LUND UNIVERSITY
School of Economics and Management

**Master programme in Economic Growth, Innovation and Spatial Dynamics**

# The Changing Nature of Employment: How Technological Progress and Robotics Shape the Future of Work

**Lennart Hoedemakers**
**Egi15lho@student.lu.se**

This thesis assesses the impact of innovation on employment, using a selection of International Patent Classifications (IPC) as proxies for technological development. It uses a 15-country, 8-sector and 15-year dynamic panel dataset, specifying a system Generalized Methods of Moments (GMM) econometric model to test this relationship. It specifically evaluates whether advances in robotics – measured by the operationalization of a robotics patent index – impact labor markets differently than other patent classifications. This dissertation suggests that robotics patents are mildly positively associated with employment, and that the results from other patent classifications are insufficiently robust for reliable conclusions. Overall, this paper supports the notion that technological progress is a driver of wage and job-polarization, and that it contributes to the current OECD trend of rising inequality. While the results from this thesis do not support the notion that innovation will result in technological unemployment in the near future, it does raise a number of new questions that indicate further research on this topic is essential. Specifically, this dissertation suggests approaching this topic by drawing on more empirical data, thus bridging the gap between on the one hand theoretical models and projections, and on the other hand empirical evidence.

*Key words:* Innovation, Robots, Technological Anxiety, Technological Unemployment

**EKHS32**
Master thesis, Second Year (15 credits ECTS)
June 2017
Supervisor: Anna Missiaia
Examiner: Erik Bengtsson
Word Count: 16921

# Table of Contents:


Preface 1

Table of Contents 2

List of tables 3

1. Introduction 4

2. Literature Review 7

    2.1 Technological Anxiety and the labor market - job quality 7

        2.1.1. Technological progress and societal impacts: labor subsitution 8

        2.1.2. Skill Biased Technical Change 12

        2.1.3. Routine Biased Technical Change 14

    2.2 Technological anxiety and the labor market - job quantity 17

        2.2.1. Innovation literature 18

        2.2.2. Robotics, machine learning and artificial intelligence 20

3. Methodology 27

    3.1. Research Questions 27

    3.2. Econometric model 28

4. Data 33

    4.1. Sources 36

        4.1.1. Employment Share 37

        4.1.2. Control variables 37

        4.1.2. Patent Data 39

    4.2. Robotics Index 40

5. Results 42

    5.1. Descriptive Tables 42

    5.2. Regression Tables 46

6. Discussion 52

    6.1. Limitations 54

    6.2. Recommendations for future research 56

7. Conclusion 58

8. References 59

Appendix 63

# List of tables:

Table 1: Sectors' share of employment for 1995-2009 ..... 42
Table 2: Patent count per PCT classification for 1995-2009 ..... 43
Table 3: Patents by ISIC sector for 1995-2009 ..... 45
Table 4: Results regression of patents and percentage change of employment shares of selected sectors ..... 46
Table 5: Results regression of patents and percentage change of employment shares of selected sectors: ..... 49
Table 6: Robotics patents – IPC categories ..... 65

# 1. Introduction

Ever since the first Industrial Revolution in the late 18th century, new technologies have been viewed ambiguously: while some welcome the prospect of increased productivity and the potential of improved wealth, there similarly exists considerable opposition, especially by those who stand to lose of a change in the status quo. Notably, this opposition is from all ages: whereas it is most commonly known from the Luddite rebellion of 1811-1816, predictions that technological progress will make humans redundant have been made regularly. In the 1920's the New York Times claimed that the 'March of the machines makes idle hands', in the 1930's Keynes coined the term "technological unemployment", in the 1960's President Kennedy declared that "automation… is replacing men", and also in the 80's there were fears that computers would result in job losses (Keynes, 1930; Economist, 2017). This dichotomy in the perceptions of technological advancements still exists today, with considerable and increasing coverage of the impact of artificial intelligence (AI), machine learning (ML), robotization and other aspects of the current technological progress. Illustratively, CEO of SpaceX, Tesla and Neurolink Elon Musk has stated that "Robots will take your jobs", Bill Gates, founder of Microsoft, the largest software company in the world, claimed that robots that steal jobs should pay taxes, and also renowned physicist Stephen Hawking argued that AI 'will automate middle class jobs' (Larson, 2017). Supplementing these anecdotes, numerous papers indicate that automation and digitalization threaten an increasing number of jobs, with a widely cited paper stating that up to 47% of jobs in developed economies are threatened in the foreseeable two decades (Frey and Osborne, 2013).

Yet there is considerable disagreement in the literature as well as amongst economists and economic historians as to the future of employment and the supposedly negative impact of technology or innovation: several papers point out how similar fears existed before or during technological pushes, and that despite the continuous transformation of our societies due to the introduction of new technologies, the population explosion of the past two centuries has been mirrored by a similar creation of new jobs (Mokyr, Vickers

and Ziebarth, 2015). It is then interesting to consider how these new jobs have been created, when they have been created, and what mechanisms facilitated their increase. Moreover, whereas there is extensive literature on the impact of technological progress on labor dynamics, a considerable proportion of this is theoretical, with fewer recent papers empirically assessing the impact of technological progress on the labor market. One of the reasons for this is that it is difficult to measure technological progress, necessitating the use of imperfect proxies. These have included computer diffusion, research and development expenditure, or patents, commonly aggregating technological developments by operationalizing one, or a number of aggregated proxies.

This paper seeks to add to the literature by distinguishing between different types of technological progress, using different patent classifications. The results of this study could help researchers and policymakers evaluate whether different kinds of innovation have a differing impact on the labor market. After all, whereas technological progress in certain sectors might have a negative impact on employment – e.g. labor-substituting automation in the case of self-driving trucks – technological progress in other sectors might have the exact opposite effect – e.g. innovations in sustainable energy have created and stimulated new industries. This paper thus seeks to assess the impact of technological progress in employment by measuring the impact of different patents on a number of different sectors; it does so for the period 1995-2009, for 15 different industrialized countries. While it would have been interesting to include more diversity or a higher number of countries (e.g. countries from the Global South, or the BRICS), the restricted data availability unfortunately has limited this dissertation to the current sample.

Additionally, this paper contributes to the existing literature by measuring robots and robotics in a new way through the construction of an index of robotics patents. Whereas a considerable number of papers have sought to assess the impact of innovation, the impact of robots and robotics on the labor market is less thoroughly documented: while there has been an increase of academic interest on the impact of robots on employment in recent years, there are few papers that empirically measure this trend. This thesis constructs a simple but arguably adequate index of patents to evaluate the impact of innovations in

robots and robotics on industrial sectors, seeking to evaluate whether indeed robots substitute or complement employment in certain sectors.

The rest of this paper is structured as follows: section 2 of this paper assesses previous literature on the impact of technology on labor markets in the developed world: the literature review first reviews literature on the impact of technology on the quality of jobs (section 2.1.), followed by an assessment of the literature on the quantity of jobs (section 2.2.), particularly assessing the literature on the impact of advances in robotics. Section 3 of this paper outlines the methodology used, discussing the strengths and weaknesses of the model this paper draws upon. Having done so, this paper delves deeper into the data in section 4, specifically evaluating the advantages and disadvantages of patents as a proxy for technological progress. Section 5 displays descriptive as well as regression tables, shortly remarking on notable findings. The actual implications are assessed in more depth in section 6, the discussion, where the results are compared and contrasted with previous literature, also considering the drawbacks of the data and methodology used. Finally this paper concludes by evaluating the findings of this thesis in light of the strengths and weaknesses of the data and methodology, deriving implications for researchers and policy makers alike.

Overall, this paper maintains that technological innovation, proxied by patents, has a modest positive implication on employment. While the differing classes of patents present different results and often are not robust, the most notable finding of this paper is that robotic patents are moderately, yet robustly, associated with a positive increase in employment in several sectors between 1995-2009**.** While these findings contribute to the discussion regarding the impact of robots on employment, the extent to which these findings can be generalized to the present and nearby future is debatable, and should be considered with care. Regardless, the development of a new index contributes to both researchers' and policymakers' understanding of robots and robotics, facilitating improved understanding of its impact on the labor market. This paper concludes with recommendations for policy-makers and for future research.

# 2. Literature review:

## 2.1. Technological anxiety and the labor market – job quality

'*Men have become the tools of their tools'* - Henry David Thoreau (1854)

As the anecdotes from the introduction illustrate, there has been increasing interest in the impact of technological progress on our societies; while recent decades have seen the introduction of numerous technological devices and innovations in our daily lives, the societal impact of these technologies has been significant, but relatively gradual. While this initially was reflected by the introduction of widespread consumption goods such as increasingly powerful phones and computers, there is growing concern that the current technological progress will not just supplement our daily lives, but increasingly will substitute for human labor. Indeed, Frey and Osborne, in a widely cited paper by both scholars as well as the mainstream media, assessed the likeliness of jobs in the U.S. being automated, particularly considering the recent advances in Machine Learning and Mobile Robotics (Frey & Osborne, 2013). Notably, controlling for education, wages and in particular the requirements of job descriptions they argue that 47% of jobs in the U.S. are susceptible to automation (Idem, 2013). Replicating their methodology, Pajarin and Rouvinen (2014), argue that 35% of jobs in Finland are susceptible to automation. Similarly reproducing this methodology for more European countries Bowles (2014) found that 45% to 60% of the jobs in European countries are at risk of being substituted in the coming two decades (Bowles, 2014). Hence, the potential for automation to substitute laborers and its supposedly increasing threat towards the foundation of industrial societies seems substantial, and therefore important to consider. Yet it should be noted that there is no consensus on the impact of technology on future employment, with statements regarding the risk of automation and their actual substitution requiring critical evaluation.

Indeed, weakening some of Osborne and Frey's (2013) as well as Bowles (2014) assumptions, Arntz, Gregory and Zierahn (2016) argue that in the OECD on average only 9% of the jobs is automatable. They argue that it is important to consider heterogeneity within occupations, rather than purely focusing on the description of the jobs as a homogenous unit (Arntz, Gregory and Zierahn, 2016). It appears then that the impact of technology on future employment is difficult to estimate, especially when considering that not only the direct effects on employment, but also the indirect effects in the form of compensation mechanisms should be accounted for when assessing the impact of technology on employment. In order to guide our understanding of current technological processes and their impact on the nearby future, it warrants assessing the economic past, potentially providing guidance as to how to best address the issues we face today. After all, microeconomic theory proposes that labor-replacing capital is introduced for the simple fact that it is cheaper than the labor it replaces. Yet, despite the ever-increasing quantity and quality of capital due to technological progress since the industrial revolution, there still is full employment. Moreover, if anything, the industrial revolution and its aftershocks have supplemented our lives, contributed to increasing standards of living all around the world and have boosted the overall development of society.

It is then important to consider how technological progress has been influencing society and labor markets in the past. Doing so allows us to understand whether the current technological progress in the form of digitalization, automation and robotization represent a break from the past similar to the first industrial revolution, or is a continuation of trends manifested in a new form.

#### 2.1.1. Technological progress and societal impacts: labor substitution

Following the post-WWII 'Golden Age of Capitalism', the end of the 70's heralded a different economic era: after the numerous shocks to the global economy, Western income structures experienced a substantial widening of the wage inequality, particularly so during the 80's (Autor, Katz and Kearney, 2006). This increasing wage inequality has

been reflected in widening wealth inequality as well, resulting in a number of papers assessing the 'squeeze', 'hollowing' or 'decline' of the middle classes, for the U.S. (Faux 2012; Kiernan 2015; Pressman 2007) similar to papers on the EU (Nolan, 2014) and a number of other cross-country comparisons (d'Ercole, 2014; Besharov, Pelaez, Sacnches-Cabezudo 2015; Piketty and Saez, 2003). While the actual definition of the middle classes is open to interpretation – one could measure it using wealth (Piketty, 2014), income (D'Agostino, 2012), or other variables such as health or education (Putnam 2015), Pressman in a comprehensive overview maintains that the middle class has indeed decreased in a number of developed countries, including the U.S. While observing that for some industrialized countries their middle class actually prospered (e.g. France since the 80's) or underwent relatively few changes (e.g. Italy and Norway), he notes that these are exceptions, and that there is a negative trend in OECD countries (Pressman, 2015). This 'decline' of the middle classes is difficult to attribute to one particular factor, and concurrent with a number of global trends; yet there is general consensus in the literature that this primarily can be attributed to: 1) globalization, and 2) technological change. Both factors are important, and difficult to completely separate (e.g. technological progress is one of the factors that facilitates globalization due to the introduction of communication technologies that allows for outsourcing and off-shoring). While also the impact of globalization on labor markets is important to consider, this paper focuses primarily on the impact of technological progress on employment and our very societies.

Indeed, the technological progress following the first Industrial revolution has caused material and societal advances, facilitated the breaking of Malthusian constraints and also contributed to the concomitant unprecedented improvements of worldwide standards of living (Keynes, 1930; Allen 2009). Clearly then, societal changes stemming from technological progress are not new, and have happened more frequently in the recent past: yet technological progress has not occurred evenly over the past centuries, nor are its societal impacts gradually felt. It is generally maintained that growth tends to occur in cycles or waves, with previous cycles indicating that the introduction of new clusters of technology similarly impacted employment, output and overall well-being.

In 1926 Nikolai Kondratieff, based on an analysis of the economies of the UK, France and the USA, suggested that economic growth occurred in long-term (40 – 60 years) cycles, which he maintained are inherent to the capitalist system (Kondratieff, 1926). Schumpeter expanded on these 'Kondratieff' cycles, arguing that these waves existed of several phases, and crucially depend on innovation as driver (Schumpeter 1934; Kuznets 1940). There has been considerable literature that further evaluated the importance of innovation on long term cycles, including amongst others Lennart Schöns's General Purpose Technologies (GPTs), and Carlota Perez's theory of techno-economic paradigms (Schön 1998, 2009, Perez, 2006, 2008). While there are differences between the causes, implications and spatial distribution of these economic cycles, there is consensus on the importance of 'innovation clusters' as the catalyzing factor at the beginning of long-term waves. Perez calls these innovation clusters techno-economic paradigms, identifying 5 distinct 'technological revolutions', starting age in brackets: 1) the Industrial Revolution (1771), 2) the Age of Steam and Railways (1829), 3) the Age of Steel, Electricity and Heavy engineering (1875), 4) the Age of Oil, the Automobile and Mass Production (1908), and the period we find ourselves in today, the Age of Information and Telecommunications (1975) (Perez, 2006). She argues that these 5 paradigms are characterized by an 'installation' period (the first half) in which the old and the new paradigm battle (e.g. water transport in the form of canals vs. new infrastructural development such as trains), and that it generally takes time for the new technological revolution to come out on top (depending on availability of financial capital and policy action). Following a recession, Perez argues that there is a 'deployment' period, which encompasses an expansion of the new paradigm, facilitated by 'production capital', and results in the growth and further expansion of technologies previously deployed (Perez, 2006). Thus considering the impact of automation, digitalization and robotization, it could be argued that recent phenomena such as the decline of the middle classes and increasing inequality partially can be explained by the state of the economy in the long-term wave, which is currently shifting from the installation period (1980's till the economic crisis), to the deployment period. While some empirical evidence is indicative of this argument, other scholars propose a different view on the current innovation cluster; rather than maintaining that the current innovation cluster is a continuation of

long-term economic waves, they argue that robotics and digitalization are different from previous innovation clusters or waves, representing a true break from the past.

