Hacettepe University Graduate School of Social Sciences

Department of Economics

ROBOTS AND HUMAN LABOR: DYNAMICS, INTERGENERATIONAL IMPACTS AND INEQUALITY

Aslı AYDIN

Ph.D Dissertation

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ABSTRACT

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In today's world, where the use of robots in production processes is increasing, future predictions about human labor constitute an important research subject. In this dissertation, the implications of rising robots on labor markets are observed. For this purpose the effect of robots on human labor is investigated through theoretical and empirical estimation methods. The first chapter illustrates a two-period overlapping generations framework, including robots, human labor and physical capital in the production process. Our model is consistent with labor-saving or labor-replacing impact of robotics and the OLG dynamics indicatea negative impact of robots on employment. Chapter 2 addresses the empirical investigation of the robotic impact on employment. We use novel panel datafor 47 countries over the period 2004-2016 to test the employment impact of robot-usage. Our SYS-GMM estimates show that each additional robot usage leads a 0.7 percent drop in employment for selected countries. The magnitude of employment impact of robots becomeshigher in high-income countries that each robot increase causes 3.1 percent drop in employment rate. The impact of robots on heterogeneous labor market is investigated in chapter 3. Heterogeneity is observed among four different age groups and gender classifications.Regarding the analyses based on age groups, dynamic panel data estimation provides empirical evidence that most negatively affected group is young people under the age of 25. In addition, while the least negatively affected group is the oldest group, the middle age group is found to be positively affected. Regarding to age group classification, results support the skill-biased technological change (SBTC) hypothesis in which different skill groups diverge against robotic impacts. The results also indicate that robots are more unfavorable to men workers. This situation is explained conceptually withtask-biased technological change(TBTC), as a result of the fact that male employees are quantitatively more involved in routine jobs than women.

Key Words: Robots, Employment, Overlapping Generations Model, System GMM, Inequality, Gender

ÖZET

AYDIN, Aslı. *Robotlar ve insan emeği: dinamikler, nesiller arası etkiler ve eşitsizlik*, Doktora tezi, Ankara, 2020

Üretim süreçlerinde robot kullanımının hızla arttığı günümüz dünyasında, insanemeğineilişkingeleceğeyöneliktahminlerönemlibiraraştırmakonusunuoluşturmaktadır. Bu tezde, kullanımı yaygınlaşmakta olan robotların işgücü piyasaları üzerindeki etkileri gözlemlenmekte; bu amaçla robotların insan emeği üzerindeki etkisi teorik ve ampirik tahmin yöntemleriyle araştırılmaktadır. İlk bölümde ücret üzerindeki etkiler, robotların, insan emeğinin ve fiziki sermayenin dahil edildiği iki dönemli ardışık nesiller büyüme modeli üzerinden analiz edilmekte, emek üzerindeki olası etkileri tartışılmaktadır. Elde edilen analitik sonuç, robotların emek tasarrufu sağlayan etkisine yönelik görüşleri desteklemekte, istihdam üzerindeki olumsuz etkisini göstermektedir. İkinci bölüm, istihdam üzerindeki robotik etkinin ampirik yöntem ile incelenmesine ayrılmıştır. Robot kullanımının istihdam etkisini test etmek için 2004-2016 dönem aralığında 47 ülke üzerinden yeni panel verileri kullanılmıştır. Sistem Genelleştirilmiş Momentler Metodunun (SYS-GMM) tahminlemesi sonucu elde edilen bulgular, her bir birimlik robot artışı sonucunda toplam istihdam oranında yüzde 0.7 düşüş yaşandığını ortaya koymaktadır. Yüksek gelir gurubundaki ülkeler için bu etki daha olumsuzdur; ilave her robot artışının istihdam oranında neden olduğu kayıp yüzde 3.1 olarak saptanmıştır. Robotların heterojen işgücü piyasası üzerindeki etkisi üçüncü bölümde incelenmiştir. Heterojenlik, dört farklı yaş grubu ve cinsiyet sınıflandırması üzerinden gözlemlenmektedir. Yaş guruplarına dayalı yapılan dinamik panel veriye yönelik ampirik analizlerde robotlardan en olumsuz etkilenen gurubun 25 yaş altı genç çalışanlar olduğu sonucuna ulaşılmıştır. Bunun yanı sıra, göreceli olarak en az olumsuz etkilenen gurup emekliliğe en yakın olan çalışanlara ait olurken, orta yaş olarak adlandırılabilecek çalışanlar robotlardan olumlu yönde etkilenmektedir. Yaş guruplarına yönelik yapılan analiz sonucu elde edilen ampirik kanıtlar, robotların farklı becerilere

sahip çalışanlar üzerinde farklı etkilerini savunan vasıf-yanlı teknolojik değişim (Skill-Biased Technological Change, SBTC) hipotezlerini desteklemektedir. Ayrıca elde edilen sonuçlara göre robotların olumsuz etkisine erkek çalışanlar daha fazla maruz kalmaktadır. Elde edilen bu bulgu, görev-yanlı teknolojik değişim (Task-Biased Technological Change, TBTC) tezi ile de uyumluluk göstermekte; erkek çalışanların daha olumsuz etkilenmeleri, kadın çalışanlara göre daha fazla rutin işlerde çalışmasının bir sonucu olarak açıklanmaktadır.

AnahtarKelimeler: Robotlar, İstihdam, Ardışık Nesiller Büyüme Modeli, Sistem-GMM, Gelir ve cinsiyet eşitsizliği.

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ABBREVIATIONS

OLG	: Overlapping Generations
SYS-GMM	: System Generalized Method of Moments
SBTC	: Skill-biased technological change
TBTC	: Task-Biased Technological Change
IR1	: The First Industrial Revolution
IR2	: The Second Industrial Revolution
IR3	: The Third Industrial Revolution
OECD	: The Organization for Economic Co-operation & Development
OLS	: Ordinary Least Square
FE	: Fixed Effect
GDP	: Gross Domestic Product
TÜBİTAK	: The Scientific and Technological Research Council of Turkey
UNDP	: The United Nations Development Programme
UN	: The United Nations
ICT	: Information and Communications Technology
IMF	: The International Monetary Fund
AI	: Artificial Intelligence

IoT	: Internet of Things
3D	: Three-dimensional
IFR	: The International Federation of Robotics
WB	: The World Bank
ETC	: Embodied Technological Change
CES	: Constant Elasticity of Substitution
R&D	: Research and Development
EU	: European Union
ISO	: International Organization for Standardization
PPP	: Purchasing Power Parity
PWT	: Penn World Tab

INTRODUCTION

The relationship between the rapid technological progress and employment constitutes an important contradiction of our century, such as in urbanization, climate change, impoverishment and income inequality. In the near future, all these conflicts will be inevitably more threatening issues to be solved by humanity. In this conjecture, the emerging trend of digitalization and automation is seen as a paradigm shift, which is escalating by the driving forces such as falling productivity gains and high transaction costs. This thesis focuses on the future of employment, in quantitative and demographic aspects, which is under the risk of accelerating robotization.

For a long time in history, technology plays an important role for wellbeing. For centuries, human beings have succeeded in transforming the opportunities offered by nature to their own benefits by the help of scientific activitiesfed by curiosity and skills. Making first tools from stone, wood, antlers, and bones, discovering fire, beginnings of human settlements and agriculture, inventing the wheel, starting to use language, inventing printing press and astronomical discoveries are such ancient inventions which had contributed to the sustainability of human life.

Although human beings invented machines to do their own work a very long time ago, recently invented robots reveal a new milestone in a history. Because, in the words of Richard Baldwin, as they are beyond a machine, so-called *"remote intelligence"*, and thus no longer just complementary to human labor (Baldwin, 2017).

I. An Inevitable Historical Debate: Technological Anxiety

Since the First Industrial Revolution (IR1) automation, as a general-purpose technology which brings the transformative side of technology in front, has been affecting life in every aspect. IR1 arose with the use of machinery instead of human labor in the production process, especially with the use of the steam engine. While it acts as an engine of productivity, it also raises a broad debate due to the fact that it replaces human labor in the production process. With the Second Industrial Revolution (IR2), the electricity adoption takes place as well as the significant manufacturing technologies such as assemblyline, and major developments in infrastructure. In the stage of the Third Industrial Revolution (IR3), robots and computers have become a part of daily life. When all these technological milestones areconsidered, it is seen that every technological revolution re-delegates the tasks created by the previous onebetween human labor and machinery. For example, as agricultural works aremechanized, human labor gathersin factories; as communication technologies evolvesand manufacturing becomesmore automated, workers startto shift to the service sector from factories. Hence the result of the interplay between machines and human labor throughout the history has been determined by the balance between the jobs destroyed and the jobs created by the technology.

That's why technology-anxiety or in other words technology-driven unemployment is not a new concern; since the Luddites movement[1] (Mokyr and Ziebarth, 2015) there has been growing fear that technological advances, in particular automation, will replace human labor and take over the jobs.

In the article of *The Economic Possibilities for Our Grandchildren*, John Maynard Keynes also expresses his concern as follows:

We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come--namely, technological unemployment. This means unemployment due to our discovery of means of economising the use of labor outrunning the pace at which we can find new uses for labor. But this is only a temporary phase of maladjustment. All this means in the long run that mankind is solving its economic problem. (Keynes, 1930)

1

This debate continues with Wassily Leontief. Leontief (1983) argues that machines will replace human labor, just as machines replaced horses in the early 20th century, and new industries will not be sufficient to employ anyone looking for a job.

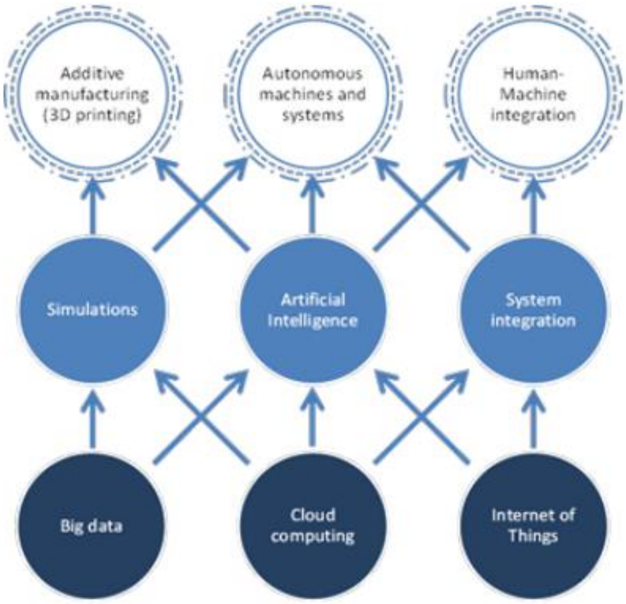
On the other hand, in Marxist thought, which claims that the only source of profit is a surplus value, robots can be found to have the power to end capitalism (Marx, 1973).According to Marx, increasing the productive power of labor and thus increasing the surplus value is the tendency of capital.Mechanization is such a dynamic that is developed as a result of this trend.He claims that through mechanization, that is, automation, labor loses control over production processes and becomes part of fixed capital. Also this brings the accelerating alienation process. Marx continues with the words: ‘The rising of automation is a consequence of falling profit rates’ and indicates that an increase in labor productivity due to automation would cause an increase in organic composition of capital (C/V) that leads to a reduction in exploitation rates (Marx, 1973). This reveals a crisis of capitalism explained by the factor of automation.

In the Schumpeterian perspective, there is an argument that an increasing number of robots will lead to the production of new products and create new markets, and as a result, these new markets will create their own demands and jobs. The replacement of this new production system with the old takes place in a process that Schumpeter refers to as 'creative destruction'. Here, those who cannot keep up with the new have no chance but to lose and disappear, and only the adaptive ones will be winners of this process(Schumpeter, 1939).

II: Current Trends in Digital Technologies and Robots

With the spread of digital technologies, the ongoing technological concern has been fueled again, and it has also initiated a series of studies on the effects of next-generation technologies such as Information and Communication Technologies (ICT), robots, Artificial Intelligence (AI) and the Internet of Things (IoT) on human labor. Looking at the common point of these technologies, it is noteworthy that they can perform not only routine tasks but also complex tasks and cognitive skills.More recently, the arrival of 3D printing, self-driving cars (Tesla, Apple, Google), agricultural manufacturing and domestic robots has again raised a widespread interest into the possibility of massive 'technological unemployment' (Pellegrino, Vivarelli and Piva, 2017).

Figure 1. Smart Technologies



Source: OECD (2017a)

Since UNIVAC I, which is the first commercial computer designed to predict the 1952 US election results, computers have taken away most of the computing and decision-making tasks from human labor. The progress of computer technology, which is widely used in all areas of the industry and in the services sector, continued with ICT technology. Nowadays the ICT sector represents 6% of GDP of the OECD member countries (UNDP, 2017). Table 1.1 lists the countries with top ICT scores in investment and employment. Recently, the United States, New Zealand and Switzerland are the three countries holding the leadership in ICT investments.As of 2010 the United States, which ranks first, allocates 32% of its total investments to the ICT sector.

