the composition effect is positive because there is a lower share of high risk automation workers (i.e. the change in high risk is negative), and when combined with the negative coefficient in 2002, this results in an increase in inequality. In other words, the increase in inequality due to composition changes occurs because there is a higher share of low risk automation jobs. Inequality within low risk automation jobs is higher than inequality in high and medium automation risk jobs as detailed in Table 2.5.3, which explains why the coefficient on high automation risk is negative. Wages for jobs in high automation risk categories remain low during the time period as they face competition not only from automation technologies that may threaten to displace them, but also a large workforce with similar skills that can fill these positions quickly.

We find evidence that relative wage returns between high and low automation workers are causing rising inequality, as predicted by Skill Biased Technological Change, in Finland, France, Hungary, Italy, Luxembourg, and to a lesser extent, the United Kingdom. However, this effect is not prevalent in all countries, and is not the largest contributor to inequality in European countries - a conclusion that is also found by Goos et. al. (2011). However, what is driving inequality across countries is a shift in the composition of jobs, a rising share of low automation jobs, and a declining presence of high automation jobs. As the share of low automation jobs increases, and will likely continue to increase given the current trend found in our results and others, inequality will rise. It's not only the difference of relative wage returns between jobs that require manual tasks compared to cognitive tasks that contributes to inequality, but polarization is also rising within jobs that require similar skillsets. For example, childcare workers and teachers are jobs that are more resilient to automation and both jobs require cognitive thinking and social skills. However, there is a large wage disparity between these two jobs. Even though these jobs are less likely to be automated, inequality remains relatively high. The lowest and highest paid occupations are both resilient to automation, while jobs that are being automated are those that tend to be near the median wage - a fact also confirmed by Goos et. al. (2011). The composition of the workforce is driving inequality towards jobs that are more resilient to automation, which tend to be either low or high paying. Jobs that are more likely to be automated tend to earn similar wages, and these jobs are disappearing as a share of employment. These results support the polarization hypothesis - that 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 were due to the wage effect and/or composition effect with a Oaxaca-Blinder decomposition. This method allows us to evaluate the effect that each characteristic has on inequality - whether that is the overall contribution, the wage effect, or the composition effect. The wage effect isolates changes in inequality that are due to the relative return of wages allowing us to identify if inequality is due to wage return differences between high and low automation jobs, while holding the composition effect constant. This effectively tests which countries experienced Skill Biased Technological Change. The composition effect identifies if changes in inequality are due to shifts in the structure of employment, while holding wage returns constant, which can therefore test for the presence of the polarization effect.

Our results show that rising inequality within European countries is largely explained by automation with the top half of the distribution impacted the most. The composition effect has a consistently large impact across all countries, however some countries also see a rise in inequality due to the wage effect (Finland, the

Czech Republic, France, Hungary, Italy, the United Kingdom and Luxembourg). The composition effect is due to the fact that low automation risk jobs have more unequal wages, and the share of these jobs are rising over time, which is also seen in the descriptive statistics in the appendix in Table 10. As the share of low automation risk increases and the dispersion within that group grows, inequality increases.

These results reveal that the polarization effect of automation - the hollowing out of middle income jobs, which have high risks of being automated - is driving inequality across Europe. The share of high risk automation jobs has been steadily declining, and these types of jobs are paid relatively similar to each other. In 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 increase. These results further support evidence that the upper tail of the wage distribution continue to increase while low wages stagnate (David et al., 2006). The polarization effect is present in a variety of European countries. While the effect of skill biased technical change is present in only six European countries, and further, its effect on inequality is not as strong as the composition effect.

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

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 2.7.5. The category represents the level of education the individual has successfully completed which are categorized into four groups below.

Table 2.7.5: ISCED Crosswalk

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

7.2 Industry

While the SES data is harmonized across the member states of the European Union there remained a few consistency issues across the waves and countries.

For this analysis the most notable concern was the industry classification changes which were grouped inconsistently depending on the country and year. In cases where two sectors were combined, we aggregated the information. Thus, our final industry classification groups is in Table 2.7.6.

Table 2.7.6: 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
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

No.	**Industry Group**	**Name**
8	45, 46	Wholesale and retail trade and repair of motor vehicles and motorcycles, Wholesale trade, except of motor vehicles and motorcycles
9	47	Retail trade, except of motor vehicles and motorcycles
10	49-52	Land transport and transport via pipelines, Water transport, Air transport, Warehousing and support activities for transportation
11	53, 61-63,79	Postal and courier activities, Telecommunications, Computer programming, consultancy and related activities; information service activities, Travel agency, tour operator, and other reservation service and related activities
12	I	Accommodation and food service activities
13	64-66, 68-75, 77, 78, 80-82, 86-88, 90-93, 95, 96	Financial service activities, except insurance and pension funding, Insurance, reinsurance and pension funding, except compulsory social security, Activities auxiliary to financial services and insurance activities , Real estate activities, Legal and accounting activities; activities of head offices; management consultancy activities, Architectural and engineering activities; technical testing and analysis, Scientific research and development, Advertising and market research, Other professional, scientific and technical activities; veterinary activities, Other service activities, Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, Activities of extraterritorial organizations and bodies, Administrative and support service activities
14	O	Public administration and defence; compulsory social security
15	P	Education
16	Q	Human health and social work activities
unknown	ZZZ	not specified

7.3 Automation Risk

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

Table 2.7.7: 2-digit Occupation Code Automation Risk

88	AR	Occupation Title	08	AR	Occupation Title
11	0.113	Legislators & senior officials	11	0.110	Chief Exec., Senior Officials and Legis.
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 profs.
33	0.151	Teaching associate profs.	26	0.179	Legal, Social and Cultural profs.
34	0.422	Other associate profs.	31	0.537	Science and Engineering Associate profs.
41	0.922	Office clerks	32	0.316	Health Associate profs.
42	0.685	Customer services clerks	33	0.491	Business and Administration Associate Prof.
51	0.476	Personal and protective services wrkrs	34	0.438	Legal, Social, Cultural and Related
52	0.771	Models, salespersons and demonstrators	35	0.536	Information and Comms. Techn.
61	0.732	Market-oriented skilled agricultural and fisheries	41	0.923	General and Keyboard Clerks
62	0.800	Subsistence agricultural and fishery wrkrs	42	0.626	Customer Services Clerks

88	AR	Occupation Title	08	AR	Occupation Title
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	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, etc.
92	0.890	Agricultural, fishery and related labourers	63	0.800	Subsistence Farmers, Fishers, Hunters, etc.
93	0.735	Labourers in mining, construction, manuf.	71	0.675	Building and Related Trades wrkrs
			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 etc.
			81	0.827	Stnry. Plant & Machine Oprts.
			82	0.946	Assemblers
			83	0.621	Drivers & Mobile Plant Oprts,
			91	0.631	Cleaners & Helpers
			92	0.910	Agricultural, Forestry & Fishery Labourers
			93	0.727	Labourers in Mining, Construction, Manuf.
			94	0.848	Food Preparation Assistants
			95	0.940	Street and Related Sales & Services wrkrs
			96	0.839	Refuse wrkrs & Other Elementary wrkrs

Table 2.7.8: 3-digit Occupation Code Automation Risk

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

88	AR	Occupation Title	08	AR	Occupation Title
231		University & Higher Education Tchrs.	244	0.130	Social science & related profs.
232	0.009	Vocational Education Tchrs.	245	0.195	Writers & creative or performing artists
233	0.008	Secondary Education Tchrs.	246	0.008	Religious profs.
234	0.083	Primary School & Early Childhood Tchrs.	311	0.534	Physical & engineering science Techn.
235	0.084	Other Teaching profs.	312	0.300	Computer Assoc. profs.
241	0.586	Finance profs.	313	0.442	Optical & electronic equipment oprts.
242	0.210	Admin profs.	314	0.211	Ship & aircraft controllers & Techn.
243	0.268	Sales, Marketing & Public Relations profsi...	315	0.508	Safety & quality inspectors
251	0.135	Software & Apps. Developers & Analysts	321	0.446	Life science Techn. & related Assoc....
252	0.030	Database & Network profs.	322	0.226	Health Assoc. profs. (except nursing)
261	0.284	Legal profs.	323	0.058	Nursing & midwifery Assoc. profs.
262	0.452	Librarians, Archivists & Curators	324		Traditional medicine practitioners & faith h...
263	0.105	Social & Religious profs.	331	0.087	Primary education teaching Assoc. profs
264	0.306	Authors, Journalists & Linguists	332	0.079	Pre-primary education teaching Assoc. profs
265	0.114	Creative & Performing Artists	333	0.012	Special education teaching Assoc. profs
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.

88	AR	Occupation Title	08	AR	Occupation Title
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

88	AR	Occupation Title	08	AR	Occupation Title
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...

88	AR	Occupation Title	08	AR	Occupation Title
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
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

88	AR	Occupation Title	08	AR	Occupation Title
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 2.8.9: RIF Regressions on Gini - Mediterranean Countries

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

	(1) ES 2014	(2) ES 2002	(3) IT 2014	(4) IT 2002
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed Cont.	0.0276***	0.0159***	0.0157***	0.00866***
	(0.000)	(0.000)	(0.000)	(0.001)
Apprentice		0.0513***	0.00949***	0.0273***
		(0.002)	(0.001)	(0.001)
Oth. Cont.	-0.00308***	0.00104		0.00259
	(0.001)	(0.001)		(0.002)
85% PT Cont.			0.00234***	0.00640***
			(0.001)	(0.002)
Firm size <50	0.00227***	-0.00476***	-0.00146***	0.000683**
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size 50-250	-0.00171***	-0.00518***	-0.000995***	0.000595**
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size all	-0.00107***	-0.00476***		
	(0.000)	(0.001)		
Age 14-19	0.0471***	0.0112***	0.0200***	0.0159***
	(0.002)	(0.001)	(0.002)	(0.001)
Age 20-29	-0.00117***	-0.0112***	-0.00129***	-0.00329***
	(0.000)	(0.000)	(0.000)	(0.000)
Age 30-39	-0.00677***	-0.00749***	-0.00460***	-0.00488***
	(0.000)	(0.000)	(0.000)	(0.000)
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***

	(1)	(2)	(3)	(4)
	ES 2014	ES 2002	IT 2014	IT 2002
	(0.001)	(0.000)	(0.001)	(0.001)
Textile	-0.0000472	0.00268***	0.00116*	0.00113
	(0.001)	(0.001)	(0.001)	(0.001)
Manuf wood	0.00101**	0.000533	-0.00328***	-0.000900**
	(0.001)	(0.000)	(0.000)	(0.000)
Manuf.	-0.00399***	-0.00419***	-0.00284***	-0.000120
	(0.001)	(0.001)	(0.000)	(0.001)
Metal Manuf.	-0.00785***	0.000253	-0.00697***	-0.00208
	(0.001)	(0.001)	(0.001)	(0.003)
Util.	-0.00221***	0.00256***	-0.00267***	-0.00115**
	(0.000)	(0.000)	(0.001)	(0.001)
Constru.	-0.00128***	0.00368***	-0.00817***	-0.00247***
	(0.000)	(0.000)	(0.000)	(0.001)
Retail	0.00123*	0.00969***	-0.00390***	0.00252***
	(0.001)	(0.001)	(0.001)	(0.001)
Transport	0.00417***	0.0132***	0.00848***	0.00892***
	(0.000)	(0.000)	(0.000)	(0.000)
Comms.	0.0127***	0.0111***	0.00601***	0.000654
	(0.001)	(0.001)	(0.001)	(0.001)
Food & Hotels	-0.0136***	-0.0115***	-0.00652***	-0.00161***
	(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 2.8.10: 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)
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***

	(1) CZ 2014	(2) CZ 2002	(3) HU 2014	(4) HU 2002	(5) RO 2014	(6) RO 2002
	(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 2.8.11: 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)

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

	(1)	(2)	(3)	(4)
	FI 2014	FI 2002	NL 2014	NL 2002
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 2.8.12: 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)
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***

	(1)	(2)	(3)	(4)	(5)	(6)
	FR 2014	FR 2002	LU 2014	LU 2002	UK 2014	UK 2002
	(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 2.8.9-2.8.12 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 2.9.13: 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 2.9.14: 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 2.9.15: 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 2.9.16: 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 2.9.17: 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 2.9.18: 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 2.9.19: 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 2.9.20: 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 2.9.21: 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 2.10.22: 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 2.10.23: 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 2.10.24: 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 2.10.25: 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 2.10.26: 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 2.10.27: 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 2.10.28: 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 2.10.29: 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 2.10.30: 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 2.10.31: Descriptive Statistics: Romania

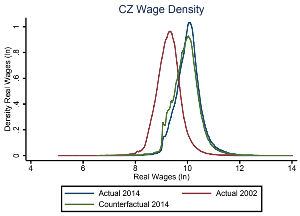
	(2002)		(2014)		(Diff in Means)
	Mean	SD	Mean	SD	Diff
Real Wage	2776.46	2981.95	2409.83	2413.89	366.63
Low AR	0.14	0.34	0.23	0.42	0.09
Med AR	0.60	0.49	0.58	0.49	-0.02
High AR	0.27	0.44	0.19	0.39	-0.08
Unk. AR	0.00	0.01	0.00	0.01	0.00
Edu	2.15	0.60	2.38	0.73	0.23
Priv. Owned	0.35	0.48	0.34	0.48	0.00
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 2.10.32: Descriptive Statistics: United Kingdom

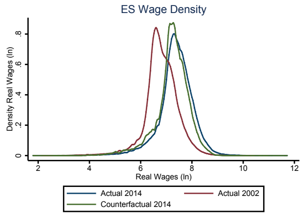
	(2002)		(2014)		(Diff in Means)
	Mean	SD	Mean	SD	Diff
Real Wage	1314.53	1220.48	2131.33	1775.09	816.80
Low AR	0.28	0.45	0.21	0.40	-0.07
Med AR	0.47	0.50	0.52	0.50	0.05
High AR	0.25	0.43	0.23	0.42	-0.02
Unk. AR	0.00	0.04	0.05	0.21	0.04
Edu	2.12	0.93	2.32	0.87	0.20
Priv. Owned	0.27	0.45	0.24	0.43	-0.03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

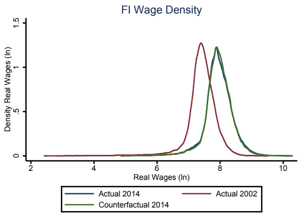
The decomposition RIF regressions consider three weighted distributions, the density of wages for the years 2002 and 2014 and the counterfactual distribution - 2014 wages with 2002 characteristics - which we display by country in Figure 2.4. While the weighted distributions closely follow the actual distribution in most cases, we do observe differences in some cases. In particular, there is an important role played by minimum wages in the cases of some East European countries - notably Hungary and Romania, with the peak of their distributions often at the lower end of the distribution. When the minimum wage law changes - that is, as we move from 2002 to 2014 - the floor shifts right suggesting an increase in minimum wages. For Western European nations the distributions are more Gaussian, though since our variable of interest is wages the natural distribution is longer tailed (results are presented in logs). Since we do not model minimum wages in our analysis, the initial density and the reweighted density are superimposed in those wage ranges. This implies that the wage setting variables are likely inadequate for modeling the distribution of wages when minimum wages matter. As such, we should be careful when interpreting results at the bottom of the distribution in those cases where minimum wages play a role. While minimum wages are found to play an important role in the distribution of wages in a number of countries, top-coding, where earnings is censored at a maximum threshold so that individuals who earn above a certain level appear to have the same income, does not appear to be an issue in any of the countries considered.



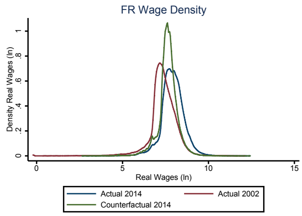
(a) Czech Republic



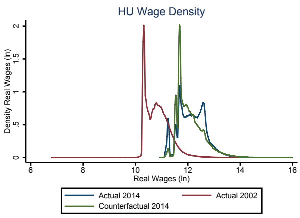
(b) Spain



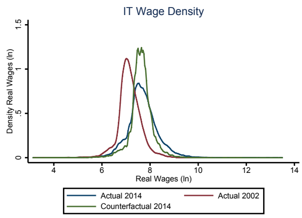
(c) Finland



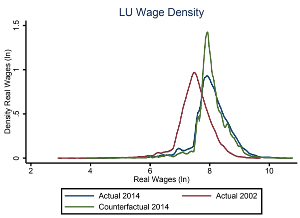
(d) France



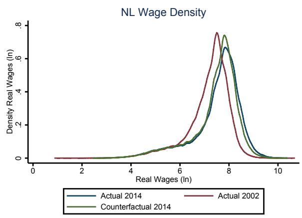
(e) Hungary



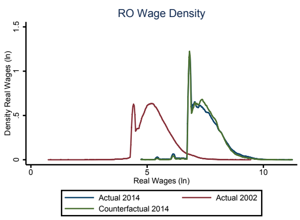
(f) Italy



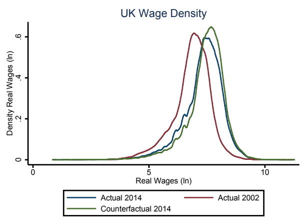
(g) Luxembourg



(h) Netherlands



(i) Romania



(j) United Kingdom

Figure 2.4: Wage Densities Across Europe: Actual and Counterfactual for 2002 & 2014

Chapter 3

The Knowledge Manager: Wage Premiums in Knowledge Diverse Industries

Larger industries are known to pay more, but are these premiums simply a reflection of industry size, or are they an expression of increased knowledge diversity? Firms operate much like a team - they coordinate a variety of tasks and specializations to produce a good or service. However, firms that have to manage diverse knowledge specializations have higher coordination costs, which are especially high for firms that combine knowledge specializations that are relatively dissimilar from one another. One way to reduce these burdensome costs is to hire individuals who are effective communicators, and offer a wage premium. As a result, workers who have more social and communication skills will sort into industries that have a high diversity of knowledge. I test this theory at the industry level, where I can empirically observe varying degrees of specialization. I develop a novel way to approximate the variety of specializations in an industry which can also capture relative knowledge distances between two occupations. Using fixed effects and matched differences regressions, my results show that workers in industries with high knowledge diversity receive a wage premium, especially for jobs that require social, communication and interpersonal skills. The diversity of knowledge in an industry explains an additional 10% of the variation in inter-industry wage premiums.

JEL classifications: J31, J21, J24

Keywords: Wage Differentials, Labor Force and Employment, Size and Structure, & Labor Productivity

1 Introduction

Why do individuals who have the same job and similar characteristics earn different wages depending on the industry? If an accountant who works in the communication sector has the same skills, abilities and competencies as an accountant in the education sector, their earnings should be similar. Workers would move towards industries that offer them the highest wages given their skillset. Contrary to this prediction, empirical evidence has found that earnings, even when controlling for a variety of characteristics, differ by industry in many country settings and time periods ((W. Dickens & Katz, 1987), (Krueger & Summers, 1988), (Abowd et al., 2000), (Abowd, Kramarz, & Margolis, 1999)).

One possible explanation as theorized by the efficiency wage theorem is that some industries pay above competitive market rates to capture higher skilled or more productive workers, while in other industries this may be less important (L. F. Katz, 1986). Workers who are well paid will feel they are fairly compensated, work harder, and therefore be more productive (Thaler, 1989). Firms have higher profit rates when they hire productive workers resulting in a win-win scenario for both players (W. Dickens & Katz, 1987). In addition to maximizing their profits, firms can reduce costs associated with supervision. Larger industries typically have higher monitoring costs than smaller industries, and will seek to reduce supervision costs. One way to reduce these costs is by hiring workers because productive are less likely to shirt. However, not all industries can offer higher wages. Large industries typically have high revenues and can therefore choose to share their rent with their employees, thereby offering wage above competitive market rates.

While this theory provides insight into possible mechanisms that cause inter-industry wage premiums, another explanation is the division of labor within an industry. Larger industries tend to have more specialization, but I argue that it is the degree of specialization that drives inter-industry wage premiums, and not the size of the industry alone. Like the pin factory that Adam Smith detailed so many years ago, specialization remains an important aspect of production to improve efficiency and productivity. Although, the organization of production is far different and workers are no longer repetitively placing bobs on pins, workers continue to specialize in parts of the production process - from highly automated production lines in car factories to platform based services like the car sharing app Lyft. As specialization increases, a coordination problem arises, and there are increasing costs in managing diverse specializations.

Consider a firm as a team who employs individuals that have a variety of specializations. Each member of the team specializes in a subset of tasks to produce the final product. The team will need to combine these tasks to optimize productivity. One way of improve the productivity of a team is by increasing the efficiency of a task through technological change, reducing coordination costs and/or increasing social skills.

The impact of technological change on productivity has long been discussed in terms of factor augmenting technological change, which is that innovation improves the efficiency of using capital and/or labor. Recent literature has highlighted how technology is changing tasks, particularly due to the impact of computers. A series of papers on skill biased technological change modeled and analyzed the type of tasks that waned or grew, and further, how these new technologies impact wages ((D. H. Autor et al., 2003), (Acemoglu, 2002), (David & Dorn, 2013), (Gathmann & Schönberg, 2010), (L. F. Katz & Margo, 2014), (Goos & Manning, 2007), (Goos, Manning, & Salomons, 2014)). They argue that routine tasks are codified, and these kind of tasks have a set of heuristics that can be followed. Computers can replicate these rules, and therefore substitute these types of tasks. However, non-routine tasks, particularly those that require cognitive thinking, are more tacit. It's difficult to explicate rules, making these tasks less likely to be automated. (D. H. Autor et al., 2003) find that the demand of routine tasks declined (where computers could substitute), while non-routine tasks increased (where computers could complement). This body of work highlighted which tasks could increase productivity more efficiently with the adoption of a computer. As technology advances, the type of tasks that computers and internet related technologies can automate also expands. More recent work has highlighted that artificial intelligence, machine learning and mobile robotics require creativity, innovation and social intelligence (Frey & Osborne, 2017). This research work surveyed experts in these new technologies to explain what type of tasks can be automated that can impact low skill and high skill jobs. Some examples they highlighted are using sensors to detect defects or assisting in legal preparation to identify important concepts. (MacCrory, Westerman, Alhammadi, & Brynjolfsson,

2014) found that there are higher occupational requirements for supervision, math and pattern recognition, but slightly lower requirements for teamwork when they applied a principal component analysis to compare job characteristics between 2006 and 2014.

More recently, demand and wage premiums associated with social skill-intensive jobs have risen ((Deming, 2017), (Weinberger, 2014)). One explanation is that these types of skills can't easily be automated because they are tacit. Rather, social skills complement technology. Deming makes the case that these type of "soft skills" are increasingly important in the labor market, especially if work is done in a team setting (2017). He builds a task-trade model, in which workers can specialize in tasks where they have a comparative advantage. Team members can trade these tasks, and for individuals who have more social skills, the costs of trading these skills decreases. Socially savvy workers can earn higher wages, by negotiating to do tasks where they have a comparative advantage. This increases their productivity and therefore their wages. Those that have low social skills will not have the advantage of trading more effectively, and end up having too many tasks to manage or do tasks where they do not have a comparative advantage.

Deming's model shows how social skills can reduce coordination costs in teams, and builds on the work of Becker & Murphy (1992). An important point of Becker & Murphy is that as the diversity of specialization increases, there are growing coordination costs. Deming focuses on the role that negotiating tasks has within a team to allow workers to effectively specialize, but there is considerably less attention given on the role of knowledge specialization. If the product that team is producing requires a variety of specializations, then the team will necessarily be larger and require more tasks. However, coordination within a team requires management of tasks and knowledge specialization. For example, imagine a company that sells software to help inventors patent. The team will require individuals who are knowledgeable about patent law, patent data, and computer programming. Optimally, if everyone knew a little bit about the patenting process, the coordination cost of creating a software program would decrease. However, if a patent lawyer doesn't know anything about data, and a computer programmer doesn't know anything about patenting, combining these varying knowledge bases can be costly. This example illustrates that what influences the total coordination cost is the degree of specialization within a team, and further, the relative knowledge base distance between specializations. Coordination cost is a function of the ease of knowledge transferability (Grant, 1996). The further the knowledge base distance, the more costly it is to transfer.

If individuals are particularly effective communicators, the cost of transmitting knowledge from these very different bases decreases, and the productivity of the entire team increases. As Deming has modeled, workers who have social skills can more effectively trade tasks, allowing them to increase their own productivity relative to others, thereby extracting a wage premium. Deming provides evidence of this at the individual level, but this excludes understanding these effects when there is a higher division of labor and knowledge diversity. Evaluating the role of social skills at the industry level provides a setting in which we can test if there are specific wage gains for individuals who work in environments that have a high diversity of knowledge, especially in regards to their returns to social skills. Workers who have higher social skills will sort into industries where they will get the most productive gains. Firms in knowledge diverse industries are willing to pay above competitive market wage rates for individuals who have more social and interpersonal skills so that firms can reduce the burden of coordination costs.

This paper contributes to the literature on inter-industry wage premiums, and illustrates that wage premiums are due to the division of labor and knowledge specialization, rather than just the size of an industry alone. An industry level setting provides an environment where it is possible to proxy the diversity of knowledge, and estimate varying returns to social skills across sectors. The estimates capture that there is a wage premium for working in a knowledge diverse industry, and reveals that this pay premium increases if the job requires more social skills.

In addition, I present estimates of these effects by occupation across industries, which indicates which particular occupations tend to receive a wage premium for being in a knowledge diverse industry. Another way to proxy the returns of social skills could be done by using firm-level information if information about wages, occupations and the department within the firm are provided, but using national level data allows us to estimate these returns across a wide variety of goods and services and can show general average effects that are not specific to the firm. One limitation that arises using industry level data is that I am unable to control for individual characteristics that may drive these wage differences. To ensure that relative wage premium differences are due to working in knowledge diverse industries and are not driven by individual attributes, I use a second source of data that is collected at the individual level and contains a variety of characteristics including occupation and education to confirm that my general results hold.

Another area of contribution is that I develop a way to measure the degree of knowledge specialization in an industry. Previous work that has looked at the relationship of the division of labor and wages focused on the complementarity of team members who work alongside educational specializations that complement one another (Neffke, 2019). Neffke's paper focused on estimating the complementarity and substitutability between educational fields, while in this paper, I directly proxy knowledge specialization using occupations. I develop a measure that approximates knowledge specialization within an industry using an industry-occupation network. Knowledge diversified industries are characterized by their labor inputs, which are the occupations that exist within an industry. I calculate the relative knowledge base distances between occupations, and use this information to characterize the similarity of occupations that exist in an industry. The measure that I develop can count the number of specialized occupations that exist in an industry, while also accounting for knowledge base distances between occupations.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 details how I measure the diversity of knowledge within an industry and the knowledge base differences between two occupations. Section 4 describes my empirical strategy in estimating knowledge diversity wage premiums across industries and occupations and is followed by a discussion of the results of these estimates in section 5. Section 6 discusses the limitations to the results and the implications these results have in a broader context.

2 Data

The main dataset used is the Occupation Employment Statistics (OES) provided by the Bureau of Labor Statistics (2015). Using this dataset, as opposed to microlevel data, provides information at the 6-digit occupational level for each 4-

digit industry. Additionally, the OES asks the establishment rather than employer about wages. This removes a common issue of underreporting income, which often occurs in self-reported earned income studies (Deaton, 1997). This is further highlighted by Abraham and Speltzer who find that occupational groups explain more variation in wages in OES compared to the Current Population Survey (CPS), and attribute this difference to using OES data (2016). Wage data are collected in 12 wage band categories and are censored above $190,000 and below the national minimum wage. The 10th, 25th, 50th, 75th and 90th percentile wages are provided, as well as, the average for each occupation and industry pair.

While this survey has been in existence since 1977, the NAICS classification system for industry identification drastically changed in 1997, as well as the standard occupational classification (SOC), which had structural changes in 2003. Hence, this dataset is compiled starting in 2003. In 2010, there was a small change in classification for 42 occupations. To smooth over this effect, occupation codes are reverted to the original 2003 classifications. Only 4 occupations[1] may have an over representativeness in their employment as they have two codes added together. However, these occupations are a very small part of the labor force and have a declining presence in the labor market.

Additionally, the BLS provides information about the ownership of establishments by industry code starting in 2009. To ensure a comparable time series, all ownership types are combined within an industry type, adding total employment and a weighted average income. Our main focus is on disaggregated enterprise industries, thus, local, state and federal government are excluded from the analysis. One limitation to using this dataset is that the publicly available data is not at the micro enterprise level data, but rather aggregated data by occupation and industry. One of the motivations in using this data is that in order to calculate knowledge diversity accurately using an industry-occupation network requires information to be at the most detailed level of occupations, ie the 6-digit level of SOC. Other datasets typically used to measure inter-industry wages tend to have broadly categorized industries or occupations profiles, such as the American Community Survey (ACS) or census data.

However, to ensure that the results are robust when using individual level

[1] Photographic process machine operators were aggregated into workers, and bookbinders were aggregated into bindery workers

data, this paper also uses ACS data extracted from IPUMS for 2003 - 2015 which include individual characteristics and which industry that person works in. Only individuals who are employed in full time work are included. The knowledge diversity measures calculated with the OES data are merged. Another variable that classifies occupations in STEM categories by Hecker is also included (Heckler, 2005).

3 Measuring Knowledge Diversity

The first task is to effectively measure knowledge diversity. Imagine a large media firm - what are the types of occupations needed for the firm to be operational? Perhaps, writers, talent agents, producers, and communication and media officers. However, they would also need coordinators, like secretaries to communicate between departments or graphic designers, to implement their ideas, and accountants to ensure their finances are in order. One can predict that there would likely be many more writers than accountants, but both jobs are vital to the firm's success. As a first step, we must count the number of occupations that are vital for the functioning of the industry.

Counting which occupation are necessary in an industry can be done in several ways. One way forward is to use relative employment as an indicator of importance. Janitors are an important occupation across many industries, but their job may not be vital to an industry. To differentiate which occupations are more important than others, we can compare the share of employment a janitor is hired compared to the total employment of the entire labor market. This provides a general outline of occupation specialization, which counts the number of different occupations that have a significant share of employment in the industry. I call this measure *diversity*. This approach is an important first step to filter which occupations are important, but it does not take into account that some occupations are more similar than others. In addition, it doesn't take into account the relative knowledge base differences between two occupations. In this section, I detail a new measure that can account for occupation relatedness, as well as identifying unique specialization which I call *weighted diversity*. This measure takes into account the similarity between occupations in an industry using an occupation-industry network, and it is inspired by the economic complexity literature (Hidalgo & Hausmann, 2009).