Called a technophobe by some, referred to current technology "*as a deadly epidemic inexorably working its way through the marketplace, the strange, seemingly inexplicable new economic disease spreads, destroying lives and destabilizing whole communities in its wake"* and that "*intelligent machines are replacing human beings in countless tasks, forcing millions of blue and white collar workers into unemployment lines, or worse still, breadlines*." (Rifkin, 1995). While his rather negative predicament from 22 years ago has not quite occurred yet, he is not the only scholar the past two decades arguing that the current technological progress is different from previous innovation clusters. In the popular and often cited book "The Second Machine Age', McAfee and Brynjolfsson take a more optimistic point of view towards technology, arguing that the current technological boom will change society to a similarly large extent as the first Industrial Revolution did, in particular benefiting consumers greatly, and in the process seriously altering the employment market (McAfee and Brynjolfsson, 2014). While acknowledging that there has been technological anxiety in the past, their core argument is that the current progress in machine learning, robotics and artificial intelligence - all sustained by the barely comprehensible exponential increases in computing power - will outstrip and pale previous techno-economic clusters such as those mentioned by Perez (McAfee and Brynjolfsson, 2014). While they consider technological progress as more beneficial for society than Rifkin, they similarly argue that the near future will be marked by fundamental changes in the labor market (Idem, 2014). While this paper will assess their argument on the future impact of technology in more detail below (section 2.2.2), it firstly evaluates whether and how technology has been impacting the labor market the past decades. Doing so allows us to identify trends, and potentially fathom also future impacts of current technologies. Notably, this paper first assesses the impact of technological progress on the quality of jobs in sections 2.1.2 and 2.1.3, after which it appraises anxiety about the future quantity of jobs in sections 2.2.1 and 2.2.2.

### 2.1.2. Skill biased Technical change

As referred to above, the recent decades have seen an increase in interest in the decline of the middle classes. Notably, this has been attributed to several potential causes, and has been related to a number of other trends that have proliferated over the past forty years. These include decreasing blue-collar occupations, changes in the supply of college and non-college educated employees, offshoring and outsourcing, declines in labor union membership, as well as the biting impact of automation (Autor, 2015). While several of these trends and processes interact, automation arguably is one of the fundamental processes underlying these phenomena (Autor, 2015). Indeed, concurrent with academic interest in the 'hollowing' middle classes, there has been considerable growth of literature on the concept of skill-biased technical change (SBTC).[1] This notion of skill-biased technical change implies that further increases of technology result in higher overall economic output, but simultaneously decrease the demand for certain types of labor, depending on the skill-level of the employees (Autor, Levy and Murnane 2003)[2]. This is generally associated with an increasing skill-premium, a stagnation of low wages and widening wage-polarization (Hemous & Olsen, 2016). While there are sub-strands in the SBTC literature, the theory is grounded on the notion that skilled workers are more capable of adapting to technological change, and are thus less likely to be replaced by it. Vice versa, low-skilled laborers are less capable of adapting to technological change, are more likely to perform simple tasks, and are therefore more susceptible to the risks of automation (idem). Thus, proponents of SBTC consider high-skilled labor and capital as complementary, but low-skilled labor and capital as substitutes, and therefore argue that due to technologically driven decreases in the price of capital, low-skilled labor has become less competitive compared to capital (Hemous and Olsen, 2016). Proponents

[1] It should be noted that skill-biased technical change is not the first economic theory to explain the drivers and impacts of technological change. Arguably the first real break with the notion that technological change was factor neutral – i.e. Hicks neutral, proportionally improving output of all factor proportions – was proposed by Atkinson and Stiglitz, who claimed it was localized and biased. (Atkinson and Stiglitz 1969, Acemoglu 2014). It was their theory, as well as Kennedy's notion of the innovation frontier that are the foundations of skill biased technical change (Acemoglu 2014). For a more detailed discussion see Acemoglu 2014.

[2] The concept of skill is fluid, and can refer to technological skill, capital skill, but generally is proxied by the length of education. See Goldin and Katz (2009) for a more detailed discussion

maintain that technical change is skill-biased, predicting that the demand for higher skilled jobs outstrips the relative demand for lower skilled jobs, and therefore disproportionally benefits high-skilled laborers (Maeda and Yugami, 2016). Suggestively, most empirical evidence is indicative of this increase in higher skilled jobs, illustrated by rising wealth- and income-inequality associated with the aforementioned decline of the middle classes: yet in recent years a number of scholars argue that the current empirical evidence does not fully match the theories of the SBTC school, and fails to explain a number of other trends. Indeed, there has not only been a documented increase of people being employed in high-skilled jobs, but also and especially a surge in the number of low-skilled jobs, resulting not only in income-inequality, but also in job and wage polarization.

Indeed, utilizing empirical evidence from the European Union Labour Force Survey (ELFS), as well as the International Standard Classification of Occuptions (ISCO), Goos, Manning and Salomons document a 'disproportionate increase in high-paid and low-paid employment' from the 90's onwards, which they argue is indicative of pervasive job polarization (Goos et al, 2009). These results are further underlined for Europe by an additional, more extensive paper from Goos, Manning and Salomons (2015), for the US by Autor et al. (2006) and also for Japan (Ikenaga, 2009). Notably, the empirical findings of these papers suggest not solely wage polarization, but also job polarization, are indicative of the growth of jobs on the relative upper and lower tails of the wage distribution, aspects that are not fully compatible with skill-biased technical change. The SBTC literature rationalizes increases in the high-skill and high-wage occupations, failing to adequately account for increases in the lower-end skill and wage occupations (Maeda and Yugami 2016). This is also highlighted by Acemoglu and Autor, who argue that the SBTC model is silent on the expansion of offshoring due to technological progress, the diffusion of new technologies that substitute middle workers and the non-monotone changes in labor earnings of workers on different parts of the earnings distribution (Acemoglu and Autor, 2011) Thus they, Goos et al., Autor and Dorn, as well as an increasing number of other authors, support a task- or routine-biased technical

change model, which endogenizes technical change as well as the evolution of technology, and thus more adequately explains also the increase in lower-end jobs.

### 2.1.3. Routine/ Task biased technical change

Proponents of the routine biased model assess the content of tasks in more detail, classifying them not only according to their skill level (low, medium and high), but also on their complexity (Acemoglu and Autor, 2011).[3] An important aspect of this framework is the so-called 'routineness' of jobs, which they argue is an important indicator of jobs substitutability by technology (Autor, Levy and Murnane, 2003). Indeed, Autor, Levy and Murnane's framework is grounded on the notion that technologies are more likely to substitute tasks that involve limited, straightforward and well-defined tasks, both cognitive and manual, and that can be completed while adhering to explicit rules. They moreover state that technology complements tasks that are less well defined, require more interpretive or creative actions, and are thus more difficult for computers to do, relative to the price of labor (idem, 2003). Expanding on these more basic papers, David Autor and Daron Acemoglu propose a model that further expands on this: they offer five task measures for jobs, allowing researchers to categorize occupations accordingly: 1) routine cognitive (e.g. accounting), 2) routine manual (e.g. manufacturing), 3) non-routine cognitive analytical (e.g. sales, medical), 4) non-routine manual (e.g. janitorial services), and, non-routine cognitive interpersonal (e.g. managerial), (Autor & Acemoglu 2011). They argue that it is mainly the routine tasks that have been replaced in recent years, contributing to the hollowing of the middle classes: it has been jobs with high routineness that have been the easiest to substitute with increasingly cheaper technology, whereas it has been the jobs on the high and low ends of

[3] A number of related task-biased models have been proposed by differing authors, which have rapidly been expanding since the early 2000's, and include Autor et al (2003), Autor, Levy and Murnane, 2003 , Goos et al(2009), Autor and Dorn (2010), Acemoglu and Autor (2011) and others. These have been referred to as task biased framework (generally attributed to Autor), the task biased technical change, or Routine Biased Technical Change (RBTC). While there are minor differences between them, this paper opts not to assess the theoretical differences of the respective economic models, instead focusing on their implications and consistency with the empirical evidence.

the job spectrum that have been complemented by technology (idem, 2011). Moreover, Autor argued that the introduction of more advanced computers and machinery amplifies the comparative advantages of labor in creativity, problem solving as well as flexibility, thus fuelling the increase in both high and low end jobs (Autor, 2015). He furthermore proposes that it is important for academics to focus also on jobs those that were *created* by technological progress – arguments that were further developed by Acemoglu and Restrepo in a recent paper on the task biased model. In this paper they further integrate technological progress, arguing that the relative price of labor and capital influences the adaptation and further development of technology. They argue that the allocation of tasks between capital and labor is influenced by the relative price and comparative strength of these factors, resulting on the one hand in decreases of the relative price of labor, and on the other hand in the creation of new complex tasks – both of which increase inequality (Acemoglu & Restrepo, 2016). While these papers draw on empirical evidence, their main contributions stem from theoretical advances; it is thus important to also evaluate the changing labor compositions, evaluating the extent to which these theories can be applied and measured using empirical data.

Prominently, this was done in a paper titled "Technological Adaptation, Cities, and New Work", in which Jeffrey Lin sought to assess cities' labor market adaptation to innovation from a spatial perspective, evaluating cross-sectional differences by developing a new methodology that draws on changes in the occupation classifications (Lin, 2009). He did so utilizing the US department of labor's *Dictionary of Occupational Titles (DOT),* as well as its successor, the Occupational Information Network (ONET), specifically focusing on the creation of new jobs, measured by new occupation titles (Lin, 2009). Finding that workers are more likely to adapt or be in 'new work' areas that are dense in college graduates and have considerable variety of industries, it was particularly his novel methodology that has been replicated by scholars adhering to the task or routine biased proposition, and referred to by authors such as Acemoglu and Autor. While it has been difficult to exactly reproduce Lin's research for Europe due to the lack of the ONET data, Goos, Manning and Solomons drew on EUROSTAT data to aggregate the datasets into the clusters from the routine-biased framework from Autor. Controlling for off-shoring

by using the proxies by Blinder and Krueger (2013), they argue that their findings indicate that also for Europe automation resulted in polarization between industries, subsequently shifting the structure of employment in line with the models from Acemoglu and Autor (Goos, Manning and Solomons, 2016). Interestingly, they also noted the impact of within-industry effects on employment, finding that automation on the one hand substitutes for labor (the 'destruction' effect), but on the other hand significantly increases the level of output, partially off-setting this initial loss by expanding the size of these industries (the 'capitalization' effect), confirming Aghion and Howitt's (1994) earlier theory. They note that this effect reduces between-industry polarization but is not enough to overcome it, making it important to take into account when considering the overall impact of technology on employment (Goos, Manning and Solomons, 2016). Furthermore, the empirical part of their paper is similar to that of Michaels, Natraj and Van Reenen (2014); also controlling for a number of other potential explanatory variables in their robustness test, they empirically assess the impact of ICT technologies on industries' share of labor for nine European countries as well as Japan and the US, also confirming that increases in ICT capital in industries generally result in surges in demand for higher-skilled workers. While indicative of the RBTC theory, they do not assess the between-industry effects that Goos et. al. maintain are more important (Michaels, Natraj and Van Reenen 2014; Goos et. al, 2016).

Overall then, the explanatory power of RBTC is theoretically sound, holds up for a number of different countries in the OECD with different institutions, and is robust to the inclusion of proxies for offshoring (the main other explanatory variable), suggesting that it is a theory that is essential to consider when discussing the impact of technology on labor markets. Yet it focuses primarily on the quality of jobs, not addressing if or whether there will be technological unemployment as feared by technophobes such as Rifkin, and suggested by Frey and Osborne (2013). To understand this then it is important to not just focus on the technology of today, but also to evaluate whether technological developments in fields such as machine learning, robotics or automation – the technologies of tomorrow – influence the quantity of employment. This can be done by

more closely evaluating the empirical evidence on the creation of jobs, and overall assess the impact of innovation on employment.

## 2.2. Technological anxiety and the labor market – job quantity

Even one of the fiercest critics of capitalism and the effects of capital on society acknowledged that technological progress can have positive impacts on employment:

*"Entirely new branches of production, creating new fields of labour, are also formed, as the direct result either of machinery or of the general industrial changes brought about by it."* – Karl Marx, 1867 [1961, 44p]

Referred to as the 'compensation theory' by Marx, there are a number of mechanisms that can be triggered by technological change, counterbalancing the initial labor-saving impact of innovation (Vivarelli, 2014)[4]. The most notable of these are 1) the creation of new products and sectors in which technological innovation drives new branches of industry, or expands already existing industries through product innovation, resulting in increased demand for labor; 2) the Keynesian notion of increases in incomes, in which overall improvements in efficiency and output lead to increased average incomes, boost overall aggregate demand and thus compensate for initial job losses; 3) technological improvements resulting in lower consumer prices, facilitating increased discretionary spending and a surge in demand for other services; and 4) via new investments directly stemming from accumulations of new capital (Vivarelli 2014; Stewart, De and Cole 2015; Boyer 1990). While these – and other - compensation mechanisms partially explain job creation following technological improvements, there is also severe critique on these mechanisms. Indeed, a number of assumptions must hold that are often problematic: the notion that profits are immediately and entirely re-invested in the economy is unrealistic, complemented by the fact that investments may be capital-intensive, rather than labor-intensive. Moreover, the price-decrease mechanism depends on the assumption that there

[4] For a more extensive discussion see Pianta 2005; Vivarelli and Pianta 2000.

is perfect competition, is related to the slope of the demand elasticity, and there often are different impacts of innovations across time, space and industrial sectors (Bogliacino and Vivarelli 2010; Freeman and Soete, 1987; Vivarelli, 2014). This is important, especially when considering that also technological change itself is far from uniform, has widely divergent impacts on different sectors of the economy, and depends also on the particularities of the innovation cluster. Illustratively, manufacturing improvements related to the production of the car and television in the 50's and 60's had a stronger positive effect on (low-skilled, high-routine) employment than did the introduction of ICT; while it created jobs in the telecommunications sector, it had a labor-saving impact in many of the service sectors (Meyer-Krahmer 1992; Kalmbach and Kurz 1990). To understand the impact of the current innovation cluster on future employment then, arguably two things are important: 1) understanding how innovation has been impacting total employment in recent decades, and 2) evaluating the current innovation cluster in more detail, specifically the potential of robotics. Doing so will allow for a more informed debate on the future impact of innovation while adjusting for aspects about the current technological push that are distinct from previous innovation clusters.