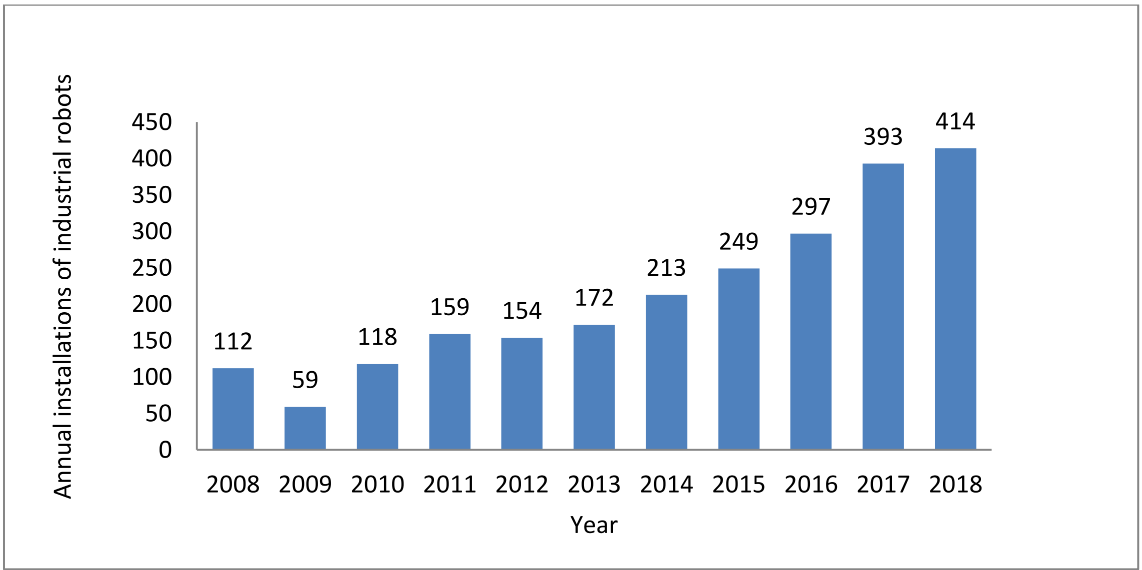
Table 1. Countries with highest ICT score

	ICT Investment (% of total, 2010)	Employment (% of total, 2011)
Unites States	32.14	3.80
New Zealand	21.24	N/A
Switzerland	18.51	5.36
Canada	17.02	2.61
Finland	15.52	6.43
Spain	13.76	2.66
Germany	12.69	3.94
Ireland	12.41	5.25
Italy	11.03	3.15
Korea	10.72	9.50

The current stage of rapidly advancing technology is defined by products such as simulation, AI and smart systems, sensors, augmented reality, IoT, robot and automation, contribution production, big data analysis, cyber security and cloud computing (TUBITAK, 2020). All these technologies, which we can further diversify, have one thing in common: they use information as the primary source of input, so they can do a lot more than humans can do by producing a lot of output without tiring once they have the knowledge. Therefore, these technologies present "creative destruction", in Schumpeter's words, in all of their production and consumption processes.

Although the world is at the beginning of the adaptation of digital technologies and smart technologies, the widespread acceleration of these technologies in the last few years puts these technologies at the center of global attention.The transformation in the composition of top 20 firms in the world makes this attraction more visible. In 2009, the world's 20 largest companies were oil-gas and mining companies. In 2018, the 20 largest companies are technology companies (UNCTAD, 2019). On the other hand, OECD (2016) finds that the amount of investments in private equity exclusively for AI[2] start-ups increased by 3% from 2011 to 2018, and in the first half of 2018, AI start-ups attracted nearly 12% of private equity investments in the world. As a sub-segment of digital technologies[3], robots attract more and more public and private investments each year. The World Robotics Report 2019, published by International Federation of Robotics (IFR), shows that more than 2.4 million robots are operating in factories worldwide today. In 2018 alone, 422,000 new robots were introduced, with a 6% increase compared to 2017. 30% of the total robots are used in the automotive industry, 25% in the electrical & electronics industry and 10% in the metal industry. According to IFR, 3 million robots (An increase of 14% compared to 2017) are expected to be employed in 2020 worldwide. And from 2020 to 2022, 2 million additional robots are expected to be loaded only at the factories worldwide (IFR, 2020).

Figure 2. Annual installations of industrial robots; the case of Asia, Australia, Europe, and US



[2]Artificial Intelligence (AI) is defined as "*Machine based system that can, for a given set of human defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy*" (OECD, 2019).

[3]Other sub-segments are sorted as follows: The Internet Of Things (IoT), Cloud Computing, Photonics and light technologies, Blockchain, Modeling simulation and gaming, Quantum computing, Big data analytics, Artificial intelligence (AI) (OECD, 2016)

The key factor that distinguishes robots from other automation technologies is the ability to perform many human skills at a higher efficiency and lower costs. The UN makes a clear distinction between automation and robotics: "*To illustrate the difference, once might refer to the distinction between software and hardware. Robots are programmable machines which are able to carry out a series of actions autonomously, or semi-autonomously. They interact with the physical world via sensors and actuators. Because they are reprogrammable, they are more flexible than single-function machines. Automation can be software automation or industrial automation. The latter is about controlling physical processes: using control systems or physical machines to automate tasks within an industrial process. A fully autonomous factory would be an extreme example" (Technological Change and The Future of Jobs, 2018 pp.10).*

Over and above, robots are well developed, complex and intelligent machines such that it revives as a return of a new species in the human mind. The ability of the robots, previously limited by the 'imitation game' by Turing (1950), has already gone beyond imitation. Thanks to humanoid robots, which are designed in a similar way to the physical characteristics of human beings, robots look like us, speak like us and now thanks to AI and Machine Learning software they containthese machines have started to think like us.Contrary to the argument of Turing (1950), these machines have ability to think uniquely rather than imitating human thinking-process. Although this smart robots are sometimes the subject of a utopia, and sometimes of a dystopia, today's rapidly evolving automation trends show that in the end robots are attractive investment area with all its cost and profit opportunities and time-saving advantages. They are indeed much more predictable than humans; they are pre-programmed to perform repetitive and also cognitive tasks with an endless effort. Furthermore, they are tempted to carry out highly dangerous activities for human beings. For example, without robots, the lives of people would be endangered today to observe Mars; or by using robots as fire workers, as saving people from fire would not be a job for humans as well as using them at welding tasks which requires working under extremely hot temperatures.

Describing robots only by the threats they pose to humankind, as well as describing them as a salvation would both be misleading. The question that needs to be discussed is whether there is a social and industrial development that is compatible with the adaptation of robots.During the period called the 'Golden Age' after two decades of the World War II, the effect of the technology used in production on the welfare of the workerswas quite strong. During this period, with the widespread use of industrial machinery productivity increased, which was also reflected in workers' wages and consequently their consumption demands (Glyn et al., 1988). After the 1970s, the relationship between productivity gains and workers' wages began to deteriorate.For example, according to US data, average workers' wages fall by 13% after the inflation adjustment, although productivity increased by 107% in 2013 compared to the early 1970s (Ford, 2015). In addition, US statistics show that job growth fell from 31% in the 1960s to 27% in the 1970s and 20% in the 1980s and 1990s.In this downward trend, when it comes to the 2000s, it is seen that the first 10 years of job growth is 0 (Irwin, 2010). Also income inequality has been increasing in most parts of the world, including most industrialized countries, since the 1980s (Berg, 2015). Thus, looking at today, it is expected that the spread of robots in a period of high unemployment and inequality all over the world, would have considerable negative consequences.

Thus, new robotic technology products compete with human labor in almost every field today. Digital supply network has created the ‘dark factories’, in which there is no light and no human intervention needed for manufacturing production due to the full automation. Moreover, robots can move digitally in a networked connection; that is, they can communicate and decide among themselves. This digital connectivity, so called “OPC Robotics Companion Specification”, offers an environment that completely excludes the human factor in the industry (IFR, 2019). In the healthcare sector, robots are widely used in almost every field such as orthopedics, urology, general surgery, gynecology, neurology, thoracic, otolaryngology, bariatric, rectal and colon, multiple oncologic fields – even dental and hair transplants (Smith, 2019). Specifically surgical robots, also named as Surgeon Waldo, are one of the most popular robots because they eliminate human error that may occur due to fatigue, stress, excitement etc. Moreover, in addition to these examples, social robots used in education, robots in transportation, restaurants, bars, and even hotels show that robots are running aggressively in this competition.

III. Understanding Inside of Robots: The evolution of robots

In previous traditional models, perception-cognition-action is the basic functioning cycle of information processes. Robots are designed based on this cycle autonomously, but in a more interactive way. Simple robots were commanded by humans by remote control. They were machines that did not have flexibility and could only move within the limits of human commands. Then, "smart robots" closer to today's technology were invented. When given a task, a robot is capable of acting based on a perception and based on this action it can develop a new perception.

Every experience provides understanding and learning. As a result, the robot is made to decide in this way. Scholars call this technique “Machine Learning”. Computerizing a learning process dates back to the 1950s. The first well known study is a learning program to play checkers developed by Arthur Samuel in 1952 for IBM Company. Checkers were chosen for the most primitive machine learning system because it was an easier game than chess. The probability and the number of strategies were less than that of chess. Therefore, it is not surprising that the development in machine learning will continue through the chess game in the following years. In 1996, the smart robot called Deep Blue defeated Garry Kasparov, who is known as a chess grandmaster of our time.

In the following years, robots, which produce strategies with big data, algorithms and complex mathematics, and can decide on their actions without human intervention began to learn how to work in a collective way. In 1997 a soccer playing robot, which is called RoboCup was established. One of the aims of the project was building a robot that can win the human world championship in 2050. But the main motivation was the establishment of a robot that acts, plays and thinks just like humans. In a next step, this project was improved towards the RoboCupSoccer, so that the robots could collectively and fully, autonomously achieve the goal given to them, which is to defeat humans and to win the match.

The development of the first humanoid robot goes back to the 2000s. ASIMO as an acronym for “Advanced Step in Innovative Mobility”, which emerged as a result of a project carried out by Honda, was named in memory of Isaac Asimov. It is a robot that traces all moving objects around it, hears the sounds and can decide the distance between the objects by having visual information with the cameras placed inside it (Eaton, 2015).

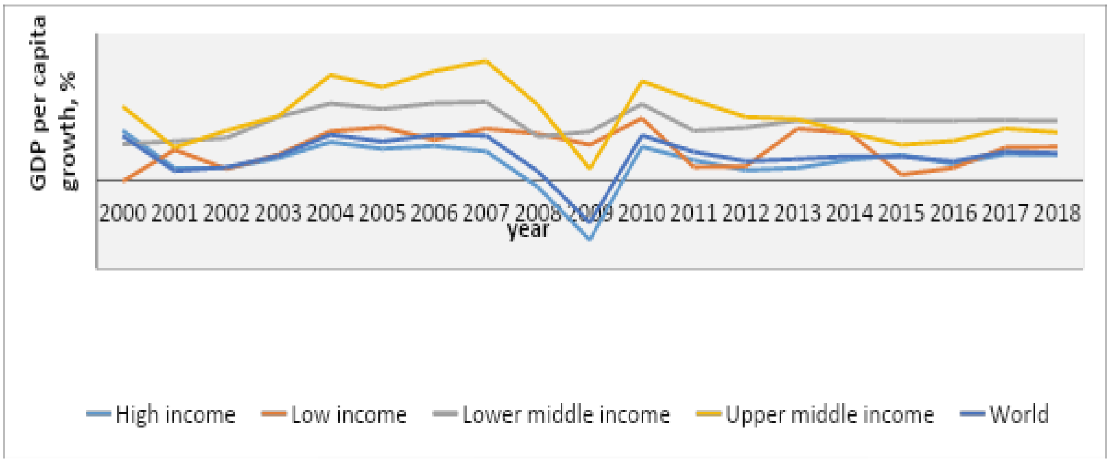
In all areas of the economy, robots undoubtedly offer great productivity opportunities with their capabilities and flexible technological features. As the use of robots becomes widespread, the price becomes cheaper, and this trend reveals 'dark factories'. As a one of the dark factories, in Philips' electric razor production plant in Netherlands each robot undertakes nine workers’ task alone (Tilley, 2017)

IV. General Views on Employment

The crash in the real economy in 2009, after the 2008 financial crisis, caused a significant drop in growth rates. This negative growth revealed the severe economic contraction that occurred after the 1929 Great Depression. Recovery strategies were implemented after the crisis, largely based on monetary expansion. Despite the improvement in the growth rates of the world economy in 2010, a decrease occurred again after 2011 and an L-type growth was experienced in the world economy. Kristalina Georgieva, the President of the IMF, described the state of the world economy as 'synchronous slowdown' at the end of 2019.

In the analysis to be made according to the country income groups, defined according to the World Bank classification, it is observed that the strongest decline in 2009 occurred in high income countries. GDP per capita has decreased there below the world average. The contraction in upper middle income countries was gradual, and the trend in GDP per capita growth fell below the lower middle income countries.

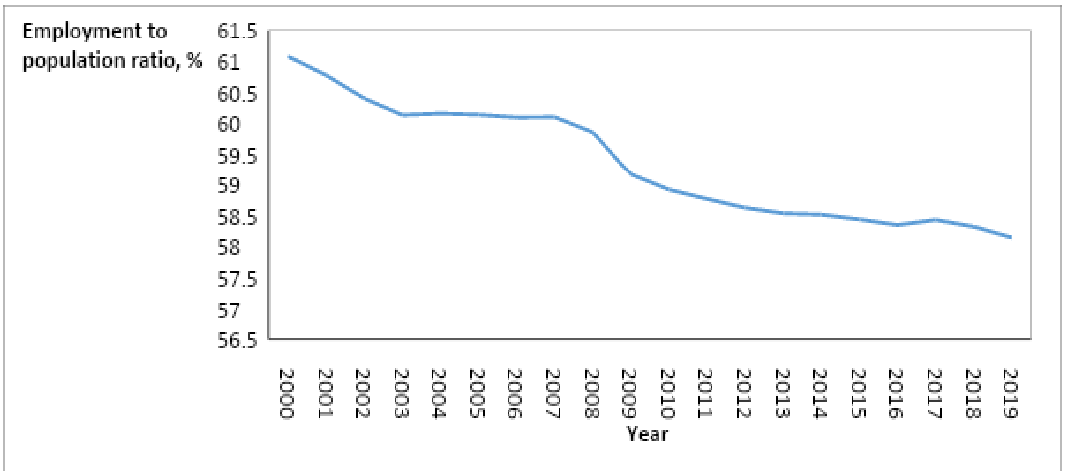
Figure 3. GDP per capita growth (annual %)



Source: World Bank Indicators, 2020

So how do employment rates accompany today's global synchronized slowdown? Worldwide employment-to-population ratio has been steadily declining since 2000. World employment-to-population ratio, which was 61.1% in 2000, dropped to 59.9 %% in 2008, then 58.8% in 2010, 58.3% in 2016 and 58.1% in 2019.

Figure 4. Employment-to-population ratio, 15+, total (%), World



Source: World Bank Indicators, 2020

In terms of income groups, employment in high income countries after 2013 shows a return to pre-2008 levels until 2018. But in 2019, the trend has turned its direction downwards again. For the upper-middle income countries, there has been a downward trend since 2000. While the employment-to-population ratio was 65.43% in 2000 for this country group, it was 60.30% in 2019. A downtrend prevails in the lower income countries. Although it fluctuated in some years (2004, 2005), the downward trend still remains between 2000 and 2019, employment-to-population ratio decreased from 57.04% to 54.28% in this period. Also the same downward trend is observed for lower income countries, although minor increases are observed in 2016 and 2017. The employment-to-population ratio in the four income groups in 2019 is as follows: for high income countries it is 57.33%; for upper-middle income countries it is 60.30%; for lower-middle income countries it is 54.28%; for lower income countries it is 68.95%.

