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Evaluating the effects of industrial robots on the European labour market

Employment and wage effects

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1. Excecutive summary

While the nature of work and skill demand has changed multiple times, the pace of the change has accelerated significantly in a way never seen before. An amount of literature explains this by the technological advances that have occurred during the past decades. Increase in automation of tasks today is accompanied by concern of the future of jobs and wages. As machines are becoming smarter and can increasingly substitute human labor in tasks that require skills previously proven challenging to codify and automate, the spectrum of jobs with labor tasks amenable to automation is increasing. While there is a large body of literature investigating the impact of technological change on labor markets, there exists yet little empirical evidence on the impact of robot adoption in particular. Increased use of industrial robots appears to follow an inverse pattern as the decrease in hours worked and employment during the last two decades in parts of Europe. The purpose of the thesis is to evaluate the effects of industrial robots on the European labor landscape, analyzing the impact of increased robot adoption on hours worked and wages over time across industries in Europe. The analysis is based on the use of a novel panel data on robot adoption within 15 industries in 18 countries from 1995 to 2015. My findings suggest there is a negative correlation between the increased use of robots and the fall in hours worked. However, the impact of increased robot adoption on overall hours worked, employment, and wages remains ambiguous, as the results cannot be validated through statistical significance. I find however, that robot adoption has had a positive impact on low skilled workers, by increasing their labor shares. Though only marginally statistically significant, results are negative for both high skilled and middle skilled workers, across five aggregate sectors in 12 of the European countries included in the sample.

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2. Contents

3. Introduction

The history of automation is not new. While the nature of work and skill demand has changed multiple times, the pace of the change has accelerated significantly in a way never seen before. Earlier automation has lead to the disappearance of some old industries and the creation of new ones, that still are important to this day. This process of Creative destruction was first coined by Joseph Schumpeter in 1942, but is still of increasing importance in our days. Increase in automation of tasks today is accompanied by concern of the future of jobs and wages. As machines are becoming smarter and can increasingly substitute human labor in tasks that require skills previously proven challenging to codify and automate, the spectrum of jobs with labor tasks amenable to automation is increasing. Together with falling investment costs in technology and computerization the past decades, firms are now faced with a choice of technology with increasing incentives to substitute robots for wages.

The automation debate today reflects both deep concerns and expectations of increased collaboration between man and machine. Profound change in robot capabilities the past decades leaves one wondering which tasks will be left for human workers, and which type of workers are more vulnerable, and likely, to be replaced by machines in the near future. Frey and Osborne (2013), for example, find that based on the tasks that workers perform, 47% of all US jobs are vulnerable to automation over the next two decades[1]. In their newly released report, McKinsey (2017) investigate the automation of jobs through 2030. They also investigate which jobs may be created in the same period. Based on various scenarios for the future of 46 developed countries, their findings suggest that from 75 million to 375 million workers (3 to 14 percent of the global workforce) will need to switch occupational categories due to technological progress. The extent to which these technologies displace workers will depend on the pace of their development and adoption, economic growth, and growth in demand for work. Documented evidence[2] on the development of labor markets in the US and OECD countries from the past decades suggest the

[1] Arntz, Gregory and Zierahn (2016) however argues that the number is closer to 9%, arguing that the approach used by Frey and Osborne takes into account the susceptibility of tasks, while it should measure the vulnerability of skills
[2] See for example Autor, Levy Murnane (2003), Acemoglu and Autor (2011), Goos and Manning (2014).

development of a so-called “employment polarization”, suggesting that middle skilled workers, typically performing routine tasks, are the most vulnerable to automation. While there is a large body of literature[3] investigating the impact of technological change on labor markets, and some on the impact of advances in Information and Communications Technology (hereafter “ICT”) there exists yet little empirical evidence on the impact of robot adoption in particular. Acemoglu and Restrepo (2017) find a negative effect on employment and wages from increased use of industrial robots in US local labor markets from 1990 to 2007. Graetz and Michaels (2017) on the other hand, analyze the economic contributions of modern industrial robots on labor productivity at firm-industry-level in OECD countries during the same period. They find no significant implications of increased robot adoption on total employment (aggregate hours worked), but do however find that robots appear to reduce low skilled workers employments share.

Increased use of industrial robots appears to follow a similar pattern as the decrease in hours worked and employment during the last two decades in parts of Europe. An industrial robot, as defined by ISO 8373:2012 (International Federation of Robotics 2016) is “An automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications”.

The purpose of the thesis is to evaluate the effects of industrial robots on the European labor landscape, analyzing the effects of increased robot adoption on hours worked and wages over time across industries in Europe. I also investigate changes in labor shares, for three defined skill groups. The analysis is based on the use of a novel panel data on robot adoption within 15 industries in 18 countries from 1995 to 2015. The empirical analysis relies on showing that the impact of robots on changes in hours worked and wages (amongst other outcomes of interest) can be estimated by regressing the change in robot density on the chosen outcome of interest. This approach is inspired by similar approaches used in studies such as Graetz and Michaels (2017) and Acemoglu and Restrepo (2017).

[3] See Acemoglu (2002), Autor, Levy and Murnane (2003), Autor (2014, 2015), among others.

This thesis contributes to the literature in this field by using the newest release of accessible data from EUKLEMS (September 2017) and from the International Federation of Robotics, hereafter "IFR"(2016) on labor characteristics and the number of operational industrial robot stock per industry. This allows me to study the changes over a larger timeframe, including the years after the financial crisis. It also allows me to include a higher number of European countries, specifically eastern European countries where robot adoption has not been introduced before 2006.

EUKLEMS data on hours worked and employment covers 18 countries for the period of 1995-2015. Together with data from IFR(2016), I create a measure of robot density across industries and countries, defined as the number of industrial robots per million hours worked in a given industry. This measure is similar to the one used by Graetz and Michaels (2017).

Changes in average European robot density from 1995 to 2015 is 2,94. This masks country differences and industrial differences within countries, as some countries and industries have experienced significantly higher changes in robot density than others. Robot adoption, on average, has increased by 238 % between 1995 and 2015 in the 18 countries included in the sample. This is explained partially from the significant increase in robot adoption in leading countries such as Germany, but also from the fact that many of the countries in the sample had not adopted robots until 2006. This provides additional motivation to investigate how robotization has affected the European labor market during the past two decades.

The remainder of the paper is organized as follows. Section 4 provides an overview of the previous literature investigating the relationship between skills, tasks and technologies, with focus also on the impact of increased robot adoption on labor markets. Section 5 gives a presentation of the regression analysis and form, while Section 6 presents the data sources, the methodology used behind the construction of the data, as well as descriptive statistics. Section 7 contains the empirical analysis and findings of this study. Lastly, Section 8 presents a conclusion.[4]

[4] Lack of data resources and time explains why this analysis does not include other controls.

4. How does technology and robotization affect the labor market: previous literature.

Two hypotheses have been central to understanding the relationship between skill, tasks and technology the past decade, namely the “Skill Biased Technological Change” hypothesis (hereafter the “SBTC” hypothesis) and the Routinization hypothesis. These hypotheses have paved the way for a large body of literature investigating the effects of technological change on skill demand, and further, its impact on wages, labor shares and employment in general. While SBTC and routinization have been documented in a large body of literature, there is little empirical evidence establishing causal effects from the increased use of technology on labor markets. The literature covering the effect from increased robot adoption is even less exhaustive. Two studies, Graetz and Michaels (2017) and Acemoglu and Restrepo (2017) provide novel evidence of a causal impact of robot adoption on employment and wages, as well as other components of the labor market.

4.1. Explaining changes in the employment structure: How technological development alters skill demand

4.1.1. The Skill Biased Technological Change Hypothesis

Since the industrial revolution, technological progress, e.g. automation, has replaced human labor in tasks that required strength and physical activity. It has long been implemented in agriculture and manufacturing industries, associated with a decline in employment in those industries. Documented data is leading to support this (Akst 2013, Autor and Acemoglu 2011). Today, technology seems to be climbing the cognitive ladder (Akst, 2013), challenging a new group of skills. The direct consequence is that skill demand has changed with the increased automation. Attention has therefore been especially brought to the potential changes in labor shares, e.g. how computerization and automation alters job skill demands.

The *"Capital Skill Complementarity hypothesis",* advanced by Zvi Griliches (1969) addresses the relationship between physical capital and different types of skills - addressing thereby both the challenges and opportunities for human labor resulting from technical advances. Griliches (1969) stated that physical capital is more complementary to skilled than to unskilled labor, although likely to complement both. This would imply that there is natural substitution pressure on unskilled labor as physical capital will tend to increase the relative demand for skilled labor.
This was later supported by Jan Tinbergen (1975), who advanced a hypothesis that since has highlighted the skill level as a significant determinant in the study of the impact of technological change on labor markets. The "Skill Biased Technological Change" hypothesis is built on the assumption that technological change has been "skill-biased", in the sense that new technologies have greater skill demands for, or are more complementary to, high skill workers, resulting in an increase of the skill premium.

Since, economists have been quite receptive to the idea that technological progress would raise relative demand for skilled workers. A wealth of relatively recent studies document a robust correlation between the increased adoption of computer-based technologies and the increased use of college-educated labor within industries, providing evidence that skill demand has been shifted in favor of more high skilled workers as a result of technological change (Katz and Murphy 1992, Acemoglu 2002). Autor (2002) provide evidence of SBTC by showing that a large number of empirical and case studies in the US and OECD countries document that industry and plant level investments in computer technology are associated with increases in skill utilization, altering the skill demand in recent decades. Autor document evidence of (high) skill demand acceleration from the 1970s to the late 1990s, as the supply of skills grew faster between 1970 and 1995 than in prior decades. Return to college also increased during the same period of time, by about 0,39 percent a year between 1970 and 1995. Further, he shows that almost all skill upgrading in U.S. and OECD occurred within detailed industrial sectors, rather than between, even as the relative price of skill was rising. Growth of earnings inequality is also documented to begin in the 1970s in the U.S, which is coincident with the period of rapid advances and investment in computer technology.

The SBTC hypothesis has previously been used to understand the shift in employment towards more educated workers. It therefore predicts a uniform shift in employment away from low-skilled and toward high skilled occupations, as technological change develops. Studies have however shown that there is growth in employment in both ends : in both the highest skilled and lowest skilled occupations, while there has been a decline in middle skilled workers. This phenomenon has been described as “job polarization”, first termed by Goos & Manning (2003), and defined by Autor and Acemoglu (2011) as “reflected through a simultaneous growth of the share of employment in high skill, high wage occupations and low skill, low wage occupations”. A more suited explanation for the polarization was suggested by Autor, Levy and Murnane (2003)´s (hereafter ALM): the “Routinization hypothesis”, which provides a natural starting point for the rest of the literature I present in this section.

4.1.2 The routinization hypothesis

ALM (2003) explain job polarization through the “routinization” hypothesis. The hypothesis focuses on the task content of occupations, suggesting that some types of tasks are negatively affected by technological progress, while other remain vexing to automate. The model describes how computerization affects the tasks that workers and machines perform, by predicting how demand for workplace tasks responds to an economy wide decline in the price of computer capital.

By investigating implications for task demand at industry- and occupation level, they assess the extent to which changes in task composition can account for the recent demand shifts favoring more educated workers. According to ALM, how technological advance (e.g. computers) will affect the task composition of human work will depend on two conditions. Firstly, it depends on how computers substitute for or complement workers in carrying out specific tasks. Secondly, it depends on how these tasks substitute for one another.

ALM classify a task as “routine” if they can be accomplished by machines following explicit programmed rules. Routine tasks are characteristics of many middle skilled cognitive and manual jobs. Non-routine tasks on the other hand involve carrying out problem-solving and complex communication activities, and are currently presenting daunting challenges for programming engineers. Tasks are further subdivided into two major categories: *“cognitive tasks”* and *“manual”* tasks. Routine manual and cognitive tasks can easily be substituted by computers. Examples of cognitive routine tasks are performing calculations or repetitive customer service. Routine manual tasks are for example tasks demanding repetitive assembly. Tasks that present strong complementarities to computerization are classified as non-routine cognitive and manual tasks. Non- routine cognitive tasks include tasks that require problem solving capabilities, intuition, creativity and persuasion. See Autor, Levy and Murnane (2003) for a more detailed description of the tasks given these labels.

The model assumes computer capital prices to fall exogenously with time, due to technological advances. The model is further built on three assumptions. Firstly, computer capital is more substitutable for human labor in carrying out routine tasks than non-routine tasks. Secondly, routine and non-routine tasks are themselves imperfect substitutes. Lastly, marginal productivity of non routine inputs is increased by greater intensity of routine inputs. Based on this model, they argue that industries invest more in computer capital as its price declines, especially industries initially intensive in labor input of routine tasks. This in turn raises the marginal productivity of non-routine tasks, causing workers to reallocate labor supply from routine to non-routine task input. As a result, labor input of routine tasks, for which computer capital substitutes, is reduced, while demand for non-routine task input, which computer capital complements, increases. This is equivalent to resulting in a raise of relative demand for highly educated workers, who hold comparative advantage in non-routine versus routine tasks.

They argue that this displacement of jobs that are intensive in routine tasks may have contributed to the polarization of employment, by reducing job opportunities in middle skilled occupations. Jobs that are intensive in either cognitive or non-routine manual tasks on the other hand have proved more vexing to automate due to the demand for problem-solving and creativity. Since routine and non routine jobs are generally found at opposite ends of the occupational skill spectrum - the ”consequence may be a partial “hollowing out” or job polarization of employment opportunities”, as described by Acemoglu and Autor (2011).

In the same paper, the authors provide evidence of routinization by studying the trends in the “quality,” skill content, and task content of U.S. jobs, they explore the changes in the composition of job tasks in the US, using representative data on task input from 1960 to 1998. They use data on detailed tasks from the Dictionary of Occupational Titles (DOT) to associate particular occupations with the intensity of use of routine and non routine cognitive and manual tasks. They find that within industries, occupations, and education groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of non-routine cognitive tasks. At a industry-level, they show that industries that were relatively intensive users of occupations that use routine tasks had more computerization and that the extent of the use of routine skills had fallen in these industries.

Similar evidence of polarization emerging in the US labor market around the 1990s are provided by Autor Katz and Kearney (2006) [5]and Acemoglu and Autor (2011). These studies build on ALM´s methodology, but extend data using additional data and extending the time period. Goos and Manning (2003) document job polarization in Britain between 1975 to 1999, another country with a large increase in wage inequality. Other literature covering the emergence of job polarization across the US and other advanced economies include Carboneri, Offermanns & Weber (2016), and Autor(2015). Though these studies use slightly different methodologies and data, the common finding is that there appears to have been job polarization in both US and other advanced countries, mainly OECD countries, during the last decades.

Job polarization has also been suggested to be explained by other recent trends in offshoring and outsourcing, which is argued to have replaced workers in certain occupations and tasks the past decades (ALM 2003, Autor et al. 2006, Acemoglu and Autor 2011, Autor and Dorn 2013, Wright (2014), Acemoglu and Restrepo 2017). Goos, Manning, & Salomons (2014) show that job polarization is pervasive across 16 Western European countries over the period 1993-2010. They also quantify the importance of routinization relative to offshoring in explaining job polarization, finding that routinization plays a much larger role.

The routinization hypothesis provides two implications for the relationship between technology and tasks. Firstly, that routine tasks are more amenable to automation. This is supported in several

[5] Autor Katz and Kearney (2006) extend ALM´s data analysis in industry-gender-education cells using data through 2002.

studies, including Autor, Katz & Kearney (2006), Goos, Manning and Salomons (2007), Autor and Dorn (2013). Secondly, that increased use of technology is, at least in part, a response to a decline in technology investment prices. Firms decide on investing in new technologies depending on relative factor prices for labor and capital. This latter has been supported by Acemoglu (2002), Autor (2014) and Decanio (2016), Arntz, Gregory and Zierahn (2016), Graetz and Michaels (2017).

As technological change alters skill demand, the excess supply of middle skilled occupations will undoubtedly have an impact on the wage levels. Most literature mentioned so far suggest that the effect of technological change on wages depends primarily on the elasticity of substitution between human and robotic labor, thus having either a positive or negative effect on wages (Decanio (2016)). Acemoglu and Autor (2011) provides an extended version of the task model used by ALM, which suggests that the nature of changes on wages will be different for the three suggested skill categories.

4.1.3. How technological improvement may alters wages (for three types of skilled workers)

The idea that substitution of human labor for machines depends on cost and comparative advantage, is further supported by Acemoglu and Autor (2011). The authors provide an exhaustive analysis of the relationship between skills, tasks and technology to link job polarization with the routinization hypothesis proposed by ALM (2003). The novelty of their study is the focus on how the direction of the technical change alters skill demand, and further how it can explain changes in wage structures.

While their model builds on the task-based model suggested by ALM, Acemoglu and Autor relaxes assumptions such as assuming that skills and tasks are equivalent. They define the distinction between a task and a skill as a task being "a unit of work activity that produces output," whereas a skill is a "worker's endowment of capabilities for performing various tasks".

They further think of technology as either factor augments high skill, middle skill, or low skill, either low, medium, and high skill workers, assuming that the assignment of skills to tasks is endogenous. Each worker is endowed with one of these types of skills, and allocate their skills to different tasks depending on labor market prices. Tasks are ranked in order of complexity. Medium skill workers are for example more productive than low skill workers, but less productive than high skill workers in more complex tasks. While all tasks can be performed by either skill workers, there exists a comparative advantage of skill groups, which will differ across tasks. Given the prices of different tasks and the wages for different types of skills in the market, firms and workers choose the optimal allocation of skills to tasks.

Skills, embodied in labor, and technologies, embodied in capital[6], offer competing inputs for accomplishing various tasks. Which of these inputs is applied depends on cost and comparative advantage, and on the direction of the technical change. The authors use comparative statics to show that wages can be obtained as the values of the marginal products of different types of skills.

For instance, a technical change making high skill workers uniformly more productive will expand the set of tasks performed by this group of workers, while contracting the set of tasks performed by low and medium skilled workers. The increase in high skill biased technical change can therefore reduce the wages of medium skilled workers by eroding their comparative advantage and displacing them from (some of) the tasks that they were previously performing.
An increase in the supply of middle skilled workers, or a middle skilled biased technical change, on the other hand, will put downward pressure on the wages of both low and high skill workers as it raises the set of tasks performed by high skilled workers, while reducing the set performed by low skilled workers.

Autor and Acemoglu´s framework also shows how technological change will alter the wage ratios. An increase in high skill biased technical change will increase ratios between high skill wages relative to both medium and low skill wages, but reduce medium skill- relative to low skill wages, despite the fact that it reduces the set of tasks performed by both medium and low skill workers.

[6] It also looks includes trade and offshoring, but I focus on the relationship between labor and capital

The direct effect contracts the set of tasks performed by medium workers. However, as medium skill workers become cheaper, firms expand the set of tasks that these workers perform. This indirect effect never dominates the direct effect, and thus wages of medium skill workers decrease relative to those of low skill workers when there is high skill biased technical change.

Their model shows that progress in technology will have different implications on the different skill groups. Depending on which set of tasks expands (contracts) more, wages of the relevant skill group increase (decrease). Changes in technology affects the allocation of tasks across skills, implying that a factor augmenting increase in productivity for one group of workers can reduce the wages for another group by shrinking the set of tasks that they are performing.

The authors provide evidence of changes in wage levels and the distribution of wages have been accompanied by "systematic, non-monotone shifts in the composition of employment across occupations", with rapid simultaneous growth in occupations in both ends of education and wage groups in the US. They also show that job polarization appears to be at least as pronounced in the European Union as in the US. Their findings suggest that job polarization seems to not only reflect a change in the composition of skills available in the labor market but also a change in the allocation of skill groups across occupations.