### 2.2.1. Technological progress and employment – innovation literature

There have been a number of studies that have evaluated the link between innovation and employment. This relationship however is complex, difficult to adequately measure, and therefore has large variety with regard to the scope of studies (micro- vs. macro-data; on the local, regional or national level; differing econometric models, amongst other factors) as well as varying proxies for innovation. Unsurprisingly then, there is considerable contention in the literature as to the exact specificity of this relationship. Illustratively, the impact of innovation depends on a number of factors, notably including institutional mechanisms, which differ at the micro-, and macro- level, and vary in different economic contests due to the diverging enforcement of Intellectual Property Right (IPR) laws and employment protection in the form of labor laws (Vivarelli, 2014). While a number of macroeconomic studies have evaluated this link, these were mainly done in the 80's and 90's, generally finding that a positive impact of innovation on employment depended on

sufficient elasticity of demand, and were moreover largely conditional on the respective institutional structures (Layard and Nickell 1985; Vivarelli, 2014). Seeking to assess this relationship more directly, more recent papers have utilized the increasing availability of data with a micro econometric approach, taking the firm as the level of analysis. Notably, Lachenmaier and Rottmann utilized a dynamic employment equation of German manufacturing firms over the period 1982-2002, with their estimates suggesting positive impacts of innovation on jobs (Lachenmaier and Rottmann, 2011). Similarly, using micro data from 15.000 French firms in the manufacturing sector, Greenan and Guellec suggest that innovating firms (as designated through a survey) create more jobs than non-innovative firms – an effect which however disappeared when controlling for the so-called 'business-stealing effect' (Greenan and Guellec, 2000). This is the notion that supposedly positive effects of innovation often also have a negative effect on business in the same sector due to changing relative competitiveness, with more innovative firms growing their market share at the costs of others, resulting in overall small net positive effects on employment (Vivarelli, 2014). This is one of the reasons why a sectorial level of analysis is arguably more appropriate, as it better accounts for the business-stealing effect – and thus the effect of both product and process innovations – facilitating a more comprehensive understanding of the impact of innovation on employment, including also the compensation mechanisms and indirect effects discussed above.

Yet also when assessing literature that considers industrial sectors as the unit of analysis the results are ambiguous, with different regions, time periods and proxies of innovation giving different results. Pianta (2000) as well as Antonucci and Pianta (2002) for example evaluate the impact of innovation on employment in manufacturing sectors in Europe, finding that innovation generally has a negative impact on overall employment. This is however countered by a similar analysis from Boglaciano and Pianta, who find a positive impact of innovation on employment for both services and manufacturing in a sample of 8 European countries (Boglaciano and Pianta, 2010). In another study, Boglaciano and Vivarelli, using R&D expenditures as a proxy for innovation, find that for the period 1996-2005 in 16 countries there is a positive effect of innovation on employment. Notably then, while an assessment of the literature that investigates the empirical effect

of innovation on employment is inconclusive, a number of notable aspects can be derived: the data used, the time period considered and features such as regional and institutional factors are relatively similar in this literature, and lend themselves to further empirical analysis. Indeed, the data and methodology of the papers using sectors as the unit of analysis are quite similar: they use a variant of the Generalized Method of Moments (GMM) methodology, generally selecting the systems variant over the differences variant (Boglaciano and Vivarelli 2012; Piva and Vivarelli 2003, 2005; Lachenmaier and Rottman 2011). While this will be discussed in more detail in the methodology section below, this paper argues that the literature reviewed in this section – which assesses the link between innovation and employment – still has gaps, and is insufficiently conclusive to rely on when considering also the future impact of innovation and employment. Thus there is a clear need for additional empirical research on the impact of technological progress on employment, specifically so for the current innovation cluster. Moreover, to understand whether the current technological progress is distinct from previous innovation clusters, it is important to understand what robots are, and especially why they are predicted to be so disruptive on the labor market in the near future.

#### 2.2.2. Robotics, machine learning and artificial intelligence.

This paper draws on the definition of a robot by the International Organization for Standardization (ISO), and endorsed by the International Federation of Robotics (IFR), as *"an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications*" (IFR, 2017).[5] While a number of aspects of this definition are important, it is in particular a robots' autonomy, or its ability to interpret its environment and adjust its actions accordingly, that distinguishes it from regular capital or machines (IFR, 2017). Notably, robotics has the second highest growth

[5] This paper uses both the terms 'robots' and 'robotics'. While technically robots are the actual devices or machines that do the work, and robotics is the field of developing robots, in this paper they are used interchangeably.

rate of all major industrial sectors in the United States, having experienced an average growth per year of 9% for the period 2006-2016, only lagging behind logistics (US Robotics, 2016). Moreover, the IFR predicts that between 2016-2019 this growth will be even higher, estimating that over 2.5 million industrial robots will be in place by 2019 worldwide, averaging a 12% growth rate for this period (IFR, 2017).

When considering the potential impact of technological improvements in robotics or artificial intelligence, it is worthwhile to recall the insight from Moravec (1988) - that also underlines the RBTC theory - who argued that there are fundamental differences between humans and machines. Occupations that are intensive in the use of vision, spatial interpretation or communication are extremely challenging to automate from an engineering point of view, but require little cognitive processing powers from humans; vice versa, tasks that require arithmetic or follow set rules such as bookkeeping are trivial from an engineering point of view, but require years of practice and training for humans (Moravec 1988; Feng and Graetz 2015).[6] While this has been true for the past decades, one of the main arguments of McAfee and Brynjolfsson is that this distinction is becoming increasingly blurred due to the impact of the exponential growth of computing power of 'Moore's law' (McAfee and Brynjolfsson, 2011). This 'law' was formulated in 1965 by Gordon Moore, predicting that the number of transistors would double every year, thus resulting in an exponential increase of computing power over time. This allows technology to reduce previously insurmountable obstacles to mere road bumps, passing into territory which many experts would initially consider impossible or beyond the time-horizon: in 2007 Nordhaus claimed that computing power had increased by a factor between 1.7 and 76 trillion (1.7^12 – 7.6^13) which by today could have increased to approximately a quadrillion, or another thousand fold (Nordhaus, 2007). The impact of these rather abstract numbers is well illustrated by the commonly cited example of Levy and Murmane, who argued in 2004 in their book 'Why People Still Matter' that replacing a human driver would not be done in the short to medium term due to the engineering-difficulties associated with finding a set of rules that combine the interaction with

[6] It is for example very difficult for engineers to build a robot that can clean both the floor, make the bed and clean the table, while any employable unskilled adult could do this without any trouble.

complex traffic, navigation, diverging traffic rules and laws all the while reacting to potential movements of a number of factors all around the car (Levy and Murmane, 2004). Only six years later Google introduced the first fully self-driving cars, which today have been introduced to the market by a number of different brands (McAfee and Brynjolfsson 2011).[7] Crucially, McAfee and Brynjolfsson argue that it has been the exponential increase in computing power that made this possible, facilitating technological progress in fields previously considered impenetrable for robots or artificial intelligence (idem, 2011). This is also a core topic of Frey and Osborne in their seminal 2013 paper, in which they evaluate the problems engineers still have to solve to make further advances in the fields of data mining, computational statistics, artificial intelligence and robotics to derive which jobs are susceptible to computerization, also trying to account for Moore's law of computational improvements (Frey and Osborne, 2013).

Berger and Frey, who similarly seek to evaluate the impact of technological change on labor markets since the 1980s – particularly machine learning and robotics - assess this in a paper for the OECD. Whereas the earlier discussed Justin Lin found that for 1990 and 2000 respectively 8.2% and 4.4% of workers were observed in new types of jobs, Berger and Frey mention that this was even lower in the 2000's, not even reaching 0.5% in new technology related industries (Berger and Frey 2016; Lin 2011). This is particularly interesting considering the calculations from Lee, who studied the impact of car production in the United States in the early 20th century, finding that employment in automobiles outgrew aggregate manufacturing by over 700%, thus particularly illustrating the differing impact of different technological clusters on employment over time (Berger and Frey 2016; Lee 2011). Moreover, Berger and Frey argue – in line with McAfee and Brynjolfsson's critique on GDP as an indicator of output – that the strongest gains from robotics and machine learning are still to come, noting that future technological change is unlikely to become less labor-saving and more job-creating, thus

[7] The exponential rise of computing power is also well illustrated by Intel's comparison of microprocessors with cars: if cars had progressed by the same rate over the same time period, cars would in 2015 have been able to reach approximately 300.000 miles per hour while costing only $0.04. – Intel '50 years of Moore's law' Accessed May 16th 2017

continuing the current trend (Berger and Frey, 2016). [8]

It appears then that the prospects of the current innovative cluster on employment are bleak, an outlook underscored by the potential of an increasing number of jobs to be automated, exacerbating trends of wage- and job-polarization, and possible resulting in technological unemployment in the near future. It is surprising then that the actual impact of robotics on employment is sparingly covered; one of the first papers to do so was authored by Georg Graetz and Guy Michaels, titled 'Robots at Work' and published in 2015. In this paper they assess the impact of 'robot density' (the number of robots per million hours worked) on the productivity and employment of a panel of industries in 17 countries from 1993-2007 (Graetz and Michaels, 2015). This paper is notable as it uses data that documents the actual impact of robot density, rather than evaluating the *potential* impact of technologies such as robotic or artificial intelligence. While finding that a higher use of robots is indeed associated with an increase in productivity, it is noticeable that they find no robust results for robots on employment, only finding a weak negative statistical significance in a limited number of cases (idem, 2015). Moreover, when they do find this weak statistical significance of robotics on employment, they only find this to be negatively correlated with low-skilled occupation, not finding statistically significant results for middle-skilled workers (idem, 2015). This is particularly striking considering the discussion above, with a number of authors arguing that technological change is biased against middle-skilled workers or those in occupations with high routineness, or has overall negative impacts on employment due to the high substitutability of jobs (Acemoglu and Autor 2011; Autor 2014; Frey and Osborne 2013; Goos and Manning 2007, 2014; Michael, Natraj and Van Reenen 2014). Interestingly, a number of recent papers underscore Graetz and Michael's findings that robots do not necessarily negatively impact employment: the International Federation of Robotics (IFR) argues that the use of robotics has the potential to increase U.S. jobs in the long term, proposing that the deployment of improved robotics could make companies more competitive in the U.S. (IFR 2017; US Robotics 2016). They suggest the introduction of robots can prevent industries from off-shoring, facilitates the combination of robotics and

[8] Issues of productivity associated with recent technological discussion.

humans, thereby leveraging both respective strengths' and complimenting one another, as well as retain intellectual property and wealth that otherwise might be outsourced (US Robotics, 2016)[9]. While it unsurprising for an organization that represents the interests of the robotics industry to defend the potential benefits of robotics and automation, a number of recently published papers support their argument, indicating that the earlier mentioned compensation mechanisms also apply to robotics, facilitating the capitalization effect as proposed by Aghion and Howitt (1994).

Indeed, Artz, Gregory and Zierahn (2016) apply Frey and Ostborne's (FO) methodology to 21 OECD countries, arguing that automation and digitalization are unlikely to destroy large numbers of jobs. While acknowledging the RBTC, they disagree with FO's methodology, stating that they neglectfully assume that workers within the same occupation have identical task structures, which they contend (Artz, Gregory and Zierahn 2016; Autor and Handel 2013). Instead drawing on individual data (self-reported by workers) on the content of their tasks, they include more heterogeneity in their model, concluding that on average only about 9% of jobs is automatable in the OECD, contrasting the 45%-60% found by Bowles (2014), who replicated FO's to OECD countries (Artz, Gregory and Zierahn 2016). This is echoed in a recent report from McKinsey, which argued that technological progress is more likely to change than to replace jobs by automation, suggesting that in the near future robots and humans will work together and compliment one another (McKinsey Global Institute 2017). Similarly drawing on the RBTC framework, also Gregory, Salomons and Zierahn (2016) develop a comprehensive model on the impact of technological change on labor demand, finding that it is positive, and can result in local demand spillovers. They thus conclude that labor races *with* machines, but that this effect can only be deduced when including the overcompensation by product demand and spillover effects (i.e. the capitalization effect): while they find that routine biased technical change reduced employment by 9.6 million due to capital replacing labor, this has been more than compensated by an increase in

[9] They for example note that in the U.S. the usage of robots has contributed to companies' decision to stay in the US rather than move abroad, as has been the case of Tesla's 'Gigafactory', Apple and Lenovo. Moreover, they argue that robotics are an important factor in making domestic manufacturing competitive again US Robotics, 2016.

employment of 21 million due to these impacts of compensation for product demand and spillover effects (Gregory, Salomons and Zierahn, 2016). Also Deloitte claims that for the UK, technology have contributed to the loss of 800.000 low-skilled jobs, but similarly helped facilitate the creation of nearly 3.5 million higher-skilled jobs as well (Deloitte LLP 2015). They similarly noted that three quarters of the UK business surveyed think that technology will have a significant or very significant impact on their business, but that they will employ more people in the future (Deloitte LLP, 2015). This is also the point of view of Price Waterhouse Coopers (PwC), who in a recent study suggested that robotics-intensive manufacturing sectors in the US employ a significantly higher number of engineers and mechanics than less intensive sectors, and that they also had considerably more maintenance and repair workers (PwC 2015), with also a study by Barclays suggesting that investments in automation in the UK could actually safeguard 73.500 jobs, as well as create over 30.000 jobs in other sectors (Barclays 2015, IFR 2017). It appears then that also the current literature is ambiguous on the impact of automation on employment in industrialized countries, with considerable disagreement on the impact of technological progress and the future labor market.

To summarize this literature review on the impact of innovation on employment, a number of factors can be underscored: firstly, whereas there has been a clear trend of wage and job-polarization, it appears this can be strongly linked to automation and the increasing usage of technology in industrialized countries, along the lines of the skill-biased technological change, but particularly the task- or routine biased technological change theories. Secondly, while a number of recent papers discuss the future potential of advances in machine learning and robotics to negatively impact employment, this to a large extent is based on the expected future developments of technology in line with Moore's law, outpacing humans' capacity to grow at the same speed, and resulting in a mismatch between the automation of jobs and the creation of jobs. However, the current empirical evidence of technological progress on employment – often proxied by indicators of innovation – is far from conclusive on this topic, with considerable ambiguity existing as to whether it results in a net improvement or net decrease, partially caused by the complex inter-dependencies of off-shoring, business stealing, job creation

and market mechanisms, compounded by difficulties of measurement inherent to this topic. Thirdly, while robots and robotics have been used in manufacturing for a number of decades, it appears that only recently they have really started increasing in both number and capabilities, becoming increasingly important. Yet the empirical evidence on the impact of robots on employment is scarce, and insufficiently robust.

Thus this paper argues that there is a clear need for additional empirical research on the impact of technological progress on employment, as well as a gap in the literature on the impact of robotics on the labor market. This then is what this paper sets out to do. In the following sections the variables, data and methodology are discussed in more detail.