Figure 5. Employment to population ratio, 15+, total (%), High income countries

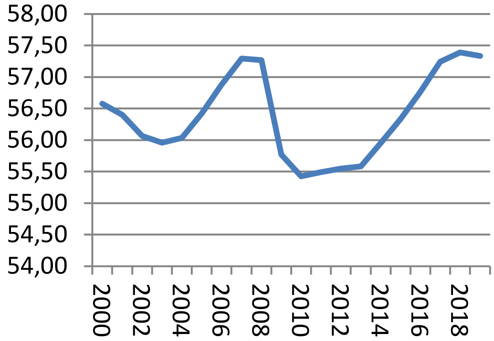


Figure 6. Employment to population ratio, 15+, total (%), Upper middle income

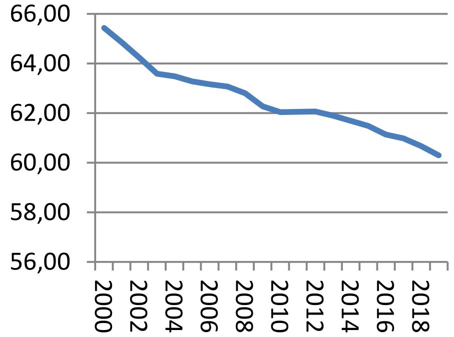


Figure 7. Employment to population ratio, 15+, total (%), Low income

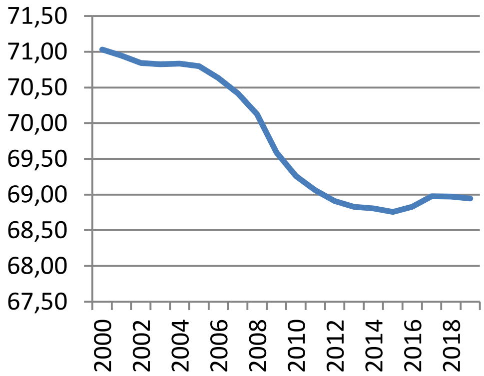
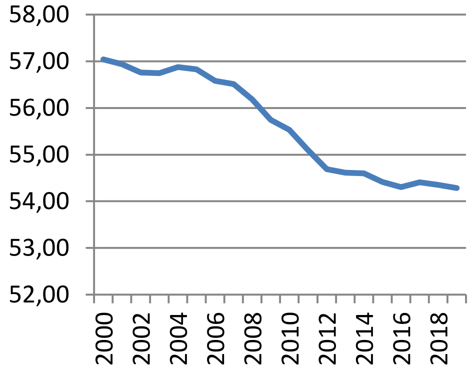


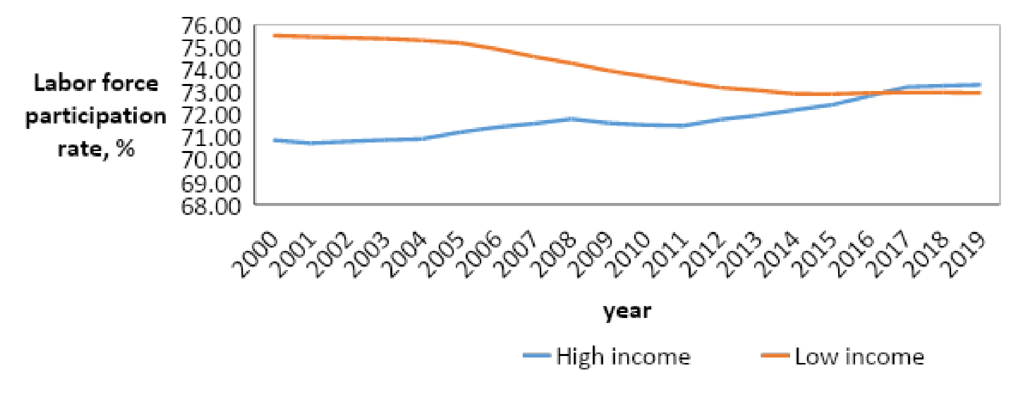
Figure 8. Employment to population ratio, 15+, total (%), Lower middle income



Source: World Bank Indicators, 2020

Lastly, trends in the labor force participation rates provide important information in terms of understanding the current dynamics of employment worldwide. When high-income and low-income countries are compared, the gap between the two country groups is closed in 2016-2017, but after 2017, the gap is widened. This time, although the trend is opposite in favor of high income countries, the downward trend for upper-middle and lower-middle income groups has been continuing since 2000.

Figure 9. Labor force participation rate, total (% of total population ages 15-64), High Income, Low Income Countries



Source: World Bank Indicators, 2020

Figure 10. Labor force participation rate (% of total population ages 15-64), Lower-Middle Income Countries

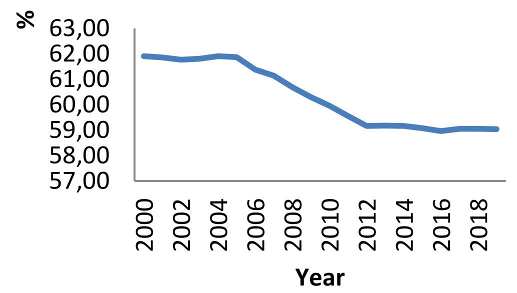
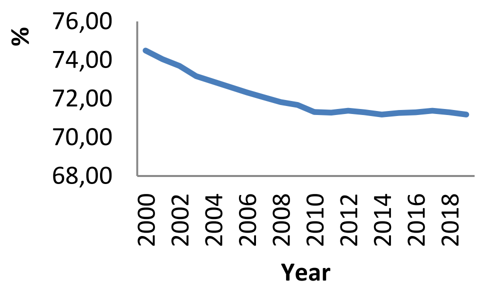


Figure 11. Labor force participation rate (% of total population ages 15-64), Upper-Middle Income Countries



Source: World Bank Indicators, 2020

Within this context, the outlook of employment reveals thefollowing facts:

a. The world economy is still far away from the pre-2008 growth pace.

b. This sluggish growth rate in GDP per capita triggers the downward trend of global employment rate. Fewer people can find jobs every day.

c. In the phase of the ‘synchronous slowdown’ of the world economy, the creation of new job sites at a lower rate.

This thesis attempts to analyze the employment in a conjuncture where robots are rapidly spreading. The scope of thesis is specified with the following research questions:

(i) How will the employment be affected by the widespread use of robots in a heterogeneous population economy?

(ii) In addition to the relative change in employment, will the inequality-effect occur when the demographic characteristics of the employees are taken into account?

Chapter 1 and Chapter 2 seek to answers for the first question with an overlapping generationsmodel and SYS-GMM estimation respectively. The second question is addressed in chapter 3, with empirical analysis taking the demographic differences within the workforce into account.

CHAPTER 1

THE ROBOTS AND HUMAN LABOR IN OVERLAPPING GENERATION ECONOMIES

1.1 BACKGROUND AND LITERATURE REVIEW

The impact of robots on aggregate employment is not straightforward. Firstly, an increase in robotsleads to an increase in GDP per capita andgenerates new jobs, primarily by providing an increase in productivity and profitability.This positive effect reveals the key role of technologyimprovements in productivity leaps, from the times of steam engine to Fordist production mode and to ICT in the 21st century (IMF, 2018). Accordingly, the recent increase in a productivity caused by robots is defined as *productivity effect* by Acemoğlu and Restrepo (2019) and *product innovation* by Pellegrino et al. (2017).

As relative prices of robots fall over timeresulting from cost reductions, this leads to a replacement of human labor for a given degree of substitutability. This negative effect is also defined as a *displacement effect* by Acemoğlu and Restrepo (2019).This impact which leads a labor-saving impact is explained as a result of the*process innovation* in Pellegrino et al (2017). This way of technological progress is also defined as embodied technological change (ETC) in which any technological progress is added to novel machines such as robots and allows producing same amount of products with less labor.

Given the extant literature on this issue, the impact of robots on human labordepends on which of these colliding effects (productivity effect vs. displacement effect)is dominant.Throughout the history, the impact of technological progress on employment has been determined by interplay of these impacts. While the productivity impact has prevailed since the IR1 and kept employment-to-population ratio growing during 20th century (Autor, 2015), it is still a lively debate as whether robots leave employment behind or whether the future will host brand new jobs to respond to the labor supply.

In general, the findings on the net effect of robots on the human labor are still inconclusive. Acemoğlu and Restrepo (2019) offers an ultimate *counterbalanced impact* resulting from neutralization of the productivity and displacement effects. This claim is based on the hypothesis that as robots' degree of substitution increases, this will result in a higher productivity effect, resulting in a higher per capita GDP and aggregate employment. During this neutralization period, some people are forced to leave their jobs, but at the same time some others take part in the new jobs created.Compensation of the reduction in employment by the rise in productivity is examined through similar counterbalance effect analyses such as Manyika et al., (2013) and Mokyr et al., (2015). Moreover, Autor (2015)points out that although robots are indeed substitutes for labor, they mostly act as a complement of labor as well by generating a higher demand for labor as a result of increasing productivity and earnings. These findings are also in line with previous opinions, such as Freeman and Soete, (1994), Autor et al.,(2006), Goos et al.,(2004), Bernman et al.,(1994),Autor et al., (1998), and Morrison and Siegel, (2001), where technologicalprogress is skill-biased technological change (SBTC). SBTC is simply a feature of technological advancement that generates new jobs that demand old skills and take old jobs, mostly routine tasks, out of human labor.

Among the studies verifying the role of productivity effect, Pellegrino et al. (2017) finds a highly significant effect of automation on job-creation while documenting no significant effect on unemployment. According to their SYS-GMM estimates, Research and Development, R&D, expenditures embedded in robotic technology has a significantimpact on job creation, but at the same timeembodied technological change[4], ETC presents a labor-saving process and ultimately these two adverse impacts neutralize each other and thus unemployment is not observed. In a similar way, Dauth et al. (2017) finds no evidence that robots lead a decline in aggregate employment. In their study for Germany, they show that although the robots cause a 23% drop in employment between 1994 and 2014, this decline is offset by new jobs in the services sector. Graetz and Michael(2018) also demonstrates that robots had no negative impact on overall employment, except for negative impact on low-skilled labor.

On the other hand, a number of studies have shed light on the dominancy of displacement effect. Brynjolsson and McAfee (2014)define the recent period as *Second Machine Age* to indicate the expansion of robots. They claim that this new age is expected to be an era carrying similar characters with the First Industrial Revolution (by their definition: “First Machine Age”) in which muscle power is replaced by machinery. Following an occupation-based approach and using Gaussian process, Frey and Osborne (2013) examine 702 detailed occupations in U.S. and estimate that 47% of jobs are at risk. More recently, PwC Survey (2017) predicts 37% of workers are worried about the possibility of losing their jobs due to the automation. Moreover, for Finland 35% jobs are found susceptible to the automation (Pajarinen and Rouvinen, 2014), for Germany it is 59% **(**Brzeski and Burk, 2015), for Europe the jobs are found to be susceptible at the range between 45% and 60% (Bowles, 2014) and for OECD countries it is found to be 9% (Arntz, Gregory, Zierahn, 2016). European Commission admits that 25% of employment in sectors that make up 20% of GDP is currently under the threat of automation. At the same time, in contrast with Kaldor’s stylized facts[5], Karabarbounis and Neiman (2014) and Piketty (2014) points out the global decline in the share of labor

[4]Embodied technological change (ETC) refers to productivity gains by a new capital embodied in technology; it exhibits labor saving nature (Sakellaris and Wilson, 2004)

[5] In his study, *Capital Accumulation and Economic Growth* in 1961, Nicholas Kaldor lists following six observations to consolidate the analysis of the literature on national income calculations:
1-labor productivity shows steady growth 2-Capital per worker shows steady growth
3- The rate of return on capital is steady 4-The ratio of capital to output is steady 5-Both labor and capital has constant shares in aggregate income 6- There are important differences in growth rates between countries. In fast growing economies, these rates vary between 2-5%.

as a result of the efficiency enhancing replacement of labor by robots. Moreover, Acemoglu and Restrepo (2017)'s static version of the model, in which capital is kept fixed and technology is defined as an exogenous factor of production, indicates a reduction in aggregate employment due to the rising automation. In an OLG economy settings, Berg et al. (2015) claims that intelligent machines are expected to replace human labor in the same way that combustion engine had substituted horses during IR1. Given the intergenerational effects, it is expected that the result of the race between robots and human labor will not favor human labor, and therefore the claim that the economy will reach equilibrium in the long run is refuted (Sachs andKotlikof, 2012, Sachs et al., 2015, Berg et al. 2015). Because savings, which are the only source of investments in OLG economy, decrease as a result of falling labor demand; this reduces investments and ultimately restricts capital accumulation. Therefore, robots that replace human labor in OLG economies drag the economy into long-term immiserization. The similar long-term immiserization is conceptualized byRifkin (1995) decades ago.In Rifkin's world of economy, this immunization is defined as 'workless world', in which existing workforce is under a danger of automation.

Although the literature is concentrated on local, regional or cross-country analyzes due to lack of available data**,** Carbonero et al. (2018) conducts a world-wide empirical analysis by showing a significant negative impact of robot exposure on employment. Working with such a wide range of data reveals an important contribution to examining the effects of robots in countries with different levels of development. In this context, Carbonero et al. (2018) finds that increase in robot usage causes 1.3% drop in worldwide employment over the period 2005-2014. In industrialized countries, or developed countries, this effect remains very limited (-0.54%), while in emerging countries it is at a very high level (-14%).

In this chapter, following Sachs and Kotlikof, 2012, Sachs et al., 2015,the effect of robots on human labor is studied within the OLG framework. Our study attempts to provide a theoretical map for understanding the robotic impact on human labor, while intergenerational dynamics, or micro foundations are taken into account. We modify OLG model (Diamond, 1965) with a unique production function in which robots are accounted as one of the essential productive units in a single-output economy. This chapter attempts analyze the consequences of a change in robots on human labor at the stationary phase (steady-state) of the economy.

1.2. MODELING ROBOTS

In the theoretical literature, modeling of robots generally takes place with two different approaches. The first one is the task-based approach, which divides the production processes into small tasks and accepts the comparative advantage of human labor in one part of these tasks and the comparative advantage of robots in the other part.