4.2. How different types of technological change affect the labor market

While trends in employment and education suggest technology to have led to job polarization, there is little evidence establishing a causal effect from the increased use of technological change on labor markets. The literature investigating a causal effect of robot adoption in particular is even less exhaustive. Two studies in particular, Graetz and Michaels (2017) and Acemoglu and Restrepo (2017), provide novel evidence of a causal impact of robot adoption on employment and wages, as well as other components of the labor market. Both studies are based on models influenced or based on the framework(s) presented above, however accounting for the effect of robots, in particular.

4.2.1. How ICT advances affect labor markets

Investigating the impact of ICT technology, Carboneri, Offermanns, Weber (2016) find that a decline in routine occupations and an increase of high skill workers are associated with a higher elasticity of substitution between labor and ICT. They investigate empirically two driving forces for job polarization: the decline of ICT investment price and the presence of frictions in the labor market. They find that cheaper ICT equipment is a promising channel to explain the decline of the documented labor share in 8 European countries, given an elasticity of substitution with labor of about 1,17. Job frictions, on the other hand, do not seem to be a driving force of the decline. Similar findings are suggested by Michaels et al (2009), who test ALM´s routinization hypothesis using data on the US, Japan and nine European countries over the period of 1980 to 2004. They find that countries and industries (within countries) that differentially increased investment in ICT technology raised their relative demand for high skill workers and reduced their relative demand for middle skill workers, consistent with ICT-based polarization. Their results suggest that technologies account for up to a quarter of the growth in demand for highly educated workers.

4.2.2. How robotization affects labor markets

ALM (2003) argue that there are strong economic incentives for firms to substitute robots for relatively expensive human labor. Similar predictions are suggested by Graetz and Michaels (2017), who classify many of the routine tasks as "replaceable" and develop a model of firms´ decisions to adopt robot technology and use robots in production. The novelty of Graetz and Michaels model is that they link the replaceability of these tasks to the improvement and increase in robot adoption, specifically. Following the same line as ALM, they predict that human labor demand over the utilization of a robots depends on changes in the respective factor price ratio. In this model, firms have a technology choice between human and robotic labor. The choice is simple: firms will adopt robots when profits from doing so exceed profits from using the human labor-technology only by at least a fixed setup cost (assuming there is a fixed cost when adopting robots).

Based on this model, Graetz and Michaels (2017) study the impact of robot adoption across 14 industries in 17 countries from 1993-2007. They define robot density as the stock of industrial robots divided by hours worked (in millions). While they find that robots appear to reduce the share of hours worked by low-skilled workers relative to middle-skilled and high-skilled workers, they find no significant implications for aggregate hours worked. Their results are thus consistent with viewing technical change as skill biased, but not with predictions provided by the routinization hypothesis. Their results suggest that robots do not polarize the labor market, as they appear to hurt the relative position of low-skilled workers rather than middle-skilled ones.

Acemoglu, Restrepo (2017) also investigate the effect of the increase in industrial robot usage, but on US local labor markets between 1990 and 2007. They use a slightly different measure than that used by Graetz and Michaels, measuring the exposure to robots defined as number of robots adopted divided by number of employees within each commuting zone in the US. Their analysis presents contradictory results to those of Graetz and Michaels, as they find large and robust effects on employment across commuting zones. Their findings suggest that a commuting zone with a value of exposure to robots equal to the average for the US experienced 0,37 percentage points

lower employment to population ratio. This fall in employment is equivalent to saying that one more robot reduces employment by 6,2 workers, thereby reducing
the employment to population ratio by about 0.18-0.34 percentage points.

On an industry-level, they find that the effects of robots concentrate in manufacturing and especially heavily robotized industries (automobile manufacturing, electronics, metal products to mention a few. They also find that there are three sectors showing positive effects in some specifications: finance, public sector, and non robotized manufacturing. When looking at effects on specific occupations, they find that the effect of robot adoption is negative on essentially all occupations, with the exception of managers. Their findings suggest that the major categories experiencing substantial declines are routine manual occupations and blue-collar workers, implying that their results are consistent with theory presented above.

Drawing attention to the effects of increased robot adoption on wages, Acemoglu and Restrepo (2017) find that robots also have a large and negative effect on wages, reducing wages by 0.25-0.5 percent. Their results suggest that a value of exposure to robots equal to the average led to a 0,73% lower wage growth compared to a commuting zone with no exposure to robots. This is equivalent to one more robot per thousand workers reducing average yearly wages by about 200 dollars in the affected commuting zone. The authors suggest that these numbers may reflect both direct effects of robots on employment and wages, but also indirect spillover effects that might arise because of a resulting decline in local demand. Graetz and Michaels (2017) on the other hand find that average wages are boosted by increased robot adoption.

The contradictory results of the two deserves commenting. Both studies include results robust to several robustness and specifications checks. Both analyses control for other trends that might be related to trends in employment, such as offshorability, routineness and imports from China. Endogeneity concerns are also controlled for, as the studies each construct an instrument variable. Differences in the results of the two studies might therefore lie in the sample of countries analyzed. Another explanation could be the different use of measure of robot density or in general different methodologies, or different IV strategies.

4.3. Why the impact on overall employment remains ambiguous

Technological change has always been accompanied by the fear that technological progress will lead to mass unemployment, i.e. “technological unemployment”, coined by Keynes in 1930. Experts today are split on the validity of this concern, as some experts are more pessimistic on the future of jobs, while others argue that there is a tendency to overestimate the technological capabilities and their negative impact on employment (Arntz, Gregory and Zierahn (2016), Autor (2014, 2015). Previous literature, both theoretical and empirical, suggest that the effect of increased robot adoption (and other technological advances) on overall employment and wages is inconclusive. The following arguments have been suggested as explanations for why the impact on remains ambiguous, and why technological improvement most likely won't result in mass unemployment.

Technology is a slow process

Firstly, the utilization of new technologies is a slow process, and its utilization can be lagging, so that technologic substitution might not always take place as expected (Arntz, Gregory and Zierahn (2016)). This study also argues that automation and digitalisation are unlikely to destroy large number of jobs, partially due to the legal, as well as ethical obstacles that may prevent a technological substitution or at least substantially slow down its pace.

New technology might lead to increased labor demand

Earlier automation has led to the disappearance of some old industries and the creation of new ones, that are still important to this day. This side effect from innovation e.g. technological development, called “Creative destruction” is reflected through the destruction of some jobs and their replacement by new jobs or/and new equipment. It was later developed by Baumol (1967): rising income may spur demand for activities in sectors that have nothing to do with the technological change, which Baumol categorized as “technologically lagging” sectors. Example of these are for example production of haircare, restaurant meals or personal fitness (Autor, 2015).[7] These sectors are neither strongly complemented nor substituted by current technologies. Further, other sectors and occupations might expand to soak up the labor freed from tasks now performed by machines and increased productivity due to new machines may even expand employment in affected industries (Acemoglu and Restrepo 2016). The concept of “creative destruction” e.g. that technological progress can interact with the labor market to increase employment in some occupations or sectors while decreasing it in others has been supported by Acemoglu, 2002, Acemoglu and Autor 2011, Autor 2014, Goos et al 2014. Komlos (2014) on the other hand argues that new technologies created today bring about larger negative externalities than in previous epochs, due to the different nature of destruction and the much higher intensity of automation. According to Komlos, components of the creative destruction were smaller in earlier waves of creative destruction, in the sense that the people who were displaced earlier did not necessarily have a problem finding a new job because the new industries were labor intensive and did not require skills that one learned at the job.

In addition, macroeconomic mechanisms may compensate for the negative labor saving effects of new technologies. According to Arntz, Gregory and Zierahn (2016), three mechanisms may result in an increase in labor demand and counteract the labor-saving impact of technological advances. Firstly, these technologies need to be produced in the first place, thereby creating a demand for labor in new sectors and occupations. Further, new technologies may increase the firm's productivity, which in turn might increase a firm's competitiveness. Increased productivity might also result in lower costs and prices, in turn leading to higher product demand. As a result, firms might demand more labor, which can partially counteract the labor-saving effect of technologies. Lastly, labor productivity might increase to the extent that new technologies complement workers. This might reflect in higher wages, or higher employment, or both, which in turn raises labor

[7] Autor argues that demand for these goods appears strongly income elastic, so that rising productivity in technology leading sectors may boost employment nevertheless in these activities.

income. As a consequence, workers may demand more products and services, thereby again increasing the demand for labor in the economy.

An additional argument provided by(Arntz, Gregory and Zierahn (2016)) is the role of the endogenous wage levels. They argue that wage levels will "react to an excess labor supply by lowering wages, hence improving worker's employment prospects again"

The second mechanism have also been described by Acemoglu and Restrepo (2017) as the positive productivity effect[8] on labor demand. According to the authors, there exists a displacement effect which will however negatively affect labor demand. It occurs as robots displace workers, thereby reducing the demand for labor as fewer workers are needed to produce a given amount of output. As a result, they estimate that technological improvement [9] can have a positive or negative effect on employment and wages, depending on how automation, e.g. robotization, interacts and shapes labor demand through different forces.

Firms decide on investing in new technologies depending on relative factor prices for labor and capital

In an increasingly complex market with consumers demanding both more quantity and quality, firms have incentives to make the right actions in order to maximize profits and/or increase competitiveness, or even just remain competitive.

Increases in competitiveness might also incentivize firms to increase robot adoption. Goos et al (2014) develop a model of labor demand at the industry level and find that routine-intensive industries that are at a higher risk of introducing labor saving technologies gain in competitiveness and face an increasing product demand. IFR (2016) predicts that increased robot adoption by firms is, and increasingly will be, a response to growing consumers markets. Global competition, the decline in products life cycle and the increase in the variety of products require modernization and expansion of production facilities, including flexible automation.

[8] The productivity effect is further decomposed into the price and scale productivity effect. The price-productivity effect is reflected through a fall in the costs of production in an industry, lowered by automation. This will expand the industry and thus increase its demand for labor. The scale productivity effect occurs when a reduction in costs results in an expansion of total output, thereby also increasing the demand for labor in all industries.

[9] Acemoglu and Restrepo look specifically at the effect from increased robot adoption

Graetz and Michaels (2017) suggest that robot adoption has an ambiguous effect on overall employment. Based on similar arguments to those presented by Arntz, Gregory and Zierahn, they argue that whether a decline in robot prices results in more workers required to meet the new output demand, or increase use of robots, depends on firms' response to the fall in the price of robots. Although decreased technology investment prices might incentivize firms to substitute human labor for machines, there is no guarantee that firms will do so.

Some tasks might still be difficult to automate - Paradoxes of technological improvement

While for a long time, automation has consisted of computerizing codifiable routine tasks, today, machines can undertake an increasing spectrum of tasks earlier challenging to automate. However, some tasks are still proved vexed to automation. This raises the following question: Why are robots proving to be able to substitute for so many different tasks previously performed by humans - while there are still some tasks that prove to be difficult to transfer to robots? This is the basis of Polanyi´s (1966) observation, which Autor (2014) refers to as *Polanyi's Paradox*: "We know more than we can tell", i.e. many of the familiar tasks we perform are difficult to codify and automate, as we don´t "know the rules". There remains tasks that we are engaging in, that we only tacitly understand how to perform. Following Polanyi's observation, Autor claims that humans are likely to retain some advantages over machines for the foreseeable future. Similarly, Arntz, Gregory and Zierahn (2016) claim most jobs probably aren't sufficiently well defined to be actually substituted by machines. They further argue that there is also societal value attached to humans performing certain tasks that tends to preserve their comparative advantage.

From an era of "man vs machine" into one of "man and the machine"

The effect of new technologies will also depend on the adjustment of workplace tasks. For some industries, an increase in automation will not necessarily mean a decline in employment, but rather a shift in the tasks needed to be done (Acemoglu and Restrepo (2017)). It can for example be associated with new entrepreneurial opportunities and jobs (Decanio 2016), or tasks involving the monitoring of machines (Arntz Gregory and Zierahn 2016).

As the tasks performed by robots become increasingly complex, the relationship between human and machine changes over time. Both are substitutes in early phases of technological development and become complements as the technology advances (Decker, Fischer & Ott (2017). Focus should therefore also be drawn to the potential shift in the relationship between human and machine from a formerly substitutional to a complementary one. Decker, Fischer, Ott (2017) focus on the relationship between human workers and robots in the service sector. They argue that depending on whether the collaboration between humans and robots constitutes a substitution of tasks or complementary task sharing, the impacts on the labor markets can be completely different.

IFR (2016) further predicts a growing trend in the use of so-called "Cobots" - collaborative robots, predicting that cobots are to "lead the departure from "man vs machine and usher into the man and machine". This implies that theory is changing with the increased intensity and complexity of automation, the new so-called era of "machine and human", by the introduction of "cobots" bound to challenge previous theory and empirical evidence investigating the relationship between technological change and human labor.

5. Introducing the regression and variables included

5.1. Regression analysis

In the regression analysis, the equation estimated takes the following form:

$$\Delta Y_{ci} = \beta_1 + \beta_2(frobots_{ci}) + \beta_3 X_{ci} + \varepsilon_{ci} \qquad (1)$$

Where ΔY_{ci} is the change in the outcome of interest, measured as the difference in the outcome between 1995 and 2015. I estimate regressions on 1995-2015 changes, because I am interested in long run trends. In the main regression, the outcome of interest is the change in log of hours worked between this time period. I also look at how the increased robot adoption may have changed other outcomes such as wages and labor shares. I also check for differences in the impact when using changes in employment as an alternative outcome of interest to changes in hours worked. The main explanatory variable, $frobots_{ci}$ is some measure of the change in robot adoption, relative to the hours worked. X_{ci} is a vector of controls, including country and industry fixed effects, as well as other inputs.

5.2. Robot density to explain changes in hours worked

The main regressor in the empirical analysis is changes in robot density, defined as:

$$Robot_{density} = \frac{Number\ of\ operational\ robots}{Hours\ worked\ (millions)} \qquad (2)$$

This measure is similar to the one used by Graetz and Michaels (2017). As with the outcome of interest, I look at changes in this measure from 1995 to 2015.

Robot density in a given industry and country in year, y is defined as

$$Robot_{density} = H_{ci\ 1995} \times \frac{Robots_{icy}}{Hicy} \quad (3)$$

Change in robot density from 1995 to 2015 is expressed by the following equation:

$$\Delta\, R_{icy} = \sum_{ci}^{H} 1995 \times (\frac{Robots_{ic_{2015}}}{Hicy_{2015}} - \frac{Robots_{ic_{1995}}}{Hic_{1995}}) \quad (4)$$

Where $H_{ci\ 1995}$ stands for the initial (1995) share of hours worked in a given industry (i) in a given country (c) stands for the total number of operational robots in industry i and country c, while H_{ci} stands for the total hours worked in that specific industry, country and year. $\frac{Robots_{ic_{2015}}}{Hicy_{2015}}$ and $\frac{Robots_{ic_{1995}}}{Hic_{1995}}$ measures robot densities in the last and first year of the analysis, respectively. Depending on the period investigated, the latter component will vary. This variable is further weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked, $\sum_{ci}^{H} ci1995$. Weighing the robot densities ensures that the average increase in robot density reflects the relative importance of industries.

5.3. Potential concerns with the regression model

Adjusted form of regression

Findings suggest that there are high differences in changes in robot density. In addition, while some countries, such as Germany, had already adopted robots in the initial 1995 year, it was not until 2006 that all countries included in the sample had adopted industrial robots. The skewness in the distribution of changes might be a concern, as it would make fitting a linear model using raw changes in density challenging. I therefore also test other alternatives to measure the impact of robot density on hours worked, finding that I using as a regressor the percentile of changes in robot density is more correct. This is further discussed in section 4.

Controlling for other trends

There is a possibility that the results are related to other trends affecting changes in employment (hours worked). For instance some industries might face adverse shocks that can also have a negative impact on the hours worked, resulting in some unexplained effect on the dependent variable. If not taken account for, such variables could create omitted variable bias, making the dependent variable correlated with the error term, and possibly confounding the results. To address this concern, I control for changes in ICT and non-ICT capital services, which might also have had an impact on employment during the past decades, as suggested in previous literature.

Other potentially confounding trends which have become more prevalent during the last decades period could be related to imports from low-cost countries[10], migration incentivized by higher wages abroad, or other industry level task characteristics, such as the potential disappearance of routine jobs and offshorability. Similar control variables have been used in other studies investigating the impact of robots on labor markets, see Graetz and Michaels 2017 and Acemoglu and Restrepo (2017). These studies find that empirical results remain statistically significant when controlling for such trends and labor market shocks, however reduced in magnitude.

[10] For example Chinese imports shocks. Studies investigating the negative effect of Chinese imports on employment, see Autor, Dorn and Hanson (2013), or Balsvik, Jensen and Salvanes (201…)

Such controls are however not included in this analysis due to limited access to data, but future analyses are advised to include these. I therefore suggest to interpret empirical findings of this analysis cautiously.

I also control for previous baseline characteristics, such as the log wage and labor productivity (measured as value added divided by hours worked). These control variables are included in the X_{ci} vector in the general regression equation (1). For instance, changes in capital services, especially ICT, might have had an impact on hours worked during the period, as seen in section 2. Excluding changes in these services might lead to an overestimation of the impact of robot adoption, on hours worked.

Exogenous robot density as a proxy of improvements in the world technology

While the control variables and robustness specifications do not solve all potential problems of omitted variables, they provide some robustness to the empirical results. There are however still concerns that other factors could confound the estimates. Another concern is that the main explanatory variable, changes in robot density, is explained by something unobserved in the error term, resulting in endogeneity.

For instance, the empirical strategy used in the analysis could be compromised if changes in robot adoption in other advanced economies are correlated with adverse shock to European industries. For instance, there may be common shocks affecting the same industries in the US and Europe. These could be in the form of import competition, or rising wages, which could cause industries to adopt robots in response.

To address this issue, I run regressions using an instrumental strategy. Instrumental variable (IV) strategies allow for consistent estimation when the explanatory variable is correlated with the error terms in a regression model.(source). The IV is a measure of exogenous robot density which I compute using the changes in robot density in the US, another advanced economy. The exogenous robot density is used as a proxy of improvements in the world technology frontier of robots. This strategy is similar to that used by Acemoglu and Restrepo (2017). Running the regression using the IV allows to focus on the variation that results solely from industries in which the use of robots has been concurrent in advanced economies. One concern is however that IFR industry-level data in the US starts only in 2004, but in 1995 in the European countries included in this analysis. This provides some concerns as to use it as an IV when analyzing the whole time period, whereas this concerns are resolved/mitigated when splitting the time period in two and only looking at the time period from 2005 and 2015. The construction of the IV is explained in more details in section 4.

The first stage will take the following form

$$\Delta R_{icyEUR} = \gamma R_{iyUS} + X_{ic} \quad (5)$$

X_{CI} is the vector of controls mentioned above, including controls for changes in ICT share in total capital services, initial log wage in 1995, and changes in labor productivity.

Other Robustness checks

I further control for different specifications. Some industries might have experienced a significantly higher increase in robot density than others, making it possible that they are the driver of the results. This might also be the case for certain countries relatively more intensive in robot adoption. To address this concern, I separate the specific industry from the sample when running the regression. Excluding this from the main regression, the robot density includes only variation coming from industries other than this industry. A similar robust test is done for the country having experienced the highest increase in robot density. Similar controls have been used by for example Acemoglu and Restrepo (2017). Other controls are investigating the impact on employment instead of hours worked, and excluding unspecified industries.

6. Data description

6.1 Data sources and methodology used for construction of the datasets

While section 3. gives an overview of the regression form and the variables needed in order to make the estimates as robust as possible, section 4 provides an explanation to how I construct the data and different control variables. I begin by presenting the two main sources of data, before I explain several problems met under the construction of the data.

Data on robot adoption

The first source of data is from International Federation of Robotics (IFR)´s newest release from 2016. IFR (2016) provides data on the number of industrial robots delivered to - and operational in - each industry, by each country and year. The latest release includes data on use until the year 2015.