# 3. Methodology

## 3.1.Research Questions:

To reiterate, this paper's main aim is to investigate the impact of technological progress on the labor market in a sample of industrialized OECD countries. This paper does so on a sectorial level, investigating the impact of patent data for several industrial sectors. Moreover, it seeks to evaluate the impact of robots, proxied by robotics patents, on those very same labor markets. Consequently, this paper essentially seeks to answer two questions:

Research Question 1:
*Distinguishing between different measures of technological change, how has technological progress impacted the occupational structure of industrialized countries between 1995-2009?*

Seeing as the literature review is inconclusive on the impact of technological progress on employment, this paper proposes both a hypothesis and a null hypothesis:

Hypothesis 1:
*Technological progress has had a negative impact on employment of the industries for the countries under consideration.*

Null hypothesis 1:
*Technological progress has had no statistically significant impact on the share of employment of the industries for the countries under consideration.*

Also for the second research question this paper proposes both a hypothesis and null hypothesis:

Research Question 2:

*How do robotics patents influence the employment shares of industrial sectors in the selected number of industrialized countries?*

Hypothesis 2:

*Robotics patents have had a negative impact on employment of the industries for the countries under consideration.*

Null Hypothesis 2:

*Robotics patents have had no statistically significant impact on the share of employment of the industries for the countries under consideration*

## 3.2. Econometric Strategy

In order to evaluate the impact of the different kinds of technological progress on the occupational structure of European labor markets, this paper utilizes a dynamic panel data model, specifying GMM-SYS estimators to do so. This section of the paper first shortly reviews a number of models which could have been used to evaluate the impact of patents on employment – notably pooled OLS or fixed effects (within group) estimators - arguing that a GMM-SYS model is the most appropriate model to analyze the impact of innovation on employment markets. It then explains in more detail the details of the GMM-SYS model, remarking on a number of the ways in which it can be utilized, specifically discussing the advantages of the systems-GMM over the differences-GMM variant. Having done so, the econometric model for this paper is specified.

Panel data has a number of clear advantages over its econometric counterparts: it allows one to control for heterogeneity across the sample, can control for state- and time-invariant variables, provides more informative data (i.e. more variability and a lower

degree of collinearity), and facilitates studying the dynamics of adjustment (Baltagi 2005; Daeton 1995). While there are a number of different kinds of panel data, there are important differences between them; the simplest version, pooled OLS, combines all data to estimate one large regression. While appealing for its simplicity, it neglects the cross-section and time-series properties of the data, thus camouflaging the heterogeneity that likely exists between the different countries and over the years, risking the error term to be correlated to some of the regressors included in the model. Thus, excepting in specific applications, pooled OLS risks making the model biased and inconsistent (Gujurati and Porter, 2009). This can be addressed using so called fixed effects (FE), which allow for heterogeneity among subjects, and permit the inclusion of country and time specific effects.[10] Thus a fixed effects model is arguably more appropriate for the dataset as compared to the pooled OLS, although it still has a number of disadvantages: notably, fixed (or random for that matter) effect models can not accommodate lags without losing their BLUE properties.[11]

In line with the literature, this paper argues that it is essential to control for lags in the context of innovation and labor markets, particularly when using patent data as a proxy for innovation (Lachenmaier and Rottman, 2011) After all, considering the time it takes for patents to be granted and actually used in the market, it is certainly conceivable that there is a lag between the application of this innovation and its eventual effect on employment. While this lag thus appears essential for a theoretically sound econometric model, the transformation from a fixed effect panel data model to a dynamic panel (i.e. by including lagged dependent variables) introduces a number of problems, best illustrated by a short example:

Assuming a simple autoregressive panel model with no regressors (for the sake of simplicity) along the lines of Baltagi (2005):

[10] There are two approaches also within the literature to estimate FE models, notably including within-group transformation and the least square dummy variable (LSDV) approach. However seeing as this paper does not draw on fixed effects models a more extensive discussion can be found in Gujurati and Porter (2009), chapter 16. The same argument can be extended to Random effect panel models.

[11] Best Linear Unbiased Estimator (BLUE), refers so the Gauss-Markov theorem, suggesting that the errors have the lowest variance, equal variance and are uncorrelated (Baltagi, 2005)

$$y_{it} = \varphi y_{i,t-1} + u_{it}$$

Where $u_{it}$ is a one-way error component, or

$$u_{it} = \mu_i + v_{it}$$

It is clear that $y_{it}$ is a function of $\mu_i$, and that therefore also $y_{i,t-1}$ is a function of $\mu_i$, making $y_{i,t-1}$ correlated with the error term (Baltagi, 2005). This renders the OLS estimator biased and inconsistent, no longer exogenous, and thus inappropriate for FE or RE models. This issue is quite well known in the literature, and has been termed the "dynamic panel bias", or "Nickell bias" (Nickell 1981). A way to solve this is by using instruments (lags) that are uncorrelated with the error term, suggested by Arellano-Bond (1991). Essentially, this implies that after differencing the data one could use lagged levels of the dependent variable as instruments, seeing as these are uncorrelated with the error term, and therefore provide valid instruments (Arrelano-Bond 1991). This then is the econometric methodology this paper utilizes: a dynamic panel data model, drawing on the GMM (generalized methods of moment) estimator adopted by Arrellano-Bond. Interestingly, this arguably is the most appropriate model to evaluate employment, considering that employment was also the example of Arellano and Bond (1991) when illustrating this very point. It should be noted that the Arrellano-Bond dynamic panel estimators in general have been designed for panels which have relatively small time periods and many individuals, have only one left hand variable, allow for variables that are not strictly exogenous, and can accommodate heteroskedasticity and autocorrelation within individuals (Roodman, 2006).

Finally, one of the reasons of the recent popularity of the GMM model in econometric analyses (as also noticeable in its increasing application in recent papers, as highlighted in the literature review, section 1.2.1.) is that it makes fewer assumptions about the underlying data-generating process, instead using more complex techniques to isolate

useful information.[12] Roodman warns for using GMM as a 'black-box', arguing that a number of distinctions of the GMM are therefore important to understand and account for: notably, he emphasizes the importance of distinguishing between difference-GMM and System-GMM estimators (Roodman, 2006). GMM-difference is realized by transforming the regressors by differencing them, using the GMM method from Hansen (1982) to do so. Arrellano-Bover/Blunell-Bond make an additional assumption in that the first differences of instruments are uncorrelated with fixed effects, facilitating improved efficiency by building a system of two equations – system GMM (Roodman, 2006).[13]
He argues that System-GMM is more adequate for this kind of panel analysis (small T, relatively large N), a sentiment shared by authors having conducted similar dynamic panel studies on the impact of innovation on employment (Bogliacino and Vivarelli (2010), Boglaciano and Vivarelli 2012; Piva and Vivarelli 2003, 2005; Lachenmaier and Rottman 2011). Moreover, Blundell and Bond show how the system estimator is more efficient than the differences estimator if it covers a relatively short time period (Blundell and Bond, 1998), as is the case for this paper, which assesses the time period between 1995-2009. Thus this paper utilizes a system GMM approach, using robust standard errors to adjust for heteroskedasiticy, also adding country dummies to account for national systems of innovation, as well as time dummies in line with similar literature on the impact of innovation on industrial sectors (Boglaciano and Pianta 2010; Freeman 1995).

Based on the discussion and in line with some of the papers above (Bogliacino and Vivarelli 2010; Boglaciano and Vivarelli 2012; Piva and Vivarelli 2003), the model this paper proposes is:

$$Log(E_{icj}) = \alpha \operatorname{Log}(E_{icj-1}) + \beta_0 + \beta_1 Log(W_{icj}) + \beta_2 Log(C_{icj}) + \beta_3 Log(Y_{icj}) + \beta_4 Log(U_{cj}) + \beta_5 Log(P_{icj}) + \gamma S + \delta T + \varepsilon_{ic} + u_{icj}$$

[12] As an interesting sidenote, he notes that this likely is due to "the plummeting costs of computation and software distribution" (Roodman, 2006)

In this model the dependent variable $Log(E_{icj})$ stands for the natural log of the employment of sector $i$ for country $c$ and year $j$. W stands for wages (i.e. labor compensation), C stands for capital formation, Y for value added, U for union density and P for the different patents. S and T represent country and time fixed effects respectively, and ε and u are the two components of the error term.

This model thus includes a lagged dependent variable, and accommodates and adjusts for heteroskedasticity across industries by using a GMM model that overcomes difficulties associated with the Nickel bias, includes robust standard errors, and allows for up to 10 lags. This paper includes a number of tests for the validity of the instruments introduced by the GMM –Sys model, notably the Sargan-Hansen tests.[14]

[14] This paper utilized the xtabond2 command in stata to execute these regressions. See Roodman (2006) for a more extensive discussion on the merits and flaws of this command.

# 4. Data

*'The science of today is the technology of tomorrow'* - Edward Teller (1991)

There are a number of inherent difficulties related to the measurement of innovation. Indeed, there are number of ways in which innovation can be measured: most papers that empirically seek to measure the impact of technological progress on middle-income jobs using either the skill- or task biased frameworks draw on different measures of technology, including ICT capital (Michaels, Natraj and van Reenen, 2014), the use of computers on the work floor (Berger and Frey, 2016), PC diffusion (Beaudry, 2010), total innovation expenditure (Antonucci and Pianta, 2002), R&D expenditure on the firm or industry level (Brouwer et al. 1993), or patents (Yang and Lin, 2008, and Feldmann (2013)). Indeed then, technological change is difficult to measure, and there is no agreed on preferential proxy for it, more so as every approach has both advantages and disadvantages, failing to capture certain dimensions of innovation: input indicators such as R&D expenditure fail to account for actual technological achievements, whereas output indicators such as patents do not fully capture technology that is not patented (e.g. trade secrets, copyrighted, or process innovations).

Indeed then, patents have well known limitations; they generally fail to account for technologies that are not patented, do not always distinguish between the varying technical and economic significance of the differing patents, and are used in dissimilar ways by the different actors that use them – private organizations like car companies and the pharmaceutical industry tend to use different patent strategies than public organizations such as universities or government research institutes. Yet patents also have a number of inherent strengths, and therefore still are a commonly used proxy for innovation or technological progress: patents account for inventions that are considered commercially viable, the applicants expect the patent to provide significant benefits, and importantly, they are a rich source of information over a longer period, also providing information on the rate, direction and kind of inventive activity (Archibugi and Pianta, 1996). Moreover, it is possible to use patent application data rather than granted patent

data, thus avoiding two further drawbacks: it improves the timeliness of the data as a grant process often consumes three to five years, and it provides a fuller picture of inventive performance (Feldmann, 2013). Finally, the data on patents is much more detailed than other proxies for innovation, which tend to be more aggregated; for example rather than using total R&D, patent data can be dissected into clean categories, thus providing valuable information on the source (e.g. industry), potential impact, and quality (i.e. high or low-tech) of the specific technological progress measured. This paper seeks to capitalize on this detailed information, striving to evaluate whether patents from different industries differently impact the labor market structure, as well as assess how robotics patents influence employment in a number of industries.

As explanatory variable this paper uses several patent categories from the International Patent Classification system (IPC), to evaluate whether distinct kinds of technological progress have differing impacts on the labor market. It does so by evaluating the impact of changes in the number of patent applications on the employment share of several industrial sectors, thus assessing whether technological progress in that sector can be linked to labor market changes of that very sector.[15] Moreover, this paper assesses the impact of robots by developing a new index of robotics patents, discussed in more detail below. In line with the literature discussed in section 2, this paper controls for wages, value added, capital formation and union density. Overall, this paper covers a time period from 1995-2009, assesses 15 different countries from the OECD, and looks into changes in the employment share of 8 sectors, using a (strongly balanced) dynamic panel data model. While a number of countries have been excluded due to missing data, there still are minor gaps in the data. Notably, this paper assumes that patents (applications) from sectors are also actually used in those sectors. This is an important assumption, and a potential weakness of this paper, thus requiring justification.

There are a number of reasons as to why it is reasonable to assume that patents from certain sectors of the International Patent Classification system (IPC) are actually also

[15] E.g. one of the sectors that is analyzed is the textiles sector; this paper thus evaluates whether patents that have been categorized under the Textile category of the IPC affect the labor share of the textile industry in the countries under consideration.

used in those sectors (e.g. the assumption that patents in sector C from the IPC, 'Chemistry', are also used in the Chemical industry): firstly, patents are inherently commercial: while companies' patent strategies differ, a considerable number of actors use patents in order to protect intellectual property they consider valuable and commercially viable, and thus will also actually be used. Secondly, particularly so for the sectors under consideration, most of the patent applicants are private entities rather than public research institutions. Companies are more likely to use and implement innovations as soon as possible, as they primarily seek practical applications of those very patents; if they do not use these it is moreover possible to license these patents to other companies in the same or similar sectors. Thirdly, this paper controls for a number of different patent categories, maintaining that there sometimes are several patent classifications that can justifiably be related to their respective sectors of employment. It is after all conceivable that innovations made by actors in particular industries can vary, and be patented in a number of categories. Therefore this paper also controls for a number of different, albeit similar, patent categories when testing for the impact of technological progress on employment. Finally, the author acknowledges that the link between patent applications and the actual usage of those patents is a potential weakness of the findings of this paper; this paper thus compares and contrasting the results of this paper with the literature review in the discussion section.

Also, whereas it is possible to use alternative measures for innovation, these have different flaws that make them less suitable for assessing the specific technological progress of particular fields on labor markets. Indeed, one of the aspects this paper seeks to assess is whether technological progress in certain sectors has a different impact on the employment share of that very sector (e.g. chemical patents on the chemical sector) compared to patents in different sectors (e.g. textiles patent on the textiles sector). It is conceivable that technological progress in certain sectors may be net labor reducing, whereas technological progress may have positive effects in other sectors due to the differing interactions of the destructive and capitalization mechanisms. Further research into this topic can facilitate improved understanding as to what sectors of the labor market are influenced most by different kinds of technological progress. It is for this

reason, as well as for the possibility of constructing a robot-index, that this paper utilizes patent data as a proxy for technological progress/innovation on employment.

## 4.1. Sources.

Two main sources of data have been used for this paper: the STAN database for Structural Analysis (ISIC Rev.4), and patent data from the OECD Patent database, specifically those covered under the global Patent Cooperation Treaty (PCT). Utilizing the STAN database has several advantages; it includes annual measures of output, labor input and a number of other variables on a industry level (as classified by the most recent International Standard Industrial Classification of all economic activities, Revision 4 - ISIC Rev.4), allowing for cross-country comparisons. Notably, the STAN is primarily based on OECD member countries' annual national accounts, and thus incorporates a number of other sources, including data from national banks, national censuses or industrial surveys conducted on the national level. Data on output is in national currencies for current price data, which however are deflated using 2005 as the reference year. The 15 countries which are included are: Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Korea, the Netherlands, Norway, Slovenia, Sweden and the United States. While the STAN officially is updated regularly and claims to have data available up to 2011, the dataset lacks sufficiently available data after 2009, similar to the period before 1995.

The patent data can be traced to the OECD's directorate for Science, Technology and Industry, which provides the patent data used in this paper. It mainly draws on patents filed under the Patent Cooperation Treaty, which are designated by the European Patent Office. This is done as the PCT covers considerably more countries than the EPO or the United States Patenting Organization, being linked to over 100 countries' patenting offices (Dernis and Guellec, 2001) The paper draws on data from the applicants' country of residence, and the units are in numbers.

### 4.1.1. Employment Share:

As dependent variable, this paper draws on employment, measured as the total number of people engaged per sector, divided by the total civilian workforce in the country in that specific year, thus providing the share of the labor population working in that particular sector. While the data from the STAN database provides the total number of people employed per sector, it is important to normalize this for the number of people in the labor force, thus accounting for differences in labor force across countries, as well as changes in the total labor force over time. In order to do so this paper draws on total civilian labor force data, calculating the sectors' share of employment per country.