There are some important considerations to keep in mind when measuring the diversity of occupations within an industry: first, ensuring that the job is vital to the functioning of that industry and secondly, minimize the effect of outlier hiring so that the measurement is not skewed. Thus, the measurement should only include occupations that have a significant contribution to the labor market and filter occupations that do not have an impact in an industry. To do this, the Balassa index commonly known as revealed comparative advantage (RCA) is applied. Let x be the number of people working in occupation o in industry i where;

$$RCA_{io} = \frac{x_{io}/\sum_o x_i}{\sum_i x_o/\sum_{io} X} \tag{1}$$

When the occupation share of an industry is greater than the share of that occupation in the entire occupation population, then occupation, o is specialized in industry, i (i.e. when RCA ≥ 1). Occupations are specialized in an industry that hold the requirement:

$$M_{io} = \begin{cases} 0, & RCA_{io} < 1 \\ 1, & RCA_{io} \geq 1 \end{cases} \tag{2}$$

Where M is the occupation-industry matrix of total employment, o is the occupation and i is the industry. Where $RCA > 1$ for all M_{io} provides the foundation to calculate two measures of variety, *diversity* and *weighted diversity*.

Diversity is the count of the number of specialized occupations in an industry defined as:

$$k_i = \sum_o M_{io} \tag{3}$$

From the M_{io} matrix, a bipartite network can be built to understand the relatedness between two occupations, in which i is connected to o if there are more employees performing o in i than can be expected just by the size of o. In the measure of *diversity* the assumption is that occupations have similar skillsets if two industries significantly hire the same occupation.

The simple diversity measure is a broad indicator of knowledge diversity, but it does not take into account that hostesses and waiters have more related knowledge than waiters and fire inspectors. This is even more important with this dataset since there are around 700 occupations, and there are distinctions between chief executives and general operations managers. The measure should take into account that those two jobs are similar and thus, shouldn't necessarily be counted as equally distinct. The Adamic-Adar index takes this into account so that links are weighted by the similarity between two occupations (Adar & Adamic, 2005). The similarity between occupation o_n and o_m is the number of common neighbors N_s multiplied by the inverse of the logged degree of nodes (Z) and is defined as:

$$AA_{o_n,o_m} = N_s \frac{1}{log(Z_{o_n})} \tag{4}$$

Information about the how many common neighbors an occupation shares tells us something about which type of jobs an occupation works closely with. For example, a talent agent may work frequently with producers, actors, musicians and writers, and thus, they likely share a similar knowledge base. However, talent agents don't typically work with physicists or chemists, and thus, their knowledge bases a further away from one another. Including information about the degree of the shared occupation tells us how important that job is in the network. The measure is discounted, so that the impact of the degree does not take precedence over the shared network that two jobs may have in common.

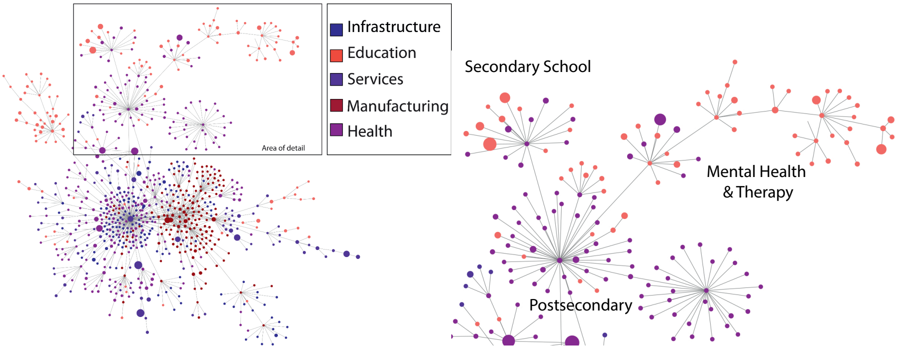
The weighted industry diversity measure is the diversity of an industry multiplied by the average normalized similarity weight (using the Adamic-Adar index) between two occupations in an industry. The measure is normalized by using the maximum Adamic-Adar index in a year so that values are between 0 and 1. The weighted diversity measure is defined as:

$$wk_i = \sum_{o_m} M_{io_m} * \frac{1}{N_{o_m}} \sum_{o_n} \frac{1}{max_{AA}} AA_{o_m,o_n} \quad (5)$$

The choice of a similarity index determines the weight between two occupations within the network, which is not trivial. In the context of using occupations within industries there are two issues that can be problematic, the varying sizes of an industry and secondly, the specialization of an occupation is an important characteristic of the industry. Typical measures for similarity, such as, cosine similarity, Jaccard indexes, conditional probability of links, or Euclidean distances do not take into account the specialization of an occupation or discount common occupations across industries. Using the Adamic-Adar index corrects for this issue because occupations that are unique are weighted more heavily than common occurring jobs in the network. 3.1b illustrates this point among education related occupations (see 3.5 for larger graph). For example, the figure shows that university professors often work with administrator managers and for certain fields, public relations managers - those professions tend to coordinate the knowledge of a variety of specialized professors.

Figures 3.1a and 3.1b visualize the occupation space network for 2015. Purely for visualization purposes, weak weight links are filtered by only drawing the top .0005% of the similarity weights in the data [2]. To best represent broader occupation categories, the Louvain community algorithm is applied to populate 5 communities or groups, which represents the color of the nodes. The size of the nodes is proportional to the total employment of that occupation for that year. The details of this visualization technique is provided in the appendix in section 7.1. While the visualizations are useful to ensure that the relatedness measure is intuitive and provides a map of the occupation space of the USA, the main purpose of this network methodology is to derive weights on occupations that work with a variety of other types of jobs.

[2] Following, a minimum spanning tree is applied using this filtered weighted network to populate the remaining edges. The threshold is arbitrary and purely based on trying to create a sparser and therefore more visible network



(a) 2015

(b) Area of detail, Education related occupations

Figure 3.1: Occupation-Industry Networks, see Appendix for enlarged 3.1b

Diversity and *weighted diversity* are the main variables of interest that reflect the variety of knowledge in an industry. Table 3.3.1 shows the correlation matrix of the calculated variety variables in 2014 and the percent of jobs that have management positions in an industry.

Table 3.3.1: Cross-correlation Table for Variety Measures

Variables	Weighted Div	Div	Mngmt %t
Weighted Div.	1.000		
Div	0.778	1.000	
Mngmt %	0.663	0.522	1.000

The calculated variables are highly correlated with each other, which reflects that the measurements are capturing similar levels of diversity, but the slight differences capture different aspects of occupational variety. Comparing the percent of management in an industry is a validity check since managers who have traditionally played a role in labor, knowledge and firm organization remain a vital part of coordination. With more complex industries there may also be a higher percentage of managers within industries for this very fact. The high correlation between the variables and the percent of management in an industry validates the intuition that the calculated variety variables likely capture the relationship between knowledge variety and the need for more coordination.

4 Estimation Strategy

With the measures of knowledge variety defined, this section details the models used to estimate knowledge diversity wage premiums. The first model is a fixed effects model to estimate the marginal returns associated with having social skills and interpersonal activities in knowledge diverse industries, and the second model estimates the returns of knowledge diversity for each occupation.

4.1 Fixed Effects Model

The fixed effects model shows meso-level effects. The dependent variable is logged annual average occupational real wages within an industry. Included in the regression are industry fixed effects, year fixed effects, occupation and industry level characteristics. There is an interaction term between knowledge diverse industries and social skills or interpersonal skills to test whether having more social skills in knowledge diverse industries pay more. A regression is run separately for social skills and interpersonal activities to assure that the results are not dependent on the type of measurement used. The regression is as follows:

$$ln\bar{w}_{oit} = \beta_1 Div_{it} + \beta_3 Div_{it} * Soc_{ot} + \beta_4 X'_{it} + \beta_5 X'_{ot} + \lambda_i + \lambda_t + \upsilon_{oit} \tag{6}$$

Our dependent variable ($\bar{w}$) is the natural log of annual real wages in US dollars at time t for occupation o in industry i. For all wage variables, real wages is calculated using the CPI index. Div is knowledge diversity, which is defined in the earlier section, where β_1 estimates the average effect at the industry level, i. We include time, t and industry i fixed effect parameters, which are represented by λ for any shocks that occur across the labor market during the observed time period (2003 - 2015), and unobservable differences between industries. The composite error term is υ_{oit}. Clustered robust standard errors are applied at the industry level to control for potential heteroskedasticity. To compare the effect among the knowledge diversity definitions, a regression is estimated for each measure discussed previously, which includes diversity, *weighted diversity*, entropy and percent of management.

Soc is a measure of social skills or interpersonal activities. This information is taken from the O*NET dataset, which provides 52 possible abilities, 35 possible skills, 41 work activities and 33 types of knowledge (U.S. Department of Labor & Administration, 2016). Each attribute is measured on a scale between 1-7 of importance for each occupation. Out of 35 skills, social skills include: coordination, negotiation, persuasion, and social perceptiveness[3]. Out of 41 activities 15 interpersonal activities are included as defined by O*NET[4] (U.S. Department of Labor & Administration, 2016).

The control variables, X'_{it}, at the industry level include industry size, industry employment growth rates, and the concentration of establishment size in an industry measured with the Herfindahl index (data from the statistics of US Businesses (SUSB), (Bureau, 2015). The controls at the occupational level, X'_{ot}, are the occupation employment size and occupation employment growth rates. A fast growing occupation may represent a job that is in high demand and potentially signals that the demand of that job outpaces the supply. This could impact wages of an occupation group, which is why it is included as a control. The occupation size may also represent the bargaining power a job may have. If an occupation is common and large across the economy, the ability of a worker to negotiate their salary is less than a worker who has a specialized skill set and hence, why this proxy is included in the model. After merging all of the datasets, 284 industries and 698 occupations remain. Summary statistics for all variables in the models are in the appendix in Table 3.7.7.

[3] The same 4 social skills is defined as Deming (2017). O*NET defines two additional social skills, service orientation and instructing, which is not included as these type of skills are not related to coordination management

[4] These include Assisting and Caring for Others, Coaching and Developing Others, Communicating with Persons Outside Organization, Communicating with Supervisors, Peers, or Subordinates, Coordinating the Work and Activities of Others, Developing and Building Teams, Establishing and Maintaining Interpersonal Relationships, Guiding, Directing, and Motivating Subordinates, Interpreting the Meaning of Information for Others, Monitoring and Controlling Resources, Performing Administrative Activities, Performing for or Working Directly with the Public, Provide Consultation and Advice to Others, Resolving Conflicts and Negotiating with Others, Staffing Organizational Units. Training and Teaching Others, Selling or Influencing Others are not included in this measure, but it is defined by O*NET as interpersonal activities. These two activities are excluded for the same reason as to why some social skills are excluded.

4.2 Fixed and Random Effects Model

The structure of the OES dataset has occupations nested within industries and this motivates our third model, which includes both random effect parameters and fixed effects. This type of model is sometimes called a multilevel or mixed effects model. It is similar to a random coefficients model, and allows for parameter variation for occupations across industries, but the model also includes fixed effects parameters, namely industry and year fixed effects. The random coefficient model has group specific least square coefficient vectors, which is why it can consider the grouping structure that exists in the data and allows occupations to be repeated within one industry to another. Of course, not every occupation exists in a particular industry with some occupations that are ubiquitous across industries and others that are specialized in a few industries. This isn't a problem since the random coefficient variance takes this into account. The variance of the estimates across occupations is accounted for as it portions some of the cross-unit variation to the parameters instead of putting all of the variation into the disturbances (Greene, 2003). Another way to view this is that the random effect parameters estimate occupation specific deviations from the general population effect, and thus, estimate the knowledge diversity wage premium for each occupation. Not every occupation will receive a wage premium. For example, a janitor is integral to the functioning of any firm, but they may not receive a knowledge diversity premium since their job doesn't require transmitting knowledge to various specializations. Occupations who receive a knowledge coordination premium are limited to a subset of occupations, and this model will capture these differences.

Weighted diversity is estimated at the industry level, and thus, weighted diversity that is associated with an occupation depends on the industry. The variance captured in the estimation model is not from within each industry, but rather, across industries, and this is why random coefficients can be estimated at the occupational level. Further, since the model is estimating the impact on wages, random intercepts are also included in the model to capture the average pay level of that occupation. The particular variable of interest (weighted diversity) for each occupation (random coefficients) is estimated, while also controlling for occupation specific and industry-wide characteristics simultaneously. In addition, the model also estimates distinct variances for each within-group error and distinct covariances for each within-group error pair. The model is estimated using maximum likelihood to find appropriate ranges of fixed and random effect parameters and optimizes until it reaches converges. The model is as follows:

$$ln\bar{w}_{oit} = \beta_1 Wdiv_{it} + \beta_2 Soc_{ot} + \beta_3 Div_{it} * Soc_{ot} + \beta_4 X'_{it} + \beta_5 X'_{ot} + \gamma_o + \lambda_i + \lambda_t + \upsilon_{oit} \quad (7)$$

The specification, variables and dataset are the same as in 6, but this model includes γ_1 as the random coefficient at the occupation level o related to knowledge diversity and the random intercept parameters for each occupation is γ_o. The model estimates the knowledge diversity wage premium for each occupation. Since industry level fixed effects are included, all of the variation of weighted diversity is captured by the occupation random effect parameters. Thus, the mean population effect at the industry level will be close to zero with the occupation random effect parameters capturing all the weighted diversity variation.

5 Results

5.1 Diversity Premiums: Skills, Activities & Abilities

The first set of results in Table 3.5.2 provides a baseline of comparison and overview of the relationship between knowledge diversity and wages that exclude occupation random coefficients, but include the controls discussed in Equation 7, year and industry fixed effects, and is estimated with OLS. There are two measures within O*NET, one that uses social skills, and another that is interpersonal activities, and for robustness, both measures are compared. Thus, a total of 8 regressions in Table 3.5.2 is reported to help understand if there is an additional wage premium due to a person being in a highly knowledge diverse industry and having a job that requires social or interpersonal skills. The results slightly vary depending on whether skills or activities is used. Weighted diversity is statistically significant at the 1% level when using either measure. Percent of management is highly significant for social skills, but not in terms of interpersonal activities. Diversity is significant at the 10% level for social skills, but significant at the 1% level for interpersonal activities. Entropy does not have a significant impact with either measure. These varying results suggest that measurement matters. Industries that hire more managers intuitively require more coordination and supervision, but it fails to distinguish whether the need for more management is due to coordination or for more supervision to deter shirking. The fact that social skills are important, but not interpersonal activities suggests that managers earn wages for their social skills, but not for the coordination activities. Managers However, the weighted diversity measure captures that doing coordination (interpersonal activities) is as important as communicating (social skills). The diversity measure captures some of this relationship, as well. However, social skills are not as important as interpersonal activities, which is evident in the magnitude of effect, and the loss of significance in social skills. This difference is due to the fact that the weighted diversity measure accounts for the difference in knowledge bases between one occupation to another, while diversity does not. Consequently, interpersonal activities when working with a wide variety of specializations is important, however, if one works in an industry where there are many types of jobs, but the work is similar to one another, communication is easier, and the cost of coordination is lower. This explains why having both social skills and interpersonal activities is important in industries that have disparate knowledge bases and diverse specializations. Finally, Entropy doesn't have a relationship to wages. The measure captures the concentration of an occupation within an industry, and this highlights that there is a difference between concentration and variety. While concentration can show the dispersion within an indicator, it is not a substitute for understanding how many different items may exist.

Beyond the measures of interest, there are two things to note in these results. First, social skills and interpersonal activities are important to earnings since no matter which measure is used, the effect is large and significant on wages. Secondly, while industry size has been shown to explain inter-industry wages in previous work, these results indicate that industry size doesn't play a strong role. Industry size is significant at the 10% level in most cases, except when weighted diversity is included, which results in industry size to lose its statistical significance, and further, the coefficients are not large suggesting that an increase of industry size by 10% is associated with a 1.4% increase in wages.

Table 3.5.2: Fixed Effects Results with Wages as Dependent Var

	Social Skills				Interpersonal Activities			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Div.	-0.0218***				-0.0110***			
	(0.003)				(0.003)			
Ent		-0.0262				0.0665*		
		(0.033)				(0.034)		
Div			0.00139*				0.00268***	
			(0.001)				(0.000)	
Mngmt %				-2.699**				-0.550
				(1.202)				(0.940)
Social Skills	0.595***	0.639***	0.713***	0.635***	0.552***	0.649***	0.666***	0.584***
	(0.011)	(0.029)	(0.017)	(0.017)	(0.011)	(0.030)	(0.012)	(0.014)
Weighted Div. × Skills/Act.	0.00850***				0.00480***			
	(0.001)				(0.001)			
Ent × Skills/Act.		0.0146				-0.0163		
		(0.010)				(0.011)		
Div × Skills/Act.			-0.000412*				-0.000846***	
			(0.000)				(0.000)	
Mngmt % × Skills/Act.				1.066***				0.392
				(0.394)				(0.305)
HH	0.413***	0.383***	0.388***	0.319***	0.412***	0.385***	0.390***	0.313**
	(0.103)	(0.103)	(0.102)	(0.116)	(0.109)	(0.111)	(0.110)	(0.126)
Ind Size	0.0135	0.0140*	0.0132*	0.0167**	0.0141	0.0143*	0.0139*	0.0180**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Occ. Growth	0.0336***	0.0339***	0.0341***	0.0340***	0.0394***	0.0394***	0.0395***	0.0395***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Occ. Size	-0.0459***	-0.0449***	-0.0448***	-0.0449***	-0.0430***	-0.0424***	-0.0425***	-0.0425***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	8.895***	8.735***	8.565***	8.738***	8.963***	8.648***	8.649***	8.813***
	(0.124)	(0.139)	(0.113)	(0.113)	(0.129)	(0.146)	(0.113)	(0.115)
N	384604	384604	384604	384604	384604	384604	384604	384604
N Industries	284	284	284	284	284	284	284	284

Standard errors in parentheses, Robust-clustered standard errors

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

Since the model has a nonlinear term between knowledge coordination premiums and social skills, the most effective way to evaluate marginal effects is through visualization. Weighted diversity, the main measure of interest, and percent of management, the baseline variable is presented. Figures 3.2 and 3.3, show the calculated marginal effect of the measure of variety and social skills on wages, respectively[5]. Figure 3.2 depicts the estimated increase in wages due to the level of knowledge diversity in an industry a person is working in as social skills and interpersonal activities. Figure 3.2 shows the estimated increase in wages due to the increase in the skill intensity requirement level as the level of knowledge diversity increases. These figures show the marginal effect of the respective variable of interest (skill or diversity measure) holding all other variables constant.

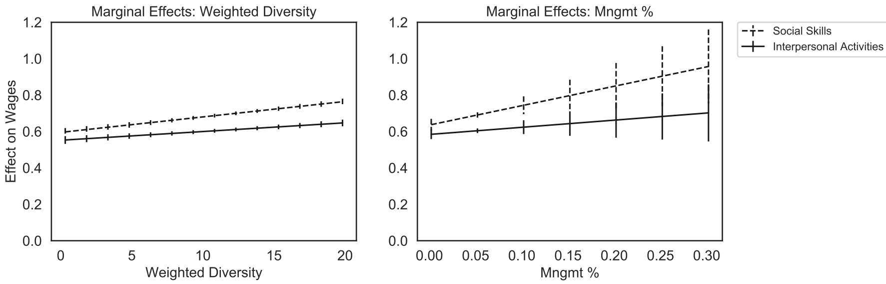


Figure 3.2: Marginal Effects of Diversity from Table 3.5.2

Knowledge diverse industries pay better, particularly for jobs that have social skills or are involved in interpersonal activities. However, those with low social skills or interpersonal activities do not see income gains from being in a knowledge diverse industry, where the knowledge premium is not statistically significant, and in the case of interpersonal activities in the weighted diversity measure, the impact is negative. An increase of one additional new occupation (weighted) in an industry is associated with an expected increase in income between -0.8% to 1.2% in conjunction with social skills, while the interpersonal activities -0.2 to 0.9 % , approximately. Keep in mind that the maximum weighted diversity measure is 21.5 and the standard deviation is 5.35. A one percentage point increase in the percent of management in an industry is associated with an expected increase in income between -1.1% to 1.56% with social skills, and when estimated with

[5] The minimum and maximum are determined by the dataset's actual minimum and maximum for that particular measure of variety

interpersonal activities, 0.13% - 1.12% approximately. The 99th percentile has 14% of employment in management positions. Knowledge diversity premiums have a fairly large effect on income as more knowledge diverse industries are associated with higher wages, and this effect is more prominent when using the weighted diversity measure as compared to the percent of management in an industry. An occupation with high social skills or does many interpersonal activities in a highly diverse industry can make around 10 percentage points more - that's similar in the pay bump one might get from having a graduate degree (as compared to a high school degree) (Heckman, Lochner, & Todd, 2006).

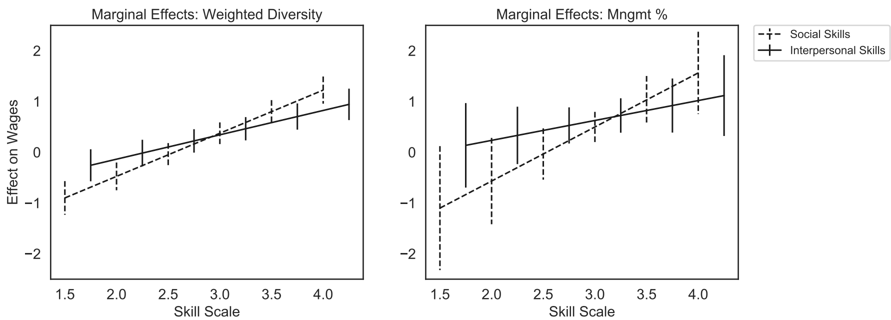


Figure 3.3: Marginal Effects of Social Skills and Interpersonal Activities from Table 3.5.2

Workers also earn a wage premium if they have more social skills or do more interpersonal activities in their work. Figure 3.2 displays the marginal effect of having social or interpersonal skills. As weighted diversity and percent of management increases, there is a slight increase in wages. The standard errors increase in percent of management as there are very few industries that have more than 15% in management occupation. The slope of the effect of variety on wages is relatively similar for both social and interpersonal skills in the weighted diversity measure, but in the case of percent of management, interpersonal activities has less of an income gain than having more social skills. The effect of social skills on wages between all measures are remarkably similar, ranging between 60% - 70%, approximately. Social skills impact wages for workers - the more social skills you have, the higher wages you will likely have, but this effect does not vary as much as knowledge diversity.

5.2 The Marginal Return of Diversity Premiums and Social Skills

This section described the knowledge diversity estimates from Equation 7. The occupation random effect parameters estimate the deviation of each occupation from the average knowledge diversity effect. The model also estimates initial wages for each occupation. The first step in model verification is to ensure that the slopes vary across occupations, i.e. that the estimated knowledge variety premium depends on the occupation, by comparing the null model, without the occupation level knowledge variety variable, to the full model in Equation 7 with a likelihood-ratio test. Our results conclude that in all cases the slopes do vary across occupations. This is further evident in Table 3.5.3, where the standard deviation of the knowledge variety slope estimates are significant. While the standard deviation is not very large, however, it supports the intuition that some occupations receive knowledge variety premium, while others do not - after all, not all occupations require the management of a variety of knowledge streams. Initial levels of income by occupation vary quite significantly given the estimated standard deviation estimates of the random effect intercepts, although this result is hardly surprising. Additionally, the random occupation intercept and slopes are statistically significantly negatively correlated as evidenced in Table 3.5.3, with the exception of percent of management. This result is reaffirmed with a likelihood-ratio test between structure and unstructured models, and suggests that jobs that have lower starting salaries tend to have higher knowledge diversity slopes meaning that knowledge diversity premiums are more important for low salary jobs as compared to higher paid jobs.

Table 3.5.3: Random Effect Model Statistics

Parameters	Estimate	Std. Err.	95% Conf. Interval
	Social Skills		
S.D.W. Div.	.010	.000	0.009,0.010
S.D. Cons	.355	.001	0.336,0.374
Corr(W. Div., Cons)	-.166	0.040	-0.243,-0.085
S.D. Residual	.128	0.000	0.128,0.129
	Interpersonal Activities		
S.D. W. Div.	0.010	.000	0.009, 0.010
S.D. Cons	0.361	.010	.0342, 0.381
Corr(W. Div., Cons)	-.132	0.040	-0.210, -0.051
S.D. Residual	0.128	0.000	0.128, 0.129

The model's advantage is that it can estimate the knowledge diversity premium by occupation. The broad occupation random effect parameter estimates (RE Est.) provided in Table 3.5.4 are averages from the detailed occupation estimates, which are available in the appendix. The table also provides average social skill and interpersonal activity for the job category, and the number of industries that the occupation is present (N. Ind.). The four categories that earn a wage premium are computer and mathematical, management, sales, and business and financial operations. The other categories do not earn wage premiums. Management, sales and business operation are occupations one might expect to earn a premium given that they are jobs that require social skills and coordination activities. However, the interesting result is the computer and mathematic occupations who earn the highest wage premiums. This suggests that those who work with digital technologies in knowledge diverse industries earn a wage premium. It pays off to have technical skills that are required in computer and mathematics along with social skills and being able to coordinate projects pays off.

Table 3.5.4: Knowledge Diversity Estimates by Broad Occupation Group

Broad Occupation Category	RE Est.	Soc. Skills	Int. Act.	N. Ind.
Computer and Mathematical	0.004	2.812	2.861	41.86
Management	0.002	3.571	3.644	68.643
Sales and Related	0.002	3.340	2.993	38.833
Business and Financial Operations	0.001	3.226	3.251	48.33
Life, Physical, and Social Science	-0.000	3.003	3.165	15.95
Transportation and Material Moving	-0.000	2.693	2.808	40.71
Arts, Design, Ent., Sports, and Media	-0.001	3.046	2.962	24.03
Protective Service	-0.001	2.889	3.089	13.571
Office and Administrative Support	-0.002	2.857	2.897	53.09
Legal Occupations	-0.002	3.325	2.908	12.250
Installation, Maintenance, and Repair	-0.003	2.635	2.763	32.93
Architecture and Engineering	-0.003	2.924	2.964	35.64
Production Occupations	-0.004	2.482	2.519	31.130
Food Preparation and Serving Related	-0.005	3.028	2.964	14.42
Education, Training, and Library	-0.005	3.089	3.241	10.27
Healthcare Practitioners and Technical	-0.007	3.139	3.340	13.50
Building and Grounds Maintenance	-0.007	2.717	2.888	18.17
Farming, Fishing, and Forestry	-0.008	2.664	2.723	12.44
Construction and Extraction	-0.008	2.631	2.784	15.89
Healthcare Support	-0.008	2.887	3.083	9.77
Community and Social Service	-0.010	3.610	3.570	14.42
Food Preparation and Serving Related	-0.011	2.777	2.894	13.73

5.3 Robustness Tests

The fixed effect model provide general associations of the effect of knowledge diversity controlling for industry and occupational characteristics at an aggregated level, but it does not control for observed individual characteristics. In this section, I present a robustness test to affirm if wage premiums are rooted in industry differences due to knowledge diversity, rather than individual characteristics. Here, I match individuals with individual level data and test for differences in earnings between knowledge homogenous versus knowledge diverse industries. Two groups are created using the American Community Survey Dataset, a "treated group" with workers who are in high knowledge diverse industries, and a "control" group that consist of individuals employed in knowledge homogenous industries. Knowledge heterogeneous industries are defined as industries that are above the 90th percentile of the weighted diversity measure, which is around 15 weighted diverse occupations. Knowledge homogenous industries are below the 40th percentile of the weighted diversity measure, which are industries that have less than 5 weighted diverse occupations. Individuals are matched using the Mahalanobis method from these two groups based on observable characteristics with the following specification:

$$\begin{aligned} Pr(T = 1|X) = x = \beta_1 Occ + \beta_2 Gender + \beta_3 StemOcc \\ + \beta_4 Gender * StemOcc + \beta_5 Age + \beta_6 MartStat \\ + \beta_7 Fertyr + \beta_9 MartStat * Gender + \beta_{10} Fertyr * Gender * StemOcc \\ + \beta_{11} Educ + \beta_{12} Race | \beta_{13} Educ * Race \\ + \beta_{14} State + \beta_{15} City \end{aligned} \tag{8}$$

Occ is the occupation that an individual works in, *Gender* is a binary variable of the gender of the individual, *StemOcc* is a dummy variable if the occupation is listed as a STEM occupation defined by Heckler (Heckler, 2005), *Age* is the age of the individual, $MartStat$ is the marital status of the individual, $Fertyr$ is a dummy variable whether that person had a new child that year, *Educ* is the highest level of education that person achieved, *Race* is the race of that individual, *State* is the state in which they live in, *City* is a dummy variable on whether that individual lives in a city or urban environment. Each of these variables contribute to explaining wages, and details on the description and motivation of the model on these characteristics and categories within each variable are included in the appendix.

Table 3.5.5 presents mean differences for some of the characteristics between the unmatched and matched knowledge homogenous group compared and the knowledge heterogenous group for 2005. I have excluded some characteristics for brevity, such as occupation code or state. The propensity score matching improves the similarity between the treated and untreated groups, but there are some limitations. The treated and untreated groups have statistically significant differences. However, the averages between the groups across the characteristics are not economically meaningful. For 2005, there are approximately 13,000 individuals in the untreated group and 4,000 in the treated group. After matching, there are approximately 850 individuals in the untreated group and 630 in the treated group of which there is common support. Since I match within each year, the sample sizes slightly change over time with 1,300 individuals in the untreated group and 850 in the treated group for those with common support in 2015. The matching reduces biasedness from the covariates by a large amount, however, given that that the matching is still limited, the estimates could be slightly biased. Thus, I caution interpreting the coefficient results as unbiased. However, the method provides insight on the persistence of the diversity wage premium, particularly over time, even when we control for a variety of individual characteristics.