An industrial robot is defined as "An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR 2016). It is important to note that each element of the definition are required to fulfilled in order for a machine to be categorized as an industrial robot. Industrial robots are further classified by their type and can be broken down by mechanical structure. They are also classified by industrial branches they are used in, which is what the data of this analysis is based on.

The increased use of service robots has also motivated literature investigating the degree of substitution between service robots and human labor (Decanio 2016). A service robot is defined by IFR as "a service robot is a robot that performs useful tasks for humans or equipment excluding industrial automation application". The classification of a robot into a service robot or industrial robot relies therefore on its intended application. Manipulating industrial robots could however also be regarded as service robots, provided they are installed in non-manufacturing operations.

The data on industrial robots is broken down by industrial branches reported in accordance with the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4.0, usually from two up til four digits. The IFR provides data on both the number of robots delivered to each industry, as well as the number of operational robots, in each country and year.

A second major source of data is EUKLEMS, using the newest release from September 2017. Using the newest release allows me to include data until the year of 2015. The analysis includes data covering two decades, from 1995 to 2015, while the analysis of the closest similar studies, Acemoglu and Restrepo (2017) and Graetz and Michaels (2017), only covers the time span of 1993-2007. Extending the time period allows me to look at changes during the last decade, which is especially interesting as some countries did not even adopt robots until the year of 2006. Figure 6 and 7 in the Appendix highlights how the increase in robot density has been remarkably higher in the last decade than from 1995 to 2015, while the increase in total robots in this specific labor market has a steady increase in both decades.

Further, countries covered in this thesis are not the same as the ones used in the studies mentioned above. Using the new data also allows me to cover more countries in the initial regression, as data on some countries where not available, or not exhaustive, in earlier releases. At the same time, data on adopted robots is available from 1995 for the countries included in the analysis.

Extending the time period allows me to analyze the effect over longer time. The risk of extending the period after 2007 is the potential concern of overestimating the impact of change in robot adoption on hours worked, as there has been large cyclical fluctuations that has had a negative impact on employment since. It is however challenging to control for potential confounders as a proxy for the financial crisis, in order to verify that results are not influenced by the potential impact of the financial crisis and from the subsequent recovery. I therefore suggest to interpret empirical findings of this analysis cautiously.

Data from EUKLEMS include information on number of people employed in labor in the various industries and hours worked per employees, as well as labor compensation.

Main outcome of interest

The main dependent variable in the analysis is change in hours worked between 1995-2015, so I create a measure for change in log of hours worked for that period. Other outcomes of interest are changes in wages and changes in labor share. I also look at changes in employment, defined as the number of people employed (in millions) as a comparison for the choice of hours worked. I choose hours worked as my main regressor because robots will not necessarily replace workers they may also simply affect the hours worked negatively or positively. In addition, it is more advantageous to use data on hours worked as the countries covered can have longer or shorter work days, more holidays or other labor characteristics of such that can differentiate from one country to another. Results from using employment instead of hours worked as an outcome are also included, as a specification check.

The release also contains information on ICT and non-ICT capital services[11], and value added, which I use to construct control variables. As with the outcome of interest, I create a measure of changes in both variables. These are used to control for potential confounders, as explained in section 3. I also include initial wages from 1995, using data on labor compensation. In addition, by using data on value added and hours worked, I create a measure of initial 1995 labor productivity[12], defined as value added per million hours worked.

To construct control variables on changes in ICT and capital services, I am able to use data on this for the period 1995-2015 from only 10 countries. Data on capital services are missing for the year 2015 for Italy, the Czech Republic and Sweden. Missing values for these countries are computed using the value from the previous year. This provides a conservative estimate of the 2015 value for these countries. Some countries do not have data on capital services at all during the period of the analysis. This regards Greece, Lithuania, Portugal, Romania. Others have data on this, but starting from a later time period, namely Netherlands, Slovakia, Slovenia and the UK[13]. Data on capital services for the whole period of the analysis is available for the following countries: Austria, Belgium, Czech Rep., Germany, Denmark, Spain, Finland, France, Italy and Sweden.

[11] Values are reported in volumes, based on 2010 indices.

[12] The newest EUKLEMS release also includes data on labor productivity, named LP_I, but data is missing on this measure for many of the countries included in the sample.

[13] Data on this in Sweden is covered from 1993, but data is missing for the industry 20-21.

When controlling for changes between 2005 and 2015, I am able to include data on capital services from 13 out of the 18 countries in the sample.

Conversion rates

All values in the EUKLEMS 2017 release are reported in national currencies. However, not all 18 countries included in the sample have adopted the euro. This regards the following countries: UK, Czech Republic, Denmark, Romania and Sweden. There is therefore a need to convert values reported in national currency into a common currency of euros. I convert other national currencies used in these countries using the annual bilateral exchange rates from Eurostat (2017). Eurostat provides values for exchange rates between national currencies and euro even in the years before 1999.

Table 5 show how units for all countries included have been converted to euros for years prior to the introduction of the euro in the European market in 1999. In the data from EUKLEMS, units for years prior to 1999 are reported in fixed 1999 exchange rates[14]. This table is similar to, and based on, the table presented in a methodology report from 2007 explaining how the EUKLEMS datasets are constructed, (Timmer, Moergastel, Stuivenwold, Ypma, O'Mahony and Kangasniemi). The latest report on the methodology used in constructing the EUKLEMS datasets is from 2009, which is the one the 2017 EUKLEMS data is based on. This report does not however include any indication of how the national currencies prior to the adoption of euro (in 1999) have been reported, or how units in countries such as Slovenia, Slovakia or Lithuania have been reported, countries that did not adopt the euro until after 2007. [15]As this remains unclear, I choose to convert values from years before 1999 using the 1999 annual conversion rate, while values for years after are converted using the annual conversion rate for each respective year. A conversion table (Table C) presenting the different conversion rates to euros is included in the Appendix.

[14] Values for labor compensation in France in the years 1995-1999 are for example reported converting French Francs to Euro with the 1999 official fixed Euro conversion rate (6.55957 FRF/EUR).

[15] I find no evidence of how EUKLEMS have converted values before 1999 in the newest release of the methodology report. Going back to the report published in 2009 I find information on how data was converted to euros for euro-adopting countries. This report includes a table showing that values from before 1999 were converted using the 1995 conversion rates given by Eurostat. I therefore assume that the newest release builds on the same methodology, and apply the same method to convert values for non-euro countries.

An early obstacle for constructing the data when using both IFR and EUKLEMS data, is that the two data sources use different industry classifications. In addition, data from IFR does not cover all industries covered in the EUKLEMS datasets, and vice versa. I am able to match 15 of the 39 EUKLEMS industries. These include sectors such as agriculture, electronics, transport equipment, to mention a few. By not including industries from the IFR dataset such as "All other non-manufacturing branches" "All other manufacturing branches" and "unspecified" we lose data on some operational robots.

Data from IFR is based on the ISIC rev. 4 classification, while EUKLEMS data is based on the NACE 2 classification. Data from EUKLEMS on Basic output, input and productivity data are according to the ISIC Rev. 4 (NACE Rev. 2) industry classification. A correspondence table provided by UNSTATS[16] (United Nations Statistics division) validates the comparison between data from both sources. Industries are however grouped differently in the two datasets, making it necessary to aggregate some in the IFR dataset in order to match the corresponding ones in the EUKLEMS dataset. Some industries also require re-coding of the industry, to make sure that the two datasets are merged correctly into one.

Information on all industries, on both detailed and aggregate sectors, is available in data from EUKLEMS. Only some are included in the IFR data. Aggregated sectors included in both are: Agriculture, Forestry and Fishing, Mining and Quarrying, Total Manufacturing, Electricity, Gas and Water Supply, Construction, and Education. The total manufacturing sector is further decomposed into industries at 2-digit level, for which data is available from both EUKLEMS and IFR. Most of these industries included in the EUKLEMS release are aggregated into industry-groups, while they are both separated as specific industries and aggregated in industry-groups in the IFR data. As I want to look at effects at the most specific industry level, I use data on the decomposed total Manufacturing industry (2 digit levels). This implies leaving out one industry from the total manufacturing industry, namely industry "Other manufacturing; repair and installation of machinery and equipment" (code : 31-33), as IFR data does not cover this industry.

[16] UNSTATS provides a correspondence table for industry codes based on NACE2 and ISIC rev 4 classifications with descriptions of the industries.

IFR further provides data on industries at a more detailed level, decomposing two digit level industries further into industries at a three, or even four-digit level. In almost all cases, data from industries at three digit level are included in a more aggregated level. This is however not the case for two industries at a three digit level, industries "229" and "289", labeled |respectively. One concern has therefore been the categorization of these "unspecified" industries in the IFR dataset.

Per definition, industry "229" should be included in the two digit industry 22 " Rubber and plastic products (non-automotive)", as industry "289" should be included in the two digit level industry 28 " Machinery and equipment n.e.c.", following the same logic used for other industries at a digit level higher than two. As they are not, this makes me unsure of how to include observations from these unspecified industries. Industry 229 is however included in the IFR industry-group "19-22"; "Plastic and chemical products", as 289 is in the industry-group "24-28"; "Metal". One alternative would therefore be to aggregate these industries in the EUKLEMS dataset. Industries 22 and 23 are however not separated in the EUKLEMS data, which would mean aggregating industries 19-23 in both datasets. Further, datasets "24-28" (including 24,25, 28, 289) would have to be aggregated in each datasets. By doing so, the industries in the analysis are bigger, implying losing the possibility of analyzing the effect of increased robot adoption at a more specific industry-level.

As I wish to analyze the effects of robot adoption at the lowest aggregated level possible, I choose to aggregate the unspecified industries with their respective two digit level industries. Excluding them might result in losing information, as there might be interesting developments in these industries, or result in underestimating true robot densities[17]. As a robustness check, I also run a regression excluding these industries. Results are presented in section 7.

A presentation of all EUKLEMS and IFR industries is provided in Table W, which also illustrates how industries from both sources are aggregated and matched.

[17] In fact, robot adoption in the unspecified industries are especially significant in countries such as Germany and…

Table W: Comparison table NACE2.0 and ISIC rev4.0

Code description	EUKLEMS industries (NACE2.0)	Corresponding IFR industries (ISIC rev4.0)	Industries incl. In both datasets	Industry labels in paper
AGRICULTURE, FORESTRY AND FISHING	A	A-B	✓	Agriculture
MINING AND QUARRYING	B	C	✓	Mining
TOTAL MANUFACTURING	*C*	D	✓	*Total manufacturing*
Food products, beverages and tobacco	10-12	10-12	✓	Food products
Textiles, wearing apparel, leather and related products	13-15	13-15	✓	Textiles
Wood and paper products; printing and reproduction of recorded media	16-18	16; 17-18	✓	Wood products
Coke and refined petroleum products	19	19	✓	Petroleum products
Chemicals and chemical products	20-21	20; 21	✓	Chemical products
Rubber and plastics products, and other non-metallic mineral products	22-23	22; 229 ; 23	✓	Rubber & Plastic products
Basic metals and fabricated metal products, except machinery and eq.	24-25	24; 25	✓	Basic metals & metal products
Electrical and optical equipment	26-27	26-27	✓	Electronics
Machinery and equipment n.e.c.	28	28; 289	✓	Industrial Machinery
Transport equipment	29-30	29;30	✓	Transport equipment
Other manufacturing; repair and installation of machinery and equipment	31-33			
ELECTRICITY, GAS AND WATER SUPPLY	D-E	E	✓	Electricity, Gas, water supply
CONSTRUCTION	F	F	✓	Construction
Education	P	P	✓	Education

Notes: Matching is done following the conversion classification table from Unstats, comparing NACE2.0. and ISIC REV4.0 classification. Matching of industries are based on the classification of the data from EUKLEMS. It follows that industries from IFR need to be aggregated. This is shown how in the column named "Corresponding IFR industries".

The final dataset includes 270 country-industries, consistent of 15 industries in 18 countries, during the time period of 1995-2015. A list of the countries included in the analysis are presented in the appendix, in Table 2.

Constructing the measure of robot density

Using data from these two sources, I am able to construct a measure of robot densification, defined as the stock of operational robots per million hours worked in a certain industry, and country. This measure is similar to that used by Graetz and Michaels (2017). Graetz and Michaels however construct their stock of robots based on deliveries using the perpetual inventory method, assuming a depreciation rate of ten percent. Because any effect robots would have on labor markets will stem from robots actually producing output, I choose to use the number of operational robots and exclude data on delivered robots

Changes in robot densities are weighted with the country-industry initial share of hours worked to ensure that the average increase in robot density reflects the relative importance of industries. I primarily weigh robot densities because the unweighted results give huge uneven differences[18]. It does not however seem to be an issue for the other variables used in the regression.

Constructing the measure of exogenous robot density

To construct the instrumental variable of my choice, I use the changes in robot density in the US, another advanced economy. I use the same data sources as used for constructing the main regressor. One shortcoming of using this instrumental variable is that data from IFR on operational robots only covers a limited period of the period used in the main analysis. While aggregate data for the United States is available from 1993, data on operational robots in the US is only available for the period from 2004 to 2015. Similarly, data from EUKLEMS on hours worked in the US is only available from 1998. I construct estimations of robots adopted in 1998 based on the assumption that industry shares were the same in 1998 as they were in 2004. In a similar way, I assume that shares of robots in the 6 industries having adopted robots by 2004 was the same 6

[18] For instance, industry "Coke and refined petroleum products" in Denmark had 303 robots in use in 2015. Given the industry´s significantly relative low share of hours, the robot density in this industry has an astonishing value of 300 (number of robots per million hours worked).

years prior. In this way, I can estimate conservative measures for the robot adoption in the 6 industries in 1998. This provides similar estimated values as when calculating estimates using average annual increases from 2004 to 2015 to calculate past values. I present calculations of estimates in Table 4A and 4B in the Appendix.

The use of this instrumental variable when analyzing the main period of time thus has some shortcomings. Firstly, there is a risk that robot adoption in these 6 industries in 1998 is overestimated. Some of the industries having adopted robots in 2004 might not have adopted robots in 1998. Real numbers could also be underestimated. This latter regards especially the Transport equipment industry. Secondly, the instrument does not cover the whole time frame, as data for three years are missing. Based on the development of robot densities in the 18 European countries included in the analysis, I argue however that robot densities did not change drastically from year to year before the 20th century, making it plausible that changes between 1998 and 1995 were rather small and insignificant. I include the results when using the IV instrument for the whole time period, but suggest that the IV is much more reliable when looking at the impact during the time period from 2005 to 2015. When looking at the impact from 2005 to 2015 data is covered for all years, making it a stronger proxy of improvements in the world technology frontier of robot to predict the changes in European robot density. As with the I main regressor, use percentiles of changes in robot density, but also provide results for when using alternative forms of both the regressor and the IV. Changes in robot densities are weighted using the 1998 initial share of hours worked, to ensure that relative importance of industries is reflected in the results.

Looking at changes in labor shares

I also consider as outcomes the changes in the labor share, using data on labor input from the 2017 EUKLEMS release. EUKLEMS draw on a number of micro data sources in order to construct the labor composition indices. Data on labor input includes information on the employment structure of the workforce, such as age, gender, and educational attainment level. In addition to the country and economic activity dimensions, the number of people employed are categorized into one of 18 employment groups within each country, industry and year cell, according to a number of demographic characteristics. These employment groups are composed based on two gender categories (male, female), three age categories (15-29 years; 30-49 years; 50 years and higher) and three educational qualifications levels (high, medium and low). I use the same measure for robot density in this analysis, defined as the number of operational robots divided by the number of hours worked.

Data available on labor share in industries are on a one-digit level, implying moving away from the a more specific analysis. The industries included in this analysis are presented in table 1, above. Industry The total manufacturing sector is composed of two-digit level industries, of which most are covered in the main regression. IFR however does not provide data on one industry group included in this sector, namely “Other manufacturing; repair and installation of machinery and equipment”. Thus, while this industry group is excluded in the main analysis, it is included in the analysis investigating the effect on labor shares, as I have both data on robots used, and hours worked in the overall manufacturing industry.

Further, sectors “Electricity and Gas” and “Water and sewerage” are aggregated into one common industry “ Electricity, Gas and Water supply” in the EUKLEMS for data on hours worked, which I use to construct my measure for robot density. These industries are however not aggregated in the data on labor shares. Ideally these industries would be aggregated by using a weighted mean of observations in both industries. As data required in order to do so is not accessible, I choose to not include these, in fear of incorrectly measuring the labor shares compared to shares in other industries. Data on labor shares is only available from 2008 to 2015. Further, data is not available for Belgium, reducing my sample of countries to 17.

Validity and quality of data used

Methodology used in constructing data in earlier releases and the 2017 release is reported in specific modules and in the following article (Kirsten Jäger (The Conference Board) EU KLEMS Growth and Productivity Accounts 2017 release - Description of Methodology and General Notes September 2017). This has also been done for previous releases. Further, the 2017 release of the EU KLEMS database is funded by the European Commission[19]. Data used in the EUKLEMS 2017 release is based on, and in almost all cases consistent with data provided by Eurostat. The data I

[19] Under the Directorate General Economic and Financial Affairs under the service contract ECFIN-163-2015/SI2.716986

use in the analysis, on output, value added and employment is consistent with official statistics as available from Eurostat at the corresponding industry levels. This provides strong validity of the EUKLEMS data in the comparability of the series across countries.

With regards to data on operational robots, validity of the quality of the data is ensured by the fact that the robot statistics provided by IFR are based on consolidated world data reported by robot suppliers as well as on the statistics of the national robot associations of North America (RIA), Japan (JARA), Germany (VDMA, R+A), Italy (SIRI), Republic of Korea (KAR), to mention some. Methodology used to construct the dataset and the classification of the industries is also described in the IFR 2017 report. Validity of the data is further confirmed considering that previous releases has been used in studies investigating the same topic as this thesis. This also regards the data coming from IFR. Graetz and Michaels (2017) and Acemoglu and Restrepo (2017), both investigating the impact of increased robot adoption on labor markets, use both earlier data from IFR and earlier releases from EUKLEMS.

6.2. Descriptive statistics

Summary statistics of average levels of robot density by country and industry are presented in tables 7, and 8. A more detailed summary statistic of the variables included is presented in table 9. Table 7 presents the average levels of robot density and other variables by industry and countries[20] included in the sample. Variables include the different independent variables, such as change in the log of hours worked, change in log of wages, change in employment, and change in labor shares. It also includes statistics on the main regressor and control variables; change in log of hourly wages in 1995, in ICT and non-ICT capital services and changes in labor productivity between 1995 and 2015. The means reported highlight that there is skewness in the distribution of robot density. Robot densities in 1995 heavily concentrated at small positive values, often close to 0. Distribution in changes of robot density varies also remarkably. In some countries, changes in robot density is however very high. This regards in particular Germany and Italy. The skewness in the distribution might make fitting a linear model using raw changes in density challenging. As an

[20] Across country values are not weighted.

alternative to investigating the impact of raw changes in robot density (weighted), I use percentiles of changes in the distribution of robot density. In order to create the percentiles of changes in robot density, I rank the weighted changes, the highest ranking number reflecting the highest change in robot density. In order to assign these rankings percentiles, I follow the Hazen's rule:

$$\frac{(\,i - a)}{n}$$

where i and n denote rank and number of values, and a takes the value of 0,5. Values range from 0 to 1, where a high percentile reflects a large increase in robot density. This method is also applied in the construction of the exogenous robot density. Figure 1 (a) and (b) shows the difference in using percentiles of changes versus raw changes of robot density. The skewness in the distribution is clear in figure (b). Figure (a) deserves some additional commenting. It appears that negative changes in hours worked are more pronounced in the 10th to 50th percentile, while industries with a high percentile (equivalent to a high change in robot density) seem to have experienced more positive changes in hours worked. This could be explained by (some of) the arguments presented in section 2.3.