### 4.1.2. Control variables:

*Wages:* Labor cost compensation of employees per sector. Includes salaries, but also other forms of compensation such as employer contributions to social security, private pensions, insurances and so forth. In constant prices, national currencies, deflated for base year 2005.

*Capital Formation*: gross fixed capital formation per sector, deflators. In national currencies, deflated for base year 2005. This is an important control variable, as it aggregates a number of factors that generally are accepted to impact employment levels, such as machinery and equipment systems, changes in other capital stock, but also, and notably ICT equipment as well as Intellectual Property Products. Thus this variable controls for the actual usage of both hardware (i.e. computers and telecommunications) and the licensing of IP.

*Value Added:* value added per sector, deflators. In national currency, deflated for base year 2005. Used to account for changes in the factors of production, in line with Boglaciano and Vivarelli (2010).

*Union Density*. Trade union density per country, measured as the % of people who are a union member per country per year. Aggregated on the country level. This paper argues that it is important to control for this, as changes of the occupational structure can also be influenced by a number of other factors, such as countries' institutional frameworks and labor protection. Alesina et. al. have shown that different labor market policies influence the adaptation of labor-saving technologies, thus making it important to control for these differences (Alesina, Battisti, Zeira, 2015; Bennett, 2016). To do so this paper uses OECD data on trade union density, which '*corresponds to the ratio of wage and salary earners that are trade union members divided by the total number of wage and salary earners'* (OECD Labour Force Statistics, 2017).

To reiterate, the variables described above will be assessed on a sectorial basis to evaluate the impact of specific kinds of technological progress on the different sectors of the economy. This paper assesses the following specific sectors for all countries of the sample, in brackets the ISIC Rev.4 code:

1) Total Manufacturing (D10T33)
2) Manufacturing of textiles, wearing apparel, leather and related (D13T15)
3) Manufacturing of chemical, rubber, plastics, fuel products and other (D19T23)
4) Manufacturing of machinery and equipment (D26T28)
5) Manufacturing of transport equipment (D29T30)
6) Electricity, gas and water supply, sewerage, waste management and remediation activities (D35T39)
7) Information and Communication (D58T63)
8) Total Services (D4ST99)

These sectors have been selected for a number of reasons, but mainly because they are relatively well specified, and are therefore more justifiably linkable to the specific patent classes. Moreover, a number of the sectors (e.g. manufacturing of machinery and equipment, or the manufacturing of transport equipment) are arguably more likely to be impacted by industrial robots, and therefore particularly interesting to consider. It should

be noted that all variables in this paper are logged in line with economic and econometric literature.

### 4.1.3. Patent data:

As stated before, this paper draws on patent application data from the International Patent Classification system (IPC), organized by the country of the applicant. Overall six different independent variables are used (i.e. 5 IPC classification categories and the robot patent index) to evaluate the impact of different kinds of technological progress on their respective industrial sectors.

*Chemical and Metallurgy patents*, classified by category 'C' from the IPC
*Textiles and Paper patents*, as classified by category 'D' from the IPC,
, as classified by category 'H' from the IPC,
*ICT patents*. This is no overarching IPC classification, but a combination of a number of patents from the 8th edition of the IPC. This patent category combines patents from telecommunications, consumer electronics, computer science, office machinery and other ICT subcategories. [16]
*Nanotechnology patents*. Composed by the nanotechnology working-group from the European Patent Office (EPO), this category identifies and combines patents that can be classified as relevant for the field of nanotechnology. While arguably this patent classification is more difficult to operationalize as an explanatory variable for either of the ISIC Rev.4. industry sectors, nanotechnology patents have major potential to impact technological development, particularly considering its recent phase of development (Drexler and Pamlin, 2013).
*Robotics Patents:* an index composed by the author. Includes a number of patent categories that an expert panel has designated as important for the development of robotics. Explained in more detail below.

[16] To illustrate, the patents from the telecommunications subcategory of the IPC that have been included in the ICT patent variable come from the categories G01S,G08C,G09C,H01P,H01Q, H01S3, H01S5,H03B,H03C,H03D,H03H,H03M,H04B,H04J,H04K,H04L,H04M,H04Q, A similar list of patent sub-classifications has been included for consumer electronics, computer science, office machinery and so forth (IPC, 8th edition)

## 4.2.Robotics patent index

Whereas previous patent categories have been composed by the IPC, or affiliated patent offices such as the EPO, to the author's knowledge there is no officially sanctioned patent category on robots or robotics. Yet, as discussed in the literature review above, while there has been increasing interest in the impact of robots and the development of new technologies such as machine learning, there is relatively little research on this topic. Moreover, the few papers that do investigate this impact of robots and robotics on employment use data on the density of robotics from the International Federation of Robotics (IFR), which is only commercially available, and which has a stake in the current debate. This paper does not draw on data from the IFR, instead composing a new index on robotics, thus evaluating how technological developments in this field impact the employment shares of the sectors described above.

It is not straightforward to compile an index of robotics patents, as robots are complex products and exist in a number of forms; indeed, recalling the definition of an industrial robot as *"an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications"* it is conceivable that patents that are useful for the advancement of robots and robotics can be sorted under a number of categories (IFR, 2017).

The British Intellectual Property Office assessed what patent classifications can be related to robotics, evaluating the source, location and quality of robotics patents, discussing the potential of robotics to transform British society in the short-medium term (United Kingdom's Intellectual Property Office, 2014). While doing so this report provides detailed analysis of the patent landscape of robotics and other autonomous systems, drawing on patent application data from the PCT to do so. Notably, their collection of robotics patent classifications has been constructed following consultation with a number of experts on robotics and autonomous systems from the Intellectual

Property Office (Idem, 2014). They provide ten PCT categories which they argue can be categorized as robotics patents, largely comprising of classifications that relate to navigation, vehicle-control as well as including a number of other aspects of autonomous systems and machines (Idem, 2014). These for example include PCT classification *G05D 1/02* ("Control of position, course or altitude of land, water, air, or space vehicles, as well as "Control of position or course in two dimensions"), *G08G 1/16* ("Traffic control systems for road vehicles (arrangement of road signs or traffic signals: Anti-collision systems - road vehicle drive control systems for predicting or avoiding probable or impending collision otherwise than by control of a particular sub-unit"), *B25J 9/16*, ("Programme-controlled manipulators"), and a number of others. See the appendix for a full table of all the included patent categories that comprise the robotics index. This paper utilizes these IPC robotics classifications by aggregating them, considering them a 6$^{th}$ explanatory variable as a proxy for advances in robotics technology.

# 5. Results

Having described the methodology, this section displays the results. Before assessing the regressions from the model, this paper first displays and discusses a number of descriptive tables:

**Table 1: Sectors' share of employment for 1995-2009**

| Employment: | *Obs* | *Min.* | *Max* | *Mean* | *Median* | *St.Dev.* |
|---|---|---|---|---|---|---|
| Manufacturing | 209 | 0.09 | 0.3 | 0.18 | 0.17 | 0.05 |
| Manuf. Textiles | 209 | 0 | 0.06 | 0.01 | 0.01 | 0.01 |
| Manuf. Chemical | 209 | 0.01 | 0.05 | 0.03 | 0.03 | 0.01 |
| Manuf. Machinery | 209 | 0.02 | 0.06 | 0.04 | 0.04 | 0.01 |
| Manuf. Transport | 209 | 0 | 0.04 | 0.01 | 0.01 | 0.01 |
| Electricity | 206 | 0.01 | 0.03 | 0.01 | 0.01 | 0.01 |
| ICT | 206 | 0.02 | 0.04 | 0.03 | 0.03 | 0.01 |
| Services | 206 | 0.49 | 0.88 | 0.72 | 0.75 | 0.09 |

Note: shows descriptive statistics on the % of the labor population employed per sector.

Table 1 displays the sectors' share of employment across all countries and over the entire time-period considered (1995-2009). It indicates that the difference between the mean and median of most sectors is relatively small, implying that the variance of the sectors is relatively similar in all countries; there are some outliers, as can be seen from the minimum and maximum columns for especially the (total) manufacturing and service sectors. Although not evident from this table, it is moreover interesting to note that the country with the lowest share of its working population in manufacturing (and also the highest share in services) is the United States, closely followed by the Netherlands; vice versa, the countries with the highest shares in manufacturing are Slovenia and the Czech republic (who also have the lowest share in services).

Table 2 displays descriptive statistics of the patent data used in this paper. Compared to table 1 there is considerably more variation, which can be attributed to the vastly different compositions of the respective economies. Considering the different sizes of the countries included in the sample, this is only to be expected: the US is the largest producer of all patents, followed relatively closely by Germany. The smaller countries on the other hand, Slovenia, the Czech republic, Hungary and to a lesser extent Belgium produce considerably fewer patents, for some years only producing between 10-100 (total) patents, compared to the tens of thousands by the US or Germany. Additionally it is interesting to note the major variation between the different patent classifications - e.g. ICT patents are considerably more numerous than textile patents or nanotechnology patents, illustrating the different output of patents in the various categories.

**Table 2: Patent count per PCT classification for 1995-2009**

| | *Obs* | *Min.* | *Max* | *Mean* | *Median* | *St.Dev.* |
|---|---|---|---|---|---|---|
| Total patents | 225 | 19 | 52854 | 4667 | 1074 | 9826 |
| ICT patents | 225 | 2 | 21979 | 1723 | 236 | 3981 |
| Nanotech patents | 225 | 0 | 939 | 55 | 7 | 155 |
| Chemistry patents | 225 | 1.8 | 7439 | 741 | 162 | 1609 |
| Textile patents | 224 | 0 | 477 | 66 | 23 | 105 |
| Electricity patents | 225 | 0.8 | 10333 | 899 | 135 | 1844 |
| Robot patents | 225 | 0 | 489 | 51 | 6 | 95 |

Note: shows the unadjusted number of patents across the different sectors

While table 2 thus indicates that there is considerable variety between the different patent classifications and classes, table 2 only shows the statistics for all the countries combined, covering the heterogeneity between the different countries. One of the factors that contributes to the large variance displayed in table 2 are the vast differences in size between the countries, influencing the absolute number of patents produced. It is however also interesting to consider the relative production of patents, controlling for the

population, thus illustrating the differing emphasis on innovation and technological progress between these countries.

Table 3 does this, displaying the number of patents for every 1000 employees per sector, controlling for countries' economies, and the number of people working in each sector. Assessing the results, a number of countries are particularly noticeable: Sweden, the Netherlands and Finland do well in most categories, with Sweden and Finland standing out for the production of electricity and ICT patents, also scoring quite high in the textile sector. Whereas the Netherlands has a relatively high number of chemistry patents, Sweden is also notable for its relatively high number of robotics patents. Moreover, the US has a relatively high number of total patents relative to the share of employees in manufacturing, although this may partially be explained by its relatively low number of people working in their manufacturing sector, as noted in table 1 above. Furthermore, on the lower side of the spectrum, the Czech republic, Hungary, and interestingly Italy produce relatively few patents per employee.

Table 3 then well reflects the different patent composition of the countries included in the sample, confirming the importance of including country-fixed effects in the econometric model to control for the rather significant differences between countries. Moreover, it confirms the importance of controlling for the size of the population, facilitating a more appropriate cross – country comparison. Finally, it is noticeable that there is missing data for the United States for a number of sectors. The reason for this is unclear.

**Table 3: Patents by ISIC sector for 1995-2009**

| | Variables | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Textile Patents/ Textiles employees | | Chem pat / Chem employees | | Elec pat /Elec employees | | ICT pat/ICT employees | | Robot pat/Manuf. Machinery employ | | Robotpat/Manuf. Transport employ. | | Total Pat/Total Manufacturing | |
| Countries | Mean | St. Dev | Mean | St. Dev | Mean | St. Dev | Mean | St. Dev | Mean | St. Dev | Mean | St. Dev | Mean | St. Dev |
| Austria | 0.437 | 0.185 | 1.031 | 0.351 | 1.555 | 0.888 | 1.304 | 0.515 | 0.038 | 0.024 | 0.131 | 0.077 | 1.047 | 0.418 |
| Belgium | 0.605 | 0.452 | 1.546 | 0.697 | 1.057 | 0.422 | 1.350 | 0.424 | 0.027 | 0.024 | 0.034 | 0.030 | 1.106 | 0.522 |
| Czech Republic | 0.046 | 0.043 | 0.087 | 0.062 | 0.054 | 0.042 | 0.112 | 0.054 | 0.004 | 0.004 | 0.007 | 0.007 | 0.065 | 0.034 |
| Denmark | 0.903 | 0.230 | 2.639 | 0.627 | 3.354 | 1.345 | 1.869 | 0.519 | 0.047 | 0.022 | 0.370 | 0.216 | 2.328 | 0.836 |
| Finland | 5.272 | 1.790 | 2.222 | 0.621 | 26.678 | 10.393 | 9.901 | 3.211 | 0.043 | 0.018 | 0.232 | 0.107 | 3.520 | 1.146 |
| France | 0.228 | 0.082 | 1.175 | 0.385 | 3.298 | 1.804 | 2.074 | 0.939 | 0.133 | 0.104 | 0.205 | 0.152 | 1.340 | 0.595 |
| Germany | 1.064 | 0.578 | 1.789 | 0.553 | 4.052 | 1.566 | 2.772 | 0.785 | 0.139 | 0.062 | 0.264 | 0.115 | 1.703 | 0.616 |
| Hungary | 0.006 | 0.009 | 0.189 | 0.080 | 0.090 | 0.050 | 0.227 | 0.096 | 0.006 | 0.006 | 0.017 | 0.018 | 0.134 | 0.039 |
| Italy | 0.061 | 0.033 | 0.339 | 0.145 | 0.586 | 0.284 | 0.485 | 0.205 | 0.019 | 0.010 | 0.058 | 0.033 | 0.362 | 0.171 |
| Netherlands | 1.326 | 0.711 | 3.624 | 1.255 | 13.394 | 5.108 | 6.466 | 2.525 | 0.120 | 0.063 | 0.404 | 0.217 | 3.614 | 1.525 |
| Norway | 0.313 | 0.197 | 1.730 | 0.444 | 1.419 | 0.664 | 1.321 | 0.373 | 0.106 | 0.056 | 0.125 | 0.066 | 1.841 | 0.429 |
| Sweden | 3.217 | 1.171 | 2.351 | 0.608 | 20.050 | 6.780 | 7.890 | 2.345 | 0.475 | 0.260 | 0.875 | 0.430 | 4.037 | 1.100 |
| US | 0.418 | 0.150 | 2.647 | 0.630 | N.A | N.A | N.A | N.A | 0.085 | 0.028 | 0.150 | 0.043 | 2.463 | 0.976 |

Note: number of patents per 1000 employees.