Task-based approach has been developed by Zeira (1998). Zeira (1998) provides a simple task-based model considering final output which is produced by either manual or automated technology is produced by a set of intermediate goods in a one output economy. Acemoglu and Restrepo (2017, 2018, and 2019) modify Zeira's task-based model by using CES production function and endogenizes the tasks. A contribution of the task-based approach to the literature is that it emphasizes the tasks in which human labor holds the comparative advantage, thus allowing a countervailing effect against the substitution effect (Acemoglu and Restrepo, 2018).

Another approach is based on the neo-classical production function that is modified to include robots as a third production factor. In this approach, the type of production technology is the key factor determining the ultimate impact of robots on human labor. Cobb Douglas and Constant Elasticity of Substitution (CES) production functions are the most preferred ones among the all production technologies. There are models using

CobbDouglas or CES, as well as studies using two-nested CES and also a combination of Cobb Douglas and CES.

Models using only Cobb Douglas production technology (Hanson, 2001) allow robots and human labor complement each other. This type of characterization underestimates the capability of robots to replace human labor in production process.

To overcome this shortcoming, most studies (Decanio, 2016;Aghion, 2017)apply CES production function. In addition to taking into account many factors (including physical capital), it also offers flexibility on the degree of elasticity of substitution and provides a control over elasticity of substitution.

The degree of substitutability of human labor depends on the range of elasticity of substitution between robots and human labor, σ. At the point where$\sigma = 0,$ equation (3) is specified as Leontief function, where the production function requires fixed proportions; i.e. there is no substitution between inputs. When$\sigma = 1,$ the production function shows constant returns to scale, specified as Cobb Douglas production technology. Gross complementarity, where the rise of robots lead a decrease in human labor demand, arises between robots and human labor where $\sigma < 1$. Robots and human labor becomes gross substitutes, where $\sigma > 0$ and perfect substitutes where $\sigma = \infty$.

Although, the empirical estimation of the elasticity of substitution between K and L is very difficult, there is a strong consensus that it takes the value in the range between 0 and 1 (Arrow et al., 1961, Bodkin and Klein, 1967, Sato, 1970, Kalt, 1978, Antràs, 2004, Klump, McAdam and Willman, 2007) and the inputs of K and L show that they have historically been complementary to each other (Rader, 1968).

On the other hand, the elasticity of substitution between robots and human is mostly predicted to be greater than 1 (Sachs and Kotlikoff, 2012, Berg et al., 2018). More concretely, Berg et al.(2018) proves that elasticity of substitution between P and L is 2.3-3 times higher than between K and L. To capture the characteristics of smart robots substituting human labor perfectly, in this thesis we adopt $\sigma \rightarrow +\infty$ case of CES technology. Automation is frequently assumed to improve capital productivity (Graetz and Michaels, 2015, and Nordhaus, 2015, Benzell et al, 2015, Sachs and Kotlikoff, 2012) and then increase or decrease labor share at a degree of elasticity of substitution (σ). The current macro-economic problem, which this thesis also questions analytically, is the direction and severity of the effect of robots that can replace human labor in all kinds of tasks on employment. Thus following Gasteiger and Prettner (2017), we apply perfect substitution,$\sigma \rightarrow +\infty$, between human labor and robots. In this type of set-up, the economy will also desperately evolve into stagnation due to the full replacement, reduced wages, reduced transfer to subsequent generations and reduced investments respectively.

In our model, we adopted the combination of Cobb Douglas and perfect substitution technology.Sachs et al. (2015)also applies Cobb-Douglas technology, case:$\sigma = 1$, in a two-sector economy. Robotic sector operates with two firms that one of them only produces with robots and the other one uses traditional technology with capital and human labor. On the other hand non-robotic sector produces traditional output only with capital and human labor. At the end, the model displays decline of wages and saving of young and old generations as a result of robots replacing human labor. Sachs and Kotlikoff (2012)also treat robots and human labor are complementary, concluding that job opportunities for future generations are reduced as wages and savings fall.

Moreover following Sachs and Kotlikoff (2012), Sachs et al (2015) and Benzell et al.(2015), we employ anOverlapping Generations Model (OLG) in order to capture the intergenerational transitions and long-term dynamics.While accumulation of capital plays a key role in the economic growth process in the standard neoclassical models, in the OLG economies investment decisions of heterogeneous households are the driving forces. This dynamic set-up allows includingdemographic features and timing of the exogenous shocks in the model.

Moreover, in this thesis the definition of robots (P) differentiates from the vast literature by limiting its scope. In the extant literature robots are frequently defined in a broader expression such as the sum of all the codes (the ones applying OLG economy; Sachs and Kotlikoff, 2012,Sachs et al, 2015, Benzel et. al, 2017). Following Graetz and Michaels(2018), in this thesis, we first limit the scope and consider only industrial robots. Then we define robots as a special kind of capital that acts as a different form of labor. Defining robots as a form of labor does not make a mathematical difference, but it emphasizes the degree of close substitution between human labor (DeCanio, 2016). Therefore in the model, robots fulfill most human skills and are equipped to replace human labor by degree of substitution, which is assumed to be greater than 2.

Our theoretical model represents a transition economy in which robots are becoming widespread, that’s why their price is sufficiently low and capable to replace human labor in all production processes. In order to allow robots to substitute human labor at every stage of the production process, we set a single output economy in which all three factors (physical capital, human labor and robots) are used.

1.3.MODEL

The modelfeaturesaone-sector overlapping generationseconomy in which agents consume identical goods and services. Economy consists of two generations, young and old, who lived for two-period in a discrete time, $t = 0,1,2 \ldots$, with infinite horizon and sharing identical preferences over consumption and saving. The size of the population follows $\mathrm{N_{t+1}} = (1 + \mathrm{n})\mathrm{N_t}$, where $N_t$is assumed to be exogenous, represents the young individuals born at period t, while $\mathrm{n} > 0$ represents the constant population growth rate.

Therepresentative firm uses a production technology, which is already automated. Thus our model differs fromthe standard OLG model[6] by including robots as a third input forthe production process. Firms, which are owned by old individuals, produce output by using three production factors: Traditional or so-called physical capital, K_t, human labor,L_t, and robot stock,K_{2t}.

Firms

The only source of investment in the economy is households' savings during their first period of life. After the young individuals invest their savings to the representative firm,the firm internally allocates these investments as K_{1t} and K_{2t}. The first part of capital, K_{1t}, solely acts as a physical capital stock, whereas the second part of the capital, K_{2t},is converted into robots without any cost.

At each period, the representative firm produces a final good, Y. The production of Y uses the Cobb Douglas technology in which elasticity of substitution between labor service and physical capital (K_{1t}) is 1; while labor service is generated by human labor, L_t,and robot stock, K_{2t}. In the production function, robots can perfectly perform the work of $\emptyset$ unit of labor.

The production of Y at period t follows:

$$Y_t = AK_{1t}{}^{\alpha}[L_t + \emptyset K_{2t}]^{1-\alpha} \quad 1$$

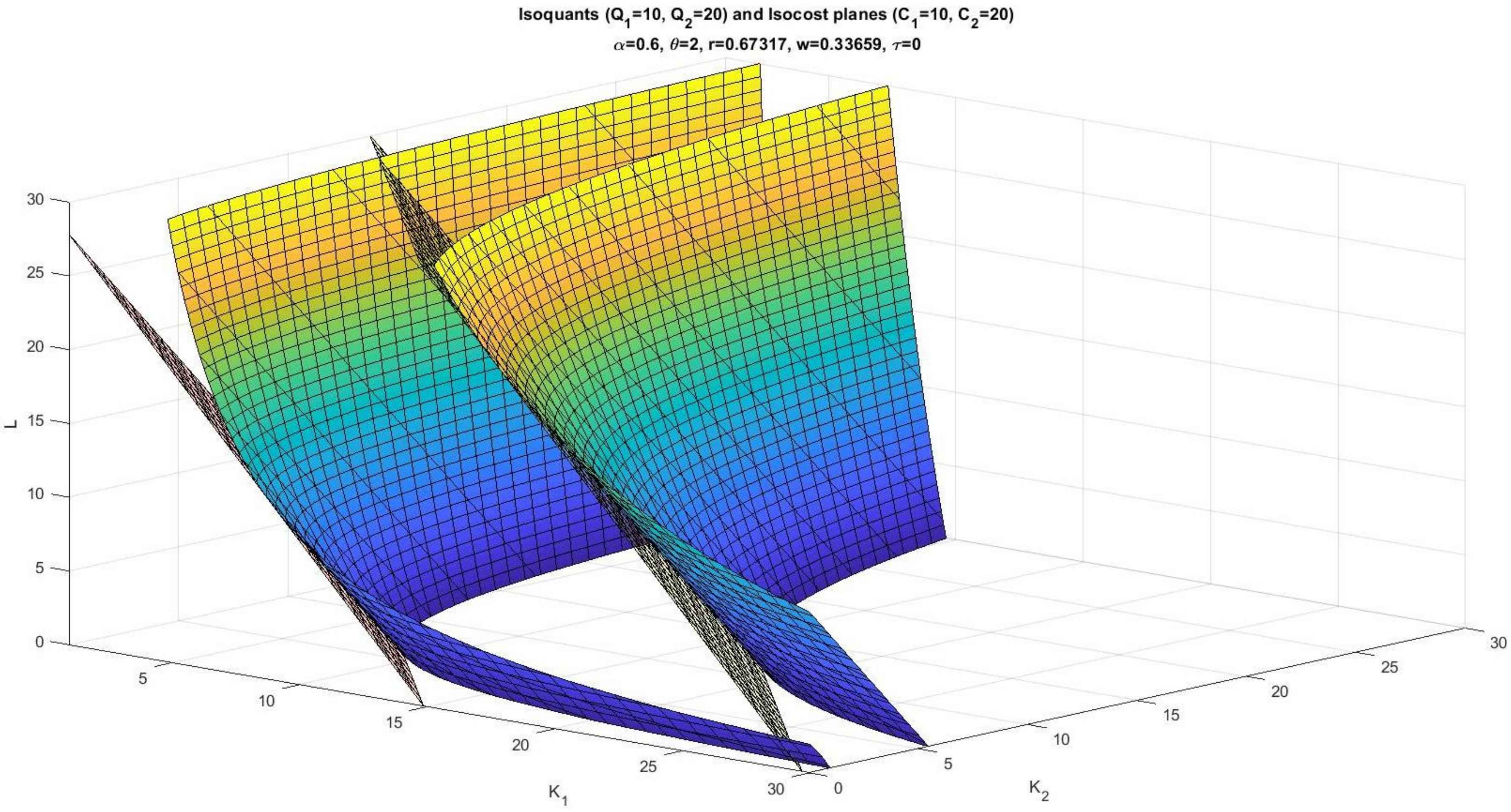
[6]For the detailed description of standard OLG model, see de la Croix and Michael (2002)

Where A stands for the total factor productivity (TFP) and α, $\alpha \in (0,1)$, is the elasticity of substitution between K_{1t} and the labor service, which is formed by a combination of human labor, L_t and robot stock, K_{2t}.

There are alsostudies in the literatureincluding human labor in robot production(Benzell et al., 2018). However, this form of labor does not include all labor; it encompasses mostly the high-skilled form of labor that represents a very small proportion of the total labor.However, most of the time, after robotic production is carried out once including human labor, it evolves without the need for human labor intervention(Sachs et al., 2015).Since the focus of this thesis is the effect of robots on human labor in full substitution, human labor is not included in robot production; ratherrobots are considered as a self-sufficient form of capital used in the tasks of human labor.

Figure 1.1 shows isoquant and isocost curves that depict the bundles representing constant output levels. The tangency between isocost and isoquant curves, model reaches interior solution.

Figure 1.1. Isoquant and Isocost Curves



Under the perfect competition market conditions, in each period the representative firm chooses the amount of capital stocks, K_{1t},$K_{2t}$and human labor, L_t by maximizing its profit.

$$\max_{K_t, K_{2t}, L_t} Y_t\,(K_{1t}, K_{2t}, L_t) - r_{1t}K1_t - r_{1t}K1_t - w_tL_t \qquad 2$$

$$K_{2t} \geq 0,\ K_{1t} \geq 0 \text{ and} L_t \geq 0. \qquad 3$$

The demands for factors of production satisfy;

$$r_t = \alpha A{K_{1t}}^{\alpha-1}(L_t + \emptyset K_{2t})^{1-\alpha} \qquad 4$$

$$r_t = (1-\alpha)\emptyset A{K_{1t}}^{\alpha}(L_t + \emptyset K_{2t})^{-\alpha} \qquad 5$$

$$w_t = (1-\alpha)A{K_{1t}}^{\alpha}(L_t + \emptyset K_{2t})^{1-\alpha} \qquad 6$$

Since the economy has single rate of return on capital, K_t, assuring the equality of equations 4 and 5 yields;

$$\alpha A{K_{1t}}^{\alpha-1}(L_t + \emptyset K_{2t})^{1-\alpha} = (1-\alpha)\emptyset A{K_{1t}}^{\alpha}(L_t + \emptyset K_{2t})^{-\alpha} \qquad 7$$

The rearrangement of Equation (7)providesK_{2t}, as a function ofK_{1t}.

$$K_{2t} = \left(\frac{1-\alpha}{\alpha}\right)K_{1t} - \frac{1}{\emptyset}L_t \qquad 8$$

Households

In their first period of life, at period t, individuals are young and endowed with L_t unit of labor that they inelastically supply to firms for to produce output (Y).Following Diamond (1965), young individuals allocate their income, which is equal to the real wage $(\mathrm{w_t})$, between current consumption$(\mathrm{c_t})$ and savings $(\mathrm{s_t})$. Savingsare invested in the representative firm operating in goods-production and the real interest rate on savings between the periods t and $t+1$ are denoted by r_{t+1}. During the old ages, in the second period of life, the return on the savings $(1+r_{t+1})s_t$ generates an income that is entirely consumed. Hence the saving function is increasing in real wage and the return on the savingsbetween the periods $t$and $t+1$, $s_t = s(\mathrm{w_t}, (1+r_{t+1}))$.

The budget constraint for the period t and $t+1$ is;

$$w_t = c_t + s_t \tag{9}$$

Accordingly, the consumption of old individuals at period $t+1$ is

$$d_{t+1} = (1+r_{t+1})s_t \tag{10}$$

All individuals are assumed to have rational expectations or perfect foresight and all are price-takers. The preferences of individuals are represented by a lifetime utility function U (.) derived from consumption in young ages (c_t) and old ages(d_{t+1})respectively.