The motivation behind the analysis of this thesis has been the decrease in hours worked, presented in Figure A below, parallel to the remarkable increase in robots adopted and robot density (Figure B) in 18 European countries from 1995 to 2015[21].

[21] Most of the descriptive figures are based on an indice=100, this is due to the large differences in robot adoption across industries and countries.

Development of hours worked and employment 1995-2015

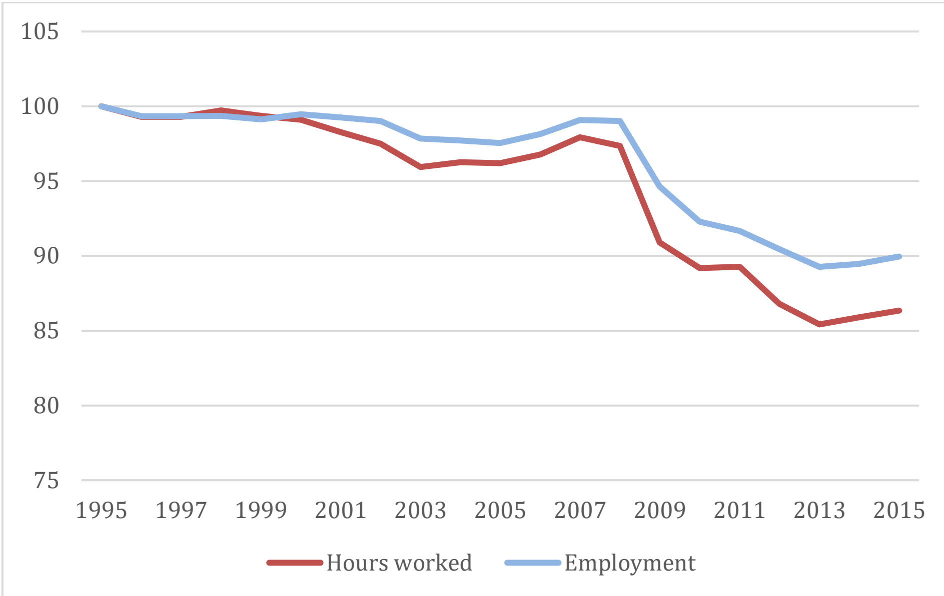


Figure A. Development of hours worked and employment across countries and industries from 1995 to 2015. Baseline is 100 (percent).

Development of hours worked, robot density and total number of robots 1995-2015

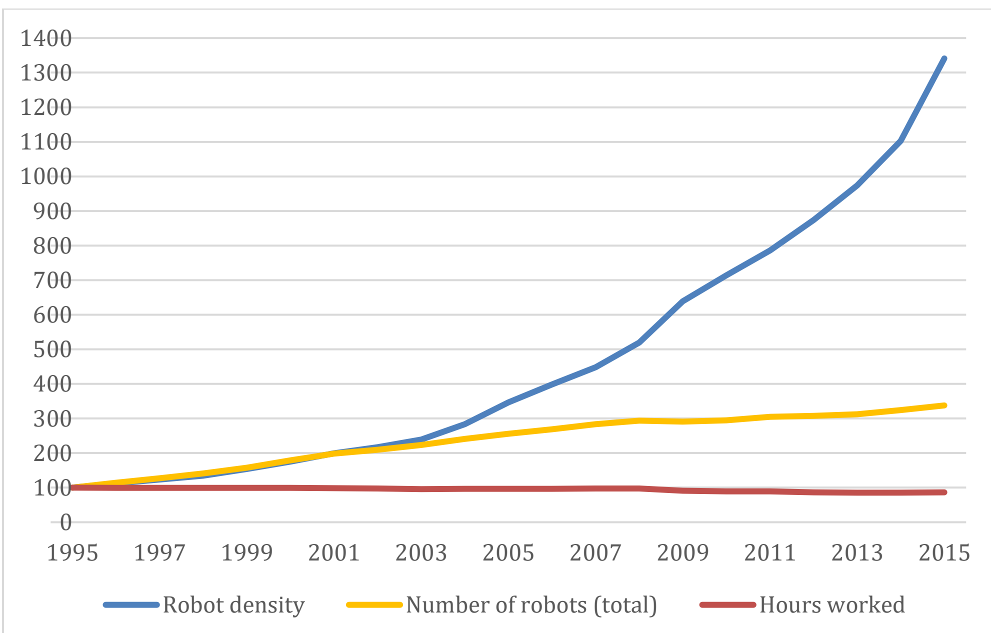
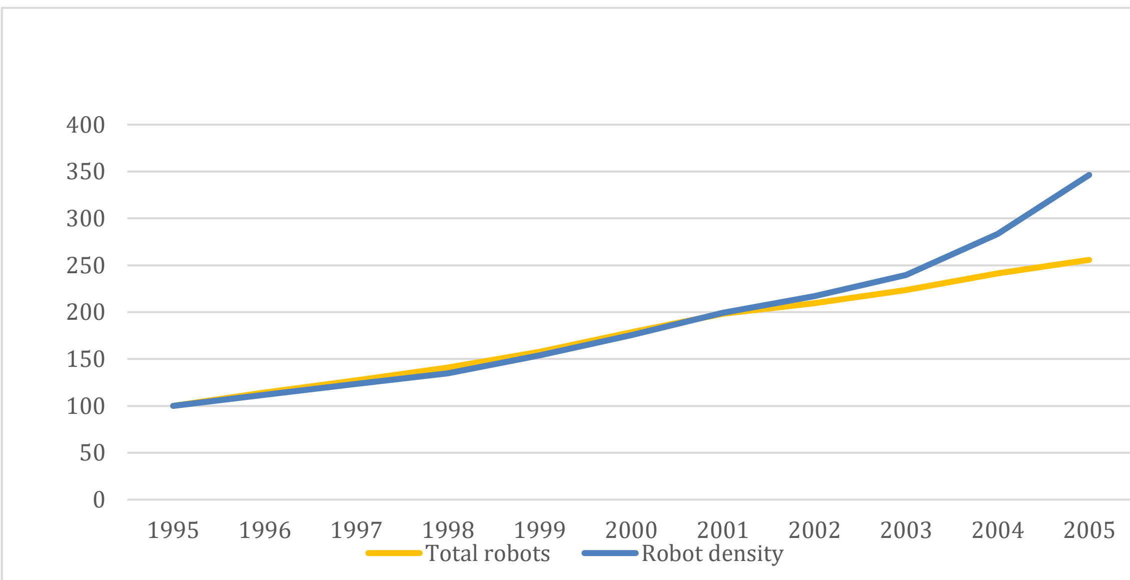


Figure B. Development of total hours worked, robot density and total number of robots across countries and industries from 1995-2015. Baseline is 100 (percent). Robot density is defined as the number of robots divided hours worked by employees (millions) and are weighted by the initial 1995 share of hours worked.

Figure C and D gives a better presentation of the development of robot density and total robots adopted in two consecutive decades, from 1995 to 2005, and from 2005 to 2015. The figures suggest that the increase in robot density has been faster in the second period than in the first, though this acceleration appears to start already in 2002-2003. The increase in total robots seems however to have dampened compared to the first period, however steadily increasing. The emerging difference between increases in robot density and the number of total robots also shows how the denominator of the robot to hours-ratio has decreased more in the second decade, as clearly visible in figure A.

Development of robot density and number of total robots



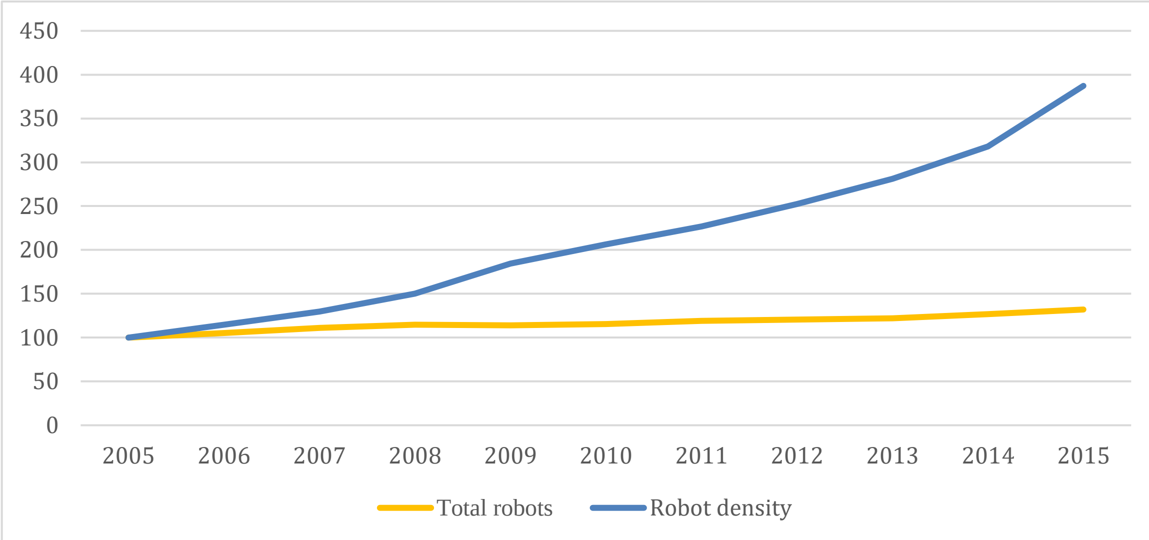


Figure C and D. In percent, baseline is 100. Development of robot density between 1995 and 2005; and between 2005-2015. Baseline is 100 (percent). Robot density is defined as the number of robots divided hours worked by employees (millions) and are weighted by the initial 1995 share of hours worked.

Noteworthy in every graph and figure showing the development through 1995 to 2015, is how the development curve kinks in the years around 2008. This is a clear sign of the impact of the financial crisis, which has had impact on both hours worked and the number of people employed in these economies. This is also visible in Figure D, as there was a slight increase in average robot density between 2008 and 2009. Cyclical fluctuations from the financial crisis might confound the estimated impact of robot adoption on changes in hours worked and other labor characteristics.

I also investigate the magnitude of differences between quartiles, looking at differences between four countries. Each representative of a different quartile (descending with Germany belonging to the 4th quartile, and Slovakia to the 1st.). Quartiles are based on the average levels in robot density from 1995 to 2015, by country. Countries represented are at the top of their respective quartile. Looking at the development in percentages, Figure E highlights the rapid increase of robot density particularly pronounced in Slovakia. Slovakia experienced the highest increase in robot densities, as average robot density increased by an astonishing 18 000 percent from 2004 to 2015. While robots were adopted already in 1995 in Germany[22], and 1996 in Denmark, Austria and Slovakia did not adopt robots until the year of 2004. Austria experienced already a relatively high increase

[22] In fact, data is provided for robot adoption in Germany already in 1993.

from 2004 to 2003, compared to Slovakia, which explains why the increase in percentages is not as pronounced.

Comparing Figure E and F shows how Slovakia started with a significantly low robot density barely over 0[23], even compared to Austria, even though neither had adopted robots until in 2004.

Figure F, which looks at the development in real numbers of robot densities (in average levels, by country) sets this however in perspective, showing that Slovakia is still in the start phase, compared to Germany and Denmark, but that robot densities are increasing and following the same trend in the four countries. In fact, Slovakia has reached half the average robot density Germany experienced back in 1995. It also highlights the leading position of Germany, which is followed closely by the other emerging countries. This reflects that while Germany still is in the leading position in terms of robot density, lagging robot adopting countries are slowly catching up. On an overall note, it also highlights that robot adoption has increased significantly the past decade, even in countries with 0 robots in use in 2004.

[23] In fact, average robot density in Slovakia in 2004 was of 0,0059, measured as the number of robots used divided by hours worked (in millions).

Development of robot density in four countries from 1995 to 2015

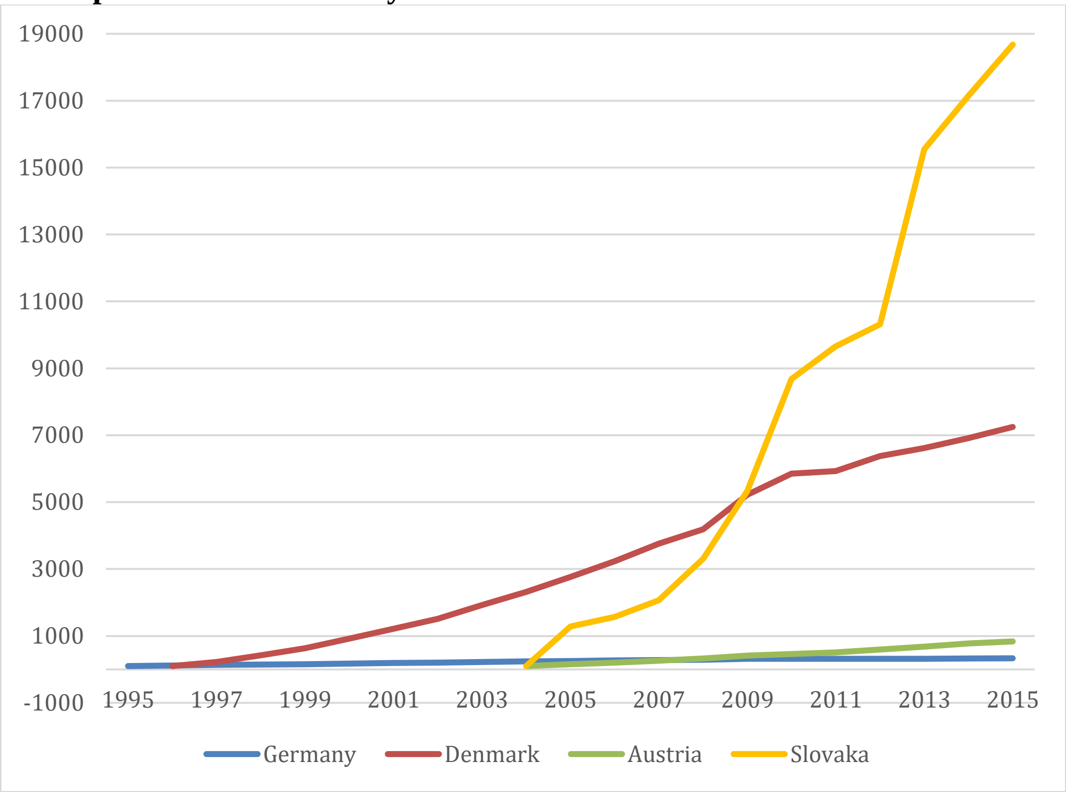


Figure E. Development in robot densities in Germany, Denmark, Austria and Slovakia from 1995-2015. Baseline is 100 (percent) The four countries are at the top of the, fourth, third, second and first quartile, respectively. Quartiles are based on average robot densities over the time period 1995-2015. Robot densities are weighted by the initial 1995 share of hours worked. Countries were chosen from each quartile to illustrate differences in density development.

Real development of robot density in four countries from 1995-2015

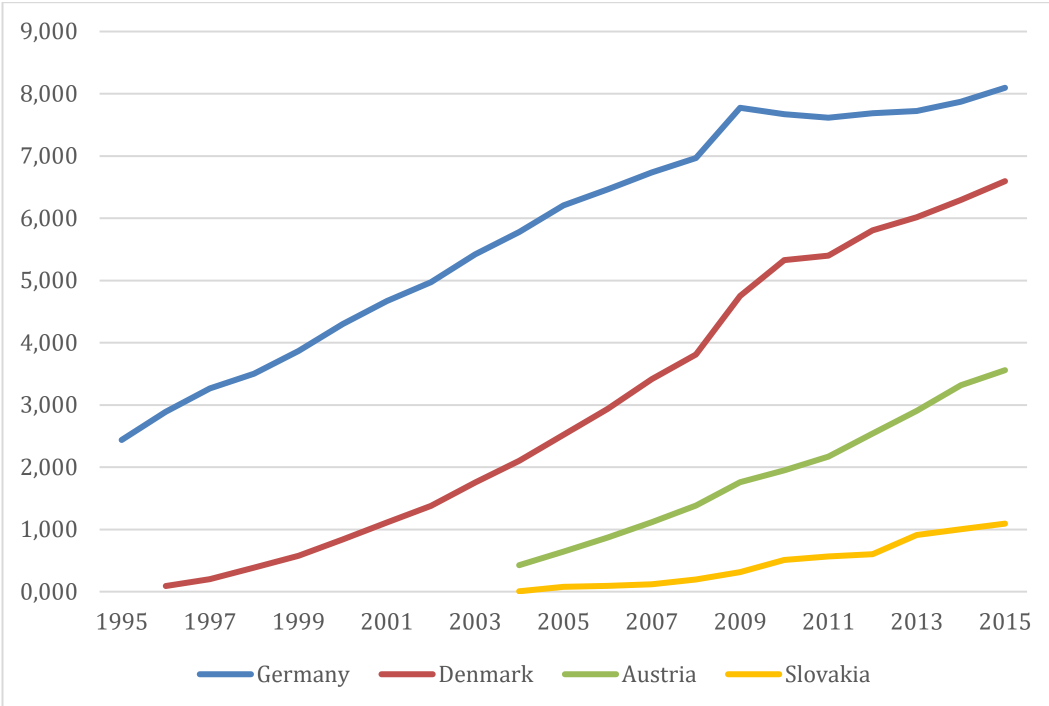


Figure F. Development of robot density in Germany, Denmark, Austria and Slovakia between 1995 and 2015. (Real values). Values robot densities in average levels, by country. Robots were not adopted until the year 2004 in Slovakia and Austria, while already in 1995 in Germany, and by 1996 in Denmark.

In a similar manner, figure G presents the development of four industries: Transport and Equipment, Basic metal and metal products, wood and paper products, and Education. Each industry belongs to a different quartile, quartiles being based on the average levels of changes in robot density, by industry. The figure highlights how robot density has increased (percentage wise) more drastically in the Education industry, while the other industries have experienced a steady increase from 1995 to 2015.

Development of robot density in four industries from 1995 to 2015

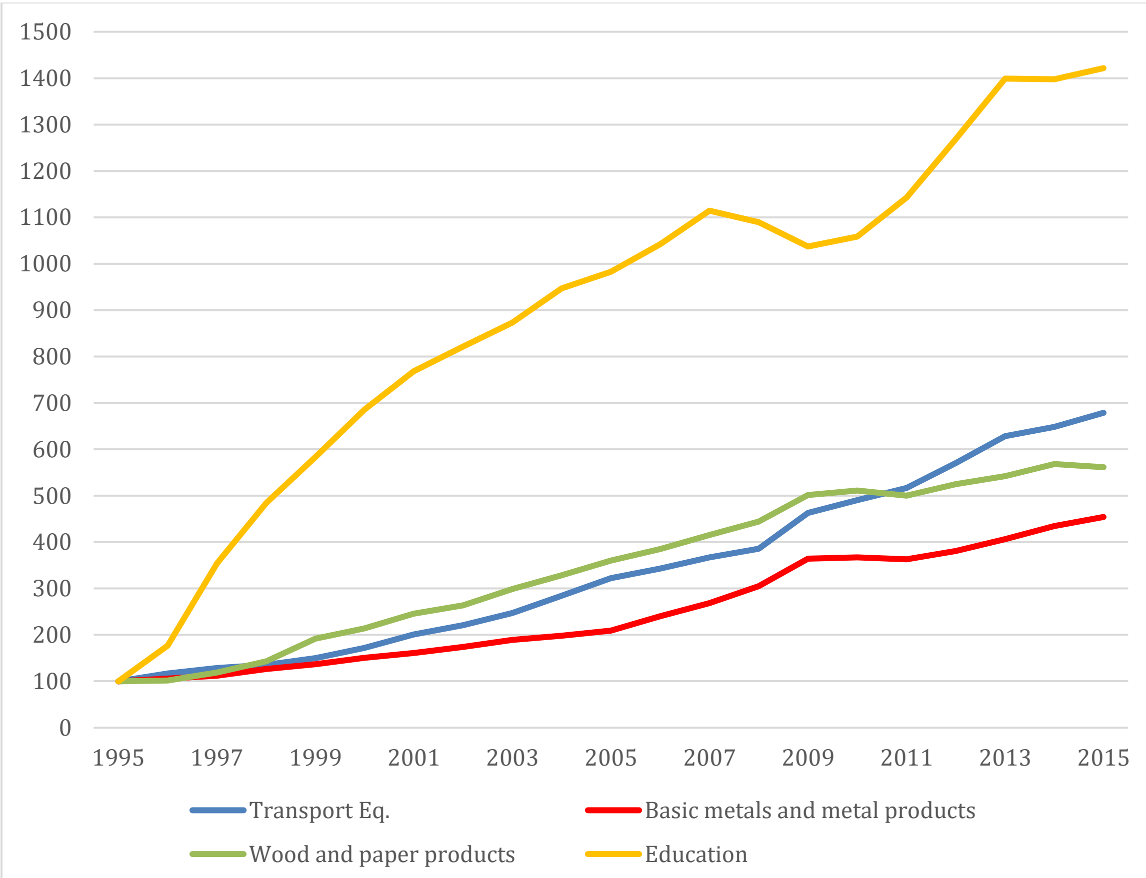


Figure G. Development in the robot density in 4 industries from 1995 to 2015. Baseline is 100 (percent). Industries Transport Equipment, Basic metals and metal products, Wood and paper products, and Education are at the top of the fourth, third, second and first quartile, respectively. Quartiles are based on the changes in robot density, by industry.