Table 3.5.5: Mean Differences between Treated and Control Groups for 2005

		Mean		
Variable	Group	Treated	Control	p
Female	Unmatched	0.30652	0.54187	0
	Matched	0.42205	0.53543	0
Age	Unmatched	43.481	41.937	0
	Matched	42.444	42.468	-0.971
No Schooling	Unmatched	0.00448	0.00374	0.512
	Matched	0	0	.
Grade 5-8	Unmatched	0.01619	0.02002	0.121
	Matched	0.00157	0.00157	1
3.educ	Unmatched	0.00921	0.01261	0.082
	Matched	0.00315	0.00315	1
Grade 10	Unmatched	0.01743	0.02552	0.003
	Matched	0.00315	0.00315	1
Grade 11	Unmatched	0.02266	0.02987	0.016
	Matched	0.00157	0.00157	1
High School Degree	Unmatched	0.40936	0.36125	0
	Matched	0.5685	0.5685	1
1 year of College	Unmatched	0.14293	0.16175	0.004
	Matched	0.13386	0.13386	1
2 years of College	Unmatched	0.08292	0.10475	0
	Matched	0.03307	0.03307	1
4 years College	Unmatched	0.18999	0.16106	0
	Matched	0.19528	0.19528	1
5+ years College	Unmatched	0.10209	0.11644	0.012
	Matched	0.05984	0.05984	1
Peripheral Metropolitan	Unmatched	0.21564	0.18055	0
	Matched	0.14961	0.14961	1
Mixed Metropolitan Area	Unmatched	0.44547	0.40984	0
	Matched	0.6189	0.6189	1
Not in a Metropolitan Area	Unmatched	0.14666	0.15694	0.115
	Matched	0.10866	0.10866	1
Unknown Metropolitan Status	Unmatched	0.08889	0.0845	0.384
	Matched	0.04409	0.04409	1
Small Industry	Unmatched	0.15886	0.0107	0
	Matched	0.00787	0.00787	1
Medium Industry	Unmatched	0.84114	0.6156	0
	Matched	0.99213	0.99213	01
Large Industry	Unmatched	0	0.3737	0
	Matched	0	0	.

The matched treatment and control groups are compared using an OLS regression to see if those in the treated group earn more than the control group. Matching and estimation is repeated for each year from 2005-2015 with bootstrapped standard errors. The average treatment effect is presented in Figure 3.4. Across all years, there is a significant difference in wages between individuals who work in high and low knowledge diverse industry, where those in high knowledge diverse industries get paid more, despite having similar characteristics which reconfirms the findings. The estimates are consistent across time periods, and the estimates suggest that if a person works in a very knowledge diverse industry they can earn approximately 135% more compared to someone who works in a similar job in a knowledge homogenous industry conditional on observed characteristics. This suggests that the measure doesn't explain rising inequality over the time period, as the estimates are similar across the time period, but it does provide evidence that the knowledge diversity premium explains part of earnings.

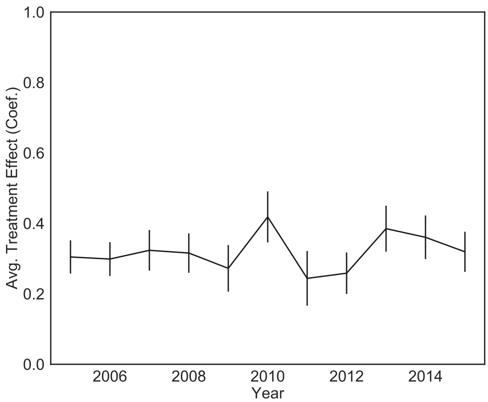


Figure 3.4: Average Treatment Effect Between High and Low Knowledge Diversity Industries

These results confirm the fixed effect results in that individuals who work in knowledge diverse industries earn a wage premium and indicate that controlling for individual characteristics and using disaggregated data do not change our main conclusions.

6 Conclusion

Inter-industry wage premiums have been a long standing puzzle within economics. Previous literature found that the size of the industry can explain part of wage differences, but even while accounting for the size of an industry, there still remains an unexplained portion. In this paper, I show that part of the inter-industry wage premium gap can be explained by the variety of knowledge in an industry. Combining a variety of tasks and knowledge can require a substantial amount of coordination. This is especially true if the good requires a combination of knowledge bases that are distant from one another. Firms who have to manage variety of knowledge have high coordination costs, and one way that they can reduce these coordination costs is by hiring individuals who are effective communicators. In this paper, I develop a novel metric using network statistics that approximates the variety of knowledge in an industry, and accounts for knowledge base distances between occupations. I apply a series of fixed effects regressions at the industry level to show that part of the inter-industry wage gap can be explained by the variety of knowledge in an industry. To ensure that my results are not driven by individual characteristics, I use a matched differences regression that illustrates that the wage gains for being in a knowledge diverse industries, even while controlling for the size of an industry, explains part of earnings. In addition, I find that social and communication skills can provide additional wage gains in knowledge diverse industries, which is especially important for computer and mathematic jobs, managerial positions, and sales related jobs.

Recently, social skills gained prominence in the literature as evidence has found that these types of skills have been growing in demand. My results are consistent with this work, but highlight the the role that social skills in easing coordination costs associated with diverse knowledge specializations. One good example that illustrates the growing importance of coordination is a telephone operator at a bank. Online checking systems have made it easier to check balances and make transfers and payments online rather than through the phone. Instead, telephone operators act as online chaperones who can guide you through more complicated problems like fraud or how to open a new account. operators used to connect individuals to the appropriate department, but now their skills are moving towards skills associated with problem solving technical issues. What is most valuable in the labor market is the skills to communicate effectively, especially when working with a varied knowledge base. This paper provides evidence that working in knowledge diverse industries can be lucrative, especially for those who have social and interpersonal skills. I also show that this premium is related to more high skilled jobs. Future work should address in more detail the mechanism as to why high skilled, and typically more unique jobs tend to receive a wage premium.

The future of the importance of certain skills related to knowledge coordination remains unclear. Aspects of social skills and interpersonal activities could be automatized in the future, such as speech clarity. Predicting which skills remain vital in the labor market is difficult. A limitation in this paper is that it does not address future employability or growing employability of these types of skills in the labor market, which have been considered by others ((Deming, 2017), (Frey & Osborne, 2017), (Arntz, Gregory, & Zierahn, 2016)). Neither does this paper discuss the impact of inequality or wage distribution due to these changing skill demands, which has also been discussed at length by others. Rather, this paper insists that organizing people, ideas and knowledge will remain vital in the labor market. Whether these organization skills will be more likely to be employed or not is unclear, but at the same time an effective secretary - often the central node of operations in a firm - clearly adds value. Automating personal skills, negotiation or persuasion seem much less likely to happen in the future. While some aspects of coordination might be undervalued, communication, social and interpersonal skills have and will likely remain important, especially for occupations such as a project manager, who has to manage a variety of knowledge streams.

Technology impacts our daily lives at rates far faster than many of us think we can adapt to. Nonetheless, adaptation is necessary because it impacts the way that we work and which skills are valued. This paper has illustrated that social and interpersonal skills are not only vital in the workplace, but profitable and valuable for individuals. Investing in social, communication and interpersonal skills should be embedded in our public education system at all levels, from primary through tertiary. However, investment in these skills go far beyond the monetary benefits. On a philosophical level, these types of skills are essential for civil society and democracy. They enable us to communicate our ideas, persuade others and find consensus in an ever-changing environment.

7 Appendices

7.1 Visualizing network graphs

An undirected network graphs of the labor market is created for every year of the industry occupation matrix/data from 2003 to 2015. The network can be projected on either the industry or occupation side. In this paper, the relevant projection is on the occupation side to measure occupational similarity rather than industry similarity. Nonetheless, the author also has similarity statistics and networks on the industry side and if interested, please contact the author directly.

For every year, 93 percentile of the similarity index distribution (ie weight) is calculated. For consistency, a percentile is chosen, which means the actual cut-off threshold changes depending on the relative weight of the year. However, the choice of the percentile is arbitrary and purely based on reducing the number of edges so the network graph is not too dense visually. Additionally, a minimum spanning tree (MST) is applied, also known as Kruskal's algorithm, as the layout algorithm (1956). The method uses the weights of the edges to prioritize which links are connected visually. Typically, this method finds an edge of the least possible weight that connects any two edges. Instead, the algorithm used finds the largest possible weight that connects any two edges. It starts by connecting two nodes with an edge that has the largest weight and continues to look for the next largest weight that does not create a cycle until the entire tree is connected. Our method doesn't effect the statistics that are used for the measures of variety and is purely used for the purpose of visualizing the network.

Our community detection algorithm is the much used Louvain method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). The method searches for high modularity partitions in large networks. The method begins by having each node as a community, it then considers a nodes links and evaluates the gain of modularity for placing it one community and removing it from another. Based on the gain, the algorithm decides which community the node best belongs. This continues until the local maxima of modularity is reached. The weights from the Adamic-Adar index are used with a resolution of .95. The resolution is arbitrary and is only used to help define communities that do not contain only a few occupations.

The program cytoscape is used to create the graphs based on the network edge list and weights calculated from the MST and community algorithms. Adobe InDesign is also used to touch up these graphs to add text and alter some edge distances so that occupation names can be more clearly read.

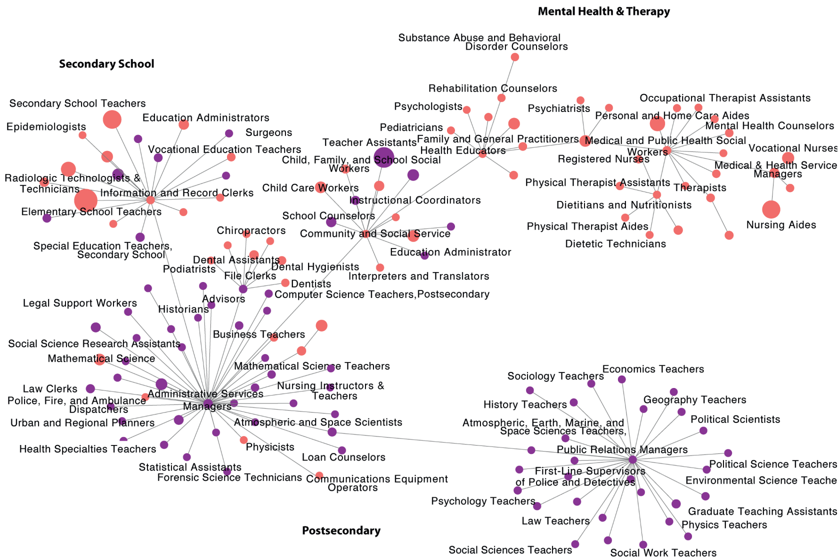


Figure 3.5: Area of Detail from 3.1a, Education Related Occupations

7.2 Entropy Measurement

Another important facet of industry diversity is the concentration of a particular occupation in an industry. Often this is done by measuring the expected information (occupations) in a distribution, which is also called *Shannon's Law* or *Entropy*. This measure is very similar to the Herfindahl index, which has been used to measure occupational concentration or specialization within establishments as opposed to industries (Handwerker & Spletzer, 2016). Entropy, or Shannon's Law, is another measure of variety, which takes into account the probability occupation, o, is likely to be in that industry where s is the share of the number of people in occupation, o, in industry, i, which is defined as:

$$E_i = -\sum_{i=o} s_o ln(s_o) \tag{9}$$

7.3 Industry Variety Statistics

Table 3.7.6: Variety Measures by Industry

Stat	Entropy	Div	W. Div	Mngmt %
Mean	2.99	73.98	12.81	0.05
SD	0.58	27.54	5.41	0.02
Min	0.82	8.00	0.38	0.01
Max	3.81	132.00	21.53	0.10
p25	2.80	56.00	9.54	0.03
p75	3.40	96.00	17.21	0.06

Source: Author's own calculations

Table 3.7.7: Summary statistics for Control Vars.

Stats	HH	LP	Ind Size*	Ind Growth	Occ. Wage*	Emp Growth	Emp Size*
Mean	0.20	106.78	12.18	0.02	5.32	0.02	12.11
SD	0.03	20.82	1.09	0.10	0.46	0.06	1.52
Min	0.19	70.75	7.98	-0.22	4.41	-0.35	4.87
Max	0.50	296.39	16.08	1.07	6.70	1.60	15.33
p25	0.19	96.93	11.47	-0.00	4.95	-0.01	11.08
p75	0.20	113.19	12.85	0.03	5.62	0.04	13.14

Source: Author's own calculations

*Variables are in natural log units

Table 3.7.8: Summary Statistics for Social Skills and Interpersonal Activities

Stats	**Social Skills**	**Interpersonal Act.**
Mean	2.94	2.99
SD	0.45	0.45
Min	1.66	1.73
Max	3.94	4.25
p25	2.60	2.66
p75	3.28	3.32

Source: Author's own calculations

Table 3.7.9: Industry Variety Measures

Industry Name	Entropy	Div	Mgt %	W. Div.
Other Electrical Equipment and Component Manuf...	3.59	102.0	0.06	21.53
Industrial Machinery Manufacturing	3.62	96.0	0.08	21.07
Commercial and Service Industry Machinery Manu...	3.80	111.0	0.07	20.72
Electric Lighting Equipment Manufacturing	3.54	84.0	0.07	20.34
Electrical Equipment Manufacturing	3.50	101.0	0.06	20.09
Other General Purpose Machinery Manufacturing	3.48	111.0	0.06	19.89
Medical Equipment and Supplies Manufacturing	3.55	129.0	0.06	19.70
Soap, Cleaning Compound, and Toilet Preparatio...	3.19	79.0	0.06	19.49
Cutlery and Handtool Manufacturing	3.44	80.0	0.06	19.41
Other Fabricated Metal Product Manufacturing	3.47	119.0	0.05	19.38
Nonferrous Metal (except Aluminum) Production ...	3.54	96.0	0.05	19.10
Agriculture, Construction, and Mining Machiner...	3.43	108.0	0.04	19.05
Ventilation, Heating, Air-Conditioning, and Co...	3.19	91.0	0.05	19.03
Communications Equipment Manufacturing	3.61	91.0	0.09	18.99
Forging and Stamping	3.41	82.0	0.05	18.89
Plastics Product Manufacturing	3.38	99.0	0.05	18.89
Pharmaceutical and Medicine Manufacturing	3.60	109.0	0.07	18.68
Navigational, Measuring, Electromedical, and C...	3.73	127.0	0.08	18.25
Pesticide, Fertilizer, and Other Agricultural ...	3.29	67.0	0.07	18.21
Semiconductor and Other Electronic Component M...	3.43	96.0	0.06	18.18
Paint, Coating, and Adhesive Manufacturing	3.19	68.0	0.08	18.08
Converted Paper Product Manufacturing	3.10	80.0	0.05	18.04
Steel Product Manufacturing from Purchased Steel	3.46	80.0	0.05	18.02
Resin, Synthetic Rubber, and Artificial Synthe...	3.42	84.0	0.06	18.02
Other Chemical Product and Preparation Manufac...	3.25	70.0	0.06	17.87
Engine, Turbine, and Power Transmission Equipm...	3.30	90.0	0.06	17.82
Other Miscellaneous Manufacturing	3.65	132.0	0.06	17.71

Industry Name	Entropy	Div	Mgt %	W. Div.
Boiler, Tank, and Shipping Container Manufactu...	3.29	81.0	0.05	17.60
Spring and Wire Product Manufacturing	3.56	78.0	0.06	17.49
Rubber Product Manufacturing	3.24	78.0	0.04	17.49
Motor Vehicle Parts Manufacturing	3.19	100.0	0.04	17.40
Professional and Commercial Equipment and Supp...	3.58	107.0	0.08	17.32
Metalworking Machinery Manufacturing	3.23	80.0	0.06	17.32
Other Nonmetallic Mineral Product Manufacturing	3.55	89.0	0.05	17.21
Glass and Glass Product Manufacturing	3.30	74.0	0.04	17.17
Basic Chemical Manufacturing	3.30	101.0	0.06	17.17
Coating, Engraving, Heat Treating, and Allied ...	3.04	76.0	0.06	17.12
Hardware Manufacturing	3.35	64.0	0.08	16.97
Chemical and Allied Products Merchant Wholesalers	3.31	82.0	0.10	16.96
Household Appliances and Electrical and Electr...	3.55	95.0	0.09	16.75
Household Appliance Manufacturing	3.01	68.0	0.04	16.70
Metal and Mineral (except Petroleum) Merchant ...	3.20	75.0	0.07	16.59
Aerospace Product and Parts Manufacturing	3.66	123.0	0.04	16.48
Architectural and Structural Metals Manufacturing	3.23	98.0	0.05	16.45
Audio and Video Equipment Manufacturing	3.35	65.0	0.10	16.39
Miscellaneous Durable Goods Merchant Wholesalers	3.23	96.0	0.06	16.39
Alumina and Aluminum Production and Processing	3.40	76.0	0.04	16.07
Drugs and Druggists' Sundries Merchant Wholesa...	3.24	89.0	0.07	15.92
Clay Product and Refractory Manufacturing	3.18	57.0	0.05	15.65
Grain and Oilseed Milling	3.20	70.0	0.06	15.62
Other Transportation Equipment Manufacturing	3.12	70.0	0.06	15.62
Machinery, Equipment, and Supplies Merchant Wh...	3.32	94.0	0.07	15.52
Machine Shops; Turned Product; and Screw, Nut,...	2.86	70.0	0.05	15.20
Manufacturing and Reproducing Magnetic and Opt...	3.65	63.0	0.07	15.19
Office Furniture (including Fixtures) Manufact...	3.27	84.0	0.05	15.13
Petroleum and Coal Products Manufacturing	3.45	104.0	0.05	15.00
Foundries	3.26	82.0	0.04	14.97
Paper and Paper Product Merchant Wholesalers	3.10	67.0	0.07	14.95
Beverage Manufacturing	3.19	78.0	0.04	14.94
Animal Food Manufacturing	3.21	71.0	0.06	14.87
Computer and Peripheral Equipment Manufacturing	3.18	69.0	0.09	14.86
Electronic Shopping and Mail-Order Houses	3.32	100.0	0.06	14.77
Motor Vehicle Body and Trailer Manufacturing	2.71	78.0	0.03	14.72
Natural Gas Distribution	3.81	116.0	0.06	14.71
Iron and Steel Mills and Ferroalloy Manufacturing	3.26	80.0	0.03	14.71
Other Food Manufacturing	3.17	71.0	0.05	14.66
Veneer, Plywood, and Engineered Wood Product M...	3.18	67.0	0.03	14.58
Newspaper, Periodical, Book, and Directory Pub...	3.54	95.0	0.06	14.44

Industry Name	Entropy	Div	Mgt %	W. Div.
Hardware, and Plumbing and Heating Equipment a...	3.03	67.0	0.07	14.38
Pulp, Paper, and Paperboard Mills	3.12	76.0	0.04	14.35
Cement and Concrete Product Manufacturing	2.83	73.0	0.04	14.02
Dairy Product Manufacturing	3.03	70.0	0.04	13.78
Furniture and Home Furnishing Merchant Wholesa...	3.08	62.0	0.08	13.62
Other Furniture Related Product Manufacturing	2.76	56.0	0.04	13.50
Railroad Rolling Stock Manufacturing	3.18	56.0	0.04	13.45
Household and Institutional Furniture and Kitc...	3.02	76.0	0.04	13.32
Sugar and Confectionery Product Manufacturing	2.93	66.0	0.04	13.19
Ship and Boat Building	3.26	89.0	0.03	13.13
Wholesale Electronic Markets and Agents and Br...	2.87	98.0	0.07	13.08
Fruit and Vegetable Preserving and Specialty F...	3.00	62.0	0.03	13.07
Software Publishers	3.05	73.0	0.10	12.95
Lumber and Other Construction Materials Mercha...	3.06	81.0	0.06	12.87
Electric Power Generation, Transmission and Di...	3.46	124.0	0.05	12.86
Printing and Related Support Activities	2.88	69.0	0.05	12.64
Oil and Gas Extraction	3.74	110.0	0.07	12.44
Apparel, Piece Goods, and Notions Merchant Who...	3.00	59.0	0.08	12.35
Lime and Gypsum Product Manufacturing	3.33	48.0	0.04	12.24
Seafood Product Preparation and Packaging	2.48	48.0	0.03	12.05
Tobacco Manufacturing	3.09	41.0	0.07	11.98
Textile and Fabric Finishing and Fabric Coatin...	2.92	50.0	0.05	11.97
Sawmills and Wood Preservation	2.88	58.0	0.03	11.81
Other Wood Product Manufacturing	3.01	77.0	0.04	11.79
Motor Vehicle and Motor Vehicle Parts and Supp...	3.08	69.0	0.06	11.74
Cable and Other Subscription Programming	3.18	71.0	0.05	11.64
Bakeries and Tortilla Manufacturing	2.89	55.0	0.03	11.54
Wired Telecommunications Carriers	2.80	73.0	0.03	11.51
Miscellaneous Nondurable Goods Merchant Wholes...	3.04	82.0	0.06	11.27
Fabric Mills	2.81	54.0	0.04	11.20
Beer, Wine, and Distilled Alcoholic Beverage M...	2.40	41.0	0.07	11.11
Wireless Telecommunications Carriers (except S...	3.02	63.0	0.05	11.01
Motor Vehicle Manufacturing	2.01	44.0	0.02	10.72
Accounting, Tax Preparation, Bookkeeping, and ...	2.41	58.0	0.06	10.60
Grocery and Related Product Merchant Wholesalers	2.88	70.0	0.05	10.54
Petroleum and Petroleum Products Merchant Whol...	2.89	64.0	0.07	10.52
Textile Furnishings Mills	2.92	52.0	0.04	10.33
Cut and Sew Apparel Manufacturing	2.13	45.0	0.04	10.23
Other Textile Product Mills	2.72	56.0	0.04	10.19
Metal Ore Mining	3.60	82.0	0.02	9.89
Radio and Television Broadcasting	3.10	69.0	0.09	9.73

Industry Name	Entropy	Div	Mgt %	W. Div.
Nonmetallic Mineral Mining and Quarrying	3.29	70.0	0.04	9.55
Direct Selling Establishments	2.89	53.0	0.05	9.54
Travel Arrangement and Reservation Services	2.58	56.0	0.06	8.96
Animal Slaughtering and Processing	2.71	59.0	0.02	8.96
Footwear Manufacturing	2.24	28.0	0.03	8.93
Warehousing and Storage	2.39	56.0	0.03	8.91
Support Activities for Mining	3.12	100.0	0.03	8.91
Farm Product Raw Material Merchant Wholesalers	2.96	54.0	0.05	8.84
Fiber, Yarn, and Thread Mills	2.13	33.0	0.02	8.03
Other Leather and Allied Product Manufacturing	2.54	37.0	0.04	7.95
Coal Mining	3.20	61.0	0.02	7.40
Vending Machine Operators	2.26	32.0	0.04	7.40
Water, Sewage and Other Systems	2.77	55.0	0.05	7.31
Apparel Knitting Mills	2.52	25.0	0.02	7.16
Furniture Stores	2.09	39.0	0.03	6.94
Leather and Hide Tanning and Finishing	2.79	23.0	0.05	6.78
Apparel Accessories and Other Apparel Manufact...	2.29	32.0	0.03	6.59
Specialized Freight Trucking	1.78	41.0	0.03	6.35
Lawn and Garden Equipment and Supplies Stores	2.51	40.0	0.03	5.98
Other Miscellaneous Store Retailers	2.09	38.0	0.03	5.93
Building Material and Supplies Dealers	2.13	38.0	0.03	5.43
Automobile Dealers	2.58	52.0	0.05	5.41
General Freight Trucking	1.38	27.0	0.03	5.14
Home Furnishings Stores	1.78	37.0	0.03	4.91
Drycleaning and Laundry Services	1.87	25.0	0.02	4.87
Electronics and Appliance Stores	1.79	29.0	0.03	4.50
Specialty Food Stores	2.57	46.0	0.02	4.34
Used Merchandise Stores	1.67	18.0	0.02	4.11
Automotive Parts, Accessories, and Tire Stores	2.19	25.0	0.03	4.02
Other Motor Vehicle Dealers	2.52	40.0	0.05	4.02
Medical and Diagnostic Laboratories	2.78	59.0	0.02	3.98
Beer, Wine, and Liquor Stores	1.31	14.0	0.03	3.95
Book Stores and News Dealers	1.32	13.0	0.03	3.84
Office Supplies, Stationery, and Gift Stores	1.55	23.0	0.03	3.62
Automotive Repair and Maintenance	2.31	32.0	0.03	3.45
Sporting Goods, Hobby, and Musical Instrument ...	1.45	35.0	0.03	3.39
Florists	1.49	14.0	0.02	3.39
Gambling Industries	3.02	72.0	0.02	3.37
Amusement Parks and Arcades	2.70	66.0	0.02	3.24
Traveler Accommodation	2.81	73.0	0.02	2.66
Other General Merchandise Stores	2.07	28.0	0.01	2.42

Industry Name	Entropy	Div	Mgt %	W. Div.
Department Stores	1.80	28.0	0.01	2.14
Jewelry, Luggage, and Leather Goods Stores	1.08	14.0	0.03	2.13
Grocery Stores	2.12	37.0	0.02	2.06
Health and Personal Care Stores	2.11	28.0	0.02	1.56
Clothing Stores	0.96	14.0	0.01	1.54
Shoe Stores	0.82	8.0	0.02	1.52
Special Food Services	2.51	26.0	0.01	1.24
Restaurants and Other Eating Places	2.28	20.0	0.01	1.14
Drinking Places (Alcoholic Beverages)	1.68	23.0	0.01	1.08
Gasoline Stations	1.01	15.0	0.01	0.77
Personal Care Services	1.66	16.0	0.01	0.38

7.4 Full Tables

Table 3.7.10: Multilevel Results with Wages as Dep. Var.

	Social Skills				Interpersonal Activities			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Div.	-0.00529*				-0.00194			
	(0.003)				(0.003)			
Social Skills	0.536***	0.565***	0.567***	0.523***	0.459***	0.484***	0.494***	0.447***
	(0.033)	(0.035)	(0.039)	(0.031)	(0.030)	(0.032)	(0.035)	(0.029)
Weighted Div. × Skills/Act.	0.00157				0.000398			
	(0.001)				(0.001)			
Div		-0.0000164				0.000160		
		(0.000)				(0.000)		
Div × Skills/Act.		0.0000241				-0.0000357		
		(0.000)				(0.000)		
Ent			0.00147				0.0144	
			(0.018)				(0.017)	
Ent × Skills/Act.			-0.00141				-0.00574	
			(0.006)				(0.006)	
Mngmt %				-3.117***				-2.326***
				(0.388)				(0.368)
Mngmt % × Skills/Act.				0.890***				0.601***
				(0.132)				(0.122)
HH	0.318***	0.310***	0.294***	0.244***	0.318***	0.310***	0.294***	0.244***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Ind Size	0.0174***	0.0163***	0.0179***	0.0191***	0.0174***	0.0162***	0.0179***	0.0191***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ind Growth	-0.0000329	-0.0000137	-0.0000326	0.000137	-0.0000319	-0.0000129	-0.0000317	0.000137
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Occ. Growth	0.00175*	0.00141	0.00156*	0.00219**	0.00175*	0.00140	0.00156*	0.00219**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occ. Size	0.00316**	0.00545***	0.00438***	0.000448	0.00336**	0.00564***	0.00457***	0.000634
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	8.586***	8.480***	8.481***	8.674***	8.773***	8.678***	8.654***	8.858***
	(0.097)	(0.103)	(0.116)	(0.094)	(0.092)	(0.097)	(0.108)	(0.088)
N	384604	384604	384604	384604	384604	384604	384604	384604

Standard errors in parentheses, Robust-clustered standard errors

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

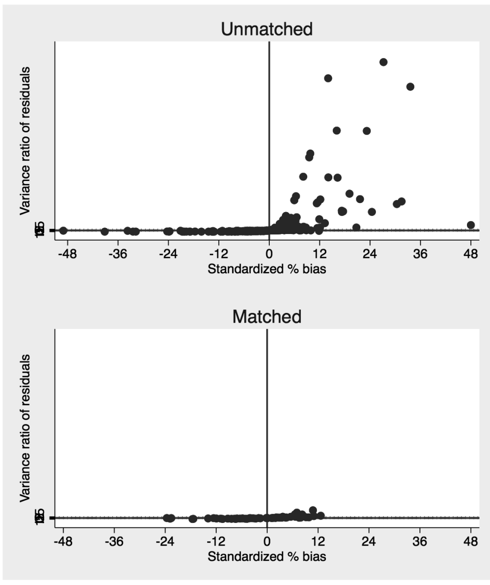
7.5 Robustness Tests

7.5.1 Matched Differences

I include a variety of variables that are well known to explain earning differences. Some earning differences are inherent to the occupation and education, which is why I include occupation code and education levels. In the United States, geography also plays a large role because of standard of living differences, and hence, I match for state and metropolitan area. Previous research has shown that marital status explains wage differences, but favor married men as compared to married women (Loh, 1996). Hence, I include an interaction term for marital status and gender. In addition, women are often penalized when they have their first child, which is why I interact gender with year of child birth. In addition, previous research has shown that there are pay differences related to STEM occupations in regards to gender, and hence, I interact gender and if the occupation is in STEM to account for this (Beede et al., 2011). I include a triple interaction between year of birth, STEM occupation and gender to account for any additional relationship between these three variables. I also interact race and education as the racial wage gap varies depending on the level of education. Last, I include match for industry size to ensue that pay differences are due to diversity and not the size of the industry, as it is possible that the larger the industry it may be more likely to have a larger diversity of knowledge. I use the Mahalanobis matching technique and consider age, occupation group, industry size, metropolitan status, and education as the most important variables for matching, and use a caliper size of .01.

Figure 3.6 displays a scatter plot between the standardized percentage bias versus the residual variance ratio of all the variables used in matching.

Figure 3.6: Bias vs. Residual Variance of Matched vs. Unmatched Groups



7.5.2 Various Fixed Effect Models

The following tables provides fixed effects for industry, occupation, and there interaction over time. Including all fixed effect interactions over time preforms poorly given the lack of variance, especially when including the interaction of occupation and year fixed effects. The results remain robust when including various other fixed effects within the regression for social skills or interpersonal activities.