The lifetime utility function U (.) is defined as follows;

$$ln(c_t) + \beta\ ln(c_{t+1}) \quad 11$$

Households discount the future consumption at a rate ρ and the subjective discount factor is $\beta = \frac{1}{1+\rho}$ and $\beta \in (0,1)$. This lifetime utility U (.) is strictly concave (decreasing marginal utility), strictly increasing (no satiation), twice continuously differentiable and satisfies the Inada conditions[7].

Given the real wage rate and the real interest rate on savings between t and $t+1$, the optimization problem of the representative is given by:

$$\max_{c_t, d_{t+1}} U_t = ln(c_t) + \beta\ ln(d_{t+1}) \quad 12$$

Subject to

$$c_t + s_t = w_t \quad 13$$

$$d_{t+1} = (1 + r_{t+1})s_t \quad 14$$

$$c_t \geq 0,\ \ d_{t+1} \geq 0, \text{ and } 1 + r_{t+1} \geq 0$$

The price of consumption goods is normalized to 1.

The first order conditions (FOC) for the optimization problem of the representative individual follows:

[7] Inada Conditions are used as a technical assumption for the smoothness of indifference curve;
$\lim_{c_t \to 0} U_{c_t}(c_t, c_{t+1}) = \infty$, $\lim_{c_{t+1} \to 0} U_{c_{t+1}}(c_t, c_{t+1}) = \infty$,
$\lim_{c_t \to \infty} U_{c_t}(c_t, c_{t+1}) = 0$, $\lim_{c_{t+1} \to \infty} U_{c_{t+1}}(c_t, c_{t+1}) = 0$,

$$c_t = \frac{1}{1+\beta} w_t \qquad 15$$

$$d_{t+1} = \frac{\beta}{1+\beta}(1+r_{t+1})w_t \qquad 16$$

$$s_t = \frac{\beta}{1+\beta} w_t \qquad 17$$

The Competitive Equilibrium

Definition: A dynamic competitive equilibrium is expressed with the feasible allocations $\{K_{1t}, K_{2t}, L_t, Y_t,\ K_{t+1}, c_t, s_t, d_{t+1}\}_{t=0}^{\infty}$ and sequence of prices $\{w_{t,} r_t\}_{t=0}^{\infty}$ satisfying equations (4), (5), (6) with the positive initial variables $\{K_{1,0}, K_{2,0}, L_{1,0}\}$ and the law of motion of K_t, firms maximize their profits, consumers maximize their lifetime utility and all the markets clear at each period t.

Under the perfect competition condition, goods market clears at;

$$Y_t = s_t N_t + c_t N_t + d_t N_{t-1} \qquad 18$$

Labor market clears at;

$$L_t = N_t, \text{ where } \mathrm{N}_{t+1} = (1+\mathrm{n})\mathrm{N}_t \qquad 19$$

The physical capital $K_{1t}$and robots K_{2t}make up the total capital stock in the economy.

$$K_t = K_{1t}(K_t, N_t) + K_{2t}(K_t, N_t) \tag{20}$$

Plugging Equation (20) into Equation (8) and expressing all variables in per capita terms yieldrespectively equations (21) and (22).

$$K_{2t} = (1-\alpha)K_t - \frac{\alpha}{\emptyset}\mathrm{L_t} \tag{21}$$

$$k_{2t} = (1-\alpha)k_t - \frac{\alpha}{\emptyset} \tag{22}$$

Since the main focus of this analysis is to see the implications of robots in an economy where robots are actively used, we only check the condition where $K_{2t} > 0$. Hence given Equation (22), for any positive values of K_{2t}, $K_{2t} > 0$, the total capital per capita must be above a certain threshold, $k_t > \frac{\alpha}{1-\alpha}\frac{1}{\emptyset}$.

***Proposition* 1.**As robot productivity increases in a country, the amount of capital that needs to be allocated to robots also increases. For this, the total capital stock per capita must exceed a certain threshold, $(\frac{\alpha}{1-\alpha}\frac{1}{\emptyset})$. However, the robotic productivity rate, $\emptyset$ plays an important factor in the threshold level. As robotic productivity rate gets higher, the threshold level declines; and this allows the economies which have lower capital stock to access to robotized production technology.

And finally capital market clears where the equality between savings and investments satisfies at;

$$s_t N_t = K_{t+1} \qquad 23$$

Combining equations (18), (19), and (23), total capital stock evolves at;

$$K_{t+1} = \frac{\beta}{1+\beta} A(1-\alpha)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \emptyset^{-\alpha} N_t \qquad 24$$

It is seen that for this economy, the growth of the economy as given by $G_{K,t} = \frac{k_{t+1}}{k_t}(1+\mathrm{n})$, is an increasing function of exogenous parameter A and decreasing function of $\mathrm{k_t}$ and $(1+n)$.

$$G_{K,t} = \frac{\beta}{1+\beta} A(1-\alpha)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \emptyset^{-\alpha} \frac{1}{k_t} \frac{1}{(1+n)} \qquad 25$$

At the *steady-state* of the economy, $k_{t+1} = k_t = k^*$, where $k_t = \frac{K_t}{N_t}$.

Defining $T = \frac{\beta}{1+\beta}(1-\alpha)$, the *long-term of stocks of total capital and robotic capital* are:

$$k^* = T\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \emptyset^{-\alpha} A \frac{1}{1+n} \qquad 26$$

***Proposition* 2.** Under the assumptions of $\mathrm{L} \gg 0, \mathrm{K}_1 \geq 0$ and existence of a linear robot production, $\mathrm{K}_2 > 0$, steady state capital stock per capita of the economy is given by Equation (26). Given exogenous parameters A and n as constant, Equation (26) implies there is only one transition dynamics in the economy. For a given $k_0 > 0$, the first order derivative $\frac{dk^*}{d\emptyset}$ indicates that the increasing robotic productivity is an immiseration of the economy, i.e. there is no growth in the existence of rising robot productivity level.

$$\frac{dk^*}{d\emptyset} = -\alpha\, TA\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}\frac{1}{n}\emptyset^{-\alpha-1} \quad 27$$

$$\frac{dk^*}{d\emptyset} < 0 \quad 28$$

This long-term immiseration of the model also supports the findings of Sachs and Kotlikoff (2012) and Sachs et al. (2015). In addition, Gasteiger and Prettner (2017) finda similar overall stagnation in the long-term of economy. Due to applying perfect substitution between robot usage and human labor, they arrive with AK-type of growth model, and relatively reduced wages, reduced transfer to subsequent generations and reduced investments.

The intuition of this immiseration result is explained by wage dynamics of the model.

The steady state level of the real wage yields;

$$w^* = (1-\alpha)^{1-\alpha}\alpha^{\alpha}A\emptyset^{-\alpha} \quad 29$$

Equation (29) and the first order derivative$\frac{dw^*}{d\emptyset}$ simply imply that the increasing robotic productivity reduces real wages $\frac{dw^*}{d\emptyset} = -\alpha(1-\alpha)^{1-\alpha}\alpha^{\alpha}A\emptyset^{-\alpha-1}$. Also checking the second order derivative,$\frac{d^2w^*}{d\emptyset^2} = (\alpha+1)\alpha(1-\alpha)^{1-\alpha}\alpha^{\alpha}A\emptyset^{-\alpha-2}$, provides a result that robots' negative effect on the wages increases gradually.Therefore savings and investments, which are solely financed by wages, also are decreasing in this regards.

***Proposition*3.**Under the assumptions of $L \geq 0, K_1 \geq 0$ and existence of a linear robot production, $K_2 > 0$, given a production technology that uses the same amount of labor,every unit increase in robot productivity pulls real wages down.

Moreover, Equation(29) also provides acomparative statics related with the impact on human labor. It's obvious that for developing an analytical explanation about the effects on employment, the model needs a departure from full employmenteconomy.In a case where robots substitute human labor perfectly, low-wage dynamics becomes persistent. In this low-wage transition, under the rising robotization conditions, labor's share in income approaches zero (Berg et al., 2018). Acemoglu and Restrepo (2016) proves the same direction of labor's share in income and employment under the endogenous labor supply conditions. Also under conditions, where wages cannot be adjusted immediately, i.e. in the presence of minimum wage level, unemployment rate is positively related with the wage level (Fanti and Gori, 2007). Among the recent studies, Leduc and Liu (2019) develops a model, in which the presence of job vacancies in the market are accepted in order to make room for robotic decisions, and come up with a result that increasing fluctuations on labor market with a rising displacement effect of robots.

In addition, by taking intergenerational effects, our study differs from Acemoğlu and Restrepo (2019), Manyika et al.(2013), Mokyr et al.(2015), Autor et al. (2006), Pellegrino, Vivarelli and Piva (2017), Dauth et al.(2017), and Graetz and Michael(2018). The most distinctive reason for this departure lies on the model selection. Acemoğlu and Restrepo (2017, 2018, and 2019)apply task-based approach, in which they allow tasks human labor has the comparative advantage.

1.4.CONCLUSION

There is a consensus in the extant macroeconomic theoretical literature that robots will substitute for human labor in the production of goods and services. However, the arguments vary that this will result in permanent unemployment. This effect of robotic technologies, which have been rapidly increasing in recent decades, on human labor is studied analytically with various theoretical models.Task-based models in the literature suggest a job growth effect that has a capability to offset the displacement effect, assuming that robots cannot replace human labor in every task.But this balancing mechanism does not always work in neoclassical models. Among the neoclassical models, the degree of substitutability of human labor plays a key factor in determining the impact on employment and wages. Our model takes the robots as perfect substitutes for human labor, or in other words we employ a model in which robots can accomplish all tasks in production process.

Moreover, in our analysis we trace the robotic impact in overlapping generations economy. This specific economy allows us to take into account the intergenerational dynamics and micro-foundations of the economy.The model has been kept general and simple for a wide analytical discussion.In summary, there are basically two factors in economy: physical capital, K, and human labor, L. Since the production processes are automated, and all firms have access for this technological adoption, robots that can perfectly replace human labor, can be produced with some part of the physical capital. Therefore, robots are used as a third production factor. Since only source of investment in the economy is savings, which are also unconsumed portion of wages of working young people, the increasing use of robotspusheswages down.This also leads to long-term immiseration in the economy due to the decline in the capital stock. Although pushing wages downward does not cause unemployment in the full employment economy, the result the model points out, implicitly allows comparative statics.In the conditions of leaving full employment, the increase of robots will result in unemployment inevitably.

For nearly the last three decades, we have been facing with novel form of machine, which differentiates from the previous ones, such as assembly lines, computers and basic robotic arms. Today's robotsare ready to take over almost all jobs performed by human labor in the production process. Therefore, the widespread use of robots reveals the new technological concern of our age. This concern is expressed in two ways: first, 'robots may take our jobs away' and second, 'robots can cause economic shrinkage in the long term, although they can increase production in the short term. These two scenarios are also interdependent, because if the emerging unemployment in the economy is not compensated, the decline in wages and savings in the long run will create immiseration in the economy. Our model supports both of these scenarios.

However, these concerns need more comprehensive analytical explanation. These analytical studies undoubtedly have a large room that includes departure from full employment and moving away from the assumption of capital is owned by all households.

CHAPTER 2

THE IMPACT OF ROBOTS ON EMPLOYMENT: THE EMPRICAL INVESTIGATION FOR SELECTED COUNTRIES

In this chapter, the robotic impact on employment is empirically analyzed. The analysis is conducted in an intergenerational framework, which is theoretically described in Chapter 1.

2.1. EMPIRICAL LITERATURE REVIEW

There is a wide range of empirical studies in the literature on how robots affect labor demand, aggregate employment. We classify the empirical literature on the effects of robots on employment first by dividing it into two- local economy analyses and cross country analyses- and then two more subgroups-quantitative analyses and qualitative analyses.

Acemoğlu and Restrepo (2017) conduct a study on the basis of US local labor markets and find that each increase in a robot per thousand workers reduces employment-to-population ratio by around 0.18%- 0.34.A similar study (Autor and Dorn, 2009) taking into account the 722 US commuting zones explains that the decline in the US employment-to-population ratio occurs mostly in routine work-intensive sectors.However, this study also shows that this decline in employment is offset in the non-routine, cognitive-intensive service sectors, thanks to the reallocation of employees according to their skills.For German manufacturing industry, the robotic displacement effect is found to be negative; Dauth et al. (2017) finds that each increase of robots resulted in two job losses.Regarding Spanish manufacturing firms, Pellegrino, Vivarelli and Piva (2017) shows that automation has no significant effect on employees in high-tech companies with high R&D expenditures, and robots in non high-tech companies affect employment negatively. Given the UK evidence (Goos and Manning, 2003), robotization has a negative effect on workers only in routine work-intensive companies, and it does not have a significant effect on employees in companies based on creativity and problem solving.

On the other hand, cross-country analysis provides more insight into robot effects.These analyses allowcapturing differences in economic structure, heterogeneity in technological adoption and capabilities, cultural factors etc. On conducting a cross-country study, there is possibility to choose the country classification on the subject to focus on. For OECD countries, De Backer, K. et al. (2018) refers to Global Value Chains and analyze the impact of robots on employment. While the effects of robots on humans are found to be positive for developed countries with off-shore possibilities, this positive effect is disappearedfor developing countries andno significant effect is found. For 17 selected countries, Graetz and Michaels (2018) estimate a neutral correlation between robots and employment, whereas for low-skilled workers and for low-skilled working density-countries this effect turns to be negative.

However, for six EU countries, the impact of robots on employment is found to be negative (Chiacchio et al. 2018). According to this study, a rise in robot per thousand workers reduces employment by around 0.16%-0.20% points. Focusing on the development scales of countries, Carbonero et al. (2018) conducts a study on 43 selected countries worldwide and finds that displacement effect is dominant for whole sample. For developed countries this negative effect is turned to be lower, whereas for developing countries, the displacement effect of robots reaches14% points.

Table 2.1. Literature Review/Local Economy Analyses

Autors	Estimation Model	Period	Sample	Findings
Acemoğlu and Restrepo, 2019	IV	1990-2007	US labor markets, commuting zone basis	Each increase in a robot per thousand workers reduces employment by 0.2%.
Dauth et al., 2017	IV	1994-2014	Germany manufacturing industry.	Each additional robot causes 2 employment losses.
Pellegrino, Vivarelli and Piva, 2017	GMM-SYS	2002-2013	Spanish manufacturing firms	Employment is not significantly affected by automation. However, in industries without high-tech capacity and R&D expenditures, this effect turns out to be negative.
Goos and Manning 2003	The dot-probe task measurement	1976-1999	UK, cross-sectoral analysis	Robotization only has negative effects on workers in companies with routine work intensity, and it does not have a significant impact on workers in companies other than that, in companies with jobs based on creativity, problem solving.
Autor and Dorn 2009	OLS	1980-2005	US labor markets 722 commuting zones	Only in routine work-intensive companies employment is negatively affected by rising robots, but due to the reallocation of workers to service sectors, this decline is offset in the economy.