The robot density in the education industry remains however relatively low, compared to these industries when looking at the development of robot density in Figure H. Figure I highlights the leading position of Germany in the Transport Equipment industry.

Real development of robot density in four industries from 1995-2015

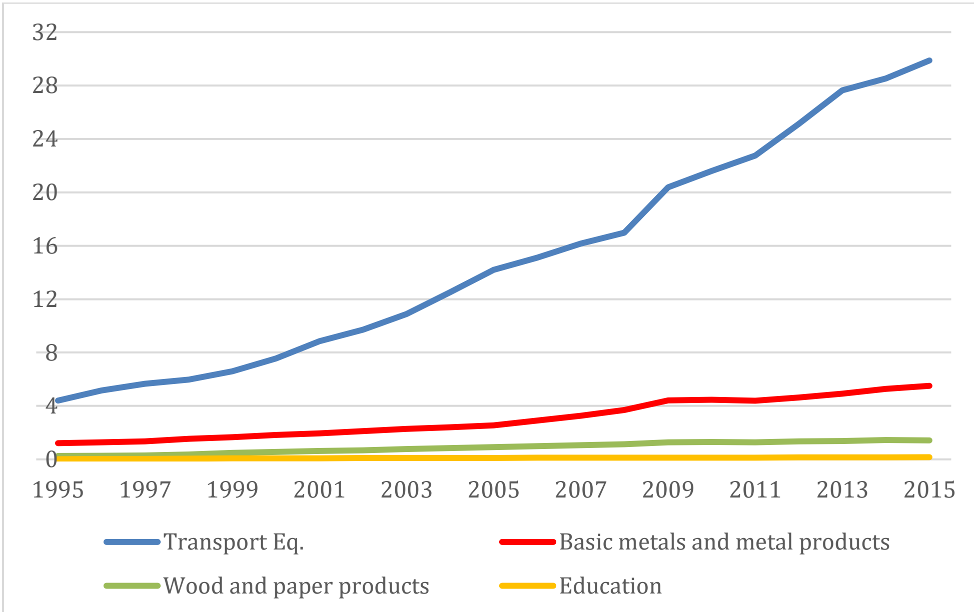


Figure H. Development in robot density in industries Transport Equipment, Basic metals and metal products, Wood and paper products, and Education, in average levels by industry.

Change in robot density in the Transport Equipment industry from 1995 to 2015

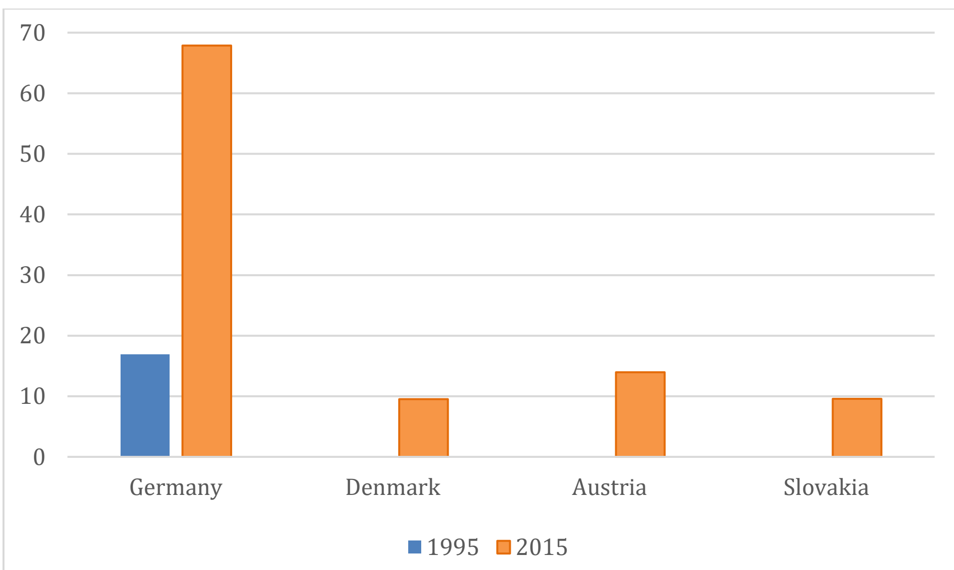


Figure I. Change in robot density from 1995 to 2015 in the Transport Equipment industry in Germany, Denmark, Austria and Slovakia. The four countries are at the top of the, fourth, third, second and first quartile, respectively. Quartiles are based on average robot densities over the time period 1995-2015. Robot densities are weighted by the initial 1995 share of hours worked.

7. Results

Full versions of the regression tables and coefficients on other variables included are presented in the Appendix (Table 9 - 25).

7.1. Results for hours worked

I begin by presenting the results from the regression analysis for my main outcome of interest, changes in hours worked from 1995-2015. The two alternative forms of the main regressor are presented in Table 9 in the Appendix. Table 9 shows how results differ significantly when using the percentiles in changes of robot density (weighted) instead of raw changes in robot density. I argue that the percentile form is more correct to predict the effect of robot density on hours worked, thus the following tables show the estimates when using percentiles of changes. Changes are always weighted by the initial (1995) share of within country hours worked, ensuring that the relative importance of industries is reflected in the results. Table 9 also provides an estimate of changes in robot density on hours worked when including all 18 countries.

Data on ICT - and non-ICT capital services are only available for 10 countries during the time period of 1995-2015. Controlling for these trends thus reduces the sample from 270 country industry cells to 149[24]. Data is also missing for the year 2015 for the following countries: Czech Republic, Italy and Sweden. Values are computed for missing years, as explained in the previous section. The final analysis for the full period from 1995 to 2015 includes 150 country-industry cells, representing 15 industries in 10 European countries.

Shown in Figure F, Germany is in the lead position in robot adoption, both in terms of number of operational robots adopted, but also in robot density. Column (3) of all regressions presents the results when excluding Germany from the sample, in order to verify that it is not the driver of the results. Similarly, Figure H highlights that the "Transport Equipment" industry has experienced a significant increase in robot density relative to the other 14 industries included in the analysis. I

[24] In addition, data on these variables are missing for industry "20-21" in Sweden, resulting in the drop of one observation when including controls.

drop this industry in order to verify that it is not the driver of the results. This robustness specification is included in Column (4).

Table A presents the results when regressing changes in robot density on changes in the log of hours worked. The coefficient in column (1) suggests that moving from the bottom to the top percentile robot adoption has reduced the log of hours worked by 0.0712. The estimate drops slightly in magnitude when controlling for changes in labor productivity and initial (1995) values for both wages and labor productivity, but remains negative. Not surprisingly, the impact of robot adoption turns positive when controlling for changes in ICT and other capital, suggesting the presence of omitted variable bias in the first column. Dropping Germany in column (4) results in the estimate becoming negative again. This suggests that Germany, overall, has been a positive driving force for hours worked. Whereas the reason behind dropping Germany from the sample was based on the assumption that Germany could be the driver of negative impact hours worked, as it is the country having experienced the largest increase in robot density during the period, results throughout the regression analysis suggest the contrary. This may be explained by the fact that Germany is the leading industrial power in Europe, disposing both high robot adoption and large sectors accounting for much of the employment in the country.

Results when dropping the "Transport Equipment industry" are however consistent with the assumptions presented in section 4. Dropping this specific industry (column 5) leads to an increase in the coefficient compared to that in column (3), suggesting that this industry is a driver of negative impact on hours worked. Results are in all cases statistically insignificant.

Table A. Changes in hours worked 1995-2015: OLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0712	-0.0582	0.00673	-0.0686	0.0290
	(-0.65)	(-0.54)	(0.08)	(-0.73)	(0.33)
Controls		✓	✓	✓	✓
Changes in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.178^{*}	-0.971^{**}	-1.412^{***}	-1.428^{***}	-1.582^{***}
	(-2.55)	(-3.14)	(-4.89)	(-4.46)	(-5.39)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. ΔH stands for the change in log of hours worked from 1995 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. By other specifications, I mean dropping Germany in column (3) and dropping industry "Transport Equipment" in column (4) from the sample. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 10 in the Appendix shows that the coefficients for changes in labor productivity and for ICT capital services are small in magnitude (even smaller for ICT capital services) and negative, and statistically insignificant in all cases. Coefficients for changes in non-ICT capital services and the initial log wage in 1995 are however statistically significant at a 1% level and positive, suggesting that changes in these trends have had a positive impact on hours worked between 1995 and 2015.

7.1.2. Two Stage Least Squares Estimates

I next use the exogenous robot density measure to compute two stage least squares estimates. Including control variables such as changes in ICT and non-ICT capital services can mitigate some concerns related to omitted variable bias. There are still some concerns about the interpretation of the results. For instance, robot adoption in European industries might have been accelerated by increased robot adoption in other advanced economies, which could confound the estimates when running OLS regressions.

To address this concern, I use the industry robot density in another other advanced economy, namely the US, as a proxy of improvements in the world technology frontier of robots. Implementing this instrumental variable strategy allows to focus on the variation that results solely from industries in which the use of robots has been concurrent in advanced economies. A slight concern is that IFR industry-level data for the US starts in 2004, but in 1995 for the European countries included in this analysis. Ideally, a measure of exogenous robot density covering the time frame 1995-2015, would be considered a stronger IV. However, there is limited access to data on robot adoption and hours worked in other countries that are suitable as good proxies for the technological improvement in the world. To extend the period for the changes in robot density in the US as much as possible, I am able construct estimates going back to 1998, explained in section 4. This however implies that the first three years of the analysis are still missing. I therefore suggest to interpret the results from the 2SLS for the time period 1995-2015 cautiously.

Table B shows the first stage regression, using the percentiles of changes in robot density in the US to predict the variation in the percentiles of changes in European robot density. The estimate suggests that the correlation between the two is strong, implying that the instrument has a strong first stage. Data on robot adoption in the US is only available from 2004, making it difficult to establish a causal effect of US robot density on European robot densification. The coefficient from Table 3 suggests that the level of robot adoption in the US explains a lot of the variance in changes in the European robot density. As the exogenous robot density is used as a proxy of the world level robot adoption, this might suggest that 78% of changes in robot adoption in Europe is caused by the change in the world level, leaving the unexplained variance to be caused by changes specific to the different countries or Europe in general. Standard errors are clustered by country and industry. The result is robust to including control variables, as seen in table 10.

Table B. First stage regression 1995-2015

	(1)
	Δ Robot adoption $_{EUR}$
Δ Robot adoption $_{US}$	0.781***
	(16.45)
Constant	0.110***
	(4.66)
N	150

Notes: Δ Robot adoption $_{EUR}$ stands for the percentile of changes in the endogenous (European) robot density from 1995 to 2015, weighted by the initial (1995) share of within country hours worked. Δ Robot adoption $_{US}$ stands for the percentile of changes in the exogenous robot density, in the US, from 1998 to 2015, weighted by the initial (1998) share of within-country hours worked. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Two-stage least squares (2SLS) estimates using exogenous robot density as an instrument for robot densification (Table C) show that increased use of robots decreased hours worked, consistent with our OLS estimates. 2SLS estimates are on the other hand negative also when adding controls and larger in magnitude, indicating the presence of measurement error in the endogenous measure of robot adoption. As with the OLS estimates, 2SLS estimates turn more negative when dropping Germany, and drop in magnitude when dropping the Transport Equipment industry.

Table C. Change in hours worked from 1995 to 2015 : 2SLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0734	-0.0375	-0.0485	-0.142	-0.0293
	(-0.51)	(-0.27)	(-0.43)	(-1.20)	(-0.24)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.177*	-0.984**	-1.369***	-1.367***	-1.535***
	(-2.11)	(-3.25)	(-4.89)	(-4.40)	(-5.37)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. ΔH stands for the change in log of hours worked from 1995 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. By other specifications, I mean dropping Germany in column (3) and dropping industry "Transport Equipment" in column (4) from the sample. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

7.1.2. Splitting the analysis period in two equal time periods: 1995-2005 and 2005-2015

Next, I look at difference in results when investigating the impact of robot density on hours worked for two consecutive decades: 1995-2005 and 2005-2015. Splitting the analysis into two periods allows me to look for differences in the impact of changes in robot adoption during two different decades that have both experienced fast changes in technology improvements, as well as in prices of investing in this technology. Based on theory mentioned previously, the decline in investment prices can provide firms strong incentives to substitute human labor for robots. Studies point to the decline in technology investment prices as being responsible for the increase in robot adoption during the past two decades. The price of industrial robots in major developed economies has been estimated to have fallen by approximately one half during 1990-2005 (Graetz and Micheals (2017).

Taking quality improvements into account, the fall in price is estimated to be even steeper: by 2005, quality-adjusted robot prices were about one fifth of their 1990 level.

Figure F and G highlights how robot density and the total number of robots have increased during these two periods. While the increase in total robots adopted and robot density followed a similar pattern from 1995 to 2005, robot density increased at a faster pace during the period of 2005 to 2015 compared to the previous decade. This appears to start already in the years 2002-2003, when looking at figure . This change of pattern could suggest that robot density grew faster and more than the number of robots adopted. This would imply that the denominator of the robot density, the number of hours worked, fell more drastically during the last decade. This makes it especially interesting to investigate impacts in the period stretching from 2005, a period which has been excluded in other similar studies. In addition, it was not until the year 2006 that robots were adopted in all the countries included in the sample. Looking at the period from 2005 to 2015 also allows me to include additional countries to the sample, as data of ICT and non-ICT capital services are available for additional countries for this period.

Changes in hours worked between 1995 and 2005

I begin by analyzing the impact on hours worked between 1995 and 2005. This analysis includes 150 country-industry cells. The OLS estimate from column (1) in Table D suggest that moving from the bottom to the top of the ranking of changes in the robot density distribution corresponds to an increase of about 0.006 in the log of hours worked. When controlling for specific country effects and initial (1995) wages and labor productivity, the estimate decreases, and loses its statistical significance. Results decrease further when controls for changes in ICT and other capital services are added, suggesting that robot adoption may not be the sole driver of the positive change in hours worked during this period. It further turns negative when dropping Germany, but increases when dropping the Transport Equipment industry, consistent with results from previous regressions.

The 2SLS estimates are larger than OLS estimates, and in all cases positive and statistically insignificant. Changes in ICT capital services also appear to have contributed to an increase in hours worked during this period (Table 14 and 15). Both OLS and 2SLS Estimates are positive and statistically significant at a 5% level (Table 14 and 15). Coefficients for changes in non-ICT capital services and log labor productivity 1995 remain statistically significant and positive when restricting the analysis to this period.

Table D. Changes in hours worked 1995-2005 – OLS and 2SLS estimates

Panel 1: OLS estimates					
	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	0.00598**	0.00332	0.000937	-0.000726	0.00466
	(2.68)	(1.38)	(0.38)	(-0.18)	(0.71)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.0896***	-0.305	-0.374	-0.422	-0.379
	(-3.56)	(-1.40)	(-1.90)	(-1.84)	(-1.84)
Panel 2: 2SLS estimates					
	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	0.0193	0.0212	0.00835	0.00239	0.00239
	(1.61)	(1.73)	(0.85)	(0.20)	(0.20)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.112***	-0.245	-0.347	-0.420	-0.420
	(-3.48)	(-1.10)	(-1.76)	(-1.88)	(-1.88)
N	150	150	149	134	134

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2005. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. ΔH stands for the change in log of hours worked from 1995 to 2005. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2005. By other specifications, I mean dropping Germany in column (3) and dropping industry "Transport Equipment" in column (4) from the sample. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Changes in hours worked between 2005 and 2015

Looking at changes from 2005 to 2015 results in an increase in the number of observations when including control variables. This is because data on ICT and Non ICT services is available for some additional countries after 2005. Countries added to the regression are UK, the Netherlands and Slovakia. The number of observations in this analysis therefore increased to 195, accounting for 15 industries in 13 countries. The IV strategy becomes more reliable when analyzing this period, as data used are provided from the IFR and not based on estimates. Robots were not adopted in all countries included in the sample until the year of 2006, which implies there are interesting changes in robot density for some countries in this period. I begin by presenting the first stage regression.

Table E. First stage 2SLS 2005-2015

	(1) Δ Robot adoption $_{EUR}$
Δ Robot adoption $_{US}$	0.642^{***}
	(11.34)
Constant	0.179^{***}
	(7.29)
N	195

Notes: ΔR_{icEU} stands for the percentile of changes in the endogenous (European) robot density from 2005 to 2015, weighted by the initial (1995) share of within country hours worked. Δ Robot adoption $_{US}$ stands for the percentile of changes in the exogenous robot density, in the US, from 2005 to 2015, weighted by the initial (1998) share of within-country hours worked. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Robot densities in both the exogenous and the endogenous measure are weighted by the 1995 share of hours worked, and I control for initial 1995 log wage and log labor productivity values to control for previous differential trends. I use the initial 1995 value, because while almost no countries had adopted robots in 1995, the majority of the countries included in the sample had by 2005.

OLS estimates are negative when investigating the impact of change in robot adoption, solely. The coefficient remains negative when adding controls in column (2), while decreasing slightly in magnitude. It turns positive when controlling for changes in capital services (column 3), suggesting that robot adoption is not the driver of the negative impact on hours worked. The constant variable is also adjusted, increasing in magnitude and statistical significance. This might suggest that the negative impact was not driven by robot adoption, but that there are other factors driving the hours worked down. Again, when dropping Germany (column 4), the coefficient decrease in value, suggesting that Germany is a driving force for increased hours worked, while the transport equipment industry has been driving hours worked down.

Table F. Changes in hours worked 2005-2015 : OLS and 2SLS estimates

Panel A: OLS estimates					
	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0334	-0.0202	0.0185	0.0112	-0.00904
	(-0.55)	(-0.34)	(0.38)	(0.21)	(-0.19)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.112**	-0.304**	-0.505***	-0.446***	-0.567***
	(-3.08)	(-2.80)	(-5.73)	(-4.72)	(-6.78)
Panel B: 2SLS estimates					
	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.175	-0.147	-0.0643	-0.0885	-0.0784
	(-1.94)	(-1.72)	(-0.80)	(-1.02)	(-1.00)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.0411	-0.221*	-0.444***	-0.373***	-0.523***
	(-0.84)	(-1.99)	(-4.68)	(-3.63)	(-5.79)
N	195	195	194	179	181

Notes: Δ Robot adoption stands for the percentile change of robot density from 2005 to 2015. Changes weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. ΔH stands for the change in log of hours worked from 2005 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 2005-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. Other specifications refer to dropping Germany in column (3) and dropping industry "Transport Equipment" in column (4) from the sample. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

2SLS estimates presented in Table F are larger than OLS estimates, and negative in all cases, while remaining statistically insignificant. The coefficient on percentiles of changes in robot density suggests that moving from the bottom to the top of the ranking corresponds to a decrease of about 0.175 in the logarithm of hours worked. When controlling for other variables, the coefficient decreases slightly in magnitude, but less when controlling for changes in capital services. Changes in the coefficient when dropping Germany are consistent with findings presented above. Interestingly, the coefficient turns negative in both the OLS and 2SLS regressions when excluding industry "Transport Equipment", with a larger coefficient in the 2SLS than in the OLS regression. Compared to the previous decade, this suggests that this industry is no longer responsible for driving the amount of hours worked down.