Table 3.7.11: Multi-level Models with Wages as Dep. Var. for Social Skills

	(1)	(2)	(3)	(4)	(5)	(6)
W. Div	-0.0218***	-0.0140***	-0.0142***	-0.126***	-0.0911***	-0.0760
	(-7.83)	(-6.96)	(-7.02)	(-39.80)	(-11.68)	(-0.01)
Social Skills	0.595***	1.312***	1.373	0.594***	1.324***	0.994
	(53.96)	(75.27)	(.)	(53.70)	(75.72)	(.)
W. Div * Social Skills	0.00850***	0.00535***	0.00539***	0.00855***	0.00539***	0.00543***
	(10.07)	(8.75)	(8.71)	(10.08)	(8.79)	(8.74)
HH	0.413***	0.315***	0.264***	129.2***	114.7***	91.73
	(4.02)	(4.44)	(4.10)	(98.08)	(13.35)	(.)
Ind Size	0.0135	0.0179***	0.0144**	4.202***	3.743***	2.924
	(1.56)	(3.43)	(2.88)	(118.89)	(12.62)	(0.09)
Ind Growth	-0.000228	-0.0000267	0.0000680	4.164***	3.843***	2.968
	(-0.37)	(-0.05)	(0.16)	(119.21)	(12.79)	(.)
Occ. Growth	0.0336***	0.00142	0.156	0.0336***	0.00185*	0.0893
	(5.48)	(1.57)	(.)	(5.42)	(2.10)	(.)
Occ. Size	-0.0459***	0.00557*	-0.0168	-0.0459***	0.00157	0.119
	(-32.88)	(2.05)	(.)	(-32.74)	(0.57)	(0.00)
Constant	8.878***	6.287***	6.381	-64.58***	-59.10***	-45.42
	(86.71)	(76.83)	(0.01)	(-102.68)	(-11.64)	(-0.01)
Year FE	Y	Y	Y	Y	Y	Y
Occ FE	N	Y	Y	N	Y	Y
Ind FE	Y	Y	Y	Y	Y	Y
Ind*Year FE	N	N	N	Y	Y	Y
Occ*Year FE	N	N	Y	N	N	Y
N	384604	384604	384604	384604	384604	384604

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7.12: Multi-level Models with Wages as Dep. Var. for Interpersonal Activities

	(1)	(2)	(3)	(4)	(5)	(6)
W. Div.	-0.0110***	-0.0115***	-0.0116***	-0.0633***	-0.0935***	-0.0732
	(-3.79)	(-6.39)	(-6.47)	(-16.58)	(-12.14)	(.)
Int. Act.	0.552***	2.027***	1.457	0.552***	2.045***	0.528
	(49.77)	(80.11)	(.)	(49.48)	(80.62)	(0.00)
W. Div. * Int. Act.	0.00480***	0.00443***	0.00447***	0.00483***	0.00446***	0.00450***
	(5.46)	(8.45)	(8.42)	(5.45)	(8.47)	(8.45)
HH	0.412***	0.314***	0.263***	68.68***	109.0***	93.99
	(3.77)	(4.45)	(4.12)	(30.34)	(11.96)	(.)
Ind. Size	0.0141	0.0181***	0.0146**	2.339***	3.760***	2.986
	(1.57)	(3.48)	(2.94)	(36.23)	(12.36)	(0.06)
Ind. Growth	-0.000410	-0.0000334	0.0000644	2.282***	3.841***	3.040
	(-0.65)	(-0.07)	(0.15)	(35.01)	(12.41)	(0.04)
Emp. Growth	0.0394***	0.00140	0.125	0.0393***	0.00183*	0.0517
	(5.97)	(1.56)	(.)	(5.91)	(2.09)	(.)
Emp. Size	-0.0430***	0.00565*	0.139	-0.0431***	0.00166	0.359
	(-31.57)	(2.09)	(.)	(-31.42)	(0.60)	(0.00)
Cons.	8.907***	3.614***	4.130	-31.21***	-60.74***	-47.81
	(83.58)	(35.00)	(0.00)	(-26.98)	(-11.53)	(.)
Year FE	Y	Y	Y	Y	Y	Y
Occ FE	N	Y	Y	N	Y	Y
Ind FE	Y	Y	Y	Y	Y	Y
Ind*Year FE	N	N	N	Y	Y	Y
Occ*Year FE	N	N	Y	N	N	Y
N	384604	384604	384604	384604	384604	384604

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

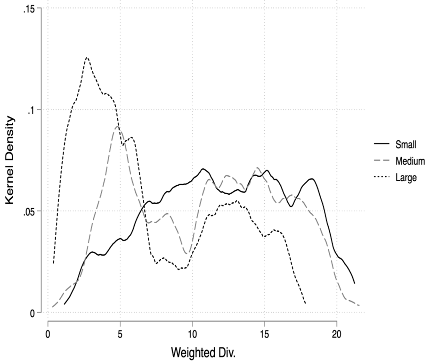
7.5.3 Industry Size

Coordination among knowledge diversity may be dependent on the industry size. I split my sample by industry size and run fixed effects models to see if there are changes in the estimates depending on the industry size. Small industries are those below the 25% of the industry size distribution, medium is the 25-75th quartiles, and large industries are defined as the 75% percentile and above.

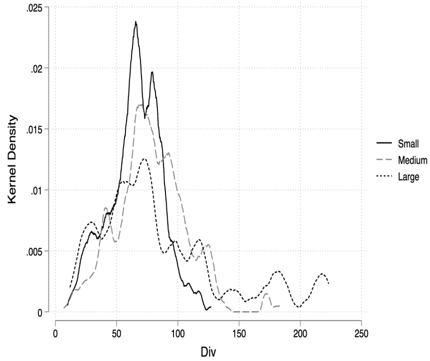
Table 3.7.13: Weighted Diversity Fixed Effects Regressions by Industry Size

	Baseline			Social Skills			Interpersonal Activities		
	(Sm)	(Med)	(Lg)	(Sm)	(Med)	(Lg)	(Sm)	(Med)	(Lg)
W. Div.	0.00232	0.00504***	0.000936	-0.0193***	-0.0185***	-0.0190*	-0.0120**	-0.00691	-0.000878
	(0.90)	(3.82)	(0.31)	(-5.32)	(-5.16)	(-2.44)	(-2.95)	(-1.92)	(-0.14)
HH	0.489***	0.696***	0.304	0.381***	0.658***	0.282	0.404***	0.649***	0.279
	(5.69)	(4.60)	(0.55)	(6.04)	(5.26)	(0.58)	(5.07)	(4.79)	(0.53)
Emp. Growth	0.0947***	0.0547***	0.0444**	0.0444***	0.0351***	0.0273*	0.0631***	0.0407***	0.0291**
	(4.50)	(4.20)	(2.67)	(4.17)	(4.31)	(2.63)	(5.31)	(4.66)	(2.97)
Emp Size (ln)	-0.0215***	-0.0342***	-0.0482***	-0.0454***	-0.0445***	-0.0490***	-0.0452***	-0.0414***	-0.0447***
	(-5.58)	(-10.32)	(-10.09)	(-20.93)	(-25.36)	(-14.07)	(-21.54)	(-23.16)	(-13.20)
Social Skills				0.632***	0.604***	0.583***			
				(42.40)	(41.90)	(27.53)			
W. Div * Soc. Sk.				0.00671***	0.00799***	0.00685*			
				(6.85)	(7.54)	(2.59)			
Int. Act.t							0.586***	0.562***	0.550***
							(34.19)	(41.58)	(27.24)
W. Div * Int. Act.							0.00425***	0.00397***	0.000674
							(3.75)	(3.73)	(0.31)
Cons.	10.54***	10.65***	10.90***	8.950***	8.953***	8.906***	9.062***	9.023***	8.912***
	(168.39)	(201.67)	(80.82)	(143.20)	(151.20)	(84.90)	(128.88)	(155.97)	(79.52)
N	96176	192187	95819	96176	192187	95819	96176	192187	95819

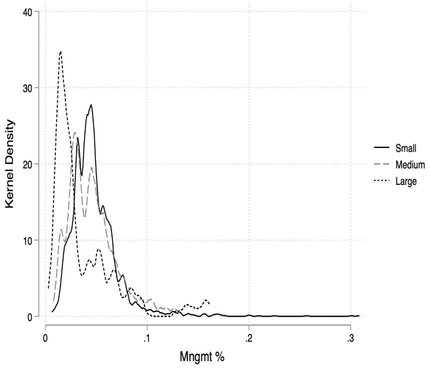
t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, Year and Industry Fixed Effects Included



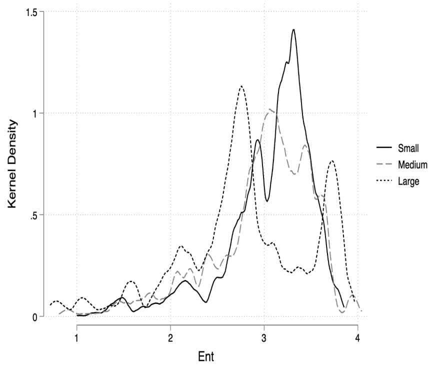
(a) Distribution of Weighted Diversity by Industry Size



(b) Distribution of Diversity by Industry Size



(c) Distribution of Percent of Management by Industry Size



(d) Distribution of Entropy by Industry Size

Figure 3.7: Distribution of Diversity Measures by Industry Size

7.6 Occupation level estimates of Knowledge Diversity Premiums

Table 3.7.14: Knowledge Diversity Estimates by Occupation

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
393092	0.06	2.90	2.82	8	Costume Attendants
532022	0.03	3.12	3.28	10	Airfield Operations Specialists
395091	0.03	2.94	3.17	6	Makeup Artists, Theatrical and Performance
132052	0.02	3.19	3.56	10	Personal Financial Advisors
472072	0.02	2.50	2.50	5	Pile-Driver Operators
537111	0.02	2.03	2.22	3	Shuttle Car Operators
474061	0.02	2.47	3.10	4	Rail-Track Laying and Maintenance Equipment Op...
535011	0.02	2.78	2.81	14	Sailors and Marine Oilers
453011	0.02	2.62	2.22	1	Fishers and Related Fishing Workers
172151	0.02	2.88	3.14	8	Mining and Geological Engineers, Including Min...
419012	0.02	2.47	1.73	7	Models
534021	0.02	2.44	2.55	2	Railroad Brake, Signal, and Switch Operators
193094	0.02	3.00	2.95	6	Political Scientists
272012	0.02	3.52	3.53	24	Producers and Directors
352013	0.02	2.63	2.43	1	Cooks, Private Household
513091	0.02	2.69	2.84	16	Food and Tobacco Roasting, Baking, and Drying ...
194092	0.02	2.81	2.87	6	Forensic Science Technicians
518011	0.02	2.97	2.76	2	Nuclear Power Reactor Operators
194041	0.02	2.67	2.52	15	Geological and Petroleum Technicians
413031	0.02	3.36	2.99	14	Securities, Commodities, and Financial Service...
535021	0.02	3.07	3.02	19	Captains, Mates, and Pilots of Water Vessels
192042	0.01	2.84	3.09	15	Geoscientists, Except Hydrologists and Geograp...
112031	0.01	3.75	3.69	40	Public Relations Managers
534011	0.01	2.44	2.74	4	Locomotive Engineers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
339099	0.01	3.00	3.32	15	Protective Service Workers, All Other*
519197	0.01	2.16	2.25	2	Tire Builders
172171	0.01	3.28	3.11	14	Petroleum Engineers
193099	0.01	3.28	3.65	8	Social Scientists and Related Workers, All Other
119071	0.01	3.72	3.79	3	Gaming Managers
152021	0.01	2.59	2.76	6	Mathematicians
111021	0.01	3.75	3.78	222	General and Operations Managers
339021	0.01	3.06	3.00	19	Private Detectives and Investigators
193041	0.01	3.28	2.97	3	Sociologists
119121	0.01	3.22	3.50	24	Natural Sciences Managers
152091	0.01	1.66	1.76	4	Mathematical Technicians
534031	0.01	3.03	2.55	4	Railroad Conductors and Yardmasters
271022	0.01	3.75	3.67	15	Fashion Designers
411012	0.01	3.72	4.07	87	First-Line Supervisors/Managers of Non-Retail ...
193092	0.01	2.84	2.90	3	Geographers
475013	0.01	2.84	3.58	9	Service Unit Operators, Oil, Gas, and Mining
132082	0.01	2.78	3.05	2	Tax Preparers
112011	0.01	3.53	3.10	54	Advertising and Promotions Managers
413011	0.01	3.66	2.87	14	Advertising Sales Agents
536041	0.01	2.91	2.77	2	Traffic Technicians
535022	0.01	2.75	2.87	6	Motorboat Operators
152041	0.01	2.77	3.02	28	Statisticians
132053	0.01	2.87	3.02	9	Insurance Underwriters
119111	0.01	3.75	3.87	18	Medical and Health Services Managers
192032	0.01	2.91	3.02	18	Materials Scientists
271011	0.01	3.34	3.30	34	Art Directors
514022	0.01	2.56	2.45	23	Forging Machine Setters, Operators, and Tender...
518012	0.01	2.75	3.10	6	Power Distributors and Dispatchers
173025	0.01	2.94	2.68	22	Environmental Engineering Technicians
499093	0.01	2.31	2.15	3	Fabric Menders, Except Garment
113011	0.01	3.41	3.31	112	Administrative Services Managers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
339011	0.01	2.97	3.16	2	Animal Control Workers
193021	0.01	2.94	3.17	103	Market Research Analysts
333051	0.01	3.63	3.69	3	Police and Sheriff's Patrol Officers
475061	0.01	2.62	2.43	4	Roof Bolters, Mining
436012	0.01	2.69	2.83	4	Legal Secretaries
132061	0.01	3.40	3.21	16	Financial Examiners
499095	0.01	3.16	3.94	5	Manufactured Building and Mobile Home Installers
434051	0.01	3.31	3.38	99	Customer Service Representatives
119141	0.01	3.62	3.74	18	Property, Real Estate, and Community Associati...
132021	0.01	2.83	2.69	12	Appraisers and Assessors of Real Estate
516061	0.01	2.53	2.40	8	Textile Bleaching and Dyeing Machine Operators...
499042	0.01	2.41	2.46	136	Maintenance and Repair Workers, General
273031	0.01	3.75	3.64	56	Public Relations Specialists*
517032	0.01	2.35	2.03	5	Patternmakers, Wood
112022	0.01	3.94	3.85	143	Sales Managers
152031	0.01	2.72	3.05	42	Operations Research Analysts
112021	0.01	3.69	3.49	103	Marketing Managers
514071	0.01	2.13	2.42	14	Foundry Mold and Coremakers
537061	0.01	2.10	2.08	42	Cleaners of Vehicles and Equipment
251194	0.01	3.00	3.54	8	Vocational Education Teachers, Postsecondary
475012	0.01	2.97	3.15	5	Rotary Drill Operators, Oil and Gas
299099	0.01	3.16	3.57	14	Healthcare Practitioners and Technical Workers...
499092	0.01	3.03	3.10	5	Commercial Divers
493052	0.01	2.66	2.21	3	Motorcycle Mechanics
513093	0.01	2.38	3.00	13	Food Cooking Machine Operators and Tenders
172121	0.01	3.00	2.96	9	Marine Engineers and Naval Architects
534013	0.01	2.72	2.66	5	Rail Yard Engineers, Dinkey Operators, and Hos...
131199	0.01	3.14	3.28	91	Business Operations Specialists, All Other*

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
151011	0.01	2.81	2.98	13	Computer and Information Scientists, Research
151099	0.01	2.98	3.03	53	Computer Specialists, All Other
413021	0.01	3.38	2.97	5	Insurance Sales Agents
514192	0.01	2.37	2.53	23	Lay-Out Workers, Metal and Plastic
292071	0.01	2.28	2.67	17	Medical Records and Health Information Technic...
413099	0.01	3.18	2.84	97	Sales Representatives, Services, All Other
119199	0.01	3.48	3.57	106	Managers, All Other
274021	0.01	2.88	2.97	16	Photographers
231011	0.01	3.78	3.38	16	Lawyers
519192	0.00	2.31	2.46	44	Cleaning, Washing, and Metal Pickling Equipmen...
331012	0.00	3.75	4.11	2	First-Line Supervisors/Managers of Police and ...
519041	0.00	2.35	2.52	49	Extruding, Forming, Pressing, and Compacting M...
232092	0.00	2.80	2.56	8	Law Clerks*
131121	0.00	3.66	3.90	47	Meeting and Convention Planners
533041	0.00	2.66	2.78	35	Taxi Drivers and Chauffeurs
339091	0.00	2.50	2.48	8	Crossing Guards
519196	0.00	2.53	2.78	10	Paper Goods Machine Setters, Operators, and Te...
193032	0.00	3.47	3.64	6	Industrial-Organizational Psychologists
119011	0.00	3.33	3.42	10	Farm, Ranch, and Other Agricultural Managers
411011	0.00	3.28	3.21	31	First-Line Supervisors/Managers of Retail Sale...
519199	0.00	2.28	2.74	99	Production Workers, All Other*
192099	0.00	2.88	2.98	11	Physical Scientists, All Other
172031	0.00	3.00	3.12	16	Biomedical Engineers
192031	0.00	2.72	2.88	39	Chemists
499099	0.00	2.60	2.76	76	Installation, Maintenance, and Repair Workers,...
393021	0.00	2.40	2.28	4	Motion Picture Projectionists
192041	0.00	3.07	3.20	25	Environmental Scientists and Specialists, Incl...

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
319096	0.00	2.62	3.05	7	Veterinary Assistants and Laboratory Animal Ca...
419041	0.00	3.22	2.31	41	Telemarketers
499051	0.00	2.81	3.58	6	Electrical Power-Line Installers and Repairers
192021	0.00	3.03	3.16	8	Atmospheric and Space Scientists
414012	0.00	3.59	2.99	107	Sales Representatives, Wholesale and Manufactu...
172111	0.00	3.04	3.41	82	Health and Safety Engineers, Except Mining Saf...
191023	0.00	3.10	3.16	6	Zoologists and Wildlife Biologists
537063	0.00	2.22	2.11	73	Machine Feeders and Offbearers
435111	0.00	2.72	2.48	83	Weighers, Measurers, Checkers, and Samplers, R...
516064	0.00	2.60	2.79	7	Textile Winding, Twisting, and Drawing Out Mac...
419011	0.00	2.97	3.03	23	Demonstrators and Product Promoters
519131	0.00	2.58	2.63	21	Photographic Process Workers
519111	0.00	2.62	2.33	75	Packaging and Filling Machine Operators and Te...
273091	0.00	2.84	3.14	12	Interpreters and Translators
434041	0.00	3.00	3.23	40	Credit Authorizers, Checkers, and Clerks
131071	0.00	3.10	3.58	98	Employment, Recruitment, and Placement Special...
492092	0.00	2.69	2.80	25	Electric Motor, Power Tool, and Related Repairers
292021	0.00	2.88	3.04	2	Dental Hygienists
499061	0.00	2.28	2.22	15	Camera and Photographic Equipment Repairers
514193	0.00	2.60	2.53	31	Plating and Coating Machine Setters, Operators...
499043	0.00	2.50	2.41	111	Maintenance Workers, Machinery
111011	0.00	3.83	3.80	155	Chief Executives
514021	0.00	2.47	2.63	39	Extruding and Drawing Machine Setters, Operato...
439111	0.00	2.77	2.78	20	Statistical Assistants
292053	0.00	3.44	3.64	8	Psychiatric Technicians
516063	0.00	2.10	2.13	7	Textile Knitting and Weaving Machine Setters, ...

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
113042	0.00	3.56	3.74	62	Training and Development Managers
492022	0.00	2.82	2.90	9	Telecommunications Equipment Installers and Re...
435061	0.00	2.94	3.02	150	Production, Planning, and Expediting Clerks
193011	0.00	2.84	2.80	14	Economists
537121	0.00	2.72	3.07	22	Tank Car, Truck, and Ship Loaders
499011	0.00	2.88	2.78	8	Mechanical Door Repairers
253021	0.00	2.88	3.07	21	Self-Enrichment Education Teachers
514072	0.00	2.38	2.28	48	Molding, Coremaking, and Casting Machine Sette...
474031	0.00	2.66	2.39	8	Fence Erectors
191013	0.00	2.82	3.33	14	Soil and Plant Scientists
431011	0.00	3.81	3.63	93	First-Line Supervisors/Managers of Office and ...
172061	0.00	2.69	2.69	23	Computer Hardware Engineers
531011	0.00	3.00	3.51	11	Aircraft Cargo Handling Supervisors
499062	0.00	2.60	2.87	17	Medical Equipment Repairers
271027	0.00	3.22	3.29	17	Set and Exhibit Designers
499041	0.00	2.56	2.20	108	Industrial Machinery Mechanics
435081	0.00	2.53	2.71	46	Stock Clerks and Order Fillers
131079	0.00	3.91	3.54	7	Human Resources, Training, and Labor Relations...
131021	0.00	3.25	3.31	31	Purchasing Agents and Buyers, Farm Products
518031	0.00	2.66	3.17	38	Water and Liquid Waste Treatment Plant and Sys...
412022	0.00	3.28	3.38	15	Parts Salespersons
514111	0.00	2.31	2.40	46	Tool and Die Makers
191041	0.00	3.34	3.31	7	Epidemiologists
519194	0.00	2.40	2.52	23	Etchers and Engravers
131041	0.00	3.18	3.27	89	Compliance Officers, Except Agriculture, Const...
474091	0.00	3.00	3.32	5	Segmental Pavers
537062	0.00	2.32	2.34	127	Laborers and Freight, Stock, and Material Move...
412031	0.00	3.50	3.17	32	Retail Salespersons
454023	0.00	2.84	3.37	6	Log Graders and Scalers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
212021	0.00	3.50	3.93	8	Directors, Religious Activities and Education
372021	0.00	3.19	2.95	2	Pest Control Workers
194091	0.00	3.00	3.19	20	Environmental Science and Protection Technicia...
519191	0.00	2.44	2.31	22	Cementing and Gluing Machine Operators and Ten...
151081	0.00	2.80	2.91	55	Network Systems and Data Communications Analysts*
518099	0.00	2.84	2.93	27	Plant and System Operators, All Other
514023	0.00	2.56	2.72	30	Rolling Machine Setters, Operators, and Tender...
514194	0.00	2.35	2.30	30	Tool Grinders, Filers, and Sharpeners
514081	0.00	2.50	2.26	47	Multiple Machine Tool Setters, Operators, and ...
518093	0.00	2.66	2.80	12	Petroleum Pump System Operators, Refinery Oper...
194099	0.00	2.78	2.74	25	Life, Physical, and Social Science Technicians...
292091	0.00	3.06	3.57	9	Orthotists and Prosthetists
537064	0.00	2.22	2.91	82	Packers and Packagers, Hand
132099	0.00	3.09	3.34	42	Financial Specialists, All Other
434071	0.00	2.60	2.58	38	File Clerks
173031	0.00	2.67	2.65	15	Surveying and Mapping Technicians
311013	0.00	3.40	3.23	8	Psychiatric Aides
499098	0.00	2.53	2.63	86	Helpers–Installation, Maintenance, and Repair...
192011	0.00	2.94	2.86	3	Astronomers
191031	0.00	3.26	3.44	6	Conservation Scientists
131011	0.00	3.94	3.42	7	Agents and Business Managers of Artists, Perfo...
271012	0.00	2.69	2.33	10	Craft Artists
274014	0.00	2.97	3.12	15	Sound Engineering Technicians
194031	0.00	2.78	2.81	48	Chemical Technicians
292011	0.00	2.66	2.83	8	Medical and Clinical Laboratory Technologists
439061	0.00	2.84	2.85	123	Office Clerks, General
475071	0.00	2.40	2.37	12	Roustabouts, Oil and Gas

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
434151	0.00	3.22	3.29	120	Order Clerks
474041	0.00	2.91	3.07	11	Hazardous Materials Removal Workers
537011	0.00	2.66	2.65	53	Conveyor Operators and Tenders
514191	0.00	2.32	2.36	31	Heat Treating Equipment Setters, Operators, an...
514035	0.00	2.34	2.53	37	Milling and Planing Machine Setters, Operators...
372011	0.00	2.35	2.26	23	Janitors and Cleaners, Except Maids and Housek...
451012	0.00	2.84	2.49	1	Farm Labor Contractors
191029	0.00	3.01	3.18	12	Biological Scientists, All Other
131061	0.00	3.66	3.95	14	Emergency Management Specialists
151041	0.00	2.90	2.89	56	Computer Support Specialists
499052	0.00	2.56	3.00	10	Telecommunications Line Installers and Repairers
274011	0.00	2.84	2.67	35	Audio and Video Equipment Technicians
131073	0.00	3.47	3.54	81	Training and Development Specialists
271021	0.00	2.90	2.49	64	Commercial and Industrial Designers
132051	0.00	2.60	2.33	53	Financial Analysts
493091	0.00	2.97	3.25	4	Bicycle Repairers
113041	0.00	3.22	3.37	51	Compensation and Benefits Managers
519012	0.00	2.56	2.34	34	Separating, Filtering, Clarifying, Precipitati...
435032	0.00	3.19	3.38	76	Dispatchers, Except Police, Fire, and Ambulance
414011	0.00	3.66	2.68	69	Sales Representatives, Wholesale and Manufactu...
151051	0.00	2.99	3.18	54	Computer Systems Analysts
433061	-0.00	3.06	2.79	110	Procurement Clerks
519051	-0.00	2.25	2.43	34	Furnace, Kiln, Oven, Drier, and Kettle Operato...
172081	-0.00	3.25	3.63	37	Environmental Engineers
499012	-0.00	2.50	2.60	27	Control and Valve Installers and Repairers, Ex...
299011	-0.00	3.31	3.46	99	Occupational Health and Safety Specialists

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
474099	-0.00	2.80	3.02	31	Construction and Related Workers, All Other*
113049	-0.00	3.81	3.82	122	Human Resources Managers, All Other
499021	-0.00	2.78	3.19	16	Heating, Air Conditioning, and Refrigeration M...
491011	-0.00	3.28	3.61	131	First-Line Supervisors/Managers of Mechanics, ...
514031	-0.00	2.28	2.32	58	Cutting, Punching, and Press Machine Setters, ...
412021	-0.00	2.97	3.16	35	Counter and Rental Clerks
514033	-0.00	2.38	2.60	42	Grinding, Lapping, Polishing, and Buffing Mach...
211012	-0.00	3.72	3.55	13	Educational, Vocational, and School Counselors
119033	-0.00	3.72	3.96	6	Education Administrators, Postsecondary
511011	-0.00	3.44	3.39	122	First-Line Supervisors/Managers of Production ...
434181	-0.00	3.22	3.29	20	Reservation and Transportation Ticket Agents a...
519032	-0.00	2.44	2.86	48	Cutting and Slicing Machine Setters, Operators...
435011	-0.00	3.06	2.88	16	Cargo and Freight Agents
151061	-0.00	2.65	2.64	58	Database Administrators
519011	-0.00	2.47	3.04	26	Chemical Equipment Operators and Tenders
333052	-0.00	3.25	3.18	2	Transit and Railroad Police
519023	-0.00	2.50	2.43	55	Mixing and Blending Machine Setters, Operators...
434011	-0.00	2.81	2.41	10	Brokerage Clerks
172199	-0.00	2.96	3.06	78	Engineers, All Other
436014	-0.00	2.78	3.01	92	Secretaries, Except Legal, Medical, and Executive
113031	-0.00	3.40	3.49	94	Financial Managers
351011	-0.00	3.44	3.58	18	Chefs and Head Cooks
533031	-0.00	2.97	2.72	43	Driver/Sales Workers
518013	-0.00	2.53	2.62	8	Power Plant Operators
194061	-0.00	2.90	3.03	11	Social Science Research Assistants
131072	-0.00	3.03	2.89	61	Compensation, Benefits, and Job Analysis Speci...