Table 2.2. Literature Review/Cross-Country Analyses

Autors	Estimation Model	Period	Sample	Findings
De Backer, K. et al. (2018)	FE	2000-2014	OECD economies	The positive correlation of robot investments with employment growth is observed in developed economies. In developing economies, the real allocation of fixed capital to robotic areas has not been seen to have a significant effect on employment.
Carbonero et al. (2018)	OLS, IV	2005-2014	43 countries	Robots have significantly displacement impact on employment worldwide. For developed countries this negative impact is much smaller, while for developing countries it is estimated by 14%.
Chiacchio et al. 2018	IV, 2SLS	1995-2007	6 EU countries	Robot increase per thousand workers reduces employment by 0.16-0.20 points. This negative effect is more pronounced in younger generations and low and middle-skilled workers.
Graetz and Michaels, 2018	OLS, 2SLS	1993-2007	17 countries	Robots have no significant negative effect on employment, although they do reduce low-skilled workers' employment share

2.2. DATA AND DESCRIPTIVE STATICS

In this chapter, dynamic panel data techniques are used to estimate the employment impact of robots. By including time and space dimension, panel data or longitudinal data provides a techniques, which allows a more comprehensive analysis by combining time series and cross-sections. Panel data also provides more efficient estimation by offering less linearity between variables and greater degrees of freedom.So,it allows working on models including complex dynamics (see Baltagi, 2005).

The data consists of 47 countries in a sample period 2004-2016.The World Bank classifies the world economies into four groups — high, upper-middle, lower-middle, and low income countries according to GINI per capita converted to U.S dollars Atlas Method[8].According to the availability of robot data, only three income groups- high, lower-middle and upper-middle income countries- are used.

Table2.3. Country Classifications Based on Income Groups

High Income Economies			**Upper-Middle Income Economies**	
Australia	United Kingdom	New Zealand	Brazil	Malaysia
Austria	Hong Kong	Portugal	China	Russian Federation
Belgium	Hungary	Singapore	Colombia	Thailand
Canada	Ireland	Slovakia	Mexico	Turkey
Switzerland	Iceland	Sweden		South Africa
Czech Republic	Israel	United States	**Lower-Middle Income Economies**	
Germany	Italy	Chile	Indonesia	India
Denmark	Republic of Korea	Greece		
Spain	Lithuania	Poland		
Estonia	Latvia	Slovenia		
Finland	Netherlands	Japan		
France	Norway	Argentina		

The time dimension is reduced to 13 years due to the availability of robot data. In accordance with the World Bank classification and data availability, data set includes 35 high-income, 2 lower-middle and 10 upper-middle-income countries.

Table 2.4 shows acronyms and definitions of the variables used in the empirical analysis and Table 2.5 lists descriptive statistics indicating detailed description of the variables.

[8]The World Bank uses the Atlas conversion factor to reduce the effect of exchange rate fluctuations while calculating the gross national income in US dollars in its analysis of GDP between countries. This factor is defined as the average exchange rate of any year and the previous two years, after purifying the country's and international inflation rate.. For details see : https://datahelpdesk.worldbank.org/knowledgebase/articles/378832-what-is-the-world-bank-atlas-method

The central tendency in panel data is captured by the mean value. According to Table 2.5, the average of employment-to-population ratio is 56.7%, whereas the range of data is between 31.2 (minimum) and 75.4 (maximum). In stock of robots data, where the average is 36,686, the data is spreading to a greater extent from average. This is because the range between minimum and maximum varies between 0[9] and 1,024,897.This highlights the huge asymmetry in the world robot distribution.

Table 2.4. Acronyms and Definitions of Data

Variable	Acronym	Unit of Measure	Source
Employment-to-population ratio	employment	As % of working-age population	World Bank Indicators
Stock of Robots	robots	Installations and operational stock	IFR
GDP per capita	gdppercapita	PPP (constant 2011 international $)	World Bank Indicators
Labor Compensation	LaborCompen.	Share of Labor Compensation in GDP	Penn World Table (version PWT 9.1)
Value Added:	ValueAdded	Industry (including construction), value added (% of GDP)	World Bank Indicators

Table 2.5. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment-to-population ratio	611	56.6621	7.049586	37.179	75.423
Stock of robots	611	36686.47	108829	0	1024897
Labor compensation	611	0.5380118	0.0761113	0.3049485	0.6899443
GDP per capita	611	30609.01	15086.58	2774.421	91452.04
Value Added	610	26.75945	7.373833	6.717173	48.52979

[9]Canada started its robot stock investments after the year 2010. Therefore, Canada's stock of robots is zero between 2004 and 2010.

2.2.1. Robots

We use industrialrobot data from International Federation of Robotics (IFR), who estimates the operational stock of robots under the assumption of an average service life of 12 years with an immediate withdrawal from service afterwards (IFR, 2018). Covering 90% of the world robot market, IFR collects robot data from suppliers via annual surveys and publishes yearly. Having their own systems and working independently is characteristic of robots within the scope of data..IFR defines industrial robots according to International Organization for Standardization (ISO 8373:2012) as "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Organization for Standardization, ISO)[10] (see Table 2.6 for details).

Table2.6. Terms Used in Definition of Industrial Robot

Reprogrammable	Designed so that the programmed motions or auxiliary functions can be changed without physical alteration,
Multipurpose	Capable of being adapted to a different application with physical alteration
Physical alteration	Alteration of the mechanical system (the mechanical system does not include storage media, ROMs, etc.)
Axis	Direction used to specify the robot motion in a linear or rotary mode

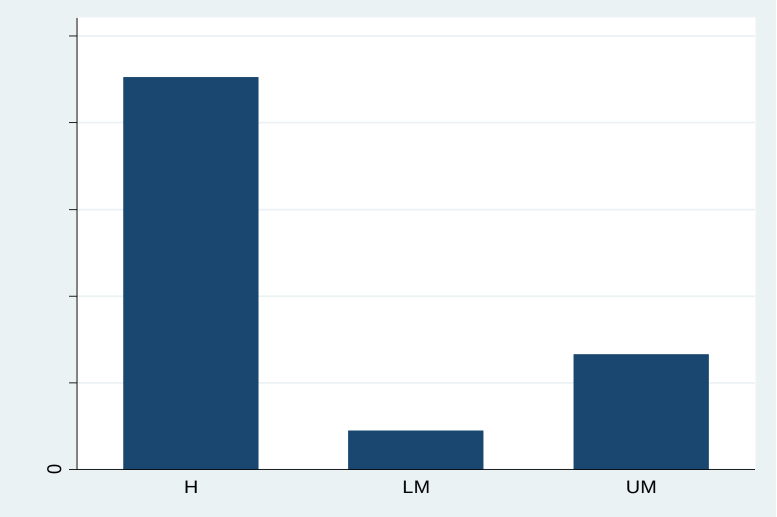
Source: ISO 8373:2012, Robots and robotic devices-Vocabulary

[10] For the long version of ISO Definition, see https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en).

In some studies, robot data is considered as a robot per thousand workers (Acemoglu and Restrepo, 2019, Chiacchio et al. 2018, Graetz and Michaels, 2018). However, following Dauth et al. (2017) and Carbonero et al. (2018), we preferred to use it as a robot stock to avoid the problem of collinearity between robots and employment.

Among selected countries, high income countries hold 98.9% of the total robot stock in 2004 and 83% in 2016. While this change shows that high income countries still have the biggest share in the robot stock, it reveals that other countries have been robotized in the past 12 years. Figure 2.1 presents the average distribution of robots among the income groups in the period of 2004-2016. In order to observe the trend of robots clearly, we use log transformation. In this way, the distribution becomes smoother and better behaved.

Figure 2.1. Robot average distribution of robots, income groups



H: High income countries; LM: Lower-middle income economies; UM: Upper-middle income countries

The trends of stock of robots in each high income countries is shown in Appendix A. Australia, Germany, Japan, Republic of Korea and United States are the ones with the largest stock of robots. Italy, Spain UK and Sweden are emerging as the followers. Canada is one of the 'delayed countries' that started investing in 2011, while Eastern and Central European countries such as Latvia, Lithuania and Estonia are showing an increasing trend.

Between 2004 and 2016, the logarithmic average of the robot stock in high-income countries is 7.87, that is lower than the averages in Australia, Japan, United States, Germany, Republic of Korea, Italy, Spain, United Kingdom, Sweden, New Zealand, Belgium, Canada, Austria, Netherlands, Singapore, Czech Republic, Switzerland, Finland, Denmark and Poland; and higher than the Portugal, France, Slovakia, Hungary, Slovenia, Norway, Argentina, Israel, Hong Kong, Ireland, Greece, Chile, Estonia, Iceland, Lithuania and Latvia respectively (for details see Appendix A).

In the comparison between high income countries, Australia is in a position of the leading country, where the robot stock exceeds 1 million in 2016. Japan started with a high robot investment in 2004, followed a downward trend after 2005, but is still the second country with the highest robot stock. On the other hand, as the third country with the highest stock, the USA is in a rising trend.

The trend of robots stocks in each upper-middle income country is presented at Appendix A in detail. Among the upper-middle income countries, China and Thailand shows a diverging trend in stock of robots by converging to the top-ranked high income countries. Thanks to China and Thailand, the average robot stock in upper-middle income countries is almost equal to that in high-income countries. However, if these two countries are excluded, it decreases to an average of 7.29. Mexico, where robot stock investments have started in 2011 stands out as the latecomers of this group.

Accompanied witha rapid rise, China shows a significant decomposition from the other upper-middle income countries.Thailand turns to follow a similar trend of China. It has begun to diverge from other countries with a small distance.

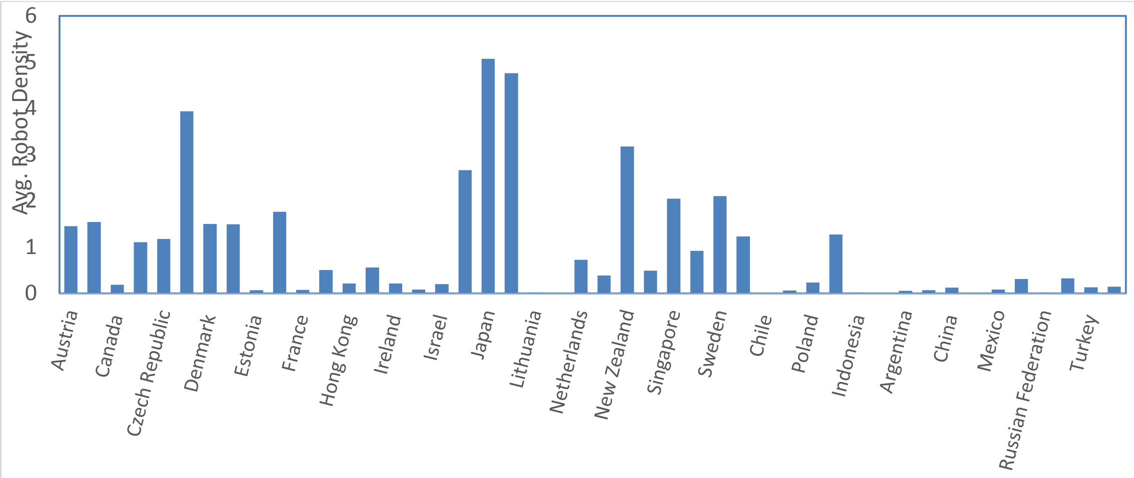
India and Indonesia are the two lower-middle income countries in our dataset. Despite low income generating economy, India is accepted worldwide as one of the world's leading outsourcing and low-cost centers, especially for technology and industry companies. According to Global Competitiveness Report 2019, India shows a considerable improvement in Global Innovation Index, by raising its ranking from 81th to 52nd (Lalwani, 2019). On the other hand, Although Indonesia is lagging far behind India in terms of stocks of robots;with having relatively high rate of technological adoption (72nd out of 141 countries) the country is promising in terms of robot usage.Although India has more robot endowment, Indonesia shows trend-like features with India. While the average logarithmic robot of India is about 8.42, it is 7.21 in Indonesia.

2.2.2. Employment

Following Carbonero et al. (2018),Chiacchio et al. (2018) and Pellegrino, Vivarelli and Piva, (2017), we use the employment-to-population data from World Bank (WB), World Development Indicators. In order to eliminate heterogeneity in population and hence labor size, we preferred to take employment-to-population into account as a dependent variable. By collecting data from International Labour Organization, ILOSTAT database, employment-to-population ratio is the ratio of the population working in the country to the total working-age population. Generally, workers aged 15 and over are accepted as a total working-age population. The stock of robots at high income countries for the period between 2004 and 2016 is shown according to the country group they belong to in Appendix A.

We created a variable called "Robot Density" to compare the number of robots per thousand employees between countries (Figure 2.1). The robot density simply provides the information about the robot-intensive levels of countries.

Figure2.2. Robot Density Average, 2004-2016



Germany, Japan, Italy and Korea, which are also the leading countries in the number of robot stocks, are ranked as the countries with the highest robot intensiveness. In countries such as New Zealand, Slovakia and Finland, where there are relatively low number of employees due to low population numbers, the robot density shows relatively high level.

Following Dauth et al.(2017) we use GDP per capita-hereafter gdppercapita- which is a significant contributor to the employment and job creation (Manyika, 2017). World Bank provides GDP per capita based on purchasing power parity (PPP), i.e. gross domestic product converted to international dollars using purchasing power parity rates on an annual basis for all the world countries.

Following Carbonero et al.(2018) and Graetz and Michaels(2015), value added as a percentage of GDP-hereafter ValueAdded- is used as an industrial development indicator. World Bank merges value added data with OECD national accounts and provides the percentage GDP including construction.

Following Graetz and Michaels (2015) we use share of labor compensation to indicate the labor's share of income. Penn World Table version 9.1 provides the share of labor compensation in GDP data in current national prices with an extended series covered the period since 1950.

In order to control unobserved time variation we also add dummy variable. For each year we created a dummy variable, $year_t$, to capture the time series trends.