**Table 4: Results regression of patents and percentage change of employment shares of selected sectors**

| | Dependent variable: employment share | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* |
| | *Total Manufacturing* | | *Machinery Manufacturing* | | *Textile Manufacturing* | | *Transport. Manufacturing.* | |
| *L1* | 0.735*** | 0.635*** | 0.7**** | 0.56*** | 0.62*** | 0.83*** | 0.62*** | 0.463*** |
| *Textilepat* | | | | | 0.007 | 0.006 | | |
| *Robotpat* | 0.0036 | 0.0054** | 0.016*** | 0.020*** | | 0.025*** | 0.0129 | 0.019*** |
| *ICTpat* | | -0.018 | | 0.036** | | 0.012 | | -0.017 |
| *Nanopat* | | 0.0089** | | 0.011* | | 0.0019 | | 0.022*** |
| *Elecpat* | | | | -0.0479*** | | | | |
| *Value added* | 0.083 | 0.077 | -0.007 | 0.06 | 0.076 | -0.033 | -0.078 | 0.041 |
| *Capital* | -0.13 | -0.182* | 0.186 | 0.039 | 0.128 | 0.39*** | 0.004 | 0.433 |
| *Wages* | -0.001* | 0.122*** | 0.003 | 0.227*** | 0.165** | 0.081* | -0.301*** | 0.17 |
| *Unions* | 0.0076 | 0.003 | -0.024 | -0.159 | 0.081 | 0.022 | 0.47 | -0.07 |
| *Country effects* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fixed year Effects* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *AB-test1* | 0.019** | 0.125 | 0.042** | 0.14 | 0.023** | 0.03** | 0.051* | 0.01*** |
| *AB-test2* | 0.46 | 0.02 | 0.217 | 0.509 | 0.472 | 0.165 | 0.386 | 0.147 |
| *Sargan* | 0 | 0 | 0 | 0 | 0 | 0 | 0.054* | 0.002*** |
| *Hansen test* | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| *Obs.* | 129 | 116 | 129 | 116 | 141 | 114 | 129 | 116 |
| *Instruments* | 84 | 84 | 85 | 85 | 85 | 85 | 85 | 85 |

Note: p-values reflect the robust standard errors. One, two and three stars indicate statistical significance at 10%, 5% and 1% respectively

Table 4 displays the results of the econometric regressions for several industrial sectors. Columns 1-2 and 3-4 display the results for manufacturing and the manufacturing of machinery respectively, and columns 5-6 and 7-8 display the results for textiles manufacturing and transportation equipment manufacturing. All regressions control for wages, capital, value added and unions, are deflated for base year 2005 and are logged as discussed in the methodology section. Moreover, country and fixed year effects are included for every regression. Table 4 thus shows the results for four sectors, displaying each sector in two columns, one from a regression with a single patent category as

explanatory variable (e.g. column 1 for total manufacturing), and one controlling for a number of patent classifications (e.g. column 2 for total manufacturing).

Overall, a number of aspects stand out: firstly, the lagged dependent variable is consistently statistically significant, with relatively high coefficients. This is similarly the case for table 5 below, and robust to changes, indicating that it is indeed important to control for a lagged dependent variable. Secondly, assessing the control variables, it is noticeable that value added and unions are never statistically significant, that capital is only statistically significant for two out of eight regressions (at the 10% and the 1%), and that wages are consistently statistically significant, excepting columns three and eight.

Thirdly, evaluating the impact of patents on employment shares, it is noticeable that a number of patent categories are statistically significant, albeit at diverging p-values. The index for robot patents is rather interesting, and statistically significant for a number of different sectors: this is the case for total manufacturing, the textile-manufacturing sector and the production of transport-equipment sectors, albeit only when controlling for a number of patent categories. Robot patents are statistically significant for the machinery-manufacturing sector both when controlling for other patent categories (column 4) and not doing so (column 3). Furthermore, assessing the coefficients, table 4 indicates that a 1% increase of robotics patents is associated with a .02% increase in the employment share of machinery manufacturing. Similarly, a 1% increase in ICT patents is associated with a .036% increase in the employment share of machinery manufacturing. Interestingly, wages have an economically stronger association with machinery manufacturing, reflected by its relatively high coefficient of .227% for machinery manufacturing, and .122% for total manufacturing. Finally, the coefficients of .025 and .019 for the textiles and the transport sectors respectively indicate that a 1% increase in robotics patents is associated with a .025% increase in employment share in the textiles industry, and .019% for the transport manufacturing industries. While these numbers at first sight appear to be of little economic significance, this arguably depends on context and interpretation: this is done in more depth in the discussion below.

Table 4 also displays the results of a number of tests: the first Arellano-Bond test (AB-test 1) is applied to the residuals in first differences, which however is problematic (due to the nature of the dynamic model), and therefore uninformative (see Roodman, 2006). The second Arellano-Bond test checks for second-order correlation in differences, thus evaluating whether there is autocorrelation; the lack of rejection of the null as the case in tables 4 above is indicative of no autocorrelation in the residuals. The Sargan and Hansen test for the joint validity of the GMM instruments is also displayed: the null hypothesis of both tests is valid results, with the tests clearly contrasting one another. This is the case in nearly all the columns, suggesting that there are issues with these regressions that require further discussion. The implications of this are examined in more detail in the discussion below.

**Table 5: Results regression of patents and percentage change of employment shares of selected sectors:**

| | Dependent variable: employment share | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* |
| *Industrial Sector* | *Chemical Sector.* | | *Electrical Sector.* | | *ICT. Sector* | | *Total Services* | |
| L1 | 0.59*** | 0.516*** | 0.585*** | 0.397*** | 0.75 | 0.62*** | 0.712*** | 0.722*** |
| Electricpat | | | -0.0039 | 0.008 | | 0.052*** | | -0.006 |
| Chempat | 0.016** | 0.009 | | | | | | |
| Robotpat | | -0.003 | | 0.010** | | 0.0028 | | 0.0094 |
| ICTpat | | -0.0053 | | -0.023 | 0.027 | -0.036** | -0.0039 | 0.0042 |
| Nanopat | | 0.0065 | | 0.006* | | 0.0049 | | 0.0038 |
| Value added | 0.072 | 0.078 | -0.048 | -0.77 | 0.13 | -0.06 | 0.091 | -0.0224 |
| Capital | -0.01*** | -0.511*** | 0.125 | -0.059 | 0.019 | -0.074 | 0.014 | 0.06 |
| Wages | -0.316** | 0.26*** | -0.01 | 0.2*** | -0.0002 | 0.271*** | -0.15** | -0.131* |
| Unions | -0.019 | -0.04 | 0.043 | 0.032 | -0.052 | 0.155*** | 0.014 | 0.043 |
| Country effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Year Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| AB-test1 | 0.024** | 0.008*** | 0.018** | 0.09* | 0.087 | 0.024 | 0.007 | 0.016 |
| AB-test2 | 0.485 | 0.236 | 0.112 | 0.296 | 0.803 | 0.266 | 0.948 | 0.839 |
| Sargan | 0 | 0.009*** | 0 | 0 | 0 | 0 | 0.006 | 0.001 |
| Hansen test | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Obs. | 155 | 116 | 152 | 113 | 152 | 113 | 140 | 112 |
| Instruments | 85 | 85 | 85 | 85 | 85 | 85 | 85 | 85 |

Note: p-values reflect the robust standard errors. One, two and three stars indicate statistical significance at 10%, 5% and 1% respectively

Table 5 is similar to table 4 in that it shows the results of the regressions for patents on the employment share of the population as dependent variables; it however displays the results for different industrial sectors, including the chemical sector, the electrical sector, the ICT sector and the total services sector. A number of aspects stand out: while chemical patents have a statistically significant association with increases in the employment share of the chemical sector, this effect disappears when controlling for several other classes of patents. Noticeably, wages and capital both have a statistically significant and robust impact on employment in the chemical sector: increases in wages

are associated with an increase in the number of people working there, whereas increases in capital are strongly negatively associated with the employment sector: only controlling for chemical patents, a 1% increase in wages is associated with a .32% increase in the share of employment working in the chemical sector. Moreover, controlling for several patents, increases in capital formation are negatively associated with the employment share in the chemical industry, indicating that a 1% increase in capital is associated with a -.51% decrease in employment share. For the electrical sector it is noticeable that electrical patents do not significantly alter the employment share of the corresponding ISIC sector: this may be due to the relatively highly aggregated nature of this sector (i.e. also includes gas and water supply, sewerage, waste management and remediation activities), but will be discussed in more detail in the discussion. Interestingly, once again the robotic patent index is statistically significant, appearing positively associated with increases in employment.

Furthermore, assessing the results of regressions for ICT as dependent variable in columns 5-6 a number of factors stand out: ICT and electric patents are statistically significant for ICT production. The coefficient of this correlation is particularly interesting, indicating that – when controlling for several patent classifications - a 1% increase of ICT patents is actually associated with a .036% *decrease* in the number of people working in the ICT sector. Curiously, electric patents are positively associated with the ICT sector. This result is rather surprising, although this potentially can be accounted for by evaluating the parameters of the ICT sector used in this paper: category D58T63 from the ISIC Rev.4 (i.e. the dependent variable in column 5-6) does not solely refer to ICT production (i.e. production of telecommunications), but also includes the number of people who work in ICT related services, such as call-centers, publishing activities, audiovisual activities and so forth (ISIC Rev.4); ICT technologies may actually have a labor-replacing impact here. Arguably, electric patents could be considered related to the actual production of ICT products, often involving highly technical electrical products.

Finally, the results from table 5 also suggest that there is no statistically significant

relationship between the services sector and any of the patent categories. While wages are (negatively) associated with the service sector, it is unsurprising how none of the patent categories is related to changes in the employment share of the service sector. It could be argued that this is due to the aggregated nature of the service sector (comprising between 48%-88% of the total workforce as indicated by table 1), although an in-depth assessment of this argument is beyond the scope of this paper. The results of the AB tests in table 5, as well as the results of the Hansen/Sargan tests are similar to table 4, and are discussed in more detail in the discussion.

# 6. Discussion

Thus having displayed the results, it is important to assess the implications in more detail, considering their economic and statistical significance. This section first highlights the most important findings from the results section, recalling the research questions while comparing and contrasting them with the literature review. It then discusses the limitations of this thesis, finally deriving a number of recommendations. Overall, this dissertation argues that the results are indicative of a positive, but mild, association between robotics patents and employment, but are insufficiently robust to support conclusions on other patent classifications. Moreover, while the results from some of the regressions should be viewed critically as indicated by the results from the Hansen and Sargan tests, another contribution of this dissertation is its novel attempt to conceptualize the impact of robots through the operationalization of a robotics patent index.

Research question 1: '*Distinguishing between different measures of technological change, how has technological progress impacted the occupational structure of industrialized countries between 1995-2009?*'

Recalling the first research question of this paper, a number of factors are important to highlight. Assessing the control variables it is noticeable how union density and value added are not statistically significant in any of the regressions. Capital is statistically significant at some of the regressions (total manufacturing at the 10% level, textiles and chemicals at 1%), with considerable differences in the coefficients. Labor compensation (wages) however is the most robust control variable, being statistically significant for a considerable number of regressions, although having rather divergent coefficients, suggesting that changes in labor compensation differently impact the different industries. These findings are unsurprising, considering the differences between sectors with regard to the skill level of employees and subsequent demand for high- or low-skilled labor.

There furthermore are a number of remarkable findings regarding the relationship between patents and employment: firstly, changes in the number of textile patents do not

have a statistically significant effect on the employment share of the textile sector, similar to the lack of a statistically significant effect of changes in electricity patents on the share of the electricity sector. Chemistry patents can only be linked when controlling for a number of other variables, and ICT, while statistically significant, is negatively associated with the employment share of ICT relative to other sectors in the economies, as displayed in tables 4 and 5. A number of factors could explain these results – e.g. both the ISIC Rev.4 electrical and textile sectors are broad, and include also the number of people employed in the 'gas and water supply, sewerage, waste management and remediation activities' in the former, and 'wearing apparel, leather and related sectors' in the latter. Moreover, the ICT sector does not merely refer to the people employed in the production of ICT, but also ICT related services, including telecommunications support and related services; the negative impact of ICT in these sectors is not surprising, with routine tasks being replaced by cheaper and more advanced technologies. This is also reflected in the literature, where the impact of ICT on employment and productivity is a contended topic, but generally considered to positively impact productivity and wages, although substituting for workers performing routine tasks - thus replacing laborers (Akerman et al. 2015; Berger and Frey, 2016). While these findings are in line with the literature, this paper argues that the results from most patent categories are insufficiently robust to support strong conclusions; thus the results neither allow for the acceptance of the hypothesis, nor for the rejection of the null hypothesis of the first research question.

Research question 2: "*How do robotics patents influence the employment shares of industrial sectors in the selected number of industrialized countries?*

Recalling the second research question, a number of factors stand out: notably, contrary to the other patent classifications in this paper, changes in robotics patents are associated with changes in the employment share of various sectors (statistically significantly at the 1% or 5% levels). Indeed, robotics patents are positively associated with increases in employment in the total manufacturing sector, the manufacturing of machinery, the manufacturing of transport equipment, the textile industry and the electrical sector. Moreover, the coefficients are relatively robust (opposed to the coefficients of wages),

hovering around .02%, indicating that a 1% increase in robotics patents is indicative of a .02% of employment share of the respective sector assessed. Whether this is also economically significant is debatable: a .02% increase in the number of people employment sector appears small, but is arguably deceptive: as can be noted in table 2, robotics patents are few compared to patent categories such as ICT: the mean (median) of robotic patents per country is only 51 (6) per year, compared to 1723 (236) for ICT patents, and 899 (135) for electricity patents. This suggests that with relatively little additional absolute investment in robotics research, robotics patents can increase relatively easily, likely spurring positive impacts on the labor market. Moreover, considering the size of the labor force of countries like Germany and the US (which are in the top 5 of robotics producers), increases of .02% in the share of labor force are equivalent to thousands of employees, considerable enough to constitute interest. When comparing the results of this paper with other empirical evidence, it warrants to recall that there currently is no clear consensus on the impact of innovation on employment: whereas there is evidence indicating that technological progress, or innovation, positively impacts productivity, section 1 of this paper has indicated that for employment the literature is ambiguous. Taking sectors as the unit of analysis, this ambiguity is illustrated by on the one hand authors such as Pianta (2000) as well as Antonucci and Pianta (2002), who argue that innovation has a negative impact on employment. On the other hand Boglaciano and Vivarelli (2010) argue that innovation positively impacts employment, a sentiment echoed by Gregory, Salamons and Zierahn (2016) when considering the larger economy, also accounting for compensation mechanisms. Moreover, actually measuring the relationship between changes in robot density and jobs, Graetz and Michaels (2015) found no statistically significant impact of robots on employment, illustrating the complexity of this relationship.

## 6.1 Limitations:

Before evaluating the implications of these findings, it warrants considering the limitations of this paper.

Firstly, this paper assumes that patents from IPC categories are also used in the sectors from the ISIC Rev.4. While this is not unlikely, it is possible that some of the patents are not used in the sectors this paper links them with, thus potentially spuriously linking patents and changes in the employment rate. Moreover, this paper assumes all patents to be of equal importance; this arguably is a limitation, as it is unlikely that every patent has a similar impact on productivity or the labor market. While it is possible to account for this by controlling for the number of patent citations, these numbers were not available for the dataset used in this dissertation.