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
259031	-0.00	3.44	3.69	13	Instructional Coordinators
474021	-0.00	2.78	2.93	1	Elevator Installers and Repairers
512092	-0.00	2.53	2.65	91	Team Assemblers
192043	-0.00	2.94	3.27	4	Hydrologists
131081	-0.00	3.16	3.35	109	Logisticians
172011	-0.00	3.09	2.86	12	Aerospace Engineers
131111	-0.00	3.44	3.67	56	Management Analysts
273041	-0.00	3.03	3.00	29	Editors
193093	-0.00	2.84	3.15	6	Historians
432011	-0.00	2.66	2.98	45	Switchboard Operators, Including Answering Ser...
254012	-0.00	3.09	3.42	10	Curators
292041	-0.00	3.28	3.61	10	Emergency Medical Technicians and Paramedics
113051	-0.00	3.32	3.44	106	Industrial Production Managers
132031	-0.00	2.75	2.88	41	Budget Analysts
432021	-0.00	2.62	2.82	10	Telephone Operators
113071	-0.00	3.47	3.52	108	Transportation, Storage, and Distribution Mana...
433011	-0.00	3.44	2.84	52	Bill and Account Collectors
435031	-0.00	3.40	3.43	8	Police, Fire, and Ambulance Dispatchers
434171	-0.00	2.78	3.05	43	Receptionists and Information Clerks
191022	-0.00	2.94	3.38	11	Microbiologists
332011	-0.00	3.16	3.55	12	Fire Fighters
151032	-0.00	2.84	2.32	40	Computer Software Engineers, Systems Software
512011	-0.00	2.53	2.78	3	Aircraft Structure, Surfaces, Rigging, and Sys...
435041	-0.00	2.56	2.65	7	Meter Readers, Utilities
499044	-0.00	2.94	2.91	45	Millwrights
499091	-0.00	2.56	2.94	20	Coin, Vending, and Amusement Machine Servicers...
433031	-0.00	2.78	2.66	151	Bookkeeping, Accounting, and Auditing Clerks
191042	-0.00	3.03	3.29	11	Medical Scientists, Except Epidemiologists
514034	-0.00	2.28	2.37	38	Lathe and Turning Machine Tool Setters, Operat...
439011	-0.00	2.84	2.48	54	Computer Operators

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
452041	-0.00	2.13	1.99	14	Graders and Sorters, Agricultural Products
131031	-0.00	3.34	3.07	7	Claims Adjusters, Examiners, and Investigators
435071	-0.00	2.66	2.72	145	Shipping, Receiving, and Traffic Clerks
492021	-0.00	2.60	2.79	14	Radio Mechanics
171021	-0.00	2.84	2.55	13	Cartographers and Photogrammetrists
439022	-0.00	2.50	2.63	18	Word Processors and Typists
292034	-0.00	2.90	3.14	5	Radiologic Technologists and Technicians*
532021	-0.00	3.19	2.79	4	Air Traffic Controllers
172072	-0.00	2.95	2.80	36	Electronics Engineers, Except Computer
518092	-0.00	2.78	2.42	10	Gas Plant Operators
434161	-0.00	2.90	3.02	95	Human Resources Assistants, Except Payroll and...
537072	-0.00	2.56	2.72	26	Pump Operators, Except Wellhead Pumpers
519198	-0.00	2.25	2.49	98	Helpers–Production Workers
273043	-0.00	3.00	2.88	36	Writers and Authors
371011	-0.00	3.16	3.26	23	First-Line Supervisors/Managers of Housekeepin...
454022	-0.00	2.34	2.40	6	Logging Equipment Operators
273011	-0.00	3.06	3.22	7	Radio and Television Announcers
194011	-0.00	2.66	3.13	19	Agricultural and Food Science Technicians
173013	-0.00	2.56	2.24	60	Mechanical Drafters
439031	-0.00	2.88	3.55	21	Desktop Publishers
493042	-0.00	2.60	2.47	42	Mobile Heavy Equipment Mechanics, Except Engines
533021	-0.00	2.75	3.05	16	Bus Drivers, Transit and Intercity
172041	-0.00	2.88	3.26	34	Chemical Engineers
516041	-0.00	2.35	2.07	8	Shoe and Leather Workers and Repairers
131023	-0.00	3.44	3.32	144	Purchasing Agents, Except Wholesale, Retail, a...
492095	-0.00	2.72	3.20	10	Electrical and Electronics Repairers, Powerhou...
319093	-0.00	2.38	3.03	10	Medical Equipment Preparers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
254031	-0.00	2.63	2.36	5	Library Technicians
433051	-0.00	2.37	2.68	110	Payroll and Timekeeping Clerks
537031	-0.00	2.56	2.54	5	Dredge Operators
536051	-0.00	2.73	2.64	21	Transportation Inspectors
475031	-0.00	2.78	3.24	13	Explosives Workers, Ordnance Handling Experts,...
537081	-0.00	2.63	2.51	8	Refuse and Recyclable Material Collectors
211091	-0.00	3.28	3.65	26	Health Educators*
475051	-0.00	2.28	2.13	4	Rock Splitters, Quarry
519121	-0.00	2.56	2.38	70	Coating, Painting, and Spraying Machine Setter...
514051	-0.00	2.34	2.10	15	Metal-Refining Furnace Operators and Tenders
492011	-0.00	2.78	2.45	16	Computer, Automated Teller, and Office Machine...
472152	-0.00	2.72	2.62	25	Plumbers, Pipefitters, and Steamfitters
518091	-0.00	2.53	2.32	13	Chemical Plant and System Operators
271024	-0.00	2.97	2.88	77	Graphic Designers
131022	-0.00	3.53	2.99	55	Wholesale and Retail Buyers, Except Farm Products
533032	-0.00	2.50	2.77	64	Truck Drivers, Heavy and Tractor-Trailer
519022	-0.00	2.31	2.60	40	Grinding and Polishing Workers, Hand
152011	-0.00	3.03	3.19	8	Actuaries
533033	-0.00	2.35	2.56	76	Truck Drivers, Light or Delivery Services
273021	-0.00	3.40	3.30	6	Broadcast News Analysts
473014	-0.00	2.53	2.30	9	Helpers–Painters, Paperhangers, Plasterers, a...
472041	-0.00	2.66	2.56	8	Carpet Installers
191011	-0.00	2.97	3.39	8	Animal Scientists
519021	-0.00	2.66	2.83	64	Crushing, Grinding, and Polishing Machine Sett...
272041	-0.00	3.12	3.09	9	Music Directors and Composers
534041	-0.00	2.84	2.57	1	Subway and Streetcar Operators
519061	-0.00	2.47	2.40	128	Inspectors, Testers, Sorters, Samplers, and We...

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
533011	-0.00	2.90	3.08	6	Ambulance Drivers and Attendants, Except Emerg...
132071	-0.00	3.31	2.95	16	Loan Counselors
512022	-0.00	2.46	2.74	30	Electrical and Electronic Equipment Assemblers
493023	-0.00	2.58	2.68	15	Automotive Service Technicians and Mechanics
191012	-0.00	3.22	3.27	22	Food Scientists and Technologists
516042	-0.00	2.00	2.25	1	Shoe Machine Operators and Tenders
273042	-0.00	2.81	2.63	54	Technical Writers
119151	-0.00	3.66	4.25	21	Social and Community Service Managers
292032	-0.00	3.12	3.18	6	Diagnostic Medical Sonographers
516021	-0.00	2.03	1.84	12	Pressers, Textile, Garment, and Related Materials
271025	-0.00	3.47	3.45	23	Interior Designers
271013	-0.00	2.69	2.11	25	Fine Artists, Including Painters, Sculptors, a...
499031	-0.00	2.69	3.06	22	Home Appliance Repairers
119081	-0.00	3.84	3.99	6	Lodging Managers
172131	-0.00	2.88	2.94	57	Materials Engineers
211093	-0.00	3.38	3.31	16	Social and Human Service Assistants
291071	-0.00	3.06	3.24	9	Physician Assistants
434021	-0.00	3.00	3.09	19	Correspondence Clerks
436011	-0.00	3.10	3.21	91	Executive Secretaries and Administrative Assis...
171011	-0.00	3.31	3.64	4	Architects, Except Landscape and Naval
292099	-0.00	2.85	3.30	8	Health Technologists and Technicians, All Other*
472071	-0.00	2.44	2.62	11	Paving, Surfacing, and Tamping Equipment Opera...
291199	-0.00	3.06	3.10	9	Health Diagnosing and Treating Practitioners, ...
531021	-0.00	3.26	3.53	133	First-Line Supervisors/Managers of Helpers, La...
292054	-0.00	3.03	3.38	5	Respiratory Therapy Technicians
194021	-0.00	2.41	2.32	13	Biological Technicians

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
531031	-0.00	3.56	3.80	104	First-Line Supervisors/Managers of Transportat...
151021	-0.00	2.60	2.42	54	Computer Programmers
119041	-0.00	3.25	3.26	86	Engineering Managers
472131	-0.00	2.69	2.67	9	Insulation Workers, Floor, Ceiling, and Wall
151071	-0.00	2.81	2.84	79	Network and Computer Systems Administrators
439041	-0.00	2.69	2.90	7	Insurance Claims and Policy Processing Clerks
396032	-0.00	3.16	2.53	13	Transportation Attendants, Except Flight Atten...
512031	-0.00	2.50	2.40	17	Engine and Other Machine Assemblers
536011	-0.00	2.88	2.79	1	Bridge and Lock Tenders
419091	-0.00	3.50	2.94	11	Door-to-Door Sales Workers, News and Street Ve...
433021	-0.00	2.64	2.88	64	Billing and Posting Clerks and Machine Operators
254011	-0.00	2.84	3.39	12	Archivists
274031	-0.00	2.69	2.41	15	Camera Operators, Television, Video, and Motio...
319094	-0.00	2.28	2.02	10	Medical Transcriptionists
151031	-0.00	2.88	2.82	40	Computer Software Engineers, Applications
395092	-0.00	2.72	2.41	2	Manicurists and Pedicurists
493031	-0.00	2.56	2.76	64	Bus and Truck Mechanics and Diesel Engine Spec...
173022	-0.00	2.75	2.92	12	Civil Engineering Technicians
519123	-0.00	2.34	2.23	34	Painting, Coating, and Decorating Workers
299012	-0.00	2.94	3.18	54	Occupational Health and Safety Technicians
119051	-0.00	3.56	3.80	14	Food Service Managers
439071	-0.00	2.63	3.12	32	Office Machine Operators, Except Computer
493041	-0.00	2.44	2.55	14	Farm Equipment Mechanics
292056	-0.00	2.88	3.25	6	Veterinary Technologists and Technicians
132011	-0.00	3.00	3.33	104	Accountants and Auditors

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
113021	-0.00	3.37	3.48	65	Computer and Information Systems Managers
493051	-0.00	2.25	2.56	12	Motorboat Mechanics
291124	-0.00	2.97	3.48	6	Radiation Therapists
291121	-0.00	3.19	3.35	9	Audiologists
172021	-0.00	3.03	3.10	8	Agricultural Engineers
519141	-0.00	2.50	2.58	3	Semiconductor Processors
439021	-0.01	2.53	2.51	63	Data Entry Keyers
232091	-0.01	2.26	2.35	2	Court Reporters
514052	-0.01	2.44	2.31	6	Pourers and Casters, Metal
132072	-0.01	3.00	3.34	10	Loan Officers
493043	-0.01	2.56	2.45	5	Rail Car Repairers
519193	-0.01	2.63	2.51	10	Cooling and Freezing Equipment Operators and T...
173029	-0.01	2.76	2.87	69	Engineering Technicians, Except Drafters, All ...
333021	-0.01	3.19	3.26	3	Detectives and Criminal Investigators
254021	-0.01	3.13	3.21	9	Librarians
512023	-0.01	2.34	2.29	26	Electromechanical Equipment Assemblers
451011	-0.01	3.30	3.26	23	First-Line Supervisors/Managers of Farming, Fi...
434141	-0.01	3.03	3.45	6	New Accounts Clerks
492097	-0.01	2.72	2.81	17	Electronic Home Entertainment Equipment Instal...
472151	-0.01	2.60	2.72	12	Pipelayers
472042	-0.01	2.66	2.76	5	Floor Layers, Except Carpet, Wood, and Hard Tiles
537073	-0.01	2.00	2.39	2	Wellhead Pumpers
399031	-0.01	2.81	2.78	8	Fitness Trainers and Aerobics Instructors
274012	-0.01	2.47	2.42	12	Broadcast Technicians
492094	-0.01	2.81	2.76	83	Electrical and Electronics Repairers, Commerci...
352012	-0.01	2.88	3.10	22	Cooks, Institution and Cafeteria
515022	-0.01	2.84	2.79	16	Prepress Technicians and Workers
439051	-0.01	2.32	2.57	38	Mail Clerks and Mail Machine Operators, Except...
119039	-0.01	3.56	3.74	17	Education Administrators, All Other

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
292051	-0.01	2.91	3.29	8	Dietetic Technicians
339032	-0.01	2.84	3.30	23	Security Guards*
493053	-0.01	2.56	2.65	14	Outdoor Power Equipment and Other Small Engine...
231022	-0.01	3.94	2.88	8	Arbitrators, Mediators, and Conciliators
514032	-0.01	2.50	2.54	34	Drilling and Boring Machine Tool Setters, Oper...
474011	-0.01	2.84	2.97	22	Construction and Building Inspectors
517042	-0.01	2.03	1.97	12	Woodworking Machine Setters, Operators, and Te...
173026	-0.01	2.82	2.68	75	Industrial Engineering Technicians
113061	-0.01	3.81	3.72	121	Purchasing Managers
472171	-0.01	2.35	2.66	8	Reinforcing Iron and Rebar Workers
413041	-0.01	3.40	3.06	4	Travel Agents
519031	-0.01	2.32	1.97	31	Cutters and Trimmers, Hand
272032	-0.01	3.53	3.74	7	Choreographers
271014	-0.01	3.06	3.19	24	Multi-Media Artists and Animators
518021	-0.01	2.75	3.02	42	Stationary Engineers and Boiler Operators
475041	-0.01	2.40	2.50	5	Continuous Mining Machine Operators
471011	-0.01	3.41	3.43	34	First-Line Supervisors/Managers of Constructio...
396022	-0.01	3.44	3.08	3	Travel Guides
472111	-0.01	2.66	2.83	60	Electricians*
172071	-0.01	3.03	2.83	55	Electrical Engineers
373011	-0.01	2.28	2.34	20	Landscaping and Groundskeeping Workers
516092	-0.01	2.72	2.62	12	Fabric and Apparel Patternmakers
373013	-0.01	2.81	3.17	3	Tree Trimmers and Pruners
292012	-0.01	2.78	2.91	8	Medical and Clinical Laboratory Technicians
472132	-0.01	2.78	2.93	10	Insulation Workers, Mechanical
492093	-0.01	2.66	2.40	21	Electrical and Electronics Installers and Repa...
513092	-0.01	2.56	2.70	15	Food Batchmakers
537051	-0.01	2.41	2.91	111	Industrial Truck and Tractor Operators

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
172051	-0.01	3.15	3.43	19	Civil Engineers
172141	-0.01	2.96	2.98	71	Mechanical Engineers
173027	-0.01	2.78	2.78	64	Mechanical Engineering Technicians
394011	-0.01	2.72	3.10	1	Embalmers
472011	-0.01	2.53	2.78	15	Boilermakers
391011	-0.01	3.50	3.22	6	Gaming Supervisors
271026	-0.01	2.81	2.97	30	Merchandise Displayers and Window Trimmers
373012	-0.01	2.69	3.06	11	Pesticide Handlers, Sprayers, and Applicators,...
395011	-0.01	2.56	2.63	1	Barbers
119061	-0.01	3.50	3.45	1	Funeral Directors *
291031	-0.01	3.60	3.91	17	Dietitians and Nutritionists
173012	-0.01	2.75	2.34	27	Electrical and Electronics Drafters
452011	-0.01	2.91	3.06	16	Agricultural Inspectors
319099	-0.01	2.91	3.14	15	Healthcare Support Workers, All Other*
474051	-0.01	2.72	2.87	4	Highway Maintenance Workers
274032	-0.01	2.81	2.68	17	Film and Video Editors
191032	-0.01	3.34	3.28	10	Foresters
131051	-0.01	3.09	3.21	60	Cost Estimators
435021	-0.01	2.50	2.18	30	Couriers and Messengers
291131	-0.01	3.00	3.38	4	Veterinarians
475081	-0.01	2.60	2.84	11	Helpers–Extraction Workers
517041	-0.01	2.22	2.23	12	Sawing Machine Setters, Operators, and Tenders...
537071	-0.01	2.50	2.84	10	Gas Compressor and Gas Pumping Station Operators
452091	-0.01	2.31	1.97	14	Agricultural Equipment Operators
499096	-0.01	2.47	2.22	33	Riggers
493022	-0.01	2.60	2.23	5	Automotive Glass Installers and Repairers
472021	-0.01	2.56	3.02	8	Brickmasons and Blockmasons
519122	-0.01	2.41	2.69	25	Painters, Transportation Equipment
493092	-0.01	2.78	2.85	7	Recreational Vehicle Service Technicians
516062	-0.01	2.56	2.83	24	Textile Cutting Machine Setters, Operators, an...
171022	-0.01	2.87	3.52	16	Surveyors

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
473012	-0.01	2.59	2.47	12	Helpers–Carpenters
274013	-0.01	2.66	2.68	1	Radio Operators
172112	-0.01	3.02	3.10	98	Industrial Engineers
172161	-0.01	3.19	3.28	9	Nuclear Engineers
514011	-0.01	2.53	2.60	44	Computer-Controlled Machine Tool Operators, Me...
436013	-0.01	2.65	2.96	12	Medical Secretaries
434061	-0.01	3.19	3.05	19	Eligibility Interviewers, Government Programs
512041	-0.01	2.32	2.13	39	Structural Metal Fabricators and Fitters
392021	-0.01	2.56	2.65	12	Nonfarm Animal Caretakers
395093	-0.01	2.53	2.87	1	Shampooers
472061	-0.01	2.56	2.61	24	Construction Laborers
492098	-0.01	2.47	2.74	8	Security and Fire Alarm Systems Installers
259011	-0.01	2.69	2.84	6	Audio-Visual Collections Specialists
473016	-0.01	2.50	3.33	2	Helpers–Roofers
292031	-0.01	3.00	3.01	5	Cardiovascular Technologists and Technicians
271023	-0.01	2.88	2.37	14	Floral Designers
292081	-0.01	3.06	3.31	6	Opticians, Dispensing
472141	-0.01	2.53	3.18	15	Painters, Construction and Maintenance
516011	-0.01	2.47	2.68	12	Laundry and Dry-Cleaning Workers
173023	-0.01	2.72	2.79	61	Electrical and Electronic Engineering Technicians
211011	-0.01	3.47	3.54	13	Substance Abuse and Behavioral Disorder Counse...
515021	-0.01	2.66	2.22	20	Job Printers*
514041	-0.01	2.69	2.34	67	Machinists
331021	-0.01	3.34	3.77	5	First-Line Supervisors/Managers of Fire Fighti...
493093	-0.01	2.50	2.77	12	Tire Repairers and Changers
499064	-0.01	2.12	2.30	3	Watch Repairers
211022	-0.01	3.56	3.83	18	Medical and Public Health Social Workers
319092	-0.01	3.25	3.49	8	Medical Assistants
173011	-0.01	2.78	2.73	21	Architectural and Civil Drafters
514061	-0.01	2.35	2.47	27	Model Makers, Metal and Plastic

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
473011	-0.01	2.38	2.49	5	Helpers–Brickmasons, Blockmasons, Stonemasons...
473013	-0.01	2.28	2.55	6	Helpers–Electricians
499097	-0.01	2.60	2.61	2	Signal and Track Switch Repairers
475011	-0.01	2.72	2.76	2	Derrick Operators, Oil and Gas
399041	-0.01	3.78	3.73	16	Residential Advisors
519195	-0.01	2.40	2.50	28	Molders, Shapers, and Casters, Except Metal an...
194051	-0.01	2.67	2.78	5	Nuclear Technicians
332021	-0.01	2.94	3.30	8	Fire Inspectors and Investigators
537032	-0.01	2.84	2.92	33	Excavating and Loading Machine and Dragline Op...
454011	-0.01	2.84	3.43	6	Forest and Conservation Workers
311012	-0.01	2.81	2.99	10	Nursing Aides, Orderlies, and Attendants*
493011	-0.01	2.81	3.10	14	Aircraft Mechanics and Service Technicians
434121	-0.01	2.72	3.01	5	Library Assistants, Clerical
132041	-0.01	2.72	2.84	35	Credit Analysts
439081	-0.01	2.03	1.83	19	Proofreaders and Copy Markers
499094	-0.01	2.53	3.05	10	Locksmiths and Safe Repairers
514122	-0.01	2.34	2.48	40	Welding, Soldering, and Brazing Machine Setter...
351012	-0.01	3.40	3.24	16	First-Line Supervisors/Managers of Food Prepar...
533022	-0.01	2.78	2.38	11	Bus Drivers, School
372012	-0.01	2.50	2.83	14	Maids and Housekeeping Cleaners
339092	-0.01	2.72	2.67	10	Lifeguards, Ski Patrol, and Other Recreational...
399032	-0.01	3.35	3.34	29	Recreation Workers
291062	-0.01	3.28	3.12	6	Family and General Practitioners
512021	-0.01	2.25	2.26	21	Coil Winders, Tapers, and Finishers
396012	-0.01	3.28	3.56	15	Concierges
514012	-0.01	2.63	2.80	39	Numerical Tool and Process Control Programmers
516091	-0.01	2.59	2.53	15	Extruding and Forming Machine Setters, Operato...
392011	-0.01	2.84	3.27	10	Animal Trainers
472073	-0.01	2.47	2.81	37	Operating Engineers and Other Construction Equ...

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
119021	-0.01	3.47	3.59	26	Construction Managers
499063	-0.01	2.88	2.92	5	Musical Instrument Repairers and Tuners
399021	-0.01	2.72	2.69	14	Personal and Home Care Aides
173024	-0.01	2.72	2.81	37	Electro-Mechanical Technicians
131032	-0.01	2.91	3.24	4	Insurance Appraisers, Auto Damage
514062	-0.01	2.47	2.51	13	Patternmakers, Metal and Plastic
319095	-0.01	2.60	3.29	10	Pharmacy Aides
193039	-0.01	3.31	3.64	9	Psychologists, All Other
517011	-0.01	2.40	2.45	15	Cabinetmakers and Bench Carpenters
434081	-0.01	3.09	3.08	6	Hotel, Motel, and Resort Desk Clerks
473015	-0.01	2.31	2.84	10	Helpers–Pipelayers, Plumbers, Pipefitters, an...
211015	-0.01	3.56	3.35	15	Rehabilitation Counselors
515011	-0.01	2.44	2.62	7	Bindery Workers
394021	-0.01	2.62	3.52	1	Funeral Attendants
259021	-0.01	3.44	3.64	6	Farm and Home Management Advisors
311011	-0.01	3.12	3.02	8	Home Health Aides
472043	-0.01	2.25	2.32	6	Floor Sanders and Finishers
312022	-0.01	2.94	3.22	8	Physical Therapist Aides
535031	-0.01	2.47	2.52	6	Ship Engineers
419022	-0.01	3.82	3.37	12	Real Estate Sales Agents
391021	-0.01	3.61	3.73	33	First-Line Supervisors/Managers of Personal Se...
493021	-0.01	2.53	2.41	13	Automotive Body and Related Repairers
516031	-0.01	2.40	2.11	38	Sewing Machine Operators
371012	-0.01	3.32	3.58	18	First-Line Supervisors/Managers of Landscaping...
319011	-0.01	2.50	2.74	4	Massage Therapists
536021	-0.01	2.60	2.60	19	Parking Lot Attendants
211013	-0.01	3.84	3.45	10	Marriage and Family Therapists
291111	-0.01	3.58	3.73	9	Registered Nurses*
193051	-0.01	3.28	3.89	8	Urban and Regional Planners
519071	-0.01	2.56	2.29	10	Jewelers and Precious Stone and Metal Workers
292052	-0.01	2.66	3.18	11	Pharmacy Technicians

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
499045	-0.01	2.41	2.44	9	Refractory Materials Repairers, Except Brickma...
412011	-0.01	2.66	2.79	38	Cashiers
472181	-0.01	2.66	3.10	5	Roofers
173021	-0.01	2.78	2.97	10	Aerospace Engineering and Operations Technicians
291021	-0.01	3.62	3.83	3	Dentists, General
519081	-0.01	2.50	2.50	2	Dental Laboratory Technicians
537033	-0.01	2.44	2.11	4	Loading Machine Operators, Underground Mining
492096	-0.01	2.84	3.05	11	Electronic Equipment Installers and Repairers,...
396021	-0.01	2.72	2.69	22	Tour Guides and Escorts
353041	-0.01	2.35	2.62	16	Food Servers, Nonrestaurant
519082	-0.01	3.03	2.79	10	Medical Appliance Technicians
472031	-0.01	2.69	2.97	30	Carpenters
191021	-0.01	2.81	2.88	12	Biochemists and Biophysicists
312021	-0.01	3.00	3.19	9	Physical Therapist Assistants
517021	-0.01	2.66	2.37	9	Furniture Finishers
516052	-0.01	2.63	2.73	17	Tailors, Dressmakers, and Custom Sewers
452093	-0.01	2.81	2.84	17	Farmworkers, Farm and Ranch Animals
339031	-0.01	2.94	3.30	3	Gaming Surveillance Officers and Gaming Invest...
396011	-0.01	2.78	2.79	11	Baggage Porters and Bellhops
359011	-0.01	2.41	2.88	11	Dining Room and Cafeteria Attendants and Barte...
517031	-0.01	2.53	2.47	6	Model Makers, Wood
359021	-0.01	2.40	2.98	12	Dishwashers
352021	-0.01	2.28	2.25	20	Food Preparation Workers
399011	-0.01	3.39	2.81	12	Child Care Workers
119031	-0.01	3.66	3.73	12	Education Administrators, Preschool and Child ...
519083	-0.01	2.40	2.48	5	Ophthalmic Laboratory Technicians
292033	-0.01	2.94	3.27	5	Nuclear Medicine Technologists
513011	-0.01	2.47	2.40	14	Bakers
514121	-0.01	2.22	2.44	77	Welders, Cutters, Solderers, and Brazers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
331011	-0.01	3.84	3.92	2	First-Line Supervisors/Managers of Correctiona...
353031	-0.01	3.06	2.63	12	Waiters and Waitresses
536031	-0.01	2.78	2.78	19	Service Station Attendants
434131	-0.01	3.18	3.04	15	Loan Interviewers and Clerks
193022	-0.01	3.16	3.57	8	Survey Researchers
393093	-0.01	2.66	2.45	14	Locker Room, Coatroom, and Dressing Room Atten...
513023	-0.01	2.22	2.43	3	Slaughterers and Meat Packers
292061	-0.01	3.50	3.70	13	Licensed Practical and Licensed Vocational Nurses
419031	-0.01	3.88	3.21	56	Sales Engineers
475021	-0.01	2.56	2.72	14	Earth Drillers, Except Oil and Gas
516051	-0.01	2.28	2.50	16	Sewers, Hand
291123	-0.01	3.25	3.22	7	Physical Therapists
472121	-0.01	2.38	2.60	8	Glaziers
291125	-0.01	3.56	3.54	11	Recreational Therapists
472051	-0.01	2.44	2.65	13	Cement Masons and Concrete Finishers
352015	-0.01	2.72	2.52	14	Cooks, Short Order
537021	-0.01	2.40	2.69	47	Crane and Tower Operators
475042	-0.01	2.78	2.35	5	Mine Cutting and Channeling Machine Operators
353011	-0.01	3.04	3.21	14	Bartenders
193031	-0.01	3.78	3.55	12	Clinical, Counseling, and School Psychologists
273022	-0.01	3.18	2.82	6	Reporters and Correspondents
291041	-0.01	3.16	3.58	4	Optometrists
419021	-0.01	3.40	3.13	10	Real Estate Brokers
492091	-0.01	2.78	2.90	10	Avionics Technicians
412012	-0.01	2.75	2.70	5	Gaming Change Persons and Booth Cashiers
319091	-0.01	2.88	3.19	3	Dental Assistants
352014	-0.01	2.56	2.60	8	Cooks, Restaurant
393012	-0.01	2.69	2.83	5	Gaming and Sports Book Writers and Runners
253011	-0.01	3.16	3.10	15	Adult Literacy, Remedial Education, and GED Te...
291051	-0.01	3.22	3.49	10	Pharmacists
359031	-0.01	3.00	2.78	8	Hosts and Hostesses, Restaurant, Lounge, and C...

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
252011	-0.01	3.41	3.20	7	Preschool Teachers, Except Special Education
472211	-0.01	2.44	2.72	26	Sheet Metal Workers
472053	-0.01	2.38	2.73	4	Terrazzo Workers and Finishers
395094	-0.01	2.78	2.73	7	Skin Care Specialists
232093	-0.01	2.78	2.81	17	Title Examiners, Abstractors, and Searchers
211023	-0.02	3.72	3.53	13	Mental Health and Substance Abuse Social Workers
291126	-0.02	3.19	3.24	7	Respiratory Therapists
512091	-0.02	2.66	3.02	20	Fiberglass Laminators and Fabricators
193091	-0.02	3.06	3.43	5	Anthropologists and Archeologists
291069	-0.02	3.34	3.61	8	Physicians and Surgeons, All Other
353021	-0.02	2.75	3.12	6	Combined Food Preparation and Serving Workers,...
211014	-0.02	3.75	3.42	14	Mental Health Counselors
212011	-0.02	3.88	3.58	13	Clergy
291081	-0.02	3.25	3.43	4	Podiatrists
433071	-0.02	2.69	2.73	5	Tellers
472221	-0.02	2.75	2.49	18	Structural Iron and Steel Workers
452092	-0.02	2.50	2.19	10	Farmworkers and Laborers, Crop, Nursery, and G...
211092	-0.02	3.47	3.18	5	Probation Officers and Correctional Treatment ...
516093	-0.02	2.63	2.74	17	Upholsterers
395012	-0.02	2.91	3.23	5	Hairdressers, Hairstylists, and Cosmetologists
171012	-0.02	3.47	3.58	8	Landscape Architects
393031	-0.02	3.04	2.67	19	Ushers, Lobby Attendants, and Ticket Takers
472022	-0.02	3.03	3.04	9	Stonemasons
513021	-0.02	2.84	3.11	5	Butchers and Meat Cutters
292055	-0.02	2.84	3.14	6	Surgical Technologists
194093	-0.02	2.91	3.23	7	Forest and Conservation Technicians
353022	-0.02	2.89	2.89	23	Counter Attendants, Cafeteria, Food Concession...
472082	-0.02	2.28	2.16	5	Tapers
454021	-0.02	2.25	1.89	3	Fallers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
254013	-0.02	2.90	2.55	6	Museum Technicians and Conservators
291122	-0.02	3.39	3.46	12	Occupational Therapists
474071	-0.02	2.84	3.10	9	Septic Tank Servicers and Sewer Pipe Cleaners
211021	-0.02	3.66	3.70	14	Child, Family, and School Social Workers
393091	-0.02	2.72	2.69	19	Amusement and Recreation Attendants
537041	-0.02	2.87	2.60	15	Hoist and Winch Operators
312011	-0.02	3.19	3.23	12	Occupational Therapist Assistants
391012	-0.02	2.84	3.03	5	Slot Key Persons
472081	-0.02	2.28	2.31	5	Drywall and Ceiling Tile Installers
333041	-0.02	2.90	3.31	2	Parking Enforcement Workers
433041	-0.02	2.75	2.82	3	Gaming Cage Workers
333012	-0.02	3.47	3.15	2	Correctional Officers and Jailers
472142	-0.02	2.44	2.52	4	Paperhangers
291011	-0.02	3.12	3.63	3	Chiropractors
393011	-0.02	3.06	2.83	3	Gaming Dealers
434111	-0.02	2.88	2.37	20	Interviewers, Except Eligibility and Loan
512093	-0.02	2.15	2.34	5	Timing Device Assemblers, Adjusters, and Calib...
291066	-0.02	3.78	3.52	12	Psychiatrists
472161	-0.02	2.53	2.94	5	Plasterers and Stucco Masons
352011	-0.02	2.47	3.01	6	Cooks, Fast Food
291127	-0.02	3.25	3.08	9	Speech-Language Pathologists
291063	-0.02	3.22	3.58	5	Internists, General
472044	-0.02	2.84	2.55	9	Tile and Marble Setters
291067	-0.02	3.22	3.54	4	Surgeons
291065	-0.02	3.28	3.33	5	Pediatricians, General
513022	-0.02	2.60	2.08	7	Meat, Poultry, and Fish Cutters and Trimmers
192012	-0.02	3.00	3.02	11	Physicists
312012	-0.02	3.03	3.18	12	Occupational Therapist Aides
452021	-0.02	2.62	2.19	3	Animal Breeders
434031	-0.03	2.78	2.90	4	Court, Municipal, and License Clerks
273012	-0.03	2.66	2.58	8	Public Address System and Other Announcers

SOC	RE Est.	Social Skills	Int. Act	N. Ind.	Occupation Name
291061	-0.04	3.19	3.39	5	Anesthesiologists
291023	-0.04	3.44	3.75	2	Orthodontists
291024	-0.05	3.19	3.88	1	Prosthodontists
291064	-0.05	3.31	3.59	2	Obstetricians and Gynecologists
291022	-0.06	3.19	3.83	4	Oral and Maxillofacial Surgeons

Chapter 4

Exporting Up: The Importance of Improving Technological Capabilities for Growth

What is the best way to measure technological capabilities? Over the past 15 years, technological capability indices have developed into two strains: aggregated capability indices and export based algorithms. We discuss the strength and weaknesses of using such measures and test at which point technological capabilities are important for low income nations to 'catch-up' with developed nations. We explore a variety of econometric estimation techniques including, random effect, fixed effect, Hausman-Taylor and GMM that compare three export based algorithms, economic complexity index, fitness and generalized fitness.