7.2. Other specification checks

Robustness check 1. Using employment as the outcome of interest

My main outcome of interest is hours worked. I argue that this measure is more interesting than looking at effects on employment in terms of the number of people employed, as robots might complement workers, thereby changing hours worked, but not necessarily replacing workers. In addition, it is more advantageous to use data on hours worked as the countries covered can have longer or shorter work days, more holidays or other labor characteristics that can differ from one country to another. As a robustness check, I also explore the impact of changes in robot adoption when the outcome of interest is employment – defined as the number of persons employed (in millions). The dependent variable is then the change in the log of employment from 1995 to 2015. I find that moving from the top percentile to the bottom; changes in robot adoption reduce employment by 0.0272 percentage points. This is equivalent to saying that saying that for industries one percentile higher in robot density, change in hours worked has been increased by 0.027 less.

The pattern appears to be the same as when investigating the impact on hours worked. Adding control variables dampens the negative effect of robot adoption on employment in both OLS and

2SLS regressions. However, while the coefficient turns positive when controlling for changes in capital services, 2SLS estimates turn negative, though remain smaller than when regressing only robot adoption on hours worked in column (1). This suggests that there are measurement errors in the OLS regression. As with hours worked, coefficients from column (4) and (5) suggest that Germany is driving the hours worked up, while the transport Equipment drives them down. In all cases, the coefficients remain statistically insignificant.

Table G. Robustness check: Changes in Employment 1995-2015: OLS and 2SLS estimates

	(1)	(2)	(3)	(4)	(5)
Panel A: OLS estimates					
	ΔEmployment	ΔEmployment	ΔEmployment	ΔEmployment	ΔEmployment
Δ Robot adoption	-0.0272	-0.0123	0.0465	-0.0206	0.0730
	(-0.25)	(-0.12)	(0.53)	(-0.22)	(0.83)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.170*	-0.959**	-1.385***	-1.369***	-1.545***
	(-2.48)	(-3.17)	(-5.07)	(-4.49)	(-5.56)
Panel B: 2SLS estimates					
	(1) ΔEmployment	(2) ΔEmployment	(3) ΔEmployment	(4) ΔEmployment	(5) ΔEmployment
Δ Robot adoption	-0.0422	-0.00210	-0.0165	-0.103	0.00787
	(-0.30)	(-0.02)	(-0.15)	(-0.86)	(0.06)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.162*	-0.966**	-1.336***	-1.301***	-1.492***
	(-1.97)	(-3.24)	(-5.01)	(-4.38)	(-5.45)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Employment stands for the change in log of employment from 1995 to 2015, which is measured as the number of people employed (in millions). Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. Other specifications refers to dropping Germany in column (3) and dropping industry "Transport Equipment" in column (4) from the sample. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Robustness check 2. Controlling for changes when excluding unspecified industries

I also test whether results are robust to dropping the unspecified industries "289" and "229" from the sample, as the inclusion/ classification of these industries was a concern when comparing data from IFR and from EUKLEMS, explained in section 4.1. I find that both OLS and 2SLS results are robust and will not be weakened by dropping these industries. Results are presented in Table H.

Table H. Robustness check : Changes in Hours worked excluding unspecified industries: OLS and 2SLS estimates

Panel A: OLS estimates					
	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0716	-0.0595	0.00688	-0.0692	0.0294
	(-0.66)	(-0.55)	(0.08)	(-0.74)	(0.33)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.178*	-0.970**	-1.412***	-1.428***	-1.582***
	(-2.55)	(-3.14)	(-4.89)	(-4.46)	(-5.39)
Panel B:2SLS estimates					
	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0734	-0.0374	-0.0485	-0.142	-0.0292
	(-0.51)	(-0.27)	(-0.43)	(-1.20)	(-0.24)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	-0.177*	-0.984**	-1.369***	-1.367***	-1.535***
	(-2.11)	(-3.25)	(-4.89)	(-4.40)	(-5.37)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. ΔH stands for the change in log of hours worked from 1995 to 2015. Industries "Chemical products, unspecified" and "Metal, unspecified are excluded from the sample, as a robust test. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. Other specifications refers to dropping Germany in column (3) and dropping industry "Transport Equipment" in column (4) from the sample. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

7.3. Other outcomes

Other outcomes of interest include changes in log wages and changes in the labor share of three defined skill-groups. Theory predicts that the impact on wages is ambiguous, while medium skilled workers are the most susceptible to automation and being replaced by machines.

7.3.1 Effects on wages

I turn to investigating the impact on wages in the reduced sample including 10 of the 18 European countries. Wages are measured using data on labor compensation from 1995 to 2015. The main outcome of interest is changes in log wages during this time period. Results from the simple OLS regression in column (1) of Table I suggest that the change in robot density has reduced wages.

When running the 2SLS regression (Table L), the coefficient however is positive and larger, indicating the presence of measurement error in the measure of robot adoption. When adding the same control variables as in the previous regressions (column 2), I find that the coefficient turns positive and increases in magnitude, both in the OLS and the 2SLS regression. Dropping Germany from the sample (column 3) however turns the coefficient negative, implying that Germany is the driver for a positive impact on wages, such as previously suggested for the impact on hours worked. Results are negative when running the 2sls regression as well, but larger in magnitude. Dropping industry "Transport Equipment" on the other hand turns the results larger and positive, and remain of same value in the 2SLS regression. Coefficients are in all cases statistically insignificant, making it impossible to establish a causal impact on changes in wages during the period of 1995-2015. The control variables (changes in ICT and non-ICT capital services and changes in Labor Productivity) however, are all positive and statistically significant, in both the results from the OLS and the 2SLS regressions. This suggests that changes in these variables have increased the wages from 1995 to 2015.

Table I: Changes in wages 1995-2015: OLS and 2SLS estimates

Panel A: OLS estimates					
	(1) Δ Wages	(2) Δ Wages	(3) Δ Wages	(4) Δ Wages	(5) Δ Wages
Δ Robot adoption	-0.00700	-0.0399	0.0494	-0.0477	0.0588
	(-0.05)	(-0.34)	(0.51)	(-0.46)	(0.61)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	0.399^{***}	1.204^{**}	0.656^{*}	0.785^{*}	0.555
	(5.11)	(3.12)	(2.18)	(2.43)	(1.83)
Panel B: 2SLS estimates					
	(1) Δ Wages	(2) Δ Wages	(3) Δ Wages	(4) Δ Wages	(5) Δ Wages
percentiles	0.120	-0.00346	0.00772	-0.111	0.0263
	(0.67)	(-0.02)	(0.06)	(-0.84)	(0.20)
Controls		✓	✓	✓	✓
Change in capital			✓	✓	✓
Other specifications				✓	✓
Constant	0.335^{***}	1.182^{**}	0.688^{*}	0.837^{**}	0.581
	(3.56)	(3.15)	(2.34)	(2.67)	(1.93)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Wages stands for the change in log of wages from 1995 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. Other specifications refer to dropping Germany in column (3) and dropping industry “Transport Equipment” in column (4) from the sample. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

7.3.2. Effects on labor shares

To investigate predictions from previous literature on changes in labor shares, I turn to investigate the changes in three different skill groups. Data on labor shares, provided by EUKLEMS only covers a limited period of time, from 2008 to 2015. I am able to use data on the five following aggregated sectors; “Agriculture, Forestry and Fishing”, “Electricity, Gas and Water supply”, “Total Manufacturing”, “Construction and “Education”. As results are controlled for, using the same variables as in previous regressions, the sample analysis includes 12 countries[25]. Further, EUKLEMS decompose data on labor input into 18 different employment groups., based on differences in gender, education and age. The following analysis investigates differences in labor shares, based on the different educational background of the workers. As a result, a worker will be categorized as low-skilled when possessing no formal education, as middle skilled when disposing a intermediate education, and high skilled if being a university graduate. The final sample thus account for 1080 country-industry-employment group cells. I run regressions for each of the skill groups. I also control for initial 1995 log wages and log labor productivity, as a proxy for existing differences in the markets, as robots were not adopted in the majority of the countries in the sample at that time, while widely adopted in the year 2008.

Table X shows the impact of robot adoption on labor shares for low skilled workers. While OLS estimates are negative, small in magnitude, and robust to different controls, 2SLS estimates are positive, highly statistically significant, and larger. 2SLS estimates suggest that moving from the bottom to the top percentile corresponds to an increase in the share of hours worked by low skilled workers. The constant is also adjusted, turning negative and gaining in statistical significance in column (1) and (3). This suggests that there are possible measurement errors in the OLS regression,

[25] Data on Belgium is not available in the latest breakdown of labor input, provided by EUKLEMS (2017).

and that the constant in the 2SLS regression captures some of the unobserved negative impact on labor shares.

Table J. Changes in share of hours worked by low skilled workers 2008-2015: OLS and 2SLS estimates

Panel A: OLS estimates			
	(1)	(2)	(3)
	Δ Share H	Δ Share H	Δ Share H
Δ Robot adoption	-0.0268	-0.0286	-0.0249
	(-1.90)	(-1.81)	(-1.52)
Controls		✓	✓
Change in capital			✓
Constant	0.0200*	0.0253	0.00170
	(2.18)	(1.40)	(0.09)
Panel B: 2SLS estimates			
	(1)	(2)	(3)
	Δ Share H	Δ Share H	Δ Share H
Δ Robot adoption	0.0839***	0.173***	0.143***
	(3.31)	(4.97)	(4.55)
Controls		✓	✓
Change in capital			✓
Constant	-0.0347**	-0.0355	-0.0609*
	(-2.76)	(-1.50)	(-2.50)
N	360	360	360

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Share H stands for the change in the share of low skilled workers 1995 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Turning to the middle skilled workers (Table K), 2SLS estimates double from OLS estimates when controlling for several trends. Both OLS and 2SLS estimates suggest that robot adoption is responsible for the decrease in hours worked by middle-skilled workers, compared to changes in ICT capital services, as the negative impact increases both in magnitude and in statistical significance when adding these controls.

Table K. Changes in share of hours worked by middle-skilled workers 2008-2015: OLS and 2SLS estimates

Panel A: OLS estimates			
	(1) Δ Share H	(2) Δ Share H	(3) Δ Share H
Δ Robot adoption	-0.0309* (-2.37)	-0.0362* (-2.55)	-0.0404** (-2.84)
Controls		✓	✓
Change in capital			✓
Constant	-0.0283*** (-3.47)	-0.0974*** (-3.77)	-0.0855** (-2.96)
Panel B: 2SLS Estimates			
	(1) Δ Share H	(2) Δ Share H	(3) Δ Share H
Δ Robot adoption	-0.0157 (-0.56)	-0.0731 (-1.90)	-0.0817* (-2.24)
Controls		✓	✓
Change in capital			✓
Constant	-0.0358* (-3.47)	-0.0863** (-3.77)	-0.0701* (-2.96)
N	360	360	360

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Share H stands for the change in the share of middle-skilled workers 1995 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Turning finally to high skilled workers, OLS coefficients are positive, and robust to adding control variables in column (2) and (3), while increasing slightly in magnitude.

Table L. Changes in share of hours worked by high skilled workers 2008-2015: OLS and 2SLS estimates

	(1)	(2)	(3)
Panel A: OLS estimates			
	Δ Share H	Δ Share H	Δ Share H
Δ Robot adoption	0.0540***	0.0627***	0.0630***
	(3.52)	(3.65)	(3.60)
Controls		✓	✓
Change in capital			✓
Constant	0.0113	0.0765**	0.0888**
	(1.17)	(2.73)	(2.85)
Panel B: 2SLS Estimates			
	(1)	(2)	(3)
	Δ Share H	Δ Share H	Δ Share H
percentiles	-0.0815**	-0.114**	-0.0747*
	(-2.61)	(-2.74)	(-1.99)
Controls		✓	✓
Change in capital			✓
Constant	0.0782***	0.130***	0.140***
	(4.92)	(4.18)	(4.28)
N	360	360	360

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Share H stands for the change in the share of high-skilled workers 1995 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 1995-2015, as well as initial (1995) values of log wages and log labor productivity. Changes in capital include changes in both ICT and non-ICT capital services from 1995 to 2015. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Interestingly, the coefficient on changes in robot adoption turns negative, and loses some statistical significance when running the 2SLS regression. 2SLS estimates suggests that when controlling for other trends, moving from the bottom to the top of the percentile reduces high skilled labor share by 0.075. The coefficient is marginally statistical significant. Further findings suggest that a third of the changes in shares of high skilled workers was negative. This regards primarily workers in the education sector (who account for 70% of the negative changes in hours worked), for which changes in robot densities have been significantly high, reflected by a high percentile. In fact, as seen in Figure 7 in section 4.2., this industry has experienced a significant increase in robot density during the last decade.

The 2SLS estimates suggest that, on overall, robot adoption has had a negative impact on both high and middle skilled labor shares from 2008 to 2015 in the 12 European countries included in the sample. The impact on low skilled workers is on the other hand positive. Results are in all cases statistically significant, though marginally for results on the impact on middle and high skilled workers. It would be interesting to see whether the results are different when controlling for other trends such as offsheaorability, migration, or routineness.

8. Conclusion

Increased use of robots appears to follow an inverse pattern to the decrease in hours worked and employment during the last two decades, implying there may be a relationship between the trends. This was the motivation for writing this thesis, which attempts to investigate the impact of increased robot adoption on hours worked in 15 industries, in 18 European countries from 1995 to 2015. My findings suggest there is a negative correlation between the increased use of robots and the fall in hours worked, when controlling for country trends and other trends that may confound the results. However, the impact of increased robot adoption on overall hours worked, employment, and wages remains ambiguous, as the results cannot be validated through statistical significance. There are several theories given in literature to explain why the impact of increased robot adoption is inconclusive, the most cited being that new technology might lead to increased labor demand. While theory predicts how robots and other technological improvement might substitute for human labor due to their cost advantage, there are still other factors in place, which might counterbalance the effect of labor saving technologies.

The findings do suggest, however, that robot adoption has had a positive impact on low skilled workers, by increasing their labor shares. This finding is the opposite of Graetz and Michaels\ (2017) when investigating the impact of robot adoption on labor shares in 17 advanced countries from 1993 to 2007. Differences in the results can be explained by the difference in country-samples, the time period investigated, or the methodology used. Though only statistically significant on a ten percent-level, results are negative for both high skilled and middle skilled workers, across five aggregate sectors in 12 of the European countries included in the sample. A consistent finding throughout the analysis is that the impact of robot adoption varies strongly when dropping Germany from the sample. Dropping Germany from the sample increases a negative impact on hours worked, while it decreased a positive impact. This suggests that observations belonging to Germany may be dampening the negative impact on hours worked. The opposite is true when excluding the Transport Equipment industry. The two belong to the 99th country percentile and industry percentile, respectively, equivalent to having the highest mean of robot density from 1995 to 2015. This would suggest that the industrial force of Germany is driving the number of hours worked upwards, even though robot adoption and robot density has significantly increased during the period investigated in the analysis. This may be explained by the fact that Germany, as a leading industrial power in Europe, disposes industries that still account for large employment shares, where hours worked have remained stable overall during the past decades. On the other hand, the Transport Equipment industry appears to be a negative driving force, though it is not solely responsible for the results.

There is relatively little evidence yet on the implications of robot adoption on labor markets, which in turn makes it difficult to establish causal effects of increased robot use on hours worked. In addition, controlling for other trends that most likely have had a negative impact on employment during the past decades might yield different results. This analysis thus provides a starting point for further research into the impact of robots on our labor markets.

Previous literature suggest that humans most likely will retain a comparative advantage over machines, especially high skilled workers. In an interview with the Wall Street Journal, Bill Gates (2017) argues that anyone with skills in sciences, engineering and economics will always be in demand. Polanyi's manifestation, which argues that there remains tasks that we are engaging in, but only tacitly understand how to perform, is challenged by recent technological inventions. Today, robots are increasingly learning tacit knowledge, this through for example machine learning. Machine learning, a term first coined by Arthur Samuel (1959), is a “field of computer science that gives computers the ability to learn without being explicitly programmed”. One of our time's most famous example of implementation of machine learning has been the creation of IBM´s robot Watson. The rise of new technologies, e.g. robots, is not necessarily bound to substitute human labor. IFR (2016) on the other hand predicts a growing trend in the use of collaborative robots - dubbed “Cobots” - predicting that cobots are to “lead the departure from “man vs machine and usher into the man and machine”. Such developments in the technological world are bound to disrupt theory on the implications of technological improvement on labor markets, and to provide motivation for a new wave of literature on how skills, technology and tasks interact.

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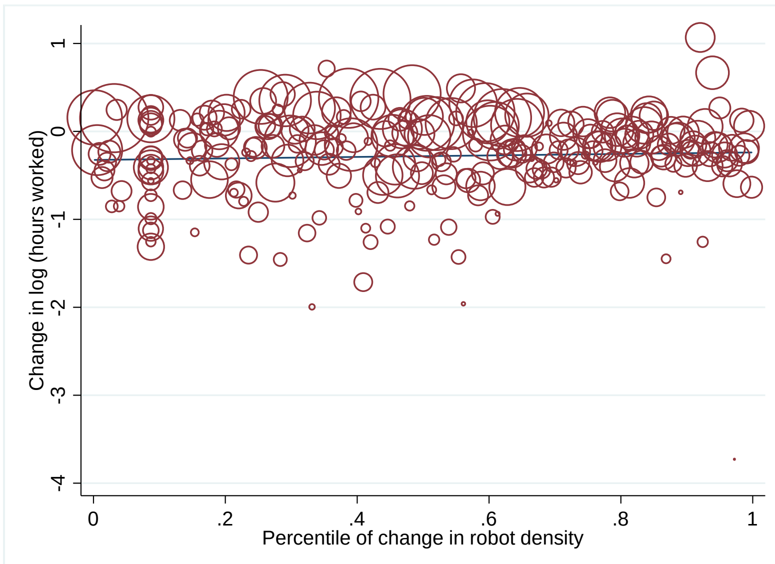
10. Appendix

(1a)

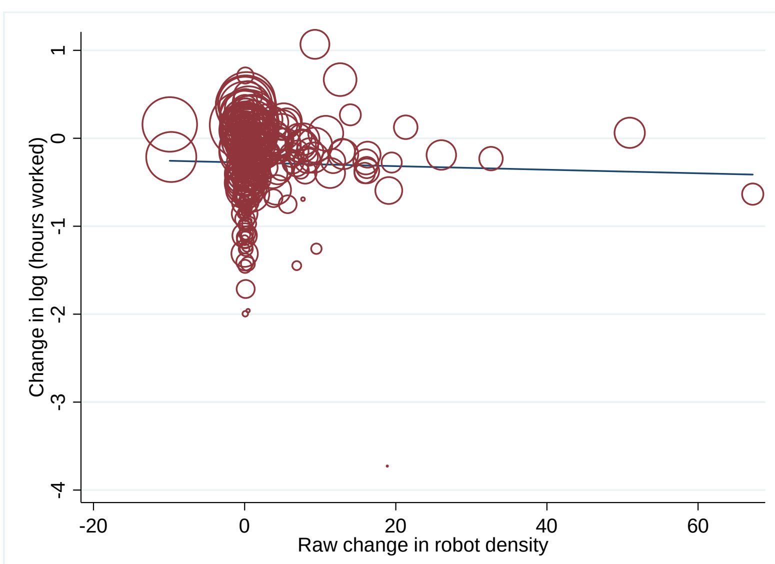
Figure 1 A&B. Growth of hours worked and robot density 1995-2015

Percentile of change in Robot Density



Notes: Panel (a) shows the variation in percentile of change in robot density. Observations are country-industry cells, with the size of each circle corresponding to an industry\s 1995 witihin country share of hours worked. Fitted regression lines are shown.