Secondly, the results from the test-statistics indicate that the results should be interpreted with caution: while the Arellano-Bond tests imply that there is no autocorrelation, the null hypothesis of the Sargan test is consistently rejected, contrasting the results from the Hansen test. Both test for the validity of the instruments of the GMM estimator, the null hypothesis being valid instruments: the results from the Sargan test suggest that the instruments are invalid, and therefore that the results should be interpreted with care. While it should be noted that both tests have a number of weaknesses, it is disconcerting that the Sargan test is consistently rejected as opposed to the Hansen test, potentially indicating endogeneity of the variables (Roodman, 2006). This partially can be attributed to the characteristics of this dataset, including a small T and also a relatively small N, causing a lack of robust results for the former (Sargan test), and robust but strongly weakened results for the latter (Hansen) due to the high number of instruments (Roodman, 2006). Henceforth it appears that the results should be interpreted with care, although not discarded outright: whereas also Boglaciano and Vivarelli (2010) experience difficulties with the Sargan and Hansen tests, the relatively small panel used in this paper may explain the consistent rejection of the Sargan test; thus the results from this paper require careful interpretation.

Finally, it could be argued – as maintained by McAfee and Brynjolfsson in 'The Second Machine Age', or Frey and Osborne in 'The Future of Employment' – that the currently available data insufficiently accounts for future technological advances, and that an empirical study of the recent past henceforth cannot be generalized to the future. There is

truth in this, although it should also be noted that their predictions are far from widely accepted, with counterarguments having been proposed by Artz, Gregory and Zierahn (2016) to Frey and Osborne, and opposing predictions by experts from leading consultants after surveying business owners (McKinsey 2017; Deloitte 2015; PwC 2015), again indicating that the future impact of technological progress on employment is complex, dependent on a number of factors, and difficult to predict. While we could indeed see a break with the past similar to the first industrial revolution, it is also possible we will move from Perez' 'installation' period to a 'development' period, and that new jobs will be created which we cannot currently foresee. Indeed, by one estimate up to 65% of children entering grade school in 2011 will work in careers that haven't been invented yet, indicating that also predictions for the future are widely divergent (Davidson, 2011). Furthermore, while the methodology and thus also the results of this paper do not lend themselves to predictions about changes in the quality of jobs, the literature review suggests there are considerable risks of automation and innovation further driving wage and job-polarization, perpetuating the already existing trend of increasing inequality. This is the case for not only the impact of technological progress on the substitution of jobs (mainly being middle-class jobs), but also for the creation of jobs, which are more likely to require non-routine, high-skilled labor due the nature of the current technological innovation cluster, in line with the task biased framework (Frey and Berger, 2016; Autor and Handel 2013; Acemoglu and Autor 2011).

## 6.2 Recommendations for future research:

Overall then, the results from this thesis are no final answer to the debate surrounding technological progress and employment. Yet it suggests that also the current technological cluster of computational advances and robotics – while likely having major societal impacts in the medium to long term, including a transformation of the employment sectors – does not yet merit widespread technological anxiety. In fact, for the time period considered, robotics patents seem to be mildly positively related to employment, thus allowing for the rejection of the null hypothesis of the second research

question. It should be noted that while we perhaps do not have to worry about technological unemployment in the near future, it is important to continue assessing the drivers of the current trends of wage and job-polarization – including technological progress – thus facilitating adequate responses that ensure that overall society benefits, rather than a select group of high-skilled employees and entrepreneurs. Moreover, the impact of technological progress on employment necessitates future research with more recent data, as well as warrants continued interest from policy-makers. This dissertation attempted to evaluate the relationship using the most recent data that allowed for a specific assessment of robotics patents, which unfortunately stretched only till 2009. Access to more recent, sufficiently detailed data, or research that can draw on IFR data would be a promising avenue for future research: seeing as to the author's knowledge there was no similarly detailed data available for more recent years, and considering his lack of financial resources to purchase IFR data, the operationalization of a robotics index has proven to be an imperfect, yet not unsuccessful venture to test this relationship.

# 7. Conclusion

*" Work keeps at bay three great evils: boredom, vice and need."* - Voltaire (1759)

This dissertation has sought to understand whether current technological anxiety is justified, specifically investigating whether 'robots will take our jobs'. Using a 15-country, 8-sector and 15-year dataset and utilizing GMM-system estimators, it evaluated the impact of innovation and robots on employment. This paper argues that the relationship between technological progress and employment is a highly relevant topic, essential to understanding the declining size of the middle classes and the future outlook of our societies, with this thesis seeking to fill some of the gaps in the literature. It has sought to do so by approaching the impact of technological progress on employment utilizing patent data – a relatively tested methodology – but also by operationalizing a new index to account for innovation in the field of robotics, one of the technological sectors predicted to greatly impact employment in the future. The results of this paper are indicative of advances in robotics mildly stimulating employment; whereas the coefficients are relatively small, suggesting low levels of economic significance, the results are robust. This indicates that between 1995-2009, robotics have not necessarily been labor-substituting, but may actually have complemented and stimulated employment, in line with a number of other papers and reports on the relationship between innovation and employment. While the results of this paper do not allow for conclusions on the impact of innovation on the quality of jobs, the literature review suggests that it is not unlikely that future technological progress in the fields related to the current innovation cluster – robotics, machine learning and artificial intelligence – will further exacerbate trends of wage and job-polarization. This is important, and necessitates discussion on the redistributive role of the government in this perspective, and related topics such as a negative income tax or a basic income.

Overall, this paper concludes that the technological progress associated with developments in the current innovation cluster should be assessed carefully by academics and the private sector, discussed by policy-makers and the public alike, but not dreaded

or opposed. After all, whereas there will be major employment market changes in the coming decades due to innovations and technological progress, this is not new, and likely can be accommodated by a combination of adequate policy response and gradual changes in society. Unsurprisingly then, this thesis recommends further research on this complex relationship, particularly so for technologies that have been designated as so potentially disruptive to the labor market; whereas this paper sought to do so for robotics, this similarly applies for advances in machine learning, artificial intelligence and related technological fields.

# References:


Acemoglu, D., 2014. Localised and biased technologies: Atkinson and Stiglitz's new view, induced innovations, and directed technological change. The Economic Journal 125, 443–463.

Acemoglu, D., Akcigit, U., Celik, M.A., 2014. Young, restless and creative: Openness to disruption and creative innovations. National Bureau of Economic Research.

Acemoglu, D., Autor, D., 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings, in: Handbook of Labor Economics. Elsevier, pp. 1043–1171. doi:10.1016/S0169-7218(11)02410-5

Acemoglu, D., Restrepo, P., 2016. The race between machine and man: Implications of technology for growth, factor shares and employment. National Bureau of Economic Research.

Aghion, P, P Howitt, 1994, Growth and Unemployment, Rev Econ Stud (1994) 61 (3): 477-494.

Alesina, A., Battisti, M., Zeira, J., 2015. Technology and labor regulations: Theory and evidence. National Bureau of Economic Research.

Allen, R.C., 2009. Why was the Industrial Revolution British? Oxonomics 4, 50–54.

Archibugi, D., Planta, M., 1996. Measuring technological change through patents and innovation surveys. Technovation 16, 451519–468.

Arntz, M., Gregory, T., Zierahn, U., 2016. The Risk of Automation for Jobs in OECD Countries (OECD Social, Employment and Migration Working Papers No. 189). doi:10.1787/5jlz9h56dvq7-en

Arellano M, S Bond, Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, The Review of Economic Studies, Vol. 58, No. 2

Automation and anxiety [WWW Document], n.d. . The Economist. URL http://www.economist.com/news/special-report/21700758-will-smarter-machines-cause-mass-unemployment-automation-and-anxiety (accessed 3.20.17).

Autor, D., Murnane, R.J., others, 2003. The skill content of recent technological change: An empirical exploration. The Quarterly journal of economics 118, 1279–1333.

Autor, D.H., 2015. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives 29, 3–30. doi:10.1257/jep.29.3.3

Autor, D.H., Dorn, D., Hanson, G.H., 2015. Untangling Trade and Technology: Evidence from Local Labour Markets. The Economic Journal 125, 621–646. doi:10.1111/ecoj.12245

Autor, D.H., Handel, M.J., 2013. Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. Journal of Labor Economics 31, S59–S96. doi:10.1086/669332

Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the US labor market. National Bureau of Economic Research.

Atkinson, A. and J.E Stiglitz, .A New View of Technological Change,. Economic Journal, LXXIX (1969), 573-78.

Antonucci T, M Pianta, "Employment Effect of Product and Process Innovation in Europe" pages 295-307

Baltagi, B. H. (2005) Econometric Analysis of Panel Data (third ed.) John Wiley. & Sons
Barclays. 2015. Future-proofing UK manufacturing. Barclays.
Beaudry, P., Doms, M., Lewis, E., 2010. Should the personal computer be considered a technological revolution? Evidence from US metropolitan areas. Journal of Political Economy 118, 988–1036.
Beaudry, P., Green, D.A., Sand, B.M., 2016. The great reversal in the demand for skill and cognitive tasks. Journal of Labor Economics 34, S199–S247.
Behar, M.A., 2013. The Endogenous Skill Bias of Technical Change and Inequality in Developing Countries. International Monetary Fund.
Bennett, J., 2016. Skill-specific unemployment risks: Employment protection and technological progress–A cross-national comparison. Journal of European Social Policy 26, 402–416.
Berger, T., Frey, C., 2016. Digitalization, Jobs, and Convergence in Europe: strategies for closing the skills gap.
Berger, T., Frey, C., 2016. Did the Computer Revolution shift the fortunes of U.S. cities? Technology shocks and the geography of new jobs. Elsevier regional science and urban economics 57(2016) 38-45 http://dx.doi.org/10.1016/j.regsciurbeco.2015.11.003
Berger, T., Frey, C., 2014. Industrial Renewal in the 21st Century:Evidence from U.S. Cities_
Besome, D. 1999. Harrod on the classification of technological progress. The origin of a wild-goose chase. BNL Quarterly Review, no.208.
Besharov, D.J., López Peláez, A., Segado Sánchez-Cabezudo, S., 2016. The Decline of the Middle Classes around the World? Journal of Policy Analysis and Management 35, 245–251. doi:10.1002/pam.21883
Blinder, A.S., Krueger, A.B., 2013. Alternative measures of offshorability: a survey approach. Journal of Labor Economics 31, S97–S128.
Blundell R, S. Bond (1998), Initial conditions and moment restrictions in dynamic panel data models, Journal of Econometrics 87 (1998)
Bogliacino, F., Pianta, M, 2010. Innovation and Employment: a Reinvestigation using Revised Pavitt classes. Research Policy 39, 799–809. doi:10.1016/j.respol.2010.02.017
Bogliacino, Francesco and Vivarelli, Marco, (2010), The job creation effect of R&D expenditures, No 2010/55, Working Papers, Institut d'Economia de Barcelona (IEB),
Bogliacino, Francesco and Vivarelli, Marco, (2012), The job creating effect of R&D expenditures around the world. *Australian Economic Papers*, 51, issue 2
Bowles, J. 2014, The Computerization of European Jobs, Bruegel, Brussels.
Boyer, Robert 1990, The Capital Labor Relations in OECD Countries: From the Fordist "Golden Age to Contrasted National Trajectories" Working paper CEPREMAP 9020
Brouwer, E, Kleinknecht, Alfred and Reijnen, Jeroen O N, (1993), Employment Growth and Innovation at the Firm Level, *Journal of Evolutionary Economics*, 3, issue 2,
Bruinshoofd, W.A., Weel, B.J., others, 1998. Skill-biased technical change: On technology and wages in the Netherlands. MERIT, Maastricht Economic Research Institute on Innovation and Technology.
Buerger, M., Broekel, T., Coad, A., 2012. Regional Dynamics of Innovation: Investigating the Co-evolution of Patents, Research and Development (R&D), and Employment. Regional Studies 46, 565–582. doi:10.1080/00343404.2010.520693
Bureau of Labor Statistics (2015),"Robots Fuel the Next Wave of US Productivity and Job Growth" Association of Advnacing Automation estimate of total employment supported by manufacturing calculated by NAM using data from the Bureau of Economic Analysis (2013, 2014) See:
http://www.nam.org/Newsroom/Facts-°©-About-°©-Manufacturing/#sthash.OprE5NBZ.dpuf
Byun, Y., 2016. The Politics of Middle Class Decline and Growth in Industrialized Democracies, 1980 to 2010.
Compaño, R., Pascu, C., Bianchi, A., Burgelman, J.C., Barrios, S., Ulbrich, M., Maghiros, I., 2006. The Future of the Information Society in Europe: Contributions to the Debate. Office for Official Publ. of the Europ. Communities.
D'Agostino, Brian. 2012. The Middle Class Fights Back: How Progressive Democrats Can Restore Democracy in America. Santa Barbara, CA: Praeger.
Davidson, C.N "Now You See It – How Technology and Brain Science Will Transform Schools and Businesses for the 21st Century" (2011) New York: Viking.SBN-13: 978-0143121268 ISBN-10: 014312126X
Daeton, A (1995), Data and Econometric Tools for Development Analysis (Chapter 33), Princeton University
Deming, D.J., 2015. The Growing importance of Social Skills in the labor market. Journal of Labor Economics 34, S199–S247.
Deloitte LLP. 2015. From Brawn to Brains: The Impact of Technology on Jobs in the UK.