Our results indicate that technological capabilities, measured with export based algorithms, contribute to economic growth for low income nations. However, we do not find conclusive evidence that these measures have an impact at all stages of the development process. We suggest that to understand how economic structures impact economic growth, future pathways of research should reevaluate how to measure complexity to include value added which is increasingly fragmented across global production chains, and to measure the complexity of service and knowledge based products which are becoming a pivotal part of economies across the world [1].

JEL classifications: O47, O30

Keywords: Technological Capabilities, Economic Complexity, Economic Growth

[1] I am thankful to Saleh Mansour Albeaik for access to the economic complexity data. This paper is a combination of two previous working papers, *Verspagen, B. & Kaltenberg, M., 2015, Catching-up in a globalised context: Technological change as a driver of growth, UNU-MERIT Working Paper* and *Albeaik, S., Kaltenberg, M., Alsaleh, M., & Hidalgo, C. A. (2017). Measuring the Knowledge Intensity of Economies with an Improved Measure of Economic Complexity. arXiv preprint arXiv:1707.05826.*

1 Introduction

What are the necessary capabilities for countries to catch up? Economists have long searched for the right ingredients that spur economic growth, Growth varies across countries and time periods from eras of global prosperity (1988 - 2008) to crisis (2008- 2013). Figure 4.1 illustrates this point showing 5 year growth rate periods between 1973 - 2013 across countries (a list of included countries is in the appendix in table 4.5.8).

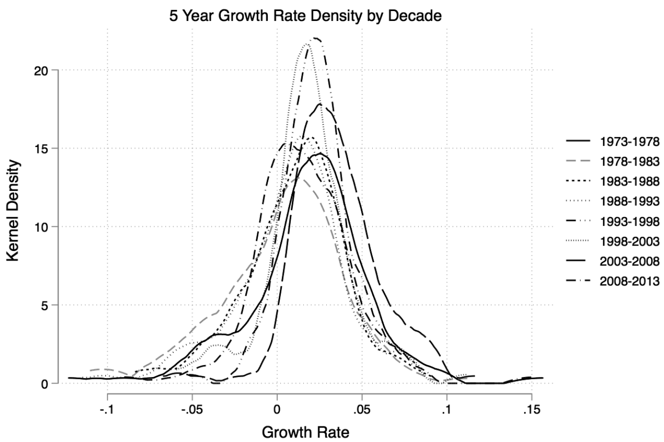


Figure 4.1: 5 year Growth Rate Density

What drives these periods of growth, especially the few nations that are able to go from "rags to riches" still remains a heated debate within economics ((Bosworth & Collins, 2003), (Durlauf, Johnson, & Temple, 2005)). One perspective in understanding the driving force of development is within the theoretical framework of catching-up, which suggests that a countries latent capabilities are at the root of the development process ((Verspagen, 1991), (Gerschenkron, 1962), (Abramovitz, 1986), (Dosi, Pavitt, Soete, et al., 1990)). An obstacle to demonstrating this theory is that capabilities are difficult to measure because many of the composites are intangible, such as knowledge or absorptive capacity (Archibugi & Coco, 2005). One of the first attempts to measure these varied contributions were through aggregate indices that weighted different composite variables such as innovation, human capital, competitiveness or infrastructure

((Wagner, Brahmakulam, Jackson, Wong, & Yoda, 2001), (Desai, Fukuda-Parr, Johansson, & Sagasti, 2002), (Lall, 2003), (Furman, Porter, & Stern, 2002)). Following this literature, another class of measures used export trade data to capture latent capabilities by understanding a nation's ability to export complex products ((Hausmann, Hwang, & Rodrik, 2007), (Tacchella, Cristelli, Caldarelli, Gabrielli, & Pietronero, 2012), (Albeaik, Kaltenberg, Alsaleh, & Hidalgo, 2017)). These measures are an improvement to estimate the productive capacity of a nation.

This paper reviews the literature of technological capabilities and catching-up, especially in regards to the variant ways to measuring capabilities, and concludes with a rigorous econometric comparison of three complexity measures, economic complexity, generalized fitness, and fitness. While these measures remain imperfect, we find evidence that capabilities are important for the catching-up process. However, the way we measure capabilities must improve to face the changing economic landscape of a service and knowledge based globalized economy of which present measures have not yet been able to include. This measurement issue may be the key to understanding why complexity indices are unable to explain growth patterns in developed economies, but are able to explain growth for developing nations.

1.1 The Catching-Up Hypothesis

Strengthening capabilities provides a means to improve economic conditions through a process of catching up. An early proponent to understanding development as a catch-up process was Gershenkron in his comparative study of European countries and the Soviet Union experience of economic growth. He saw advantages in *economic backwardness* where countries could overcome initial obstacles and "select those paths along which they will be able to increase the yield in terms of human welfare and human happiness" ((Gerschenkron, 1962)), p.51). While there was great possibility, he also identified constraints and certain conditions, what we may call capabilities, to catch up. He noticed, "there are considerable differences, as compared with more advanced countries, not only with regard to the speed of development (the rate of industrialized growth) but also with regard to the productive and organizational structures of industry which emerged from those processes" ((Gerschenkron, 1962), p.7). These productive and organizational structures include many capabilities, such as the importance of the banking structure, skills and technological knowledge.

What exactly are nations catching up to? The catch-up hypothesis views development as a process of closing a technological gap. Highly developed nations are at a frontier of technology or knowledge, while the great majority of other nations lag behind. In this way, technological gap theory sees the variety of development levels primarily due to technological differences. Therefore, countries should aim towards technological advancement, which can ignite high growth rates and place a country on a path to development. Within this tradition, there are many evolutionary and Schumpeterian scholars who have developed theoretical models and additional empirical evidence on catching up and technological gaps ((Dosi et al., 1990), (Godinho & Fagerberg, 2005), (Fagerberg & Verspagen, 2002), (Nelson & Pack, 1999), (Verspagen, 1991), among others).

Following a similar thought of Gerschenkron, Abramowitz noted that technological advancement has necessary pre-conditions, which he coined as technological congruence and social capability (Abramovitz, 1986). This requires significant effort, coordination, and investment tailored to the country's environment, internally and externally. The rate of speed to catch up also depends on the relative position to the frontier. Even though a country may be far behind, there is opportunity for rapid growth. Abramowitz noted, "that being backward in level of productivity carries a potential for rapid advance" ((1986), p. 386). The farther back a country is from the frontier, the larger the potential for high growth rates to catch up.

Social capability is loosely defined, but includes current processes of knowledge diffusion, conditions of technical competence (ie education), labor market structure and migration, organization of firms (ie business environment), political stability, macroeconomic conditions affecting investment and effective demand, and financial institutions to mobilize capital ((Abramovitz, 1986), (Fagerberg, Srholec, & Verspagen, 2010)). These are the foundations for the catch-up process to occur. While social capabilities include a number of factors within a country, technological congruence is a measure of relatedness between two countries in terms of matching resources, markets, consumer preferences, scale and capital intensity (Abramovitz

& David, 1996). One technology may not adapt well in another setting, but also the product created must match the tastes and needs of demand. For example, the United States' agricultural production uses vast amounts of land and large-scale combines and processing facilities. This technology would not adapt well in the Netherlands where land is scarce. Alternative agricultural technologies, such as capital-intensive techniques of green-house farming are far better for a land-scarce nation. Additionally, the United States benefits from a large, homogenous market, while the Netherlands has a much smaller market and must be able to sell their products outside of their country, which may not have the same tastes. Summarized by Abramovitz, "countries have unequal abilities to pursue paths of progress that are resource-biased or scale-dependent" ((1986), p.398).

1.2 Technological Capabilities and Learning

Innovation and technology is not always a public good and rarely diffuses freely and instantaneously throughout the world as was once thought in offshoots of Solow growth models. It takes skills, investment and effort to adopt or generate new technology. While knowledge can be codified in blueprints or instructions, much of it is actually tacit and embodied within a person (Lundvall & Johnson, 1994). For example, while we can read the instructions of an Ikea kitchen cabinet, the practice of actually putting together all of the parts to install the cabinet securely requires previous experience using tools and usually, the first try will not result in the optimal result. There is some tacit knowledge in the process that can't be easily expressed in a manual. Technological knowledge is imperfectly imitated, tacit and requires learning (Lee, 2013, p. 223). This is why knowledge access and learning is an important part to catch up - adopting a new technology requires a different type of learning and not only human capital stock can account for this (Lee, 2013). For a firm to catch-up, learning must take place throughout an organization in a dynamic process, where the, "prior knowledge base and intensity of effort affect the dynamics of knowledge conversion through a spiral process that starts at the individual level and moves up to the organizational level" ((Kim, 1980), p. 508).

Given the special nature of technology, there requires a certain set of capabilities, technological capabilities, that are a combination of firm level technological capabilities (FTC), and national technological capabilities (NTC), which mutually reinforce each other (Lall, 1992). A number of scholars have identified different types of technological capabilities, the mechanism of accumulation of such capabilities and the inter-linkages with consensus that there are three general aspects of technological capabilities: product capability, investment capability and innovation capability ((Bell, Pavitt, et al., 1995) (Dahlman, Ross-Larson, & Westphal, 1987), (Kim, 1980), (Lall, 1992)). Product capability refers to the efficient management and adaption during changing conditions of human resources, inputs and physical capital. Investment capability is the training, project planning and execution of building or expanding facilities. Innovation capabilities refer to knowledge generation and applied research to new products, processes or services ((Kim, 1980), p.5).

1.3 National Technological Capabilities

A series of case studies have documented the experience of successful catch-up economies in East Asia ((Dahlman et al., 1987), (Hobday et al., 1995), (Kim, 1998), (Nelson & Pack, 1999), (Wade, 1990)) and other nations who were unsuccessful in Latin America ((J. M. Katz, 1987b), (J. M. Katz, 1987a), (Teitel, 1981), (Vera-Cruz, 2006)) and India ((Aggarwal, 2001), (Lall, 1986)). Their work has illuminated that institutions must organize, invest and facilitate capability-building processes in a series of stages.

The most influential case studies analyzed the remarkable success of Korea (Kim, 1980). Kim studied Korea's dynamic technological learning as a means to understand what conditions and policies explain the catch-up process, "examining how firms learn and unlearn in response to the changes in market and technology" ((1980), p. 17). He noted three important steps for importing technology to catch-up; transfer of technology from abroad, diffusion within an economy, and indigenous R&D to adapt, improve and innovate their own technology ((Kim, 1980), p. 23). In a study of Latin American countries, Katz proposes that there are two phases to modernize or adopt new technologies at a national level. As a first step, there must be a period of accessing technology, an *acquisition phase* where the technology must be selected, bought, installed and used within a country (J. M. Katz, 1972). But, as we said earlier, technology is a special kind of learning and requires appropriate institutions and preconditions for a country to successfully adapt, imitate, produce, and diffuse a product of higher technological inputs or complexity in the local environment during a second phase, which he calls *assimilation and learning* (Vera-Cruz & Torres-Vargas, 2013).

In a literature survey by Sanjay Lall, he doesn't identify stages, but rather highlights different capabilities at the firm or national level. At the firm level, he emphasized; i) investment capabilities, the ability to plan, acquire technology, provide human resources and establish a new project; ii) production capabilities, the skills to operate, maintain and improve process or product innovations and; iii) linkage capabilities, the ability to coordinate inputs, information, services and institutions. At the national level, Lall recognized the importance of i) physical investment, ii) human capital and iii) technological effort, which is the combination of these inputs with "efforts by productive enterprises to assimilate and improve upon the relevant technology" ((1992), p. 170). Technological effort is difficult to measure, but as a proxy Lall suggests R&D, patents and technical personnel (Lall, 1992). He also notes that importing technology is necessary, but it must be done in such a way that countries can also gain the learning benefits from the innovative process. Similar to Katz's *assimilation and learning phase*, Lall also sees the, "Central role to indigenous technological effort in mastering new technologies, adapting them to local conditions, improving upon them, diffusing them within the economy and exploiting them overseas by manufactured export growth and diversification and by exporting technologies themselves" ((1992), p.166). Capability building requires a balance and must consider the combination of economic factors and incentives between firm and national capabilities that influences the development process.

Another way to look at this adaption process for new technology is through *absorptive capacity*, which refers to the institutional environment of which a country can absorb new investments and new knowledge ((Eckaus, Rosenstein, et al., 1973), (Rostow, 1980)). While institutional factors enable general characteristics for technology to be receptive within a country, absorptive capacity also occurs at the firm level. Cohen and Levinthal further refined the definition of absorptive capacity as the, "ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends, "that is largely dependent on a firms prior related knowledge, which is their awareness of recent scientific developments (Cohen & Levinthal, 2000). This is often used interchangeably with technological capabilities, as Kim defines this as the, "use of technological knowledge in efforts to assimilate, use, adapt, and change existing technologies. It also enables one to create new technologies and to develop new products and processes in response to changing economic environment" ((Kim, 1980), p.4).

Along the way Institutions, which take form through policy, must make many choices, including selectivity of industrial sectors, R&D activities for firms, and possible protection of certain domestic markets. This is one of the reasons that macroeconomic environment and context shapes the particular policies that should be implemented. While there are general capabilities necessary for development, there is no single recipe that works for every country, as Lall expressed, "The experience of NICs shows clearly that there are many roads to success" (p. 182, 1992). Development is influenced by historical, cultural, geographic, and the international environment of a particular country, in other words, "to have any chance for success, policy has to be tailored to each country's conditions and constraints" ((Ocampo, Rada, & Taylor, 2009), p. 249). The mixture of capabilities needed to secure development vis-Ã -vis technological progress is dependent on the country, which remains a recurrent theme within the capability literature.

2 Technological Capability Measures

From the literature review, we find that capabilities are multifaceted. Measuring them has often been inadequate because of the inter-linkages among them, multiple requirements at different levels and intangible organizational strength at many levels needed to maintain them. Nonetheless, it is important to continue to make strides toward measuring them. We find that there is a distinction between two types of technological capabilities indices which we call, aggregate capability indices and export based algorithms. They share a goal in ranking country technological capabilities between countries. The ranking methods is the major differentiation between the two, where one counts the number of 'medals' of success and the other utilizes one dataset to uncover latent capabilities or economic complexity. Aggregated indices have the capability to decompose each variable to consider the relative importance of each category, while algorithm measures do not have this ability, but can capture part of the latent capability and benefits from inter-linkages between the composite indicators.

2.1 Aggregate Capability Indices

Aggregated capability indices are indices that aggregate proxies of factors impacting technological advancement. These indices share the aggregation of four main technological capabilities: innovation/technology generation, infrastructure, human capital, and competitiveness (Archibugi & Coco, 2005). They differ based on which datasets they use as a proxy for each of these categories and the weighting mechanism assigned to each variable. A comprehensive discussion and overview on aggregate capability indices is provided by Archibugi & Coco (2005).

The aggregated capability indices include:

- Index of Science and Tech Capacity (Wagner et al., 2001)
- Tech Achievement Index (Desai et al., 2002)
- Tech Effort Index (Lall, 2003)
- WEF Tech Index (Furman et al., 2002)
- ArCo Index (Archibugi & Coco, 2005)
- Fagerberg & Srholec Index (Fagerberg & Srholec, 2008)

When aggregating indices across countries there is a trade off between the time and country coverage, and quality of data of the indicators. Country coverage between these indices can range between 72 - 162 countries beginning in 1987 (although, most start at around 1995) and often developing country data is usually poor quality. If one wants to understand the contribution of technological capability to growth, this method severely limits the possibility to analyze long run growth processes. Many technological 'leaders' or even those that have caught up started accumulating technological knowledge stock decades ago. Thus, capturing the dynamics or accumulation of such stocks on growth is limited.

Another concern is choosing the appropriate weighting mechanism and/or choosing which variables to include in the index are a subjective choice made by the researcher, which can alter the sensitivity of the rankings. This is true for all of the indicators listed with one exception, the index developed by Fagerberg and Srholec, who use principal component analysis (PCA) to provide a weighting scheme of each indicator (2008). Their approach is to collect data on as many aspects of capabilities that are feasible to measure for a large set of countries and let the method work out a weighting scheme for creating composite indicators of the main "dimensions" of country capabilities. PCA requires one to choose the number of final categories for these measures to aggregate under, and thus, is still not completely free of bias from the researchers. However, it does make analysis more succinct to understand which indicators are related to another.

Overall, the limited time and country coverage in conjunction with the requirement for researchers to make choices on weights of importance of the indicators that build the index makes testing our theoretical framework on the catching-up hypothesis unreliable. We continue our search for additional measures and overview the approach of export based algorithms to help us test the importance of catching-up via technological capabilities.

2.2 Export Based Algorithms

The other type of capability indices are export based algorithms. They have four common features, (i) they all use the same data type and data sources (ie product level export data from UNCOMTRADE/BACI ((Gaulier & Zignago, 2010), (Comtrade, 2010)) and for earlier time periods are merged with Feenstra's trade data (Feenstra, Lipsey, Deng, Ma, & Mo, 2005)), (ii) they use recursive algorithms, (iii) they create rankings of countries *and* products, and (iv) have a theoretical foundation based on economic complexity or latent capabilities.

Economic complexity, in this context, is the idea that international markets require varying degrees of capabilities to produce goods. Some products require complex production processes, and hence only countries with high levels of capabilities can specialize in them. Products embed many of the capability characteristics that we have described earlier within itself. They hold a series of complex processes, which are necessary to realize - they are a reflection of latent capabilities, silently composed of technological, social and absorptive capabilities. Thus, the type of products that you produce is a reflection of capabilities at all levels; i) the national level, the institutional capacity and political determinism to organize, manage and implement the necessary human and physical capital investment, legal framework and financial services over a long time period, and ii) the firm level, management of networks, people and processes to develop or improve upon products and processes. There are a number of inter-linkages between these levels that must respond, adapt and operate together to ultimately catch-up in a globalized environment. Essentially, the idea is that countries with high capabilities produce complex products, which is a statement that can also be formulated reversely (complex products are produced by countries with high capabilities).

For example, to produce chocolate there must be a combination of raw products and an industrial processing facility to mix, cut and package bars of chocolate. However, as we all know, not all chocolate is the same. Even within a broad product category, chocolate, there are different technologies to produce more complex chocolates like truffles or variety boxes. A more advanced set of capabilities is required to produce more varied types of chocolate and export them to a global market. Aggregating all goods that contain cocoa would not capture the capabilities the chocolatiers have in combining the raw materials with innovative ways to produce more complex treats. Thus, we need to distinguish the difference between the two products. In the example described, our measure can distinguish sugar confectionary products as more complex compared to chocolate bars. We cannot measure either capabilities of a country or complexity of a product on its own. Rather, these measures start with an approximation of either capabilities or complexities, and then iterate through the formulas to converge to find a meaningful solution - a stable ranking of countries and products in which both capabilities and complexities do not change from one stage to the next.

Using a disaggregated product-level trade dataset allows us to not only rank more products, but also measure the capabilities of a country more accurately indirectly measures latent capabilities via observed trade patterns. However, using export data has its caveats. Most notably, we are unable to capture services, domestic production (non-exported goods and services). Additionally, specializations of some commodity goods such as oil, tin, copper, soy, etc., may be artificially higher due to over valuation during booms (Felipe, Kumar, Abdon, & Bacate, 2012). Nonetheless, the product variety and number of countries allows for far more comparability over time than aggregated indices.

These measures use a widely available dataset with a near global country coverage and time series that can start as early as 1970 (there is sparse country and low quality coverage earlier, so most studies prefer to start in 1970 and beyond). It's simplicity to calculate also makes these measures appealing to utilize. Both aggregate measures and algorithm based measures have weaknesses, on the one hand aggregate measures require subjective weighting of importance and have limited time and scope, while export based algorithms are limited to analyzing products and have yet to take into account the service sector. We choose, though to discuss four export based algorithms in more technical detail for the remainder of our analysis so that we can focus on the role technological capabilities have on long term growth, which requires a long time series and large country selection.

2.2.1 PRODY EXPY

The first measure of this type of index sought to understand specialization patterns through the type of products a country produces to reveal that there is a relationship with economic growth and latent capabilities called the EXPY PRODY index (Hausmann et al., 2007).

They define:

$$PRODY_p = \sum_c \frac{(x_{pc}/X_c)}{\sum_c (x_{cp}/X_c)} Y_c \tag{1}$$

and

$$EXPY_c = (\frac{x_p}{X_c})PRODY_p \tag{2}$$

Where X_c is total exports for country index, c, product index, p, and Y is GDP per capita. This essentially provides the weighted GDP per capita for a particular product and use the export basket of a country to produce the weighted average of the type of products a country exports.

This was a great step in understanding that particular products exported by countries are related to growth. This measure opened a literature exploring what a country exports is important for economic development and growth. It helped to uncover what are the particular sectors or product categories that seem to be produced by developed or 'caught-up' nations? This answer is much less clear when GDP per capita is included in the weights as it implies that high income nations produce highly productive products, which bias country rankings intrinsically.

2.2.2 Economic Complexity Index

Realizing this issue, Hausmann & Hidalgo improved upon quantifying highly productive products by removing GDP as a factor (2009). Rather, they developed the "Method of Reflections", which takes advantage of the bipartite structure of trade data and iteratively calculates 'diversification', the variety of goods a country produces and 'ubiquity', the type of goods, measuring if it is a common product or a specialized product, that the country produces. The method of reflections provides information about the latent-capabilities of a country.

They start by creating using the revealed comparative advantage (RCA) of a product, p in country c:

$$RCA_{cp} = \frac{X_{cp}/\sum_c X_{cp}}{\sum_c X_{cp}/\sum_c \sum_p X_{cp}} \tag{3}$$

To binarize the values of what countries product to either take a value of 0 or 1, which is a matrix, M_{cp}, they assume that an RCA above one is considered relatively specialized for that producer and otherwise it is not specialized. M_{cp} operates as our sparse network, also called an edge list, where countries are linked to each other through products that they both export and *vice versa*. Our binary matrix or edge list is created by the following rules or mathematical formulation:

$$M_{cp} = \begin{cases} 1 & RCA_{cp} \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Using this matrix, the method of reflections recursively solves the following two equations:

$$k_{c,n} = \frac{1}{k_{c,0}} \sum_p M_{cp} k_{p,n-1} \tag{5}$$

$$k_{p,n} = \frac{1}{k_{p,0}} \sum_c M_{cp} k_{c,n-1} \tag{6}$$

where the initial conditions are $k_{c,0} = \sum_p M_{cp}$; $k_{p,0} = \sum_c M_{cp}$. Equation 5 represents the country representation, while equation 6 represents the product characteristic. This is iteratively calculated until the solution to these two equations converge to a stable ranking, where each additional calculation doesn't change the ranking. They use the normalized second largest eigenvector to produce a ranked list of countries and products for each year of trade data observed.

The method expanded the toolkit of economists who began to use networks as a way to understand economic structure and how this structure contributes to growth. Not only did it produce a ranking of country technological capability, but also opened a new way of understanding products through the product space. This provided a framework on how products are related to one another (ie, the importance of valves across many manufacturing industries), and created a ranking of the technological complexity of products without the need for subjective classification. The product space suggested that there are many possible pathways for countries to move from their current production capabilities to higher value added and complex goods on their trajectories of development.

2.2.3 Fitness

To further improve this methodology, a group of Italian physicists have methodologically expanded upon the methods of reflections ((Tacchella et al., 2012), (Cristelli, Tacchella, & Pietronero, 2015)). Their method also starts from the bipartite network, M_{cp}, but they change the functional form of the recursive formuals.

The initial conditions for diversity of a country is similar, which they call Fitness:

$$\tilde{F}_{c,n} = \sum_{p} M_{cp} Q_{p,n-1} \tag{7}$$

However, the complexity of the product, $Q_{p,n}$, is inversely proportional to the number of countries that produce it:

$$\tilde{Q}_{p,n} = \frac{1}{\sum_{c} M_{cp} \frac{1}{F_{c,n-1}}} \tag{8}$$

They normalize after each iteration the following equations:

$$F_{c,n} = \frac{\tilde{F}_{c,n}}{\frac{1}{C}\sum_c \tilde{F}_{c,n}} \tag{9}$$

$$Q_{p,n} = \frac{\tilde{Q}_{p,n}}{\frac{1}{P}\sum_p \tilde{Q}_{p,n}} \tag{10}$$

where C is the total number of countries in the sample and P is the total number of products. This reformulation of the method improved a technical issue with the ECI. At the limit, if you iterate the method of reflections, the rankings converge to an eigenvalue, a single number. To create a ranking, they normalize the second largest eigenvalue after around the 15th iteration when the rankings become stable. Fitness improves this technical caveat so that rankings do not converge to a single value, but rather converge to stable rank orders between countries or products.

A generalized measure of fitness[2], which does not require the use of RCA to define whether a country exports a product, is also possible to derive. We find this particular measure to be important in our comparative analysis because the RCA requires us to discretize the data (as in M_cp), which can be problematic when datasets can be sensitive to small changes in exports from year to year. For one, there is sensitivity in whether a country is considered to specialize in a product that is marginally below the threshold. This leads to a product specialization to become very sensitive year to year so that a country may be specialized in it for 8 years, but may skip one or two years in between. Secondly, some countries have products that are considered highly complex because they are one of the few producers of vintage products (such as typewriters). Thus, we prefer to use a measure that is a function only of export values (X_cp), smooths the measure with a geometric average for the normalization process, and also converges to stable rankings as quickly as Fitness.

[2] In previous work, this was called ECI+ in (Albeaik et al., 2017). It was pointed out by (Gabrielli et al., 2017) that the measure is very similar to Fitness' generalized form indicated in a footnote in their original paper (Tacchella et al., 2012). The addition in this version of the measure is the geometric mean. Thus, ECI+ is renamed to give homage to the Fitness measure as *generalized fitness*.

More generally, we replace the matrix of M_{cp} with export values to give us the iterative map ((Tacchella et al., 2012), (Gabrielli et al., 2017)):

$$X_c^N = \sum_p X_{cp} \frac{1}{\sum_c \frac{X_{cp}}{X_c^{N-1}}} \tag{11}$$

To guarantee the numerical convergence of the mapping we normalize X_c at each step (including X_c^0) by its geometric mean:

$$X_c^N = \frac{X_c^N}{(\Pi_{c'} X_{c'}^N)^{\frac{1}{C}}} \tag{12}$$

where C is the number of countries in the sample. Similarly, we define the generalized product complexity index as the iterations of the mapping:

$$X_p^N = \sum_c \frac{X_{cp}}{\sum_p \frac{X_{cp}}{X_p^{N-1}}} \tag{13}$$

and also normalizing at each step by its geometric mean:

$$X_p^N = \frac{X_p^N}{(\Pi_{p'} X_{p'}^N)^{\frac{1}{P}}} \tag{14}$$

This version, as mentioned, allows for full use of the export product data as well as normalizing values using a geometric mean that smooth product specialization jumps of a country from year to year and an improved order of product rankings.

After reviewing these export based algorithms, we still remain asking ourselves, are capabilities measured in these ways related to economic growth and development? Can they provide an approximation of the technological and absorption capabilities that were introduced in the previous section? These are the next questions we explore in the following section.

3 Capabilities & Growth: A Comparison

We compare three measures of export based algorithms for the remainder of our analysis. We exclude EXPY/PRODY measure because it biases wealthy countries *de facto* and we find the comparisons of ECI and Fitness (Generalized and RCA based) more comparable given the similarity of the algorithms.

3.1 Data

We use international trade data from MIT's Observatory of Economic Complexity (Simoes & Hidalgo, 2011). We choose the SITC-4 revison 2 data set, which provides the longest time series from 1962 to 2014. The dataset captures trade information for 250 countries and 986 products. We focus on countries with a population of more than 1.25 million in 2008 and exports of more than 1 billion in that year. We also exclude Chad (TCD), Iraq (IRQ), and Afghanistan (AFG) because of unreliable data partly caused by political instability. Moreover, we run four time dependent filters. For each year, we exclude products when the dollar value of exports is equal to zero for more than 80% of the countries. In 2010, those products are only Copra, Manila Hemp, and Uranium and Thorium. We also exclude a country if it's dollar value equals zero for 95% of the products (in 2010 no country would have been excluded). We also exclude a product if global exports are less than 10 million and round to zero any country-product combination that involves less than USD 5,000 in exports. After these filters, our final sample for 2010, consists of 121 countries who add up to 96.75% of global GDP and 83.37% of global trade. We use GDP, population, human capital, number of workers, and capital data from the Penn World Tables (PWT 9.0). GDP data is real GDP National Accounts, which measures GDP in constant USD in 2005 (Feenstra, Inklaar, & Timmer, 2015).

3.2 Traditional Growth Model Comparisons

While are a variety of factors that contribute to economic growth, our main interest is twofold; first, to test whether capabilities, as we have defined previously, contribute to growth, and secondly, understand at what stage in the economic process is capabilities most important. Our framework to understand this process is through the literature on catching-up in which technology adoption is the spark that ignites the economic growth engine to catch up with developed nations. The technological adoption process is done through latent-capabilities, and thus, we hypothesize that these capabilities are much more important for low-income countries than high income countries. Ultimately, low income nations benefit much more from latent-capabilities than high income nations.