2.3. METHODOLOGY

In the extant literature, three approaches are commonly used to understand economic relations empirically: Cross-country analysis, time series analysis and panel data analysis. Compared to cross-country analysis and time series analysis, the use of panel data provides important advantages in understanding the economic relations, which are generally dynamic in nature. Having N cross sectional units and T time periods, panel data allows more sample variability and more degrees of freedom (Baltagi, 2005).

An economic relationship becomes dynamic by taking the lagged value of the dependent variable, i.e.;

$$y_{i,t} = \alpha y_{i,t-1} + X'_{i,t}\beta + \vartheta_{i,t}$$

$$\text{where } \vartheta_{i,t} = \mu_i + \varepsilon_{i,t}$$

In this dynamic specification, with dependent variable$y_{i,t}$ and dependent variable $X'_{i,t}$, $\vartheta_{i,t}$ represents the sum of unobserved time-invariant heterogeneity (μ_i) and idiosyncratic error term ($\varepsilon_{i,t}$).

The inclusion of lag dependent variable poses significant problems in estimating the model with OLS, FE and GLS estimators.In OLS estimation, both $y_{i,t}$ and $y_{i,t-1}$ are a function of $\vartheta_{i,t}$. So following the OLS estimation approach gives biased and inconsistent outcomes. In addition to Fixed Effect (FE) model suffering from a large loss of degrees of freedom, it yields biased and inconsistent outcomes. The FE regression forms with averaging over time and having the differences give respectively;

$$\overline{y}_i = \alpha\overline{y}_{i.-1} + \overline{X'}_i\beta + \overline{\varepsilon}_i$$

$$y_{i,t} - \overline{y}_i = \alpha\left(y_{i,t-1} - \overline{y}_{i.-1}\right) + \beta\left(X'_{i,t} - \overline{X'}_i\right) + \left(\varepsilon_{i,t} - \overline{\varepsilon}_i\right)$$

With FE estimator, although μ_i is canceled out in the model, $\left(y_{i,t-1} - \overline{y}_{i.-1}\right)$ is still correlated with the error term$\left(\varepsilon_{i,t} - \overline{\varepsilon}_i\right)$.

A similar problem occurs with random effect GLS estimator. Since $\left(y_{i,t-1} - \overline{y}_{i.-1}\right)$ is correlated with$\left(\vartheta_{i,t} - \overline{\vartheta}_{i.-1}\right)$, the inconsistency and bias problems are not solved via GLS estimator.

The instrumental variable, IV estimation (Acemoğlu and Restrepo, 2019, Wolfgang et al., 2017) and two-Stage least squares, 2SLS (Graetz and Michaels, 2015) approaches is also preferred in empirical literature to overcome biased and inconsistent results. In this study, IV approach is not preferred because it doesn't take into account of all available moment conditions and ignores differenced structure on the residual disturbances ($\Delta\varepsilon_{i,t}$).

2.3.1. Generalized Method of Moments

Following Pallegrino, Piva, Vivarelli(2017), in this thesis system-GMM (Generalized Method of Moments) method is applied based on the dynamic characteristics of the panel data used. GMM coefficient levels are expected to be at a level between the coefficients found from OLS and Fixed Effect estimation results (Bond, 2002 pp: 158-159), therefore we also report Ordinary Least Squares (OLS) and Fixed Effect (FE) estimates for completeness.

System-GMM method developed by Arellano and Bond(1991), Arellano and Bond(1995), Blundell and Bond (1998) and popularized byHoltz-Eakin et al. (1998).Either differenced-GMM or system-GMM is used most commonly for estimating standard dynamic panel data models. Both are developed for;

(i) Small (T) and large panels (N),
(ii) The models with dynamic dependent variable,
(iii) Not strictly exogenous independent variables (Roodman, 2009).

What distinguishes the system-GMM from the others is that it takes account of the potential correlation between instrument variables and fixed effects.

One important concern that arises with dynamic panels is *endogeneity bias*. Regarding to our study, we come across the following concern: It may not be the current year's robot level that is affecting employment-to-population ratio, but rather the previous year's level that could be the significant actor. System-GMM is often argued (Baum,

2006) as the best identification method in dealing with the dynamic nature resulting from the impact of explanatory variables on the dependent variable, i.e. *endogeneity bias*. Static models are very restricted to consider the dynamics of endogeneity. Endogeneity, which can be defined simply as the impacts of past on present, arises from the correlation between dependent variable and error term. To solve this problem, first difference-GMM was developed (Arellano and Bond, 1991) by instrumenting lagged dependent variable by differencing regressors. Then the estimator was improved to system-GMM by Arellano and Bond(1995) and Blundell and Bond(1998) by allowing more instruments to overcome some existing limitations.

Therefore, system GMM allows us to deal with this endogeneity bias by using lagged values of dependent variable as an instrument. Thus by internally transforming the data, which refers statistical process that subtracts past value of the variable from the present value (Roodman, 2009), we overcome the endogeneity bias. Generally, the one-step GMM and two-step GMM estimators are used for this transformation. Due to the limitations of one-step GMM estimator, which causes too many losses in observations, Arellano and Bover(1995) developed two-step GMM estimator.

One another problems arise from dynamic panel estimation are heteroskedasticity and autocorrelation within the error terms. By the method of two-step GMM, this problem can also be removed.

We first construct the simple regression model equation panel data model;

$$\mathrm{lnemployment}_{\mathrm{i,t}} = \beta_0 + \beta_1 lnrobot_{i,t} + \beta_2 \mathrm{lnLaborCompen.}_{i,t} + \beta_3 lndppercapita_{i,t} + \beta_4 ValueAdded_{i,t} + year_t + \emptyset_i + \varepsilon_{i,t}$$

In order to test the employment impact of stock of robots, we apply GMM estimator approach, and for that we move from the static expression to the dynamic specification as follows:

$$\text{lnemployment}_{\text{i,t}} = \alpha\text{lnemployment}_{\text{i,t}-1} + \beta_1 lnrobot_{i,t} + \beta_2 \text{lnLaborCompen.}_{i,t} + \beta_3 lndppercapita_{i,t} + \beta_4 ValueAdded_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

$$i = 1,2, \dots, N$$

where$\emptyset_{\mathrm{i}}$ is time-invariant individual fixed effect and ε is the usual error term.

2.3.2. Panel Unit Root Test Results

In order to check the stationarity properties of dynamic panel data, Panel Unit Root Test was applied.The most significant property that distinguishes Panel Unit Root Test from Unit Root Test is, it considers asymptotic behavior of the time-series dimension (T)and the cross-sectional dimension (N).

To run the unit root test, the following simple dynamic heterogeneous panel regression is assumed;

$$\Delta y_{i,t} = (1 - \theta_i)\mu_i + \theta_i y_{i,t-1} + \vartheta_{i,t},$$

$$\Delta y_{i,t} = a_i + B_i y_{i,t-1} + \vartheta_{i,t},$$

$i = 1,2.., N \ and \ t = 1,2, \dots T$ and initial values are assumed to be given

$$a_i = (1 - \theta_i)\mu_i, B_i = -(1 - \theta_i)$$

$$H_1: B_i = B < 0, \text{ for all } i.$$

$$H_0: \ B_i = 0 \ or \ \theta_i = 1, \text{ for all } i.$$

In order to meet the requirements arising from the properties of the panel data**,** Panel Unit Root Test was developed first by Levin, Lin and Chu (2002)and thenimproved by Im, Pesaran and Shin (2003). In both methods, the null hypothesis (H_0) is tested. Commonality of two methods is that, with the null hypothesis(H_0) all or at least one of the panel members is assumed to contain unit roots whereas under alternative hypothesis(H_1), the first order serial correlation coefficient is assumed to be identical in all cross-sectional units.

In this thesis, Levin-Lin-Chu (LLC), Im, Pesaran and Shin (IPS), Fisher-type (Fisher) and Hadri LM panel unit root tests are used. The reason for to apply all these tests is that all the four methods are act as a complementary each other and offer more powerful explanation altogether. For instance, LLC unit-root test has an explanatory power only if not all units are stationary. In the other case, i.e. when rejecting null hypothesis, the evidence that all series are stationary would become not convincing (Pesaran, 2012).Hence IPS test is used in order to take heterogeneity and asymmetry features of null and alternative hypothesis into account. Fisher test is applied as an alternative to IPS test; while Fisher test presents exact test (N goes to infinity), IPS test reveals an asymptotic (T goes to infinity) feature (Maddala and Wu, 1999)

Unit root test results for all variables are presented in Table 2.7. LLCindicates that all stock of robots and GDP per capita panels contain unit roots whereasIPS panel unit root test indicates non-stationary for all panels. On the other hand LLC shows that number of employees and Value-Added panels are stationary. For the first differenced panel series, except stock of robots, all panels become stationary. Fisher test indicates unit root for all variables except labor compensation and all panels except stock of robot becomes stationary for the first differenced panel series. Lastly Hadri LM test reveals that unit root n some panels and for the first differenced series- except the number of employee and stock of robots- all panels become stationary.

Table 2.7. Panel unit root test results

	Employment	**Robot**	**GDP Per Capita**	**Value Added**	**Labor Compensation**
	Prob.	Prob.	Prob.	Prob.	Prob.
LLC	0.0000	1.0000	0.0917	0.0042	0.0000
IPS	0.0345	-	1.0000	0.9988	0.0370
Fisher	0.0146	1.0000	0.9994	0.9991	0.0131
Hadri LM	0.0000	0.0000	0.0000	0.0000	0.0000
First Differences					
LLC	0.0000	0.8014	0.0000	0.0042	0.0000
IPS	0.0002	-	0.0000	0.0000	0.0000
Fisher	0.0001	0.8927	0.0000	0.0000	0.0000
Hadri LM	0.0049	0.0000	0.0012	0.0909	0.5629

LLC: Levin-Lin-Chu unit-root test (H_0: Panels contain unit roots; H_1: Panels are stationary)
IPS: Im, Pesaran and Shin unit root test (H_0: All panels contain unit roots; H_1: Some panels are stationary)
Fisher: Fisher-type unit-root test, Based on augmented Dickey-Fuller test (H_0: All panels contain unit roots; H_1: At least one panel is stationary)
Hadri LM: Hadri LM test(H_0: All panels are stationary; H_1: Some panels contain unit roots)

2.4. EMPIRICAL RESULTS

Estimation results of the dynamic panel are presented in tables 2.8 and 2.9. OLS, FE and one-step system GMM results are included in the results for completeness. Considering the AR(2) and Hansen Test results, two-step system GMM results are takeninto account.

In general the empirical results indicate that the impact of robots on labor is negative and significant. In this way, the empirical results show consistency with the findings in chapter 1.

Table 2.8 reports the empirical results on the impact of robots on employment for all countries. According to Arellano-Bond (AB) two-stepsystem GMM results, the first lag of employment is positive and significant at a 5 percent significance level. The coefficient of the stock of robots is negative and significant with a 10 percent significance level. Results reveal that each increase in robots causes0.7%drop in employment-to-population ratio. As a price indicator of labor, labor compensation affects the employment level negatively as expected. Each unit labor compensation increase leads to a 0.1% decrease in the employment-to-population ratio. Also results reports that GDP per capita and value added have no significant impact on employment-to-population ratio.

Table2.8. System GMM Estimation Results I

	Dependent Variable: lnemployment			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.485 (0.000)*	0.625 (0.033)**
lnrobot	-0.001 (0.571)	-0.007 (0.028)**	-0.016 (0.052)***	-0.007 (0.067)***
lnvalueadded	0.139 (0.000)*	0.199 (0.000)*	0.137 (0.029)**	0.068 (0.326)
lnLaborCompen.	-0.009 (0.980)	0.264 (0.000)*	0.016 (0.858)	-0.001 (0.01)**
lngdppercapita	0.068 (0.000)*	0.189 (0.000)*	0.083 (0.259)	0.044 (0.198)

First and second are coefficient levels and probability levels respectively
Number of groups: 47, Number of instruments: 23
One-Step GMM/AR(2): 0.538 Two-Step GMM/AR(2): 0.515
One-Step Hansen Test: 0.269 Two-Step Hansen test: 0.390
*, **, *** represents the significance at 1%, 5%, 10% respectively

Table 2.9lists the empirical results where the dependent variable is employment-to-population ratio in high-income countries. Similar to the whole sample estimation, robots have significant -according to 5 percent significance level- and negative impact on employment. However, robots have slightly more negative impact on high income countries than the all countries. Each increase in robots causes3.1% drop in employment-to-population ratio.For high-income countries, employment is also affected by the GDP per capita. According to estimation results, GDP per capita has positive and significant impact on employment.

Table2.9. System GMM Estimation Results II

	Dependent Variable: lnemployment in high income countries			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.909 (0.001)*	0.754 (0.002)*
lnrobot	-0.013 (0.000)*	-0.007 (0.028)**	-0.024 (0.087)***	-0.031 (0.017)**
lnvalueadded	0.103 (0.000)*	0.204 (0.028)*	0.076 (0.754)	0.048 (0.711)
lnLaborCompen.	0.145 (0.000)*	0.270 (0.000)*	-0.304 (0.334)	-0.028 (0.179)
lngdppercapita	0.229 (0.000)*	0.187 (0.000)*	0.322 (0.059)***	0.417 (0.014)**

First and second are coefficient levels and probability levels respectively
Number of groups: 35 Number of instruments: 24
One-Step GMM/AR(2): 0.250 Two-Step GMM/AR(2): 0.515
One-Step Hansen Test: 0.444 Two-Step Hansen test: 0.335
*, **, *** represents the significance at 1%, 5%, 10% respectively

The overall results are supporting the findings ofCarbonero et al. (2017), Bartelsman et al. (2009), Bassalini (2010), and Fargerberg (2000). Carbonero et al. (2017) finds the employment impact of robots stock at -0.5% at the world level. Considering the US local labor markets, Acemoglu and Restrepo (2017) finds 0.37% reduction in aggregate employment in each increase in robot per thousand workers under the assumption of no-trade between commuting zones. Compared to the results of both studies, the -0.7% impact found in this study indicates a more negative outcome on employment compared to Carbonero et al.(2017) but points to a less negative impact compared to Acemoglu and Restrepo (2017).