(1b) Raw change in robot density



Notes: Panel (b) shows the correlation using raw changes in robot density. Observations are country-industry cells, with the size of each circle corresponding to an industry\s 1995 witihin country share of hours worked. Fitted regression lines are shown.

Table 1. Overview countries included in the analysis

Landcode	Countries	Country number
AT	Austria	1
BE	Belgium	2
CZ	Czech Rep	3
DE	Germany	4
DK	Denmark	5
ES	Spain	6
FI	Finland	7
FR	France	8
GR	Greece	9
IT	Italy	10
LT	Lithuania	11
NL	Netherlands	12
PT	Portgual	13
RO	Romania	14
SE	Sweden	15
SK	Slovakia	16
SL	Slovenia	17
UK	UK	18
	Controls	
US	*United States*	*19*

Table 2. Average levels of robot density in 2015

Year 2015		
Country	Average - weighted	Average- unweighted
Austria	3,558	5,958284
Belgium	6,875	7,891648
Czech Rep.	1,729	2.579333
Germany	8,096	13.478
Denmark	6,595	27.95
Spain	4,346	6.25
Finland	3,824	6.534
France	3,592	7.94
Greece	0,281	.5870987
Italy	5,488	7.978
Lithuania	0,084	.2984301
Netherlands	3,506	5.511877
Portgual	0,883	2.138986
Romania	0,259	.392013
Sweden	6,606	8.829333
Slovakia	1,093	2.506777
Slovenia	4,398	40.58339
UK	1,893	4.715559

Notes: Average $_w$ levels are weighted using the initial 1995 within country share of hours worked. Average unweighted level for Austria is found in the following way, based on the sum presented in Table 2B: 89,3742646/15= 5,958284*

Table 3. Calculation of weighted robot density using Austria as an example

2015	Robot density	Share Hours	Robot density w
Food products, beverages and tobacco	1,155	0,0816	0,094
Textiles	0,290	0,0443	0,013
Wood and paper products	0,874	0,0674	0,059
Coke and refined petroleum products	16,235	0,0027	0,044
Chemicals and chemical products	0,117	0,0261	0,003
Rubber and plastics products	17,242	0,0629	1,085
Basic metals and fabricated metal products	7,927	0,0903	0,716
Electrical and optical equipment	4,499	0,0649	0,292
Machinery and equipment n,e,c,	3,353	0,0592	0,198
Transport equipment	35,633	0,0262	0,932
Agriculture, Forestry and Fishing	0,101	0,0208	0,002
Mining and Quarrying	1,309	0,0083	0,011
Electricity, Gas and Water supply	0,025	0,0507	0,001
Construction	0,163	0,2415	0,039
Education	0,45	0,1500	0,068
Sum	89,375429	0,9968798	3,558

Notes: Robot density is defined as the number of robots divided per million hours worked. Share hours are the initial (1995) within country share of hours worked.

Table 4A. Total number of robots and number in total manufacturing industry in 2004 and 1998

Year	All industries	Total Manufacturing	Share
2004	123663	13110	0,11
1998	70466	7470	0,11

Notes: 1998 value for total manufacturing number is estimated by assuming that the within country share was the same in 1998 as it was 2004.

Table 4B. Number of robots in the total manufacturing industry in 1998 and 2004

Year	Industry	Number of robots 1998	Share
	Total Manufacturing	7470	100
	Food products, beverages and tobacco	358	0,05
	Coke and refined petroleum products	131	0,02
	Rubber and plastics products	522	0,07
1998	Basic metals and fabricated metal products	785	0,11
	Electrical and optical equipment	745	0,10
	Transport equipment	4930	0,66
	Total Manufacturing	7470	100
Year	**Industry**	**Number of robots 2004**	**Share**
	Food products, beverages and tobacco	628	0,05
	Coke and refined petroleum products	230	0,02
	Rubber and plastics products	916	0,07
2004	Basic metals and fabricated metal products	1378	0,11
	Electrical and optical equipment	1307	0,10
	Transport equipment	8651	0,66
	Total Manufacturing	13110	100

Notes: Other industries included in Total Manufacturing had not adopted robots yet in 2004. Values for 1998 are estimated assuming that the share was the same in 1998 as in 2004.

Table 5. Currency units and conversion methods for all 18 countries

Currency units in EUKLEMS		
Country	Currency	Comment
Austria	Euro	In Euros from 1999 onwards, Before 1999, Austrian Schilling converted to Euro with the 1999 official fixed Euro conversion rate (13,7603 ATS/EUR),
Belgium	Euro	In Euros from 1999 onwards, Before 1999, Belgian Francs converted to Euro with the 1999 official fixed Euro conversion rate (40,3399 BEF/EUR),
Czech Republic	Czech Koruna	Converted using Eurostats annual exchange rates
Germany	Euro	In Euros from 1999 onwards, Before 1999, Deutsche Marks converted to Euro with the 1999 official fixed Euro conversion rate (1,95583 DEM/EUR)
Denmark	Danish Krone	Converted using Eurostats annual exchange rates
Spain	Euro	In Euros from 1999 onwards, Before 1999, Spanish Pesetas converted to Euro with the 1999 official fixed Euro conversion rate (166,386 ESP/EUR),
Finland	Euro	In Euros from 1999 onwards, Before 1999, Finnish Marks converted to Euro with the 1999 official fixed Euro conversion rate (5,94573 FIM/EUR),
France	Euro	In Euros from 1999 onwards, Before 1999, French Francs converted to Euro with the 1999 official fixed Euro conversion rate (6,55957 FRF/EUR),
Greece	Euro	In Euros from 2001 onwards, Before 2001, Greek Drachmas converted to Euro with the 2001 official fixed Euro conversion rate (340,750 GRD/EUR),
Italy	Euro	In Euros from 1999 onwards, Before 1999, Italian Liras converted to Euro with the 1999 official fixed Euro conversion rate (1936,27 ITL/EUR),
Lithuania	Euro	N/A
Netherlands	Euro	In Euros from 1999 onwards, Before 1999, Dutch Guilders converted to Euro with the 1999 official fixed Euro conversion rate (2,20371 NLG/EUR),
Portugal	Euro	In Euros from 1999 onwards, Before 1999, Portuguese Escudos converted to Euro with the 1999 official fixed Euro conversion rate (200,482 PTE/EUR)
Romania	Romanian Leu	Converted using Eurostats annual exchange rates
Sweden	Swedish Krona	Converted using Eurostats annual exchange rates
Slovakia	Euro	N/A
Slovenia	Euro	N/A
UK	British Pound Sterling	Converted using Eurostats annual exchange rates

Notes: Based on EUKLEMS 2007 Methodology report (Timmer…,). Countries are sorted by landcode. The final analysis only includes 13 of the 18 countries listed, Greece, Lithuania, Portugal, Romania and Slovenia are not included, as data needed to construct control variables is not available for these countries.

Table 6. Conversion table with exchange rates from national currencies to euro 1995-2015

Year/ Currency	Czech koruna	Danish krone	Pound sterling	Romanian leu	Swedish krona
1995	36,884	7,4355	0,65874	1,6345	8,8075
1996	36,884	7,4355	0,65874	1,6345	8,8075
1997	36,884	7,4355	0,65874	1,6345	8,8075
1998	36,884	7,4355	0,65874	1,6345	8,8075
1999	36,884	7,4355	0,65874	1,6345	8,8075
2000	35,599	7,4538	0,60948	1,9922	8,4452
2001	34,068	7,4521	0,62187	2,6004	9,2551
2002	30,804	7,4305	0,62883	3,1270	9,1611
2003	31,846	7,4307	0,69199	3,7551	9,1242
2004	31,891	7,4399	0,67866	4,0510	9,1243
2005	29,782	7,4518	0,68380	3,6209	9,2822
2006	28,342	7,4591	0,68173	3,5258	9,2544
2007	27,766	7,4506	0,68434	3,3353	9,2501
2008	24,946	7,4560	0,79628	3,6826	9,6152
2009	26,435	7,4462	0,89094	4,2399	10,6191
2010	25,284	7,4473	0,85784	4,2122	9,5373
2011	24,590	7,4506	0,86788	4,2391	9,0298
2012	25,149	7,4437	0,81087	4,4593	8,7041
2013	25,980	7,4579	0,84926	4,4190	8,6515
2014	27,536	7,4548	0,80612	4,4437	9,0985
2015	27,279	7,4587	0,72584	4,4454	9,3535

Notes: For values before the euro adoption (1999), conversion rates are based on 1999 rates. Source: Eurostat (2017), Romania is not included in the final analysis, as data needed to construct control variables is not available for this country.

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Table 7A: Summary statistics by country

Table A: 1995 Levels Averaged by Country

	#robots/H	ln(H)	ln (EMP)	ln(LAB)
Austria	0	4,37	-3,05	7,55
Belgium	0	4,27	-3,06	7,65
Czech Republic	0	5,31	-2,15	6,19
Germany	2,44	6,78	-0,55	10,03
Denmark	0	3,87	-3,50	7,00
Spain	0,59	5,77	-1,67	8,46
Finland	1,18	3,87	-3,54	6,93
France	1,31	6,01	-1,34	9,21
Greece	0	4,24	-3,35	6,47
Italy	1,95	6,26	-1,21	9,18
Lithuania	0	3,60	-3,87	4,25
Netherlands	0	4,66	-2,73	7,90
Portugal	0	4,73	-2,79	6,72
Romania	0	6,07	-1,50	4,30
Sweden	2,07	4,50	-2,97	7,33
Slovenia	0	4,49	-2,97	5,40
Slovakia	0	3,38	-3,99	5,14
UK	0,67	6,28	-1,26	9,40
Mean	0,57	4,91	-2,53	7,17

Table B: Change in Levels Averaged by Country (1995-2015)

	#robots/H	ln(H)	ln(EMP)	ln(LAB)
Austria	3,56	-0,15	-0,11	0,33
Belgium	6,88	-0,21	-0,21	0,21
Czech Republic	1,73	-0,32	-0,29	1,13
Germany	5,66	-0,26	-0,20	0,14
Denmark	6,60	-0,39	-0,33	0,28
Spain	3,75	-0,05	-0,10	0,38
Finland	2,65	-0,14	-0,08	0,46
France	2,28	-0,32	-0,29	0,21
Greece	0,28	-0,30	-0,27	0,18
Italy	3,53	-0,21	-0,15	0,31
Lithuania	0,08	-0,24	-0,32	1,27
Netherlands	3,51	-0,19	-0,17	0,38
Portugal	0,88	-0,26	-0,25	0,34
Romania	0,26	-0,63	-0,58	2,80
Sweden	4,54	-0,10	-0,08	0,53
Slovenia	1,09	-0,43	-0,38	1,09
Slovakia	4,40	-0,55	-0,55	0,65
UK	1,22	-0,32	-0,31	0,44
Mean	2,94	-0,28	-0,26	0,62

Notes: Robot densities are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked.

Table 7 B&C: Summary statistics by industry

Table B: 1995 Levels Averaged by Industry

Industry	#robots/H	ln(H)	ln(EMP)	ln(LAB)
Food products, beverages and tobacco	0,16	5,44	-1.997341	7,53
Textiles	0,14	5,18	0,20	7,05
Wood and paper products	0,25	5,16	0,15	7,25
Coke and refined petroleum products	0,00	2,37	0,01	5,04
Chemicals and chemical products	0,00	4,49	0,10	6,89
Rubber and plastics products	1,25	5,01	0,16	7,16
Basic metals and fabricated metal products	1,21	5,42	0,24	7,53
Electrical and optical equipment	0,85	4,91	0,15	7,08
Machinery and equipment n,e,c,	1,17	4,87	0,16	6,97
Transport equipment	4,40	4,71	0,15	6,90
Agriculture, Forestry and Fishing	0,00	5,24	0,19	8,18
Mining and Quarrying	0,00	3,49	0,04	5,76
Electricity, Gas and Water supply	0,00	4,87	0,12	7,16
Construction	0,00	6,31	0,56	8,54
Education	0,01	6,24	0,59	8,53

Table C: Change in Levels Averaged by Industry (1995-2015)

Industry	#robots/H	ln(H)	ln(EMP)	ln(LAB)
Food products, beverages and tobacco	3,87	-0,18	-0,01	0,62
Textiles	1,21	-1,02	-0,11	-0,04
Wood and paper products	1,18	-0,46	-0,05	0,42
Coke and refined petroleum products	66,06	-0,76	-0,01	0,26
Chemicals and chemical products	0,11	-0,19	-0,02	0,74
Rubber and plastics products	8,38	-0,21	-0,03	0,65
Basic metals and fabricated metal products	4,29	-0,12	-0,03	0,78
Electrical and optical equipment	2,64	-0,28	-0,03	0,70
Machinery and equipment n,e,c,	3,12	-0,14	-0,01	0,83
Transport equipment	25,48	-0,18	0,00	0,75
Agriculture, Forestry and Fishing	0,27	-0,24	-0,03	0,32
Mining and Quarrying	0,42	-0,49	-0,02	0,52
Electricity, Gas and Water supply	0,04	-0,02	0,00	0,88
Construction	0,11	-0,07	-0,06	0,84
Education	0,15	0,14	0,11	0,99

Notes: Robot densities are not weighted.

Table 7D & E: Summary statistics by country

Table D: 1995 Levels Averaged by Country

	#robots/H	ln(H)	ln (EMP)	ln(LAB)
Austria	0	4,37	-3,05	7,55
Belgium	0	4,27	-3,06	7,65
Czech Republic	0	5,31	-2,15	6,19
Germany	2,44	6,78	-0,55	10,03
Denmark	0	3,87	-3,50	7,00
Spain	0,59	5,77	-1,67	8,46
Finland	1,18	3,87	-3,54	6,93
France	1,31	6,01	-1,34	9,21
Greece	0	4,24	-3,35	6,47
Italy	1,95	6,26	-1,21	9,18
Lithuania	0	3,60	-3,87	4,25
Netherlands	0	4,66	-2,73	7,90
Portugal	0	4,73	-2,79	6,72
Romania	0	6,07	-1,50	4,30
Sweden	2,07	4,50	-2,97	7,33
Slovenia	0	4,49	-2,97	5,40
Slovakia	0	3,38	-3,99	5,14
UK	0,67	6,28	-1,26	9,40
Mean	0,57	4,91	-2,53	7,17

Table E: Change in Levels Averaged by Country (1995-2015)

	#robots/H	ln(H)	ln(EMP)	ln(LAB)
Austria	3,56	-0,15	-0,11	0,33
Belgium	6,88	-0,21	-0,21	0,21
Czech Republic	1,73	-0,32	-0,29	1,13
Germany	5,66	-0,26	-0,20	0,14
Denmark	6,60	-0,39	-0,33	0,28
Spain	3,75	-0,05	-0,10	0,38
Finland	2,65	-0,14	-0,08	0,46
France	2,28	-0,32	-0,29	0,21

Greece	0,28	-0,30	-0,27	0,18
Italy	3,53	-0,21	-0,15	0,31
Lithuania	0,08	-0,24	-0,32	1,27
Netherlands	3,51	-0,19	-0,17	0,38
Portugal	0,88	-0,26	-0,25	0,34
Romania	0,26	-0,63	-0,58	2,80
Sweden	4,54	-0,10	-0,08	0,53
Slovenia	1,09	-0,43	-0,38	1,09
Slovakia	4,40	-0,55	-0,55	0,65

ble 7 F: Summary statistics by industry

Table A: 2008 Levels Averaged by Industry

Industry	(1) Δ Share H Low	(2) Δ Share H Middle	(3) Δ Share H High
Agriculture, Forestry and Fishing	0,06	0,09	-0,03
Mining and Quarrying	0,04	0,09	0,00
Total Manufacturing	0,07	0,19	-0,01
Construction	0,05	0,10	0,02
Education	0,01	0,05	0,10

Table B: Changes in levels from 2008-2015 : Averaged by Industry

Industry	(1) Δ Share H Low	(2) Δ Share H Middle	(3) Δ Share H High
Agriculture, Forestry and Fishing	-0,03	-0,03	0,07
Mining and Quarrying	0,00	-0,04	0,05
Total Manufacturing	-0,01	-0,05	0,06
Construction	-0,02	-0,06	0,08
Education	0,09	-0,03	-0,06

Notes: Δ Share H stands for labor share of five industries of hours worked. Industry " Electricity, Gas and Water supply " is removed, as explained in section 6.2.

Table 8. Summary statistics for variables

A: 1995 levels

	Mean	Std Dev	Min	Median	Max	Number of obs.
Robot density	0,57	1,99	0,00	0,00	16,91	270
ln(H)	4,91	1,46	0,32	4,93	8,46	270
K_{ICT}	53,80	46,40	0,52	44,98	335,31	149
K_{OTHER}	82,90	28,15	17,38	80,44	190,37	149
Productivity	3,37	1,02	-2,09	3,52	7,39	270

B: Changes from 1995-2015

	Mean	Std Dev	Min	Median	Max	Number of obs.
Δ Robot density	2,94	6,84	-0,80	0,31	67,23	270
Δ ln(H)	-0,28	0,49	-3,73	-0,21	1,07	270
Δ K_{ICT}	179,77	755,51	-246,64	71,99	8571,91	149
Δ K_{OTHER}	19,54	44,20	-122,83	18,77	312,75	149
Δ Productivity	0,95	0,91	-1,26	0,67	6,10	270

Notes: Robot density stands for the number of operational robots per million hours worked. Δln(H) stands for the change in log of hours worked from 2005 to 2015. Controls include country-industry fixed effect, namely the variation in labor productivity from 2005-2015, changes in both ICT (K_{ICT}) and non-ICT capital (K_{OTHER}) services from 1995 to 2015.

Table 9: Simple OLS regression 1995-2015

	(2)	(3)
	ΔH	ΔH
Δ Robot adoption $_{UNW}$	-0.00203	
	(-0.39)	
Δ Robot adoption $_{PERC}$		0.0820
		(0.72)
Constant	-0.276***	-0.322***
	(-9.33)	(-5.26)
N	270	270

Notes: ΔH stands for the change in log of hours worked between 1995 and 2015. Δ Robot adoption stands for percentiles of changes in robot density, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 10. Changes in hours worked 1995-2015: OLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0712	-0.0582	0.00673	-0.0686	0.0290
	(-0.65)	(-0.54)	(0.08)	(-0.73)	(0.33)
Wage $_{1995}$		0.0622^{**}	0.0786^{***}	0.0901^{***}	0.0863^{***}
		(2.68)	(4.13)	(3.93)	(4.47)
Productivity $_{1995}$		0.0813	0.132^{**}	0.125^{*}	0.160^{**}
		(1.46)	(2.65)	(2.43)	(3.35)
Δ Labor Productivity		0.0260	0.00223	0.000534	0.00510
		(0.62)	(0.04)	(0.01)	(0.09)
Δ K $_{ICT}$			0.0000256	0.0000203	0.0000348
			(0.81)	(0.63)	(1.11)
Δ K $_{OTHER}$			0.00600^{***}	0.00592^{***}	0.00596^{***}
			(7.74)	(7.20)	(8.27)
Constant	-0.178^{*}	-0.971^{**}	-1.412^{***}	-1.428^{***}	-1.582^{***}
	(-2.55)	(-3.14)	(-4.89)	(-4.46)	(-5.39)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentiles of changes in robot density, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Robot densities are defined as the number of operational robots per million hours worked. ΔH stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 11: First stage regression 1995-2015

	(1)
	Δ Robot adoption $_{EUR}$
Δ Robot adoption $_{US}$	0.777^{***}
	(16.69)
Δ K $_{ICT}$	-0.0000251^{**}
	(-2.90)
Δ K $_{OTHER}$	-0.000589
	(-1.71)
Wage $_{1995}$	-0.00645
	(-0.76)
Constant	0.180^{*}
	(2.34)
N	149

Notes: Δ Robot adoption $_{EUR}$ stands for the percentile of changes in the endogenous (European) robot density from 1995 to 2015, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Robot adoption $_{US}$ stands for the percentile of changes in the exogenous robot density, in the US, from 1998 to 2015, weighted by the initial (1998) share of within-country hours worked. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 12. Change in hours worked 1995-2015 : 2SLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0734	-0.0375	-0.0485	-0.142	-0.0293
	(-0.51)	(-0.27)	(-0.43)	(-1.20)	(-0.24)
Wage $_{1995}$		0.0622**	0.0783***	0.0897***	0.0858***
		(2.72)	(4.23)	(4.03)	(4.60)
Productivity $_{1995}$		0.0820	0.128**	0.120*	0.157***
		(1.50)	(2.63)	(2.37)	(3.34)
Δ Labor Productivity		0.0263	0.00158	-0.000895	0.00296
		(0.63)	(0.03)	(-0.02)	(0.05)
Δ K $_{ICT}$			0.0000216	0.0000148	0.0000310
			(0.71)	(0.48)	(1.02)
Δ K $_{OTHER}$			0.00597***	0.00586***	0.00593***
			(7.78)	(7.23)	(8.33)
Constant	-0.177*	-0.984**	-1.369***	-1.367***	-1.535***
	(-2.11)	(-3.25)	(-4.89)	(-4.40)	(-5.37)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile of changes in robot density, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Robot densities are defined as the number of operational robots per million hours worked. ΔH stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 13: Changes in hours worked 1995-2005 – OLS estimates

	(1)	(2)	(3)	(4)	(5)
	ΔH	ΔH	ΔH	ΔH	ΔH
Δ Robot adoption	0.00598**	0.00332	0.000937	-0.000726	0.00466
	(2.68)	(1.38)	(0.38)	(-0.18)	(0.71)
Wage $_{1995}$		0.0296	0.0235	0.0362	0.0231
		(1.59)	(1.46)	(1.77)	(1.42)
Productivity $_{1995}$		0.00639	0.0184	0.0115	0.0227
		(0.20)	(0.58)	(0.35)	(0.69)
Δ Labor Productivity		-0.0942	-0.178*	-0.209**	-0.201**
		(-1.26)	(-2.42)	(-2.80)	(-2.62)
Δ K $_{ICT}$			0.00119**	0.00113*	0.00115*
			(2.63)	(2.43)	(2.53)
Δ K $_{OTHER}$			0.00656***	0.00653***	0.00659***
			(5.64)	(5.01)	(5.45)
Constant	-0.0896***	-0.305	-0.374	-0.422	-0.379
	(-3.56)	(-1.40)	(-1.90)	(-1.84)	(-1.84)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Robot densities are defined as the number of operational robots per million hours worked. ΔH stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 14: Changes in hours worked 1995-2005: 2SLS estimates

	(1)	(2)	(3)	(4)	(5)
	ΔH	ΔH	ΔH	ΔH	ΔH
Δ Robot adoption	0.0193	0.0212	0.00835	0.00239	0.0195
	(1.61)	(1.73)	(0.85)	(0.20)	(1.06)
Wage $_{1995}$		0.0191	0.0193	0.0353	0.0212
		(0.93)	(1.11)	(1.69)	(1.30)
Productivity $_{1995}$		0.00512	0.0174	0.0120	0.0253
		(0.16)	(0.56)	(0.37)	(0.77)
Δ Labor Productivity		-0.100	-0.179*	-0.207**	-0.195*
		(-1.38)	(-2.50)	(-2.86)	(-2.52)
Δ K $_{ICT}$			0.00119**	0.00111*	0.00106*
			(2.68)	(2.46)	(2.35)
Δ K $_{OTHER}$			0.00643***	0.00652***	0.00669***
			(5.71)	(5.21)	(5.62)
Constant	-0.112***	-0.245	-0.347	-0.420	-0.390
	(-3.48)	(-1.10)	(-1.76)	(-1.88)	(-1.95)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Robot densities are defined as the number of operational robots per million hours worked. ΔH stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 15. First stage regression 2005-2015

	(1)
	Δ Robot adoption $_{EUR}$
Δ Robot adoption $_{US}$	0.642^{***}
	(11.34)
Constant	0.179^{***}
	(7.29)
N	195

Notes: Δ Robot adoption $_{EUR}$ stands for the percentile of changes in the endogenous (European) robot density from 1995 to 2015, weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Robot adoption $_{US}$ stands for the percentile of changes in the exogenous robot density, in the US, from 1998 to 2015, weighted by an industry's initial (1998) share of hours in the country-wide amount of hours worked. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 16. Changes in hours worked 2005-2015 : OLS estimates

	(1)	(2)	(3)	(4)	(5)
	ΔH	ΔH	ΔH	ΔH	ΔH
Δ Robot adoption	-0.0334	-0.0202	0.0185	0.0112	-0.00904
	(-0.55)	(-0.34)	(0.38)	(0.21)	(-0.19)
Wage $_{1995}$		0.00973	0.0225**	0.0142	0.0257**
		(0.95)	(2.61)	(1.39)	(3.03)
Productivity $_{1995}$		0.0340	0.0486**	0.0495**	0.0635***
		(1.62)	(2.61)	(2.62)	(3.67)
Δ Labor Productivity		-0.0249	-0.0239	-0.0220	-0.00964
		(-0.52)	(-0.48)	(-0.44)	(-0.22)
Δ K $_{ICT}$			0.0000290	0.0000287	0.0000300
			(1.80)	(1.76)	(1.91)
Δ K $_{OTHER}$			0.00351***	0.00346***	0.00336***
			(5.14)	(4.98)	(5.39)
Constant	-0.112**	-0.304**	-0.505***	-0.446***	-0.567***
	(-3.08)	(-2.80)	(-5.73)	(-4.72)	(-6.78)
N	195	195	194	179	181

Notes: Δ Robot adoption stands for the percentile of changes in robot density, weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. ΔH stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 17. Changes in hours worked 2005-2015 :2SLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.175	-0.147	-0.0643	-0.0885	-0.0784
	(-1.94)	(-1.72)	(-0.80)	(-1.02)	(-1.00)
Wage $_{1995}$		0.00776	0.0209*	0.0121	0.0248**
		(0.77)	(2.48)	(1.21)	(2.99)
Productivity $_{1995}$		0.0325	0.0471*	0.0474*	0.0626***
		(1.55)	(2.56)	(2.55)	(3.70)
Δ Labor Productivity		-0.0233	-0.0224	-0.0204	-0.00942
		(-0.54)	(-0.49)	(-0.46)	(-0.24)
Δ K $_{ICT}$			0.0000258	0.0000248	0.0000279
			(1.56)	(1.48)	(1.74)
Δ K $_{OTHER}$			0.00344***	0.00337***	0.00332***
			(5.08)	(4.89)	(5.40)
Constant	-0.0411	-0.221*	-0.444***	-0.373***	-0.523***
	(-0.84)	(-1.99)	(-4.68)	(-3.63)	(-5.79)
N	195	195	194	179	181

Notes: Δ Robot adoption stands for percentile of changes in robot density, weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. ΔH stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 18. Robustness check 1A : Changes in Employment 1995-2015 : OLS estimates

	(1)	(2)	(3)	(4)	(5)
	Δ Employment	Δ Employment	Δ Employment	Δ Employment	Δ Employment
Δ Robot adoption	-0.0272	-0.0123	0.0465	-0.0206	0.0730
	(-0.25)	(-0.12)	(0.53)	(-0.22)	(0.83)
Wage $_{1995}$		0.0562*	0.0718***	0.0779***	0.0786***
		(2.48)	(3.81)	(3.37)	(4.12)
Productivity $_{1995}$		0.0915	0.141**	0.135**	0.168***
		(1.66)	(2.93)	(2.70)	(3.62)
Δ Labor Productivity		0.0415	0.0199	0.0173	0.0232
		(1.03)	(0.44)	(0.38)	(0.51)
Δ K $_{ICT}$			0.0000216	0.0000169	0.0000301
			(0.75)	(0.58)	(1.06)
Δ K $_{OTHER}$			0.00585***	0.00579***	0.00579***
			(7.67)	(7.08)	(8.14)
Constant	-0.170*	-0.959**	-1.385***	-1.369***	-1.545***
	(-2.48)	(-3.17)	(-5.07)	(-4.49)	(-5.56)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. Δ Employment stands for changes in the number of people employed (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 19. Robustness check 1B: Changes in Employment 1995-2015 : 2SLS estimates

	(1) Δ Employment	(2) Δ Employment	(3) Δ Employment	(4) Δ Employment	(5) Δ Employment
Δ Robot adoption	-0.0422	-0.00210	-0.0165	-0.103	0.00787
	(-0.30)	(-0.02)	(-0.15)	(-0.86)	(0.06)
Wage $_{1995}$		0.0562*	0.0714***	0.0774***	0.0780***
		(2.52)	(3.89)	(3.43)	(4.22)
Productivity $_{1995}$		0.0919	0.137**	0.130**	0.164***
		(1.70)	(2.89)	(2.61)	(3.57)
Δ Labor Productivity		0.0417	0.0191	0.0157	0.0208
		(1.04)	(0.44)	(0.35)	(0.46)
Δ K $_{ICT}$			0.0000171	0.0000107	0.0000259
			(0.61)	(0.38)	(0.93)
Δ K $_{OTHER}$			0.00582***	0.00573***	0.00575***
			(7.70)	(7.10)	(8.18)
Constant	-0.162*	-0.966**	-1.336***	-1.301***	-1.492***
	(-1.97)	(-3.24)	(-5.01)	(-4.38)	(-5.45)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. Δ Employment stands for changes in the number of people employed (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 20. Robustness check 2A : Changes in Hours worked excluding unspecified industries: OLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0716	-0.0595	0.00688	-0.0692	0.0294
	(-0.66)	(-0.55)	(0.08)	(-0.74)	(0.33)
Wage $_{1995}$		0.0622^{**}	0.0786^{***}	0.0901^{***}	0.0863^{***}
		(2.68)	(4.13)	(3.93)	(4.47)
Productivity $_{1995}$		0.0812	0.132^{**}	0.125^{*}	0.160^{**}
		(1.46)	(2.65)	(2.43)	(3.35)
Δ Labor Productivity		0.0259	0.00224	0.000443	0.00514
		(0.62)	(0.04)	(0.01)	(0.09)
Δ K $_{ICT}$			0.0000256	0.0000203	0.0000348
			(0.81)	(0.64)	(1.11)
Δ K $_{OTHER}$			0.00600^{***}	0.00592^{***}	0.00597^{***}
			(7.74)	(7.19)	(8.27)
Constant	-0.178^{*}	-0.970^{**}	-1.412^{***}	-1.428^{***}	-1.582^{***}
	(-2.55)	(-3.14)	(-4.89)	(-4.46)	(-5.39)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, excluding unspecified industries "Chemical products, unspecified" and "Metal, unspecified". Changes are weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. Δ H stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 21. Robustness check 2B: Changes in Hours worked excluding unspecified industries: 2SLS estimates

	(1) ΔH	(2) ΔH	(3) ΔH	(4) ΔH	(5) ΔH
Δ Robot adoption	-0.0734	-0.0374	-0.0485	-0.142	-0.0292
	(-0.51)	(-0.27)	(-0.43)	(-1.20)	(-0.24)
Wage $_{1995}$		0.0622^{**}	0.0783^{***}	0.0897^{***}	0.0858^{***}
		(2.72)	(4.23)	(4.03)	(4.60)
Productivity $_{1995}$		0.0820	0.128^{**}	0.120^{*}	0.157^{***}
		(1.50)	(2.63)	(2.37)	(3.34)
Δ Labor Productivity		0.0263	0.00153	-0.00106	0.00293
		(0.63)	(0.03)	(-0.02)	(0.05)
Δ K $_{ICT}$			0.0000217	0.0000148	0.0000310
			(0.71)	(0.48)	(1.02)
Δ K $_{OTHER}$			0.00597^{***}	0.00586^{***}	0.00593^{***}
			(7.78)	(7.23)	(8.32)
Constant	-0.177^{*}	-0.984^{**}	-1.369^{***}	-1.367^{***}	-1.535^{***}
	(-2.11)	(-3.25)	(-4.89)	(-4.40)	(-5.37)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, excluding unspecified industries “Chemical products, unspecified“ and “Metal, unspecified”. Changes are weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. Δ H stands for changes in hours worked (in millions). Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 22. Changes in wages 1995-2015: OLS estimates

	(1) Δ Wages	(2) Δ Wages	(3) Δ Wages	(4) Δ Wages	(5) Δ Wages
Δ Robot adoption	-0.00700	-0.0399	0.0494	-0.0477	0.0588
	(-0.05)	(-0.34)	(0.51)	(-0.46)	(0.61)
Wage $_{1995}$		-0.0378	-0.0178	-0.0170	-0.0152
		(-1.52)	(-0.96)	(-0.79)	(-0.82)
Productivity $_{1995}$		-0.168*	-0.102	-0.122*	-0.0782
		(-2.56)	(-1.82)	(-2.12)	(-1.45)
Δ Labor Productivity		0.137	0.110*	0.0873*	0.105*
		(1.49)	(2.22)	(2.06)	(2.35)
Δ K $_{ICT}$			0.0000655	0.0000567	0.0000718*
			(1.89)	(1.66)	(2.12)
Δ K $_{OTHER}$			0.00640***	0.00636***	0.00620***
			(7.38)	(6.70)	(7.84)
Constant	0.399***	1.204**	0.656*	0.785*	0.555
	(5.11)	(3.12)	(2.18)	(2.43)	(1.83)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for percentile of changes in robot density, weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. Δ Wages stands for changes in wages. Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 23. Changes in wages 1995-2015: 2SLS estimates

	(1)	(2)	(3)	(4)	(5)
	Δ Wages	Δ Wages	Δ Wages	Δ Wages	Δ Wages
Δ Robot adoption	0.120	-0.00346	0.00772	-0.111	0.0263
	(0.67)	(-0.02)	(0.06)	(-0.84)	(0.20)
Wage $_{1995}$		-0.0378	-0.0180	-0.0174	-0.0156
		(-1.55)	(-1.00)	(-0.83)	(-0.87)
Productivity $_{1995}$		-0.167**	-0.105	-0.127*	-0.0802
		(-2.59)	(-1.91)	(-2.25)	(-1.52)
Δ Labor Productivity		0.138	0.109*	0.0861*	0.103*
		(1.53)	(2.23)	(2.05)	(2.35)
Δ K $_{ICT}$			0.0000625	0.0000520	0.0000697*
			(1.85)	(1.56)	(2.08)
Δ K $_{OTHER}$			0.00638***	0.00631***	0.00618***
			(7.44)	(6.74)	(7.91)
Constant	0.335***	1.182**	0.688*	0.837**	0.581
	(3.56)	(3.15)	(2.34)	(2.67)	(1.93)
N	150	150	149	134	139

Notes: Δ Robot adoption stands for the percentile of changes in robot density, weighted by the initial 1995 industry\ s share of hours worked. Robot densities are defined as the number of operational robots per million hours worked. Δ Wages stands for changes in wages. Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.

Table 24. Changes in labor shares 2008-2015: OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low skilled workers			Middle skilled workers			High skilled workers		
	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H
Δ Robot adoption	-0.0268	-0.0361*	-0.0321*	-0.0309*	-0.0253	-0.0266	0.0540***	0.0590***	0.0562**
	(-1.90)	(-2.41)	(-2.08)	(-2.37)	(-1.91)	(-1.96)	(3.52)	(3.46)	(3.20)
Wage $_{1995}$		0.000938	0.00224		0.00489*	0.00494		-0.00629*	-0.00766**
		(0.45)	(1.09)		(1.99)	(1.89)		(-2.33)	(-2.66)
Productivity $_{1995}$		-0.0100**	-0.00891**		0.0191***	0.0181***		-0.00837	-0.00858
		(-2.93)	(-2.64)		(4.49)	(3.94)		(-1.76)	(-1.74)
Δ Productivity		0.00201	0.00409		0.000465	0.000871		-0.00262	-0.00514*
		(0.91)	(1.84)		(0.20)	(0.34)		(-1.36)	(-2.42)
Δ K $_{ICT}$			0.000000960			-0.00000420			0.00000304
			(0.63)			(-0.83)			(0.72)
Δ K $_{OTHER}$			0.000580***			0.000107			-0.000694***
			(4.27)			(0.55)			(-3.96)
Constant	0.0200*	0.0488**	0.0260	-0.0283***	-0.136***	-0.133***	0.0113	0.0916**	0.112**
	(2.18)	(2.94)	(1.53)	(-3.47)	(-4.78)	(-3.96)	(1.17)	(2.88)	(3.06)
N	360	360	360	360	360	360	360	360	360

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Share H stands for the change in the share of high-skilled workers 1995 to 2015. Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with $***$ are significant at the 1% confidence level; with $**$ are significant at the 5% confidence level; and with $*$ are significant at the 10% confidence level.

Table 25. Changes in Labor shares 2008-2015: 2SLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low skilled workers			Middle skilled workers			High skilled workers		
	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H	Δ Share H
Δ Robot adoption	0.0839***	0.132***	0.109***	-0.0157	-0.00726	-0.0168	-0.0815**	-0.138***	-0.106**
	(3.31)	(4.27)	(3.79)	(-0.56)	(-0.19)	(-0.46)	(-2.61)	(-3.30)	(-2.80)
Wage $_{1995}$		-0.00614*	-0.00301		0.00413	0.00458		0.00202	-0.00165
		(-2.31)	(-1.23)		(1.39)	(1.56)		(0.60)	(-0.50)
Productivity $_{1995}$		0.000239	0.00115		0.0202***	0.0188***		-0.0204***	-0.0201***
		(0.06)	(0.28)		(4.12)	(3.59)		(-3.60)	(-3.49)
Δ Productivity		-0.00136	0.00188		0.000103	0.000719		0.00133	-0.00261
		(-0.54)	(0.80)		(0.04)	(0.28)		(0.46)	(-0.99)
Δ K $_{ICT}$			0.00000609***			-0.00000384			-0.00000284
			(3.48)			(-0.73)			(-0.64)
Δ K $_{OTHER}$			0.000746***			0.000118			-0.000884***
			(4.73)			(0.58)			(-4.62)
Constant	-0.0347**	-0.00509	-0.0330	-0.0358*	-0.142***	-0.137***	0.0782***	0.155***	0.180***
	(-2.76)	(-0.26)	(-1.59)	(-2.26)	(-4.55)	(-3.72)	(4.92)	(4.36)	(4.53)
N	360	360	360	360	360	360	360	360	360

Notes: Δ Robot adoption stands for the percentile change of robot density from 1995 to 2015. Changes are weighted by an industry's initial (1995) share of hours in the country-wide amount of hours worked. Δ Share H stands for the change in the share of high-skilled workers 1995 to 2015. Wage $_{1995}$ is the initial (1995) wage, while Productivity $_{1995}$ is the initial (1995) level of labor productivity in a given industry, country and year. Δ Labor Productivity stands for changes in labor productivity, Δ K $_{ICT}$ and Δ K $_{OTHER}$ stand for changes in ICT and non-ICT capital services, respectively. The coefficients with ∗∗∗ are significant at the 1% confidence level; with ∗∗ are significant at the 5% confidence level; and with ∗ are significant at the 10% confidence level.