To test this hypothesis, we will continue to use one econometric functional form throughout all of our estimation techniques, which includes an interaction between income, GDP per capita, and capabilities, economic complexity, fitness and generalized fitness. This allows us to test at which level of economic growth do capabilities have an effect. Previous work on estimating the impact of capabilities on growth focused on the overall effect and when there an interaction term between GDP and complexity, it often didn't go beyond fixed effect models to test for robustness ((Hausmann et al., 2014), (Felipe et al., 2012), (Gala, Rocha, & Magacho, 2018)). The growth process, economic structure and growth rates are much different for higher income countries that have lower growth rates as compared to lower income countries, which have varying rates of economic growth. Successful catching-up countries have high growth rates until they reach income convergence with high income nations. Thus, to reflect this stylized fact, our base model is as follows:

$$Growth_i = \beta_1 GDP_{i,t-y} + \beta_2 ECI_{i,t-y} + \beta_3 GDP_{i,t-5} * ECI_{i,t-y} + \gamma X'_{t-y} + \delta D_t + u_{it} \quad (15)$$

Where *Growth* of country i is the compound annualized growth rate for the period observed (CAGR). *GDP* is the initial GDP per capita for country i at time period t minus the period span observed, y. *ECI* is the initial complexity measure for country i at time period t minus the period span observed. X is a vector of control variables that include initial population levels, initial human capital, and initial capital per worker[3]. D_t are dummy variables for the respective year to control for any time effects on growth, such as a global economic recession. The error term is u_{it}, but for the random effect model, the error term is composed of $\alpha_i + u_{it}$, where α_i are the random intercepts.

As a first step to compare the performance of our export based algorithms, we run an OLS regression for the entire period under observation. Table 4.3.1 uses a cross sectional OLS regression to predict annualized growth from 1973 - 2013. Our variables of interest are the generalized fitness (F gen), economic complexity index (ECI), and fitness (F), which are all annually standardized indices, holding constant initial levels of income, human capital, capital per worker, and population. The regressions provide a broad picture of long-term economic growth. Though we can't rely on the OLS for the coefficient estimates, we still find that all three measures, along with the interaction terms with GDP per capita, are significant at the 1% level. As expected from previous work on growth convergence, we also find that initial income is negatively correlated with growth in all three regressions and that human capital is positive and significant (Bosworth & Collins, 2003). From our variables of interest, generalized fitness explains most variance in future growth, although it is only marginally better than ECI and Fitness.

[3] All variables are initial values for each period of growth observed. For example, we have 5-year growth periods of 1973-1978, 1978-1983, the regression includes the initial value of GDPpc in 1973 and 1978

Table 4.3.1: Cross-Sectional 40 Year Growth (1973- 2013)

	(1)	(2)	(3)
Initial F gen	0.0416***		
	(0.013)		
Ini GDPpc * F gen	-0.00395***		
	(0.001)		
Initial ECI		0.0462***	
		(0.016)	
Ini GDPpc * ECI		-0.00440***	
		(0.002)	
Initial F			0.0986***
			(0.035)
Ini GDPpc * F			-0.0100***
			(0.003)
Initial GDPpc	-0.0111***	-0.0114***	-0.0142***
	(0.003)	(0.004)	(0.004)
Initial Human Capital	0.00984***	0.00996***	0.0147***
	(0.004)	(0.003)	(0.003)
Initial Pop	0.0000128*	0.0000156*	0.0000168**
	(0.000)	(0.000)	(0.000)
Initial Capital	-0.000259	-0.000410	0.000995
	(0.003)	(0.003)	(0.003)
Constant	0.101***	0.106***	0.109***
	(0.014)	(0.014)	(0.017)
N	87	87	87
Adj. R^2	0.485	0.479	0.427
RMSE	0.0114	0.0115	0.0121

Standard errors in parentheses

Robust-clustered standard errors

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

While the long run growth model gives us a general idea of our model comparisons and that our functional form specification is, as of now, a good choice, we move onto comparing the export based algorithms more rigorously. For one, we are interested in understanding growth rate periods. Annual growth rates are noisy and can fluctuate a lot from a variety of shocks, such as natural disasters or natural resource price volatility. This is why we, and many others in the growth literature, present results for 5, 10 and 20 year growth rates. This also provides a scope for us understand if a measure impacts growth in a shorter time span, over 5 year growth rates, or a longer time period, over 10 or 20 years. For example, education requires a longer time period for which its investment can contribute to growth as skill building takes years to accumulate and impact the economy as compared to to capital per worker, which may have more immediate initial returns. Our export based algorithms could be capturing different parts of capabilities, some that require longer time periods to mature than others, and thus, might be effective at different time period lengths. We balance our panel data set and only include countries for which we have information for the entire time period 1973 - 2013 and end up with 98 countries [4]. This is to ensure that countries that drop in and out of the data are not driving our estimates. Please see the appendix for the full list of countries that we include.

We start our comparison with traditional empirical growth estimation techniques, pooled OLS panels, random effect (RE), and fixed effect (FE) methods (4.3.2-4.3.4). Across the three specifications, all three complexity measures, along with the interaction are fairly consistent and statistically significant, with the exception of the 5 year growth FE model for ECI, where the coefficient preserves its sign, but is not significant. Note that to test the significance of the various complexity measures as whole, that is to understand if the complexity measure has a general statistically significant effect, we run a joint f-test between the complexity coefficient and the corresponding interaction coefficient for the FE models and find that in the 5 year growth regressions, fitness and the generalized fitness are significant, in the 10-year growth regressions fitness and ECI are significant in the 20-year growth regressions, only ECI is significant[5]. This suggests that the measure one is analyzing is time scale dependent. ECI can better identify long run impacts, while the generalized fitness and fitness indicated that its effects are largely transitory. Finally, we also note that we find that the coefficient for initial human capital is generally positive and significant and that of initial income is generally negative and significant.

[4] We ran OLS, FE, RE regressions with the full unbalanced panel and found all estimates to be slightly higher as compared to our balanced panel data set results.

[5] We have also run these regressions without the interaction and find similar statistical significant levels of the export based algorithms as reported. Th linear POLS regressions are provided in the appendix. However, because of our interest in understanding the relationship between income and complexity, as well as the fact that the interaction term remains significant across our regressions, leads us to believe that this functional form specification is the best choice.

Table 4.3.2: Annualized 5 Year Growth Rates

	Gen. F			ECI			F		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
Initial F Gen	0.0563***	0.0570***	0.0621**						
	(0.012)	(0.013)	(0.026)						
Ini GDPpc * Ini F Gen	-0.00508***	-0.00533***	-0.00720**						
	(0.001)	(0.001)	(0.003)						
Initial ECI				0.0679***	0.0612***	0.0249			
				(0.015)	(0.016)	(0.016)			
Ini GDPpc * Ini ECI				-0.00633***	-0.00569***	-0.00268			
				(0.002)	(0.002)	(0.002)			
Initial F							0.131***	0.122***	0.116***
							(0.022)	(0.022)	(0.029)
Ini GDPpc * Ini F							-0.0127***	-0.0120***	-0.0113***
							(0.002)	(0.002)	(0.003)
Initial GDPpc	-0.0109***	-0.0133***	-0.0443***	-0.00931**	-0.0120***	-0.0424***	-0.0140***	-0.0170***	-0.0490***
	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.010)	(0.005)	(0.005)	(0.009)
Initial Human Capital	0.0100***	0.0133***	-0.00318	0.00940**	0.0117***	-0.00486	0.0144***	0.0171***	-0.0103
	(0.004)	(0.004)	(0.016)	(0.004)	(0.004)	(0.015)	(0.003)	(0.004)	(0.015)
Initial Pop	0.000296	0.000697	0.0156	0.00153	0.00169	0.0156	0.00101	0.00126	0.00699
	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)
Initial Capital	-0.00278	-0.00187	0.00311	-0.00314	-0.00215	0.00126	-0.00122	-0.000209	0.000127
	(0.003)	(0.003)	(0.008)	(0.003)	(0.003)	(0.008)	(0.003)	(0.003)	(0.008)
Constant	0.128***	0.133***	0.347***	0.116***	0.124***	0.349***	0.132***	0.141***	0.454***
	(0.015)	(0.018)	(0.100)	(0.016)	(0.018)	(0.090)	(0.018)	(0.020)	(0.091)
N	716	716	716	716	716	716	716	716	716
Within R^2		0.200	0.301		0.201	0.292		0.210	0.306
Between R^2		0.409	0.0349		0.361	0.0372		0.326	0.0254
Overall R^2		0.252	0.0420		0.240	0.0419		0.235	0.0378
Adj. R^2	0.242			0.229			0.226		
RMSE	0.0262	0.0248	0.0218	0.0264	0.0248	0.0220	0.0265	0.0247	0.0217
N Country	91	91	91	91	91	91	91	91	91

Standard errors in parentheses

Robust-clustered standard errors & Year FE

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

Table 4.3.3: Annualized 10 Year Growth Rates

	Gen. F			ECI			F		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
Initial F Gen	0.0527***	0.0505***	0.0385*						
	(0.012)	(0.011)	(0.021)						
Ini GDPpc * Ini F Gen	-0.00458***	-0.00442***	-0.00404*						
	(0.001)	(0.001)	(0.002)						
Initial ECI				0.0711***	0.0660***	0.0304**			
				(0.016)	(0.016)	(0.013)			
Ini GDPpc * Ini ECI				-0.00671***	-0.00625***	-0.00356**			
				(0.002)	(0.002)	(0.002)			
Initial F							0.134***	0.126***	0.120***
							(0.024)	(0.024)	(0.026)
Ini GPCpc *Ini F							-0.0131***	-0.0124***	-0.0120***
							(0.002)	(0.002)	(0.003)
Initial GDPpc	-0.0126***	-0.0150***	-0.0502***	-0.0111***	-0.0137***	-0.0495***	-0.0155***	-0.0189***	-0.0553***
	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.010)	(0.005)	(0.005)	(0.009)
Initial Human Capital	0.00936**	0.0117***	-0.00106	0.0104***	0.0128***	0.00253	0.0152***	0.0183***	-0.00504
	(0.004)	(0.004)	(0.016)	(0.004)	(0.004)	(0.016)	(0.003)	(0.003)	(0.016)
Initial Pop	-0.0000522	0.000123	0.0136	0.00146	0.00157	0.0136	0.00102	0.00123	0.00257
	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.010)
Initial Capital	-0.00184	-0.000822	0.00342	-0.00216	-0.00103	0.00359	-0.000275	0.00107	0.00272
	(0.003)	(0.003)	(0.008)	(0.003)	(0.003)	(0.008)	(0.004)	(0.004)	(0.008)
Constant	0.127***	0.132***	0.386***	0.112***	0.118***	0.372***	0.126***	0.135***	0.476***
	(0.016)	(0.017)	(0.089)	(0.015)	(0.015)	(0.083)	(0.017)	(0.018)	(0.080)
N	357	357	357	357	357	357	357	357	357
Within R^2		0.250	0.445		0.256	0.442		0.276	0.462
Between R^2		0.426	0.0543		0.382	0.0443		0.325	0.0252
Overall R^2		0.311	0.0645		0.297	0.0576		0.282	0.0471
Adj. R^2	0.296		0.431	0.282		0.427	0.270		0.448
RMSE	0.0211	0.0197	0.0150	0.0214	0.0197	0.0151	0.0215	0.0194	0.0148
N Country	91	91	91	91	91	91	91	91	91

Standard errors in parentheses

Robust-clustered standard errors & Year FE

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

Table 4.3.4: Annualized 20 Year Growth Rates

	Gen. F			ECI			F		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial F Gen	0.0467***	0.0432***	0.0457**						
	(0.011)	(0.011)	(0.021)						
Ini GDPpc * Ini F Gen	-0.00411***	-0.00382***	-0.00494**						
	(0.001)	(0.001)	(0.002)						
Initial ECI				0.0588***	0.0571***	0.0603**			
				(0.015)	(0.016)	(0.024)			
Ini GDPpc * Ini ECI				-0.00557***	-0.00545***	-0.00713***			
				(0.001)	(0.002)	(0.003)			
Initial F							0.0959***	0.0808***	0.0930***
							(0.021)	(0.022)	(0.031)
Ini GDPpc * Ini F							-0.00958***	-0.00816***	-0.0101***
							(0.002)	(0.002)	(0.003)
Initial GDPpc	-0.0127***	-0.0145***	-0.0418***	-0.0120***	-0.0145***	-0.0444***	-0.0143***	-0.0163***	-0.0451***
	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)	(0.007)
Initial Human Capital	0.00849***	0.00975***	-0.0118	0.00992***	0.0113***	-0.00570	0.0148***	0.0162***	-0.0137
	(0.003)	(0.003)	(0.017)	(0.003)	(0.003)	(0.015)	(0.003)	(0.003)	(0.016)
Initial Pop	0.0000390	0.000154	0.00102	0.00140	0.00144	0.00119	0.00146	0.00162*	-0.00989
	(0.001)	(0.001)	(0.009)	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.010)
Initial Capital	-0.000701	0.000328	0.00111	-0.000866	0.000340	0.00279	0.000777	0.00198	0.00246
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
Constant	0.129***	0.131***	0.416***	0.120***	0.125***	0.409***	0.113***	0.113***	0.467***
	(0.017)	(0.018)	(0.073)	(0.016)	(0.017)	(0.066)	(0.016)	(0.017)	(0.075)
N	195	195	195	195	195	195	195	195	195
Within R^2		0.385	0.659		0.425	0.673		0.404	0.669
Between R^2		0.437	0.0491		0.392	0.0381		0.343	0.0189
Overall R^2		0.425	0.0819		0.406	0.0685		0.364	0.0412
Adj. R^2	0.408		0.646	0.388		0.661	0.347		0.657
RMSE	0.0161	0.0139	0.00787	0.0164	0.0136	0.00770	0.0169	0.0137	0.00775
N Country	108	108	108	108	108	108	108	108	108

Standard errors in parentheses

Robust-clustered standard errors & Year FE

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

While the OLS, RE, FE models are informative, they have notorious weaknesses. First, we will duly note our inability to control for clear endogeneity issues of how our capability measures may impact growth and consequently, growth may impact capabilities. Secondly, OLS is unable to capture any omitted variables, which is particularly problematic when estimating growth where there are various contributing factors not contained in our list of control variables (and decades of research on hunting for all of the factors). Fixed effects model have the capacity to control for omitted unobservable variables, but only capture the within country effect, which is particularly limiting in a cross-country analysis where we have an interest in effects between countries. Our RE model also show this importance with around 45% of the explained variance is coming from between country variation as shown in tables 4.3.2-4.3.4. While our RE models are able to capture the between country variation, the model requires quite a strong assumption that individual country effects should be random or uncorrelated with our other independent variables. To test this assumption, or rather if one should prefer the fixed effect versus the random effect model, one can apply the Hausman test. Our models rejected the null hypothesis of this test across all measures and time period regressions. While the fixed effects model provides an understanding of the potential magnitude or directional bias in our coefficients, we also lose efficiency in our estimator, which can be problematic with macroeconomic data which has limited observations, and furthermore, we remove the interesting part of the variance (between R^2). This is why we choose to also run Hausman-Taylor models to further analyze our comparisons as the method allows us to account for omitted variable bias, but also captures the between country variance.

3.3 Hausman-Taylor Model

The Hausman-Taylor (HT) model takes the time demeaned average of each variable ($x_{it} - \bar{x}_i$)) also known as Mundlak's device, and then instruments the particular variables that violate the random effect assumption that individual effects must be uncorrelated with the independent variables. The estimation method first runs a two staged least squares (2sls) instrumental variable regression with the time demeaned variables and then uses the retained estimated coefficients from the 2sls regression and applies a random effects model estimated with feasible generalized least squares (FGLS).

The instrument needed for this method requires one that is time invariant. We used the percent of land area in temperate zones as our instrumental variable as it is time invariant, has been correlated with economic growth, and has also been applied previously ((Gallup, Sachs, & Mellinger, 1999), (Szirmai & Verspagen, 2015)). The method helps capture some of the between country variance that would have otherwise been lost using the fixed effect model. In order to capture this variance, the instrument is only applied to variables that break the random effect assumption and identify which variables are endogenous. To uncover these variables, we follow the procedure by Baltagi to identify our exogenous and endogenous variables by preforming Hausman tests for each of the independent variables one by one (2003). Using this method, we find that our only exogenous variable is capital per worker. An important consideration with this type of model is to ensure that we don't have a weak instrument with small samples as it is well known that estimates can be severely biased with weak instruments (Baltagi & Khanti-Akom, 1990). Consistent and unbiased estimates with small samples are a particular concern for macroeconomic regressions as they are often a victim to having few observations. Table 4.3.5 is the correlation table for our endogenous variables with our instrument. The table suggest that our variables of main interest, ECI, fitness and generalized fitness, is highly correlated with our instrument, percent of land area in temperate zones, and thus, are unlikely to have a weak instrument problem. Population could be the only variable facing a weak instrument problem, but it is not a focus of our comparative analysis.

Table 4.3.5: Cross-correlation table of endogenous variables

Variables	Instrument	ECI	Gen. F	F	GDPpc	HC	Pop
Instrument (% Temp Zone)	1.000						
ECI	0.745	1.000					
Gen. F	0.667	0.915	1.000				
F	0.695	0.832	0.741	1.000			
GDPpc	0.516	0.606	0.676	0.481	1.000		
Human Capital (HC)	0.652	0.723	0.697	0.628	0.720	1.000	
Pop	0.019	0.094	0.174	0.306	-0.204	0.009	1.000

Table 4.3.6 shows the results of the HT regressions for 5, 10 and 20 year periods. In many of the measures, the HT estimates of the complexity measures are lower than the FE and RE estimates, but the standard deviations are similar. The change in the coefficient estimates results in many variables lose statistical significance. The generalized fitness performs well at the 5-year growth periods, while the economic complexity measure performs well at the 20 year growth period and no measure performs well at the 10 year growth period. This insists, as noted earlier, that the type of measure analyzed is dependent on the time scale one observes. The estimates of the population variable becomes statistically significant (though unreliable), while capital per worked becomes marginally significant across many of the specifications.

Table 4.3.6: Hausman Taylor Regressions

	5 year			10 year			20 year		
	F Gen	ECI	F	F Gen	ECI	F	F Gen	ECI	F
Initial F Gen.	0.0674***			0.0279			0.0391		
	(0.021)			(0.022)			(0.031)		
Ini GDPpc * Ini F Gen	-0.00819***			-0.00339			-0.00492		
	(0.002)			(0.003)			(0.004)		
Initial ECI		0.0126			0.0188			0.0547**	
		(0.019)			(0.020)			(0.028)	
Ini GDPpc * Ini ECI		-0.00147			-0.00247			-0.00675**	
		(0.002)			(0.002)			(0.003)	
Initial F			0.0559*			0.0490			-0.0153
			(0.030)			(0.030)			(0.042)
Ini GDPpc * Ini F			-0.00548*			-0.00520			0.00101
			(0.003)			(0.003)			(0.004)
Initial GDPpc	-0.0387***	-0.0377***	-0.0396***	-0.0422***	-0.0431***	-0.0439***	-0.0351***	-0.0399***	-0.0329***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Initial Capital	0.00919*	0.00746	0.00674	0.00919*	0.00963*	0.00940*	0.0121**	0.0149***	0.0131**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Initial Human Capital	0.0284***	0.0270***	0.0285***	0.0291***	0.0304***	0.0312***	0.0109	0.0135	0.00871
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)
Initial Pop	0.0227***	0.0232***	0.0230***	0.0253***	0.0243***	0.0233***	0.0282***	0.0274***	0.0248***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Temperate	0.0332**	0.0234	0.0184	0.0266	0.0287*	0.0233	0.0314**	0.0366**	0.0293**
	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.015)	(0.016)	(0.015)
Constant	0.137***	0.147***	0.172***	0.159***	0.161***	0.174***	0.0975**	0.105**	0.0766
	(0.042)	(0.042)	(0.044)	(0.044)	(0.044)	(0.045)	(0.046)	(0.044)	(0.048)
N	684	684	684	341	341	341	187	187	187

Standard errors in parentheses

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

While this method provided an improvement from our FE and RE models, we believe HT doesn't resolve a concern on time effects. In particular, the method doesn't quite solve is the endogeneity between initial income and future growth or in other words the impact of past values determining future values. This leads us to our last econometric model under consideration, a generalized methods of moments model that accounts for both the effects of time and differences between countries.

3.4 GMM Model

Our final model is a generalized method of moments model (GMM) that can account for endogeneity in the variables, as well as time effects via a time differencing instrumental variable and wipes out individual effects through first differences (Bond, 2002). The system GMM uses lagged levels as instruments for first differences and lagged first differences as instruments for levels. Particularly, the system GMM allows for initial levels to not be systematically related to individual effects and in some circumstances, can be more robust in the presence of highly persistent series, such as the persistent effects of education on growth((Blundell & Bond, 1998), (Arellano & Bover, 1995)).

We apply both a first difference for comparison and system GMM model with third order lags, the results are shown in table 4.3.7. The first difference results are comparably similar, but slightly higher than the HT showing that HT were slightly downwardly biased compared to our GMM results. The system GMM results are higher than the first difference estimate and become statistically significant across the measures, although marginally in the case of generalized fitness. Our choice of instruments passes exogeneity tests via the Hansen test statistics for the system GMM for the generalized fitness and ECI, but not fitness. The Arellano-Bond tests reveal that the second order lags are not statistically significant in the system GMM models, suggesting that autocorrelation is not affecting our estimations. As our test perform better with the system GMM, we prefer that model compared to the first-difference GMM.

Table 4.3.7: GMM Annualized 5 Year Growth Rates

	Gen. F		ECI		F	
	(1)	(2)	(3)	(4)	(5)	(6)
	FD GMM	Sys GMM	FD GMM	Sys GMM	FD GMM	Sys GMM
Initial Gen. F	0.0709	0.0960				
	(0.079)	(0.069)				
Initial Gen. F * Ini GDPpc	-0.00903	-0.0125*				
	(0.009)	(0.007)				
Initial ECI			0.0338	0.170**		
			(0.073)	(0.082)		
Ini ECI * Ini GDPpc			-0.00293	-0.0185**		
			(0.009)	(0.008)		
Initial F					0.0764	0.408***
					(0.097)	(0.123)
Ini F * Ini GDPpc					-0.00460	-0.0394***
					(0.010)	(0.012)
Initial GDPpc	-0.0592**	-0.0470*	-0.0538*	-0.0803**	-0.0633**	-0.0655**
	(0.023)	(0.027)	(0.031)	(0.040)	(0.029)	(0.031)
Initial HC	-0.0588	0.0664***	-0.0680	0.0715**	-0.0935	0.0403**
	(0.042)	(0.020)	(0.044)	(0.033)	(0.059)	(0.016)
Initial Pop	0.0975***	0.0208	0.0956***	0.0190	0.0875***	-0.00360
	(0.023)	(0.017)	(0.024)	(0.015)	(0.031)	(0.012)
Initial Capital	0.0529**	0.0127	0.0385	0.0225	0.0318	0.00461
	(0.022)	(0.026)	(0.025)	(0.033)	(0.022)	(0.022)
Yr FE	Y	Y	Y	Y	Y	Y
N	625	716	625	716	625	716
Hansen p-value	0.202	0.116	0.0660	0.124	0.0470	0.0385
AR1 p-value	0.0628	0.0254	0.0582	0.105	0.0752	0.0259
AR2 p-value	0.0368	0.147	0.0346	0.144	0.0684	0.206
N Country	91	91	91	91	91	91

Standard errors in parentheses

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

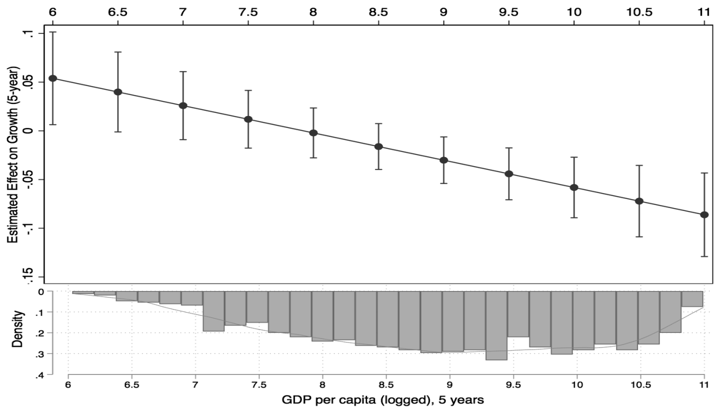
3.5 Marginal Effects of Preferred Model

Our analysis focused on finding an appropriate estimation method, but we have not compared nor analyzed the estimates from our results in detail. In this section, we will use our preferred model, the system GMM and compare the marginal effects of our three complexity measures, generalized fitness, fitness, and the economic complexity index. We standardize our complexity measures so that inference is comparable across the measures and thus can interpret that a one unit increase in the referred complexity measure corresponds to an increase of one standard deviation, which is quite a large jump for any one country to make within a 5 year time period.

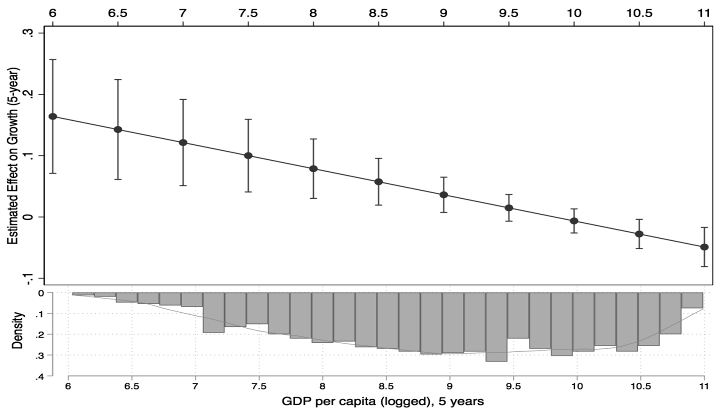
To summarize our discussion in the previous section, the fixed effect, random effect and Hausman-Taylor models have a few weaknesses, which led to our choice of the system GMM as our preferred model. The random effect model is unable to remove omitted variable biasedness. While the fixed effect model can remove this source of bias, it is unable to account for between country variation, which is important for us to understand differences in growth patterns between nations. This led us to use the Hausman-Taylor model, which provides a blended approach that allowed us to observe the between country variation, while allowing our effects to be correlated with independent variables. However, the model does not take into account persistent series, where the initial levels can be correlated with our error term (for HT this leads to inefficient estimators when this is violated). Thus, our preferred model is the system GMM, which can account for persistent effects on our variables and any endogeneity issues that might arise from omitted variables (ie it can account for issues due to time and missing variables).

Across our estimate techniques, the functional form specification we used includes an interaction term with two continuous variables and thus, the effect of the complexity measure depends on the level of income of a country. We visualize our results in figure 4.2 which presents the marginal effects of each complexity measure on 5 year growth periods using 90% confidence intervals from the system GMM regression estimates in table 4.3.7. Below the x-axis is a histogram plotting the density of countries by GDPpc to help understand how frequent a country is in that income category in our sample. The impact of economic complexity declines with the level of development across all of the complexity measures and is also expressed by the negative interaction sign across in table 4.3.7. The impact of economic complexity is positive and significant for the poorest nations across all the variables, however at which point the measure becomes statistically insignificant and in some measures, negative and statistically significant, depends on the measure under consideration. For generalized fitness, the measure becomes insignificant at around $1,000 GDPpc, and significantly negative at $13,000 GDPpc, while fitness shows a positive and statistical significant contribution to growth until around $22,000 GDPpc with no measure that is negatively statistically significant, and ECI is positively statistically significant until around $1,000 GDPpc and negatively statistically significant at around $36,000 GDPpc.

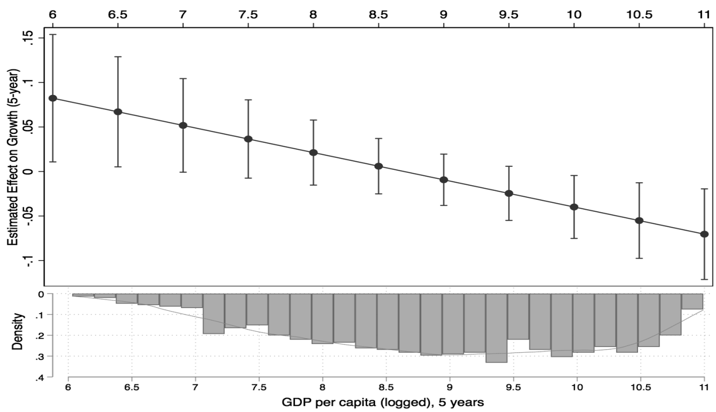
We may be observing statistically negative growth rates because of convergence. Once a nation catches-up and approaches the technological frontier, they tend to have lower growth rates as the growth slows down from previous time periods until the growth rates stabilize over time at a lower level (Barro, Sala-i Martin, Blanchard, & Hall, 1991). The results indicate that economic complexity is particularly important for poorer nations and fitness shows that this benefit lasts longer than the other measures. Eventually, though, complexity no longer becomes a driving factor for economic growth as countries catch-up and reach higher levels of income. For long standing high income countries, the effect of economic complexity is not as important as these nations have little scope for technology adoption and likely other mechanisms, such as generating innovation, are more important in explaining economic growth.



(a) Marginal Effects: Gen. Fitness, GMM



(b) Marginal Effects: Fitness, GMM



(c) Marginal Effects: ECI, GMM

Figure 4.2: Marginal Effects for System GMM Across Complexity Measures

4 Conclusion

Finding the set of variables that are the most important determinants to economic growth has long been sought and remains a highly contested discussion that defines schools of thought among economists. With limited resources, nations want to target investment in projects that can lead to the highest return - investments that can lead to high economic growth. Whether high investment in institutions, education, capital, innovation or industrial policy will put a nation onto the path of economic success is still an open question. Macroeconometric techniques that try to pull apart the conjoining effects of these variables, unfortunately, have not been unable to provide a clear idea on which variables have the most important and largest impact. The advantages and disadvantages to almost every one of the techniques applied in our comparison of the impact of export based algorithms of technological capability on growth have been detailed by Durlauf et. al. in a seminal overview of macroeconometric techniques, and hotly debated in the discussion section of Bosworth and Collins' overview ((Durlauf et al., 2005), (Bosworth & Collins, 2003)). We reiterate many of their conclusions in our own investigation, which is in regards to the sensitivity of these type of cross country comparisons. The time scale of evaluation, as this paper has detailed, shows varying effects of economic complexity and how it is measured. We hypothesize that this is due to the fact that the important capabilities is transitory, where it is more important at early development stages, but this effect fades over time as a nation develops. Furthermore, though not detailed here, the choice of control variables easily changes the estimates as our ability to control for time-changing unobservable characteristics is limited even while we did our best to use instruments. Finally, the econometric specification one chooses to use will drastically change conclusions. This paper chose to see the interaction of economic complexity and GDP as a pivotal relationship following the literature of the catching-up hypothesis. Certainly, if one sees the nature of economic development in a different viewpoint, they will find different conclusions than ours.