Forhigh-income economies, some studies find a positive coefficient for robot exposure. While estimating employment impact of distinct types of innovative investments at Spanish manufacturing sector on a firm-basis level, Pellegrino, Piva, Vivarelli (2017) find a positive effect on employment at the level of 0.6%.For Germany, Dauth et al.(2017) finds 2% increase in aggregate employment in each robot installation. This result challenges the findings of Bessen (2018), where the author argues that high-income countries diverge on this issue, but not positively. Bessen (2018) explains this argument with the large unmet needs of the markets:such a market may have an impact on growth and employment growth as it can reflect productivity increases to sales (Bessen, 2018). HoweverDe Backer et al. (2018), points out the position of low and medium-income countries in global value chains, arguing that such a mechanism will not work, that global offshore rates will decline, and that potential increases from productivity gains will be hampered by weakening global trade.

Also our results also support the findings of Bartelsman, Pieter, and Wind (2009) indicating that countries where technological progress poses high risk of unemployment lack relatively laws protecting workers. According to author’s empirical evidence, employment-protecting laws prevent the risk of jobs destruction as well as reducing the aggregate employment in the danger of rapid technological adoptions. This countermeasure partly explains why employment in high-income countries has less damage than the whole world.

2.5. CONCLUSION

In this chapter, the robotic impact on employment is investigated. In extant literature, there is ongoing debate about the effect of robots on human labor. The net effect of robots, which can perform almost all the work of human labor alone, on employment is still argumentative. On the one hand, robots are anticipated to replace human labor thanks to their labor-saving nature; on the other hand due to productivity improvements including robots in production leads new jobs and therefore additional employment. Although there is no consensus on the net effect in the literature yet, it is possible to find empirical studies on both views despite their insufficient number. The distinctive contribution of this study to the literature is the aggregate employment analysis for selected countries around the world including different income country groups. Specifically, the industrial robots are taken into account for 47countries in the period of 2004-2016.

The dynamic panel regression results show that each robot increase causes a 0.7% drop in employment-to-population ratio. This impact slightly rises for high-income countries; that each increase in robots leads3.1%fall in employment-to-population ratio for this country group. For overall country sample, the share of labor compensation has positive but very small impact (0.1%) on employment. On the other hand for high-income country group, while labor compensation has no significant impact on employment, GDP per capita has andpositive and a greater effect than robots.

The empirical results show that for all countries the increase in robot use clearly causes a negative effect on employment. Therefore, the estimation results support the displacement impact literature (Carbonero et al., 2017, Bartelsman et al., 2009, Bassalini, 2010, and Fargerberg, 2000, Carbonero et al., 2017).

In addition, the empirical results support real life experiences. The key determinant of the question is the rapid progress of the technology in the direction of fulfilling the work of human labor.In other words, the trend in technological progress is that machines become workers by leaving from their complementary role to workers.For instance, in the age of the Second Industrial Revolution, workers put in a complementary role. But now the world is welcoming intelligent machine-learning algorithms, that can learn all business processes, as long as they have big data and software. Hence the displacement effect is getting stronger.

Also the US example mentioned in the introduction section also confirms this trend; the fact that the rate of job growth in the country fell from 31% in the 1960s to 0% in the 2000s reveals the magnitude of negative effect of these intelligent machines on employment and shows that the offset mechanism or so-called counterbalance effect (Acemoglu and Restrepo, 2019; Manyika et al., 2013; Mokyr et al., 215) is almost nonexistent.This situation also explains why the displacement effect is much stronger in high-income countries. Higher and widespread robotization causes a more negative effect on employment in these countries with developed economies.

CHAPTER 3

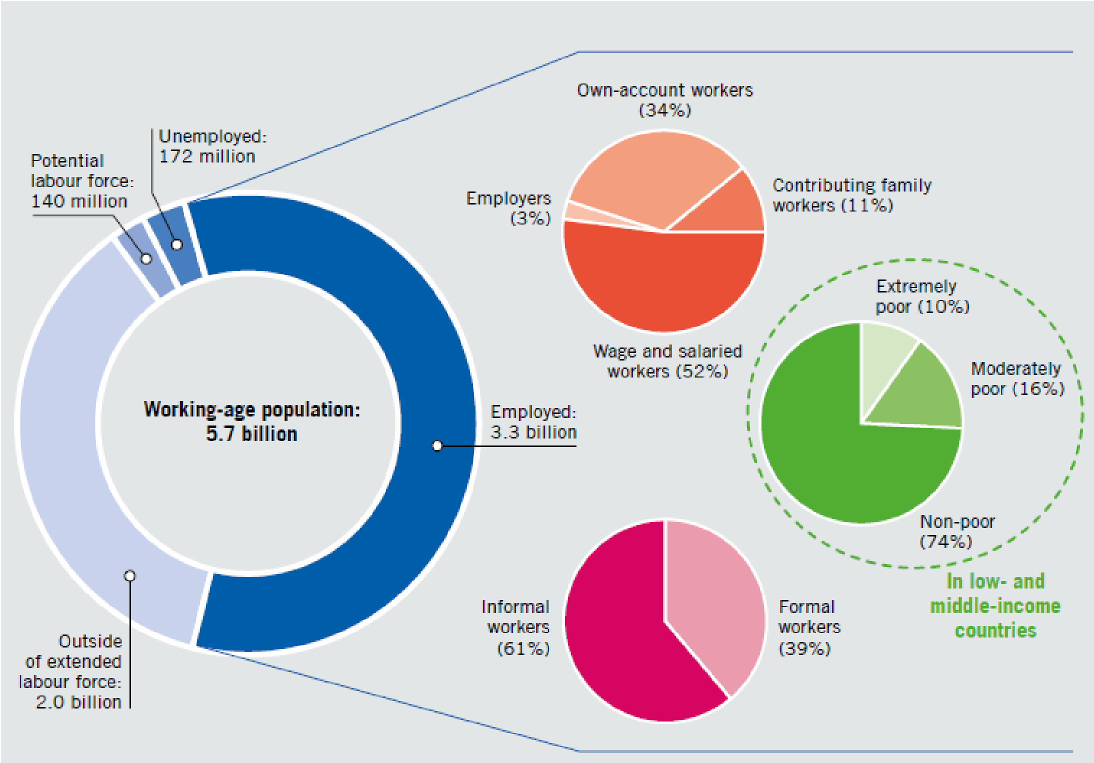
RISING INEQUALITY AMONG EMPLOYEES

3. 1. GENERAL VIEWS ON ROBOTS AND INEQUALITY

The way that robots interact with generations and among workers is complex and co-evolutionary. As automation leads a reduction on the demand of labor (Autor et al., 2006; Acemoglu and Autor, 2011; Brynjolfsson and McAfee 2014, Acemoğlu and Restrepo 2015, Graetz and Michaels, 2015, Arnzt et al. 2015, Hemous and Olsen, 2016, PrettnerandHolger, 2017) the need of special attention on the demographic variations is growing as well. This need stems from the question "who will be most affected by robot expansion?".

According to ILO, there are currently5.7 billion people are in working-age population, i.e. capable of workingin all over the world. However, 3.3 billion people out of 5.7 billion make up the workforce; this is represented by the 61.4% labor force participation rate. Moreover, 172 million people are unemployed; and140 million people are counted in potential labor force, which means “people who are looking for a job but are not yet available to take up employment, or who are available but are not looking for a job” (ILO, 2018). This alarming picture highlights that 2.2 billion people included in working-age population are unable to find a job.In other words, the current global economy on earth cannot provide jobs to 36.6 percent of those in working-age population (Figure 3.1).

Figure 3.1. Global Labor market, 2018



Source: World Employment and Social Outlook-Trends 2018, ILO modeled estimates, November 2018; ILO, 2018a.

When we put our focus on demographic features, inequality among employees becomes a pronounced era. 3 out of every 5 employed people are male. Besides, while male labor force participation is 75%, female labor force participation remains at 50% level. This wide gap provides striking data that reveals gender inequality amongthe workforce.

Another remarkable statisticsis that a significant share of the drop in the labor force participation rate in the last 25 years belongs to young people. Every year, 33 million people, mostly young generations, join the workforce. As of 2018, youth participation in labor force was only 42%, indicating that there has been a sharp drop by 15% in youth participation since 1993. On the other hand the world population has increased by 50% since 1990 and the employment rate has decreased from 62.6% to 58.15% between

1991 and 2019 (ILO, World Employment and Social Outlook, 2019).This fact shows that the world economy cannot provide sufficient job opportunities to new generations.

As labor force participation is following a downward trend and the inequality among the labor force is increasing rapidly, the effect of robots that is anticipated to replacehuman labor is becoming an argumentative and important topic. In the first chapter of the thesis, the effect of robots on employment is theoretically and empirically proven to be significant and negative. This chapter focuses on the effect of robots on inequality among workers, based on their demographic characteristics. We investigate the intergenerational effects of robots, assuming a positive correlation of experience, knowledge and skills with age.It’s predicted that the negative impact of the growing number of robots on employment will be felt mostly by the younger generations and maleworkers.In this context, the study is based on the hypothesis that the young generation and male workers represent two demographic groups that have the most difficulties in responding to the increasing skill demands arising from robotization. This study consists of four sections. Section 2 reviews the theoretical and empirical literature focusing on inequality caused by robots. Section 3 empirically estimates the impact of robots on employment according to age and gender groups. Lastly, section 4 summarizes the results.

3. 2. THEORETICAL AND EMPIRICAL BACKGROUND

A vast literature documents the varying opinions and findings on the impact of robots on heterogeneous labor force. Nevertheless there is a strong consensus among scholars that robots increase inequality among workers (Prettner and Holger, 2017, Acemoglu and Restrepo 2018, Graetz and Michaels, 2015, Hemous and Olsen, 2016, Arnzt et al. 2015).

In his extensive study-*Capital in the Twenty-first Century*- Thomas Piketty argues that if the rate of return of capital exceeds the rate of growth in the economy, the nature of working changes and inequality is expected to increase among working class. In parallel, a widespread opinion in the recent literature supports that robots mostly take over the repetitive tasks which are undertaken by low and middle-skilled workers. Goos, Manning and Salomons (2009) analyzes inequality resulting from technological progress in 15 EU countries and argues that high-paying, high-skill demanding jobs have increased and middle-paying jobs have decreased relatively, from the early 1990s to the end of the 2000s. More recently, Education Comission[11]- shortly Comission- claims that the young generation in the world is at high risk due to the accelerating automation, which has ahigher labor substitution power previous stages of technological progress. The Comission also underlines that half of the world's total work - about 2 billion - is at high risk of extinction due to the automation.

By conducting local labor market equilibrium approach on 6 EU countries which make 85.5% of EU robot market, Chiacchio et al. (2018) finds a significant and strong displacement effect of robots on young workers. Muro et al. (2019) indicates that for the near future, the automation and AI will affect mostly men and young workers. They found that the most vulnerable demographic segment in the society that is affected by robots is men. Through the Brookings analysis of 2016 American Community Survey, where the demographic impacts of robots on US labor market are investigated, it is found that 42.6% of jobs that men are working are automatable, whereas 39.6% of women’s jobs are at risk of automation. On the other hand, the situation is more frightening for employees under the age of 25. 50% of the total tasks of employees under the age of 25 faces with automation risk. Similar effects are found by Dauth et al (2019) for Germany. Dauth et al (2019)reveals that young people are affected by robotization more negatively. The need for young workers is decreasing in the sectors where robots are expanding, and therefore, young people are directed to the servicesector relativelydemanding low-skills.

[11] The International Commission On Financing Global Education Opportunity

Although there is a growing interest on labor market polarization, the empirical study on this question is limited due to lack of statistical data. This gap is often tried to be narrowed by firm or local-level survey analysis. As one of these studies, Morikawa (2017) conducts a survey on Japanese companies and reveals that the AI technology, which has a strong labor substitution, effects post-graduate employees to a minimum, and even this effect, may turn to be a positive impact for this worker group. Also Frey and Osborne (2013) predict a downward trend in labor market polarization. Their acclaimed work *The Future of Employment* shows that computerization will not only be in routine tasks involving low-skilled workers, but also in cognitive tasks, because of the high progress in machine learning process.

World Bank warns that the share of middle-skilled jobs is falling in 20 out of 22 developing countries (World Bank, 2015). These observations and predictions are based on the following fact: All robots are a product of human intelligence at the end. They are the machines designed and produced by mankind for their own interest. Therefore some human activities are needed to manufacture, operate, develop and maintain robots such as; designing, coding, programming, R&D activities and auditing. Regarding these tasks, robots can be defined as very complex machines embodied with high technology, high labor skills, high knowledge and experience. On the other hand, robots are the special type of machines that can imitate human production activities therefore can replace human labor not only in routine tasks, also in cognitive and decision-making tasks.

In an industry-country panel setting and using data for 17 countries over the period 1993-2007, Graetz and Michaels (2018) shows that despite no evidence on significant negative impact of robotics on employment, there’s a remarkable reduction of low-skilled employment share. Noting the wage aspect of inequality**,** Dauth et al. (2017) empirically reveals that there is a sharper fall in the wages of medium-skilled workers thanks to increasingnumber of robots. In the same labor price context, Berg et al. (2018)

found that the impact for automation is negative and strong for the upcoming next generations.

The inequality impactof robots is also explained by theoretical models. Prettner and Holger (2017) offer a framework where high-skilled employees are complementary to machines and low-skilled employees are substituted under the R&D-based growth model. In a task-based approach and with endogenizing capital accumulation, the findings of Acemoglu and Restrepo (2018) support the positive causality between robotization and inequality by providing theoretical evidence on asymmetrical employment effects of robots on heterogeneous labor force. By constructing the endogenous growth model Olsen and Hemous (2016), demonstrates the positive relationship between automation and skill premium. Accepting the effect of increasing skill premium, Benzell et al. (2018) poses the risk of job loss for all employees due to insufficient capital accumulation and relatively slowdown in growth by looking long run.

The one conceptual explanation behind increasing inequality due to the robots lies in the *Skill-Biased Technological Change* (SBTC). SBTC generally takes two skill groups- high skilled and low-skilled workers- into account; this may often be extended with third category by including middle-skilled workers. According to general acceptance, highly educated and experienced employees are categorized as high-skilled, while low-educated and inexperienced are defined as low-skilled (Krueger, 1993;Autor, Katz and Krueger, 1999; Goldin and Katz, 2018). SBTC specifies two forces that technological improvements affect labor demand. On the one hand, as technology advances, each new stage requires higher skills, thereby it causes an increase in demand for complementary labor. On the other hand, every advanced stage in the technology brings with a greater proportion of the replacement of works, which are previously done by human labor. On a large scale, these jobs are those undertaken by low skilled workers in the production process. In short, the advancement of technology does not