Deloitte. 2015. Technology and People: The Great Job Creating Machine
Demis H and D Guellec (2001). Using Patent Counts for Cross-Country Comparisons of Technology Output. OECD Directorate for Science, Technology and Industry, STI Review No. 27
Drexler. E and Pamlin D, 2013. Nano-Solutions for the 21st Century – Unleashing the fourth technological revolution. Center for stustainable Development.
D'Ercole M.M and F. Murtin 2014, Household wealth inequality across OECD countries: new OECD evidence, OECD statistics Brief, NO. 21
Erickson. J (2014). The Middle-Class Squeeze: A Picture of Stagnant Incomes, Rising Costs, and What We Can Do to Strenghten America's Middle Class, Center for American Progress
Europäische Kommission (Ed.), 2012. New skills and jobs in Europe: pathways towards full employment, EUR. Publ. Off. of the Europ. Union, Luxembourg.
European Commission, Directorate-General for Employment, S.A. and I., European Commission, Eurostat, 2015. Analytical web note: measuring skills mismatch. Publications Office, Luxembourg.
Faux, Jeff. 2012. The Servant Economy: Where America's Elite are Sending the Middle Class. Hoboken, NJ: John Wiley.
Feldmann, H., 2013. Technological unemployment in industrial countries. Journal of Evolutionary Economics 23, 1099–1126.
Feng, A., Graetz, G., 2015. A question of degree: the effects of degree class on labor market outcomes. IZA Discussion Papers.
Freeman, C. and L. Soete (eds) (1987) Technical Change and Full Employment, Oxford, Basil Blackwell.
Freeman, C, 1995, The 'National System of Innovation' in historical perspective, Cambridge Journal of Economics, Vol. 19, 5-24
Frey, C.B., Berger, T., 2016. Structural Transformation in the OECD (OECD Social, Employment and Migration Working Papers No. 193). doi:10.1787/5jlr068802f7-en
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technological Forecasting and Social Change 114, 254–280.
Frey, C.B., Rahbari, E., 2016. Technology at work: How the digital revolution is reshaping the global workforce. VoxEU.org.
Goldin Claudia, and Lawrence F. Katz, 2009, The race between education and technology, The Belknap Press of Harvard university Press,
Goos, M., Hathaway, I., Konings, J., Vandeweyer, M., 2013. High-technology employment in the European Union.
Goos, M., Konings, J., Vandeweyer, M., 2015. Employment growth in Europe: The roles of innovation, local job multipliers and institutions.
Goos, M., Manning, A., Salomons, A., 2014. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. American Economic Review 104, 2509–2526. doi:10.1257/aer.104.8.2509
Goos, M., Manning, A., Salomons, A., 2009. Job polarization in Europe. The American Economic Review 99, 58–63.
Graetz, G., 2015. Rise of the machines: The effects of labor-saving innovations on jobs and wages. IZA DP No. 8836
Graetz, G and Guy Michaels, 2015 Robots at Work, Centre for Economic Performance discussion paper No 1335
Greenan, Nathalie and Dominique Guellec. (2000): "Technological Innovation and Employment Reallocation." Labour 14, 547-590.
Gregory, T., Salomons, A., Zierahn, U., 2016. Racing with or against the machine? Evidence from Europe.
Gujurati, D and Dawn Porter, 2009, Basic Econometrics, 5th Edition
Handel, M.J., 2012. Trends in Job Skill Demands in OECD Countries (OECD Social, Employment and Migration Working Papers No. 143). doi:10.1787/5k8zk8pcq6td-en
Handel, M.J., 2008. Measuring job content: skills, technology, and management practices. University of Wisconsin-Madison, Institute for Research on Poverty.
Hemous, David and Morten Olsen, 2016, The Rise of the Machines: Automation, Horizontal Innovation and Income Inequality, 014 Meeting Papers 162, Society for Economic Dynamics. <https://ideas.repec.org/p/red/sed014/162.html>
Holzer, H., 2015. Job market polarization and US worker skills: A tale of two middles. Economic Studies, The Brookings Institution.
Ikenaga, T. (2009) Polarization of the Japanese Labor Market: The Adoption of IT and Changes in Task Contents]," The Japanese Journal of Labour Studies 584, 73-90.

International Federation of Robotics (IFR), 2017. The Impact of Robots on Productivity, Employment and Jobs. A Positioning paper by the International Federation of Robotics
International Patent Classification, 8th Edition, 2006, World Intellectual Property Organization (WIPO)
Kalmbach, Peter and Heinz D. Kurz. "Micro-Electronics and Employment: A Dynamic Input-Output Study of the West-German Economy." Structural Change and Economic Dynamics 1, 2 (1990): 371-386.
Karamanis, K., Triarchi, E., Pappa, P., 2016. Market Liberalization in a Small Open Economy and Its Impact on Employment Characteristics. Strategic Change 25, 361–369. doi:10.1002/jsc.2068
Kiernan, Peter D. 2015 American Mojo: Lost and Found: Restoring our Middle Class Before the World Blows By. Nashville, TN: Turner Publishing Company.
Keisner, A., Raffo, J., Wunsch-Vincent, S., others, 2015. Breakthrough technologies-Robotics, innovation and intellectual property. World Intellectual Property Organization-Economics and Statistics Division.
Keynes, J.M., 1930 (1991). Economic possibilities for our grandchildren. Entropy Conservationists.
Kondratieff, N. D. 1979. The long wave in economic life, Review vol. 11, no. 4. The original translation can be found in Review of Economic Statistics, vol. XVII, no. 6. The Russian version was first published in 1925.
Korsten, J., Lintsen, H., Schot, J., 2015. Technologie en werkgelegenheid in historisch perspectief.
Kuznets, S., 1940. Schumpeter's business cycles. The American Economic Review 257–271.
Lachenmaier, S., Rottmann, H., 2011. Effects of innovation on employment: A dynamic panel analysis. International Journal of Industrial Organization 29, 210–220. doi:10.1016/j.ijindorg.2010.05.004
Larson, Q., 2017. A warning from Bill Gates, Elon Musk, and Stephen Hawking [WWW Document]. freeCodeCamp. URL https://medium.freecodecamp.com/bill-gates-and-elon-musk-just-warned-us-about-the-one-thing-politicians-are-too-scared-to-talk-8db9815fd398 (accessed 5.23.17).
Layard, R and Stephen Nickell. 1985 "The Causes of British Unemployment." National Institute Economic Review 111, 1 62-85.
Lee, J. 2015, "Measuring Agglomeration: Products, People, and Ideas in US Manufacturing", pp. 1880-1990, Mime
Levy, F and Richard J. Murnane (2005) Why people still matter, Chapter 2 of "The new division of labor: How computers are creating the next Job market",
Lin, J., 2009 (2011) Technological adaptation, cities, and new work. Review of Economics and Statistics 93, 554–574.
Maeda, I., Yugami, K., 2016. The Impacts of Technical Change on Labour Markets in Europe and Japan.
Marx, Karl. Capital. Moscow: Foreign Languages Publishing House, [1867] 1961.
McAfee, A and Erik Brynjolfsson, 2014, The Second Machine Age: Work Progress and Prosperity in a Time of Brilliant Technologies, W.W. Norton & Company.
McKinsey Global Institute. 2011. An Economy that works: Job creation and America's future
McKinsey Global Institute. 2017. A Future That Works: Automation, Employment and Productivity
Meissner, D., Kotsemir, M., 2016. Conceptualizing the innovation process towards the "active innovation paradigm"—trends and outlook. Journal of Innovation and Entrepreneurship 5. doi:10.1186/s13731-016-0042-z
Meyer-Krahmer, Frieder. 1992: "The Effects of New Technologies on Employment." Economics of Innovation and New Technology 2, 1 131-149.
Michaels, G., 2015. CEP Discussion Paper No 1335 March 2015 Robots at Work Georg Graetz.
Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. Review of Economics and Statistics 96, 60–77. doi:10.1162/REST_a_00366
Mira d'Ercole, M. 2014. The middle class: Who are they, where did they go, and why does it matter? Presentation at the Decline of the Middle Classes around the World? APPAM 2014 International Conference, Segovia, Spain
Mokyr, J., Vickers, C., Ziebarth, N.L., 2015. The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? Journal of Economic Perspectives 29, 31–50. doi:10.1257/jep.29.3.31
Moravec H, 1988, Mind Children: The future of robot and Humand intelligence,
Mortensen, D.T., Pissarides, C.A., 1998. Technological progress, job creation, and job destruction. Review of Economic dynamics 1, 733–753.
Nickell, S, 1981, Biases in Dynamic Models with Fixed Effects, *Econometrica*, 49, issue 6, p. 1417-26
Nilsson, N.J., 1984. Artificial intelligence, employment, and income. AI magazine 5, 5.
Nolan, B. 2014. The middle class: Who are they, where did they go, and why does it matter? Presentation at the Decline of the Middle Classes around the World? APPAM 2014

International Conference, Segovia, Spain.
Nordhaus, W.D., 2007. Two centuries of productivity growth in computing. The Journal of Economic History 67, 128–159.
OECD Labour Force Statistics, 2017, Trade Union Density [WWW Document], n.d. URL https://stats.oecd.org/Index.aspx?DataSetCode=UN_DEN (accessed 4.6.17).
Page, M., New Zealand, Statistics New Zealand, 2010. Annual measures of job creation and destruction in New Zealand using linked employer-employee data. Statistics New Zealand, Wellington, N.Z.
Pajarinen, Mika & Rouvinen, Petri (13.1.2014). "Computerization Threatens One Third of Finnish Employment". ETLA Brief No 22. http://pub.etla.fi/ETLA-Muistio-Brief-22.pdf
Perez, C, 2006, Re-specialization and the deployment of the ICT paradigm – an essay on the present challenges of globalization. Published in "The Future of the information soeicty in Europe: Contributions to Debate. By R Compañó, C Pascu, A Bianchi, J-C Burgelman, S Barrios, M Ulbrich and I Maghiros. Institute for Prospective Technological Studies
Perez, C. (Ed.), 2008. A Vision for Latin America: A resource-based strategy for technological dynamism and social inclusion, 1. ed. ed, Innovación y desarrollo. Universidad Autónoma Metropolitana : Adiat : M.A. Prrúa, México.
Pianta, M., 2005. Innovation and employment. Chapter 1 of Fagerberg /The Oxford Handbook of Innovation,
Piketty, Thomas, Capital in the 21st Century, Harvard University Press, 2014. Technical appendix available on-line at http://piketty.pse.ens.fr/capital21c.
Piketty, T., Saez, E., 2003. Vol. CXVIII February 2003 Issue. Technology 1.
Piva M, E. Santarelli and M. Vivarelli, 2003. "The Skill Bias Effect of Technological and Organizational Change: Evidence and Policy Implications" Working papers 486
Piva, M., Vivarelli, M., 2005. Innovation and Employment: Evidence from Italian Microdata. Journal of Economics - Zeitschrift für Nationalökonomie 86, 65–83. doi:10.1007/s00712-005-0140-z
Pressman, S., 2015. Defining and Measuring the Middle Class. American Institute for Economic Research, Working paper 007
Putnam, Robert D. 2015. *Our Kids: The American Dream in Crisis*. New York, NY: Simon & Schuster.
PwC. 2014. The New Hire: How a New Generation of Robots is Transforming Manufacturing.
PwC. 2016. Upskilling manufacturing: How technology is disrupting America's industrial labor force. Price Waterhouse Coopers in conjunction with the Manufacturing Institute.
Rayner, S., Malone, E.L., 1998. Human choice and climate change: an international assessment. Citeseer.
Rifkin, J. The End of Work, p1. 1995
Roadmap for US Robotics From Internet to Robotics, 2016 Edition 11.07.2016, Variety of American Universities.
Roodman, D., 2006. How to do xtabond2: An introduction to difference and system GMM in Stata.
Roy, R., Sarkar, M., 2016. Knowledge, firm boundaries, and innovation: Mitigating the incumbent's curse during radical technological change: Mitigating Incumbent's Curse During Radical Discontinuity. Strategic Management Journal 37, 835–854. doi:10.1002/smj.2357
Sachs, J.D., Kotlikoff, L.J., 2012. Smart machines and long-term misery. National Bureau of Economic Research.
Schumpeter, J. A. (1934). The Theory of Economic Development. Cambridge Mass.: Harvard Economic Studies.
Smith, A., Janna, erson, 2014. AI, Robotics, and the Future of Jobs. Pew Research Center: Internet, Science & Tech.
State, B., Rodriguez, M., Helbing, D., Zagheni, E., n.d. Highly skilled immigrants are losing interest in the United States: LinkedIn data.
Schön, L. 1998, Industrial Crises in a Model of Long Cycles; Sweden in an International Perspective, in Myllyntaus, T. (ed), Economic Crises and Restructuring in History. Scripta Mercaturae Verlag, Katharinen.
Schön, L. 2009. Technological Waves and Economic Growth - Sweden in an International Perspective 1850-2005. (Circle Electronic Working Paper series; Vol. 6). CIRCLE, Lund University.
Stewart, De and Cole (2015), Technology and People: The great job-creating machine, Deloitte LLP,
Tarnawska, K., Mavroeidis, V., 2015. Efficiency of the knowledge triangle policy in the EU member states: DEA approach. Triple Helix 2. doi:10.1186/s40604-015-0028-z
The Changing Task Composition of the US Labor Market: An Update of Autor, Levy and Murnane (2003)*, n.d.
The onrushing wave [WWW Document], n.d. . The Economist. URL http://www.economist.com/news/briefing/21594264-previous-technological-innovation-has-always-delivered-more-long-run-employment-not-less (accessed 3.20.17).

Upper, I.D., Wage, L.-T., 2006. The Polarization of the US Labor Market, in: Papers and Proceedings of the Annual Meeting. American Economic Association., p. 189.
United Kingdom's Intellectual Property Office Informatics Team, 2014, "Eight Great Technologies – Robotics and Autonomous Systems, A Patent Overview, Intellectual Property Office Concept House Cardiff Road Newport NP10 8QQ United Kingdom
U.S. Robotics, 2016 " A Roadmap for US Robotics, From Internet to Robotics"
Van Leeuwen, M.H., Maas, I., Miles, A., 2004. Creating a historical international standard classification of occupations an exercise in multinational interdisciplinary cooperation. Historical Methods: A Journal of Quantitative and Interdisciplinary History 37, 186–197.
Van Roy, V., Vertesy, D., Vivarelli, M., others, 2015. The Employment Impact of Innovation: Evidence from European Patenting Companies. Università Cattolica del Sacro Cuore, Dipartimenti e Istituti di Scienze Economiche (DISCE).
Violante, G.L., 2008. Skill-biased technical change. The New Palgrave Dictionary of Economics, 2nd Edition
Vivarelli, M., 2014. Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature. Journal of Economic Issues 48, 123–154. doi:10.2753/JEI0021-3624480106
World Economic Forum (2016), The future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution. Globacl Challenge Insight Report
World Intellectual Property Report (2015), Breakthrough Innovation and Economic Growth, Economics and Statistics Series
Yang, C and C A. Lin (2008), Developing Employment Effects of Innovations: Microeconometric Evidence from Taiwan, *Developing Economies*, Vol. 46, No. 2, pp. 109-134.
50 Years of Moore's Law [WWW Document], n.d. . Intel. URL http://www.intel.com/content/www/us/en/silicon-innovations/moores-law-technology.html (accessed 5.16.17)

# 8. Appendix:

| | |
|---|---|
| G05D 1/02 | Control of position, course or altitude of land, water, air, or space vehicles, e.g. automatic pilot: Control of position or course in two dimensions |
| G08G 1/16 | Traffic control systems for road vehicles (arrangement of road signs or traffic signals: Anti-collision systems - road vehicle drive control systems for predicting or avoiding probable or impending collision otherwise than by control of a particular sub-unit |
| B60W 30/00 | Purposes of road vehicle drive control systems not related to the control of a particular sub-unit, e.g. of systems using conjoint control of vehicle sub-units, { or advanced driver assistance systems for ensuring comfort, stability and safety or drive control systems for propelling or retarding the vehicle |
| B60W 10/06 | Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle: including control of propulsion units |
| B25J 9/16 | Programme-controlled manipulators: Programme Controls |
| B60W 10/04 | Conjoint control of vehicle sub-units of different type or different function for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle: including control of propulsion units |
| B60W 10/18 | Conjoint control of vehicle sub-units of different type or different function for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle: including control of braking systems |

| | |
|---|---|
| B60W 30/18 | Purposes of road vehicle drive control systems not related to the control of a particular sub-unit, e.g. of systems using conjoint control of vehicle sub-units: Propelling the vehicle |
| B60R 21/00 | Arrangements or fittings on vehicles for protecting or preventing injuries to occupants or pedestrians in case of accidents or other traffic risks |
| B60W 10/10 | Conjoint control of vehicle sub-units of different type or different function (...)(for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle: including control of change-speed gearings |

**Table 6: Robotics patents – IPC categories**

Source; United Kingdom's Intellectual Property Office, 2014