Despite these notable drawbacks, the strongest and consistent result that we can draw from our cross-country growth regression results is that there is a positive effect of export based technological capability algorithms (ie economic complexity) on growth for low income nations. We believe this is a reflection of differences in the development process, which is that what is important for low income nations to grow is vastly different for wealthier countries. For low income nations, countries benefit from industrialization - moving from raw goods production into more complex manufactured goods and furthermore, have potential to catch up via technological adoption. However, for high income nations, the development process is less about adopting new technologies, as most of these nations have already learned and applied these tools, but rather these nations are often creating new technologies and pushing forward the technological frontier. Our belief, which requires further research and better data, is that the source of growth for wealthy nations is within service and knowledge based goods. These goods are not present in our dataset nor is there a clear way to measure the complexity of varying software products, for example. We know that there is a growth slow down for wealthy nations, so it would not be surprising if the source of growth is reliant on a different set of mechanisms rather than within the catch-up process of technological adoption. Our results provide some insight that the catch-up process relies on moving towards more complex manufactured goods, but the source of growth for developed nations lies within a different process.

Anyone who has worked with export trade data will know its limitations, which are threefold. First, exported products by definition are tradable manufactured or physical goods where complex products are therefore defined to be mid to high technological *manufactured* goods. This means that the neither service sector nor knowledge based goods are considered. Over the past 20 years, many nations have moved towards service and knowledge based economy of which this index is unable to capture. Perhaps more complex goods are actually software or web based and our data is unable to capture these effects. Measuring the complexity of such knowledge based goods is even more difficult, as well as, the ability to connect service and knowledge based goods to product level trade data. One might argue that we could have used manufacturing value added data as the dependent variable, include the share of services as a control or a measure of the quality of institutions as a control. A major issue with this is the constraining existing data - manufacturing value added data, share of services and quality of institutions does not have as long of a time scale as economic growth. This paper investigated how measures of economic complexity can capture the development or 'catching-up' process, which is a slow and gradual process and requires a longer time series that begins prior to the 90s. As many macroeconomists know, research is often constrained on whether to have a long time-series or to have a shorter time series with more data availability. We chose to look at the longer time horizon, especially given the context of the literature and its current debate. Others have previously used the controls of the share of services and quality of institutions for shorter time period analysis ((Simoes & Hidalgo, 2011), (Hartmann, Guevara, Jara-Figueroa, Aristarán, & Hidalgo, 2017)) However, we suggest that future research utilizing this type of trade dataset should investigate the shorter time period of how export based indices impact the growth of manufacturing value added. Secondly, this trade data considers final goods as an exported good and the valuation of these goods does not consider the value added. What this means is that it does not capture the value that is added along the global production network which are becoming much more common. Value is now created across supply and production chains that occur at different stages in various places across the world. Lastly, the quality of the data has increasingly become easier to compare across countries and more consistently reliable. However, the further in the past that we evaluate growth the more unreliable the data becomes. Which means that our long-term growth models likely have larger errors and are less reliable. This becomes problematic since we are interested in understanding the long-run determinants to growth as we know that development is a timely process and even countries who have managed to develop "quickly" took at least 40 years to do so.

These indices rank products and countries that naturally hide import mechanisms underlying technological jumps in product sophistication and thus, are unable to show the direct link between export based algorithms and economic growth. Some general correlations remain clear in that technologically sophisticated exported products have a role in economic development - at what point and how does a country apply this successfully remains unclear. Furthermore, upgrading our datasets to include service and knowledge based goods is essential in understanding export sophistication's impact on growth and understanding how sophistication along the value chain impacts economic growth are two paths for future research.

5 Appendix A

Table 4.5.8: Country List

Angola	Albania	Argentina	Australia
Austria	Belgium	Bangladesh	Bulgaria
Bolivia	Brazil	Canada	Switzerland
Chile	China	Côte d'Ivoire	Cameroon
Dem. Rep. Congo	Rep. Congo	Colombia	Costa Rica
Germany	Denmark	Dominican Republic	Algeria
Ecuador	Egypt	Spain	Ethiopia
Finland	France	Gabon	UK
Ghana	Greece	Guatemala	Hong Kong
Honduras	Hungary	Indonesia	India
Ireland	Iran	Israel	Italy
Jamaica	Jordan	Japan	Kenya
Cambodia	South Korea	Kuwait	Laos
Sri Lanka	Morocco	Madagascar	Mexico
Myanmar	Mozambique	Mauritania	Malaysia
Nicaragua	Netherlands	Norway	New Zealand
Pakistan	Panama	Peru	Philippines
Poland	Portugal	Paraguay	Qatar
Romania	Saudi Arabia	Sudan	Senegal
Singapore	El Salvador	Sweden	Togo
Thailand	Trinidad & Tobago	Tunisia	Turkey
Tanzania	Uruguay	United States of America	Venezuela
Vietnam	South Africa	Zambia	

For 20 year regressions we also include, Nigeria, Lebanon, United Arab Emirates, Oman, & Syria

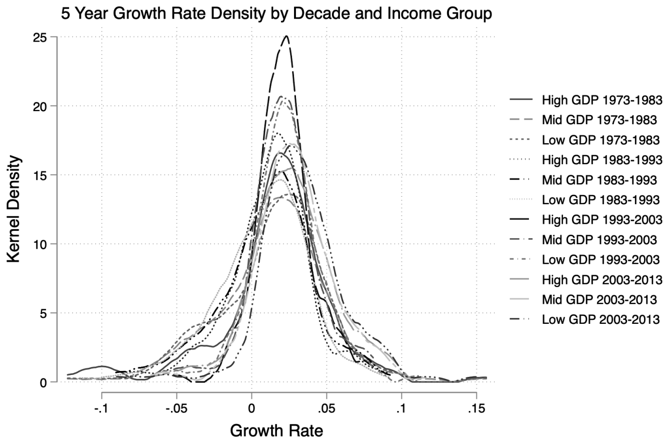


Figure 4.3: 5 year Growth Rate Density by Decade and Country Income Group

6 Appendix B

Table 4.6.9: Joint F test Results from tables 4.3.2- 4.3.4 for FE Model

Measure	Growth Period	F	p-value
Gen. F	5	2.88	0.0613
F	5	8.30	0.0005
ECI	5	1.16	0.3167
Gen. F	10	2.05	0.1353
F	10	10.54	0.0001
ECI	10	2.67	0.0746
Gen. F	20	2.35	0.3081
F	20	0.91	0.6355
ECI	20	5.85	0.0536

6.1 Linear Tables

Table 4.6.10: Annualized 5 Year Growth Rates: Linear

	Gen. F			ECI			F		
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) RE	(6) FE	(7) OLS	(8) RE	(9) FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Gen. F	0.0116***	0.00987***	0.00103						
	(0.003)	(0.003)	(0.006)						
Initial ECI				0.00726***	0.00729***	0.000631			
				(0.002)	(0.002)	(0.004)			
Initial F							-0.00146	-0.000826	0.00755
							(0.002)	(0.002)	(0.005)
Initial GDPpc	-0.00965**	-0.0124***	-0.0420***	-0.00671*	-0.0108***	-0.0416***	-0.00572	-0.0107**	-0.0425***
	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.009)
Initial Human Capital	0.00587*	0.00957***	-0.00487	0.00693*	0.0100**	-0.00464	0.0156***	0.0185***	-0.00612
	(0.003)	(0.004)	(0.015)	(0.004)	(0.004)	(0.015)	(0.004)	(0.004)	(0.015)
Initial Pop	0.000165	0.000567	0.0151	0.00175	0.00180	0.0153	0.00320***	0.00308**	0.0162
	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)
Initial Capital	-0.00216	-0.00129	0.000640	-0.00228	-0.00127	0.000685	-0.00167	-0.000357	-0.000729
	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)
Constant	0.115***	0.122***	0.352***	0.0850***	0.104***	0.348***	0.0509***	0.0756***	0.371***
	(0.017)	(0.020)	(0.101)	(0.015)	(0.016)	(0.091)	(0.018)	(0.018)	(0.095)
N	716	716	716	716	716	716	716	716	716
Within R^2		0.191	0.290		0.204	0.290		0.200	0.293
Between R^2		0.329	0.0369		0.237	0.0363		0.183	0.0458
Overall R^2		0.223	0.0414		0.200	0.0412		0.181	0.0452
Adj. R^2	0.215		0.278	0.192		0.278	0.173		0.281
RMSE	0.0267	0.0250	0.0220	0.0271	0.0248	0.0220	0.0274	0.0249	0.0219
N countries	91	91	91	91	91	91	91	91	91

Standard errors in parentheses, Robust-clustered standard errors & Year FE

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

Table 4.6.11: Annualized 10 Year Growth Rates

	Gen. F			ECI			F		
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) RE	(6) FE	(7) OLS	(8) RE	(9) FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L10.Initial Gen. F	0.0126***	0.0117***	0.00476						
	(0.003)	(0.003)	(0.004)						
L10.Initial GDPpc	-0.0113***	-0.0144***	-0.0492***	-0.00828**	-0.0127***	-0.0485***	-0.00732*	-0.0126***	-0.0488***
	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.010)	(0.004)	(0.004)	(0.009)
L10.Initial Human Capital	0.00529	0.00842**	-0.00128	0.00723**	0.0106***	0.00293	0.0167***	0.0203***	0.00149
	(0.003)	(0.003)	(0.016)	(0.004)	(0.004)	(0.016)	(0.004)	(0.004)	(0.016)
L10.Initial Pop	-0.000211	-0.0000566	0.0115	0.00154	0.00154	0.0128	0.00311**	0.00304**	0.0131
	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)
L10.Initial Capital	-0.00141	-0.000271	0.00191	-0.00151	-0.000121	0.00250	-0.000866	0.000854	0.00148
	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)
L10.Initial ECI				0.00748***	0.00739***	-0.000749			
				(0.002)	(0.002)	(0.004)			
L10.Initial F							-0.00183	-0.00167	0.00466
							(0.001)	(0.001)	(0.004)
Constant	0.115***	0.125***	0.396***	0.0827***	0.100***	0.373***	0.0468***	0.0683***	0.389***
	(0.017)	(0.019)	(0.088)	(0.015)	(0.015)	(0.083)	(0.017)	(0.017)	(0.085)
N	357	357	357	357	357	357	357	357	357
r2_w		0.254	0.439		0.267	0.437		0.265	0.439
r2_b		0.348	0.0539		0.246	0.0453		0.190	0.0538
r2_o		0.278	0.0647		0.235	0.0581		0.206	0.0636
r2_a	0.266		0.427	0.223		0.424	0.195		0.426
rmse	0.0216	0.0197	0.0151	0.0222	0.0197	0.0151	0.0226	0.0197	0.0151
N_clust	91	91	91	91	91	91	91	91	91

Standard errors in parentheses, Robust-clustered standard errors & Year FE

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

Table 4.6.12: Annualized 20 Year Growth Rates: Linear

	Gen. F			ECI			F		
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) RE	(6) FE	(7) OLS	(8) RE	(9) FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Gen F.	0.0107***	0.00959***	0.00382						
	(0.002)	(0.002)	(0.003)						
Initial ECI				0.00634***	0.00612***	-0.00287			
				(0.002)	(0.002)	(0.004)			
Initial F							-0.00192	-0.00220*	-0.00383
							(0.001)	(0.001)	(0.005)
Initial GDPpc	-0.0119***	-0.0140***	-0.0409***	-0.00941***	-0.0121***	-0.0403***	-0.00932***	-0.0123***	-0.0392***
	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)
Initial Human Capital	0.00559*	0.00734***	-0.0135	0.00752**	0.00900***	-0.00892	0.0165***	0.0178***	-0.00982
	(0.003)	(0.003)	(0.017)	(0.003)	(0.003)	(0.017)	(0.003)	(0.003)	(0.016)
Initial Pop	-0.000214	-0.000129	-0.00376	0.00107	0.000984	-0.00212	0.00238**	0.00228**	-0.00254
	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)	(0.010)
Initial Capital	-0.000214	0.000832	0.000146	-0.000386	0.000716	0.000623	0.000548	0.00173	0.000925
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)
Constant	0.121***	0.124***	0.431***	0.0930***	0.102***	0.406***	0.0583***	0.0688***	0.396***
	(0.017)	(0.018)	(0.072)	(0.015)	(0.015)	(0.067)	(0.017)	(0.017)	(0.069)
N	195	195	195	195	195	195	195	195	195
Within R^2		0.388	0.647		0.406	0.646		0.404	0.646
Between R^2		0.384	0.0402		0.317	0.0311		0.282	0.0306
Overall R^2		0.391	0.0715		0.346	0.0606		0.317	0.0602
Adj, R^2	0.376		0.636	0.329		0.635	0.300		0.635
RME	0.0166	0.0139	0.00798	0.0172	0.0139	0.00799	0.0175	0.0139	0.00799
N Countries	108	108	108	108	108	108	108	108	108

Standard errors in parentheses, Robust-clustered standard errors & Year FE

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

Chapter 5

Conclusion

As the diffusion of the internet and computers perambulates the global economy, it has changed not only the way we work, but how we work together within an industry and across countries. The first home computer was introduced in the 1970s and became ubiquitous in homes, businesses and schools by the 1980s. This launched a series of digital related technologies that revolutionized the way we work. The 1990s was marked by the rise of world wide web, which connected computers across the globe. In the 2000s, computers made their way into our pockets through the launch of the first touch-screen smart phone, the iPhone. More recent technologies such as machine learning, artificial intelligence, and smart-sensors are in their infancy. While they are automating a variety of tasks, all of the ways in which these tools will impact society is still developing.

This thesis evaluates how technology influences earnings between individuals, industries and nations. Starting at the individual level, detailed information about workers is used to characterize inequality within 10 European countries. Using detailed individual level information provides an opportunity to analyze distributional changes rather than only looking at aggregated mean differences. Further, using this level of data allows one to decompose specific characteristics, including the risk of automation for a particular job, and attributes which characteristics have a wage effect and/or composition effect on inequality. Individual level data provides a glimpse into how specific characteristic changes may impact within-country inequality. The dissertation then moves on to understand meso-level earning differences, and develops an industry level measure of knowledge diversity. This level of analysis shows that occupation specific skills, which are influenced by technological change, may be paid at different rates depending on the industry. Industry level data shows how the returns to a specific skillset can vary across industries. Finally, detailed trade data can measure the technological capabilities of a country, and explain national income differences reflected in varying economic growth rates. At the highest level of aggregation, the macro-level, technological capabilities provide evidence on how nations 'catch-up'.

At all level of analysis one can observe that technological change impacts earnings. The specific research questions explored are, **(Using individual level data (Chapter 2),** which characteristics impact inequality in Europe, and is this through a wage or composition effect? **(At the industry level (Chapter 3),** does the diversity of knowledge in an industry explain part of the inter-industry premium, and if so, which occupations benefit the most? **(Across countries and overtime (Chapter 4),** when does technological capabilities impact economic growth and does the way we measure this have an impact in our analysis?

1 Micro-level: Decomposition of Characteristics and their Impact on Inequality

Inequality has risen across many European countries. Previous work suggests that there are a few causes to this rise including from education, institutional changes, firm and industry pay differences, and automation. Using micro-level data from 10 European countries, this chapter analyzed a variety of characteristics including, age, education, experience, gender, automation risk, industry, firm size, firm ownership, employment contract, union type, and industry, and their contribution to inequality between 2002 and 2014 with a RIF decomposition technique. The method provides insight as to whether the contribution of inequality is due to the wage effect, the return to wage for a given characteristic, or if this was due to a composition effect, wage changes that are a result of the composition of characteristics in the labor market.

Automation explained the largest portion of increased inequality across the countries observed as compared to individual, institutional or firm characteristics. Furthermore, the rise of inequality due to automation was due to the composition effect for all nations, and half of the countries saw a rise in inequality due to the wage effect, as well. This suggests that the rise in inequality due to automation is because of structural employment changes. There are more low automation jobs as compared to high automation jobs in 2014. Inequality is rising because the share of more unequally paid jobs, which are low automation jobs, are increasing as compared to the share of high automation jobs, which are more equitably paid. These results suggest how the "creative destruction" may increase inequality. If new jobs are highly unequal - the creative force - replace jobs that are paid more equitably - the destruction force - this can result in rising inequality.

2 Meso-level: Explaining Inter-industry Earning Differences

Understanding inter-industry wage differences uncovers a major source of inequality since industry wage differences can explain up to 75% of wage variation (Handwerker & Spletzer, 2016). A major puzzle to understanding industry wage variation is to explain why individuals who have similar characteristics may earn different wages due to the industry that they work in. Chapter 3 shows that individuals who have social skills and do interpersonal activities (relating to team work and coordinating) can earn a wage premium depending on the industry in which they are employed within. Industries that have higher knowledge diversity tend to pay occupations with these types of skills more. Individuals with high social skills or do interpersonal activities can earn up to 10 percentage points more in a knowledge diverse industry compared to a knowledge homogenous industry.

When industries adopt a new technology, labor inputs must adapt by changing the task requirements of existing jobs, and creating new specializations that can complement the new technology. Since industries adopt technology at varying rates, the number of specializations within an industry will vary. Industries who adopt the new technology will have higher marginal productivity, which is also reflected in earnings since more productive workers earn more. One of the limiting factors on whether an industry will adopt a new technology is whether the industry can coordinate an additional specialization. More specializations will require more coordination within the firm, and coordination is costly. One way to reduce coordination costs is for firms to employ individuals with social and interpersonal skills. Thus, firms are willing to pay individuals who have effective communicators more as they can reduce coordination costs in knowledge diverse industries.

Measuring the number of specializations, which is also called knowledge diversity is difficult. The chapter overcomes this obstacle by applying a network approach using labor inputs, an industry-occupation network. The measure, called weighted diversity, captures additional features that other types of measures miss. First, it includes specialized occupations, which are occupations that have a larger share in that industry as compared to the entire labor market. Secondly, it provides a weighted approach, which is that it can estimate the relative distance between two occupations. Occupations that are closer together are weighted less than occupations that are farther away. The weighted approach measures occupational similarity to approximate knowledge bases, which is that the knowledge base of a chief financial officer is closer to an accountant than it is to a physicist. The measure is also able to weight unique occupations within an industry over common occupations, for example a bioengineer is weighted more than a computer programmer in the biochemical industry. Weighted diversity could explain more of the inter-industry wage premium than other types of diversity measures, such as only counting the number of specialization, the concentration of occupations in an industry, and the percent of management in an industry.

Some occupations receive a knowledge diversity premium compared to other types of jobs since the concentration of social skills and interpersonal activities vary by occupation. The estimation of knowledge diversity premiums, or the additional earnings one receives for working in a knowledge diverse industry, by occupation reveal that computer science and mathematic jobs earn the highest knowledge diversity premiums. These results confirm that jobs that are associated with the most recent wave of technological change, digital and mobile robotics, earn knowledge diversity premiums. This also echos the work of Deming who finds that wages associated with social skills are increasing over time (Deming, 2017).

An important policy implication of this chapter is that educational policies should invest in teaching social and interpersonal skills. These type of skills are an important income determination, and since these skills are less likely to be automated, investment can be a worthwhile over the long term (Frey & Osborne, 2017).

3 Macro-level: Technological Capabilities and Economic Growth

Earnings and economic growth vary significantly across countries, and few countries have managed to catch-up over the past 50 years. Chapter 4 investigates the 'catching-up' hypothesis, which is that countries who catch-up tend to follow a similar pathway - improve technological capabilities to spur high economic growth rates. Improving technological capabilities is difficult and requires coordination, investment and effort. The first obstacle to test this theory is measuring technological capabilities, and two types of methods exist - aggregate capability indices, and export based algorithms. The latter measurement can be estimated over a long time series, doesn't require subjective weighting of characteristics, and captures unseen inter-linkages of country coordination to export and produce complex products. This motivated the chapter to compare export based algorithms to test the 'catching-up' hypothesis, and understand under which conditions some measures may explain economic growth better than others.

Using export based measures, technological capabilities are found to increase economic growth for the poorest nations, but when nations became middle income, the impact on economic growth from technological capabilities vanished. This result is consistent across models and estimation techniques tested, which include fixed effects, random effects, Hausman-Taylor, first-difference and system generalized method of moments. Poorer nations benefit from investing in exporting more complex goods, but as countries develop, the significance of this strategy no longer had an impact on economic growth. This provides evidence of 'catching-up', in that poorer nation benefit from upgrading their technological capabilities, but doesn't explain economic growth for wealthier nations.

More questions than answers about the impact of technological capabilities on economic growth arose from this chapter. An important limitation to using trade data as a proxy for technological capabilities is its inability to capture services, knowledge based goods and the increasing fragmented global value chains that impact trade patterns. To test the importance of technological capabilities, new radical data is needed to measure knowledge based products and services is indispensable as these types of goods can be as or even more complex than technologically advanced mechanical products like computers or airplanes. The greatest limitation that remains is the ability to peer back in the past - how has the service sector and the rise of knowledge based products changed as compared to 50 years ago.

4 Summary of the Contributions

This dissertation researched questions about how technology impacts earnings between individuals, industries and nations through various quantitive techniques.

Briefly, the main contributions of this thesis is as follows:

- Decompose a variety of characteristics' contribution to inequality of earnings using micro-level data of 10 European countries. This resulted in finding that the largest impact on inequality is due to automation, and specifically due to the composition effect.
- Introduce a novel measure of knowledge diversity using an industry-occupation network. The metric captures which occupations an industry specializes in while accounting for the relative distance between two occupations, and discounting occupations that are common across the labor market.
- Show that knowledge diversity explains the inter-industry wage gap because earnings from interpersonal and communication skills are paid up to 10 percentage points more in knowledge diverse industries.
- Overview and compare a variety of technological capability measures, including aggregate capability indices, and export based algorithms.
- Show that export based algorithms, sometimes called economic complexity indices, have a limited role in economic growth. These measures can explain economic growth for poorer nations, but fail to capture economic growth patters of wealthier nations.

5 Recommendation for Future Work

Europe is known for strong labor market institutions that aims to protect workers by providing stable and well-paid jobs. Despite this fact, the most recent wave of technological change threatens this outcome. Chapter 2 revealed that inequality is rising among employed individuals due to automation, and suggests that current European labor market institutions are ill-prepared to battle rising inequality. This wave of innovation requires a different set of regulations to mitigate inequality. As high automation jobs diminish, one way forward is to re-skill workers through vocational education programs that teach skills and tasks that complement digital and robotic technologies. Some of the skills that are worthwhile of investment - social skills and interpersonal activities, as chapter three points out. One avenue of future research that may benefit policy makers to investigate how new technologies have changed employment and wages by occupation. A fine-grain analysis of the rise and fall of particular occupations due to specific classes of new technology could be investigated with detailed firm level data - this can help predict the rise of particular occupations, and the fall of others. Consideration of employment contract legislation may also provide insight into how low automation risk jobs like taxi drivers may have much lower and unstable pay as compared to high-paying low automation risk jobs such as a computer programmer.

Two chapters of this thesis applied a network-based approach to approximate variables that are difficult to measure directly -chapter three measured knowledge diversity using an industry-occupation network, and chapter four used the product space to measure technological capabilities. There a wide variety of ways to use network statistics within economics, and this thesis showed one particular pathway - approximating inter-connected variables to measure specific outputs. Future work can follow a similar approach, especially with non-traditional data sources. For example, Chapter 4 concluded that there is a need to measure the complexity of knowledge based services and products. One future direction to measure the complexity of software is to use Github data, which is a repository of computer programming code, and apply a network based approach with the data. Github users are connected to each other through coding projects - it's a network of users and projects. Applying a network approach based with this data may uncover the complexity of projects.

This dissertation has provided insight on how technological change can impact earnings for individuals to nations. It has applied a variety of empirical methods, as well as developed a new methodology on measuring diversity in the labor market, to analyze wage dispersion using individual, industry and country level data. Generally, the thesis has found that technological change has contributed to rising differences in wages. At the individual level, automation is a strong force to rising pay differences. At the industry level, technology has influenced the diversity of specializations and consequently, requires more social and interpersonal activities. At the national level, nations who invest in technological capabilities can benefit by increasing economic growth.

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Valorization

In accordance with article 23.5 of the 'Regulation governing the attainment of doctoral degrees at Maastricht University' decreed by resolution of the Board of Deans, dated 3 July 2013, this chapter on addendum discusses the valorization opportunities of this doctoral thesis.

There has been a resurgence of interest from popular media, academia, and policy makers in the relationship between technological change and income inequality, and the growth of income. Each chapter of this thesis expands on this ongoing discussion by investigating the relationship between technological change and income at the individual, industry and national level, and provides insights for policymakers and researchers.

The first study, Chapter two, is particularly useful for European policymakers concerned about rising income inequality. By providing an in-depth decomposition analysis, policymakers have insight into which factors remain an important driver of inequality in their country. Unlike cross-country analysis which seeks to find patterns across many countries, this chapter first analyzes each country in depth, and then compares the drivers across nations. Since countries are idiosyncratic, not every factor will impact a nation in the same way. Thus, this chapter informs policymakers within each country to address particular factors that may be quite large. However, when there are strong shared experiences across many European countries, as this chapter found, this can inform policymakers for the European Union. The strongest result in this chapter is the role that automation plays on driving inequality. This chapter highlights that each European labor market uniquely adopt automation in their own way, but all nations have been impacted by automation. By large, policy makers must confront that automation is polarizing employment, and the current set of labor institution policies are not equipped to combat this effect. Some ways forward is to promote vocational education that includes apprenticeships and short-term training programs such as ”coding bootcamps” that can help displaced workers re-skill.

The main contribution of Chapter three is providing a novel way to measure knowledge diversity within industries, and is particularly useful for researchers. The method is a general approach to measuring knowledge diversity, which can be applied in a variety of contexts beyond industries. For example, another area of research where this can be applied is in co-authorship networks to understand the role that multidisciplinary research can have on advancing scientific output. There is ongoing discussion on understanding which fields benefit or promote multidisciplinary research, but measuring field specialization, specifically, how field specialization relate to one another, remains quite difficult. This measure provides one way to estimate the relationship between various fields in scientific research. Beyond a new measure of knowledge diversity, the chapter also highlights how knowledge diversity plays a role in wage formation, particularly in regards to the inter-industry wage premium, which has not been previously identified to the best of the author’s knowledge. The chapter provides insight into the possible mechanism as to why individuals received wage premiums for working in knowledge diverse industries, specifically how social and interpersonal skills could reduce coordination costs for firms. This conclusion builds on previous research that establishes rising wage premiums are associated with social skills, and further promotes that these types of skills should be taught in primary school education as it remains an important skill in the labor market.

In the final study of the thesis, the main contribution is providing an in depth overview of measuring country capabilities. Previous work has not identified nor linked the relationship between aggregated and export based algorithm approaches to measuring country capabilities. It provides a detailed assessment of the various measures available, and their strengths and weaknesses, that can guide researchers on when and how to use these measures of country capabilities. In addition, the chapter highlights a main limitation to export based algorithms, which is that it fails to explain economic growth patterns for developed nations. For developing nations to “catch-up,” they must invest in a broad range of capabilities that may allow them to innovate and participate in exporting. Developed nations must invest in measuring services more robustly. A large source of their growth patterns may be hidden within the knowledge sector. Traditional measures that use export information or production metrics fail to capture that a large part of economic growth for these countries lie in their ideas and services.

This thesis will be available for governments, researchers, policymakers. These findings have already been presented in conferences to both academic, non-academic and international organizations. Chapter three was presented at the IBS Jobs Conference: Tech., Demography and the Division of Labour in Warsaw, Poland, B4: Bits, Bots, Brain and Behavior in Valparaiso, Chile, Festival of Economics in Edinburgh, UK and the Geography of Innovation and Complexity in Utrecht, NL. Chapter three of this thesis was presented at UNU-MERIT Research Theme 3 Meeting on Economic Development, Innovation, Governance, and Institutions, and parts of the chapter were included in the UNIDO IDR Report 2016, UNIDO working paper series, and the Innovation Space CCES research project.

Overall, the thesis provides insight into how automation is increasing income inequality from a variety of perspectives. By using individual detailed data, the thesis provides a fine grained understanding of the factors that contribute to rising inequality in Europe, and specifically, if this is driven due to pay differences or employment composition changes. The thesis also contributes a new measure of knowledge diversity. Knowledge specialization is notoriously difficult to capture, but by using an applied network approach allows this thesis to proxy knowledge specialization, and specifically to estimate the relative distances between any two occupations. Finally, the thesis aims to understand how technological change across countries contributes to economic growth by comparing and applying capability metrics.

Abstract

Recently, there is a growing concern about the relationship between technological change and income inequality. This thesis investigates the nature of this relationship between individuals, industries and nations using a breadth of data sources. The benefits or concerns of the impact of technological change on income depends on the perspective of analysis. Within many European countries, the main driver of rising inequality is due to automation, and this effect is caused by the fast-changing composition of the workforce. While, at the industry level, one factor that is important in explaining wage differences between industries is knowledge diversity - individuals who work in knowledge diverse industries tend to earn more, and it is especially true for occupations that have more social and interpersonal skills. At the national level, technological capabilities has a positive effect on explaining economic growth rates, particularly for lower income countries. Technological change can have positive and unintended negative effects, and understanding the context in which technological change benefits or harms can help guide policy makers.

About the Author

Mary Kaltenberg received her Bachelor of Arts (B.A.) degree from Eugene Lang College, The New School, and her Master of Arts (M.A.) degree in Economics from The New School for Social Research in New York City. She has worked at UNICEF on resource mobilization and contributed to UNICEF, UNIDO, and IDB reports. She was a visiting researcher and research assistant at the MIT Media Lab in 2016. She has taught data science and econometrics courses to graduate students at the Maastricht School of Governance. Currently, she is a Post-doctoral Researcher at Brandeis University in Waltham, MA, USA.

Her main areas of interest are applied economics in labor markets and innovation, and she approaches these topics with a mixture of quantitative methods using econometrics, machine learning, and networks analysis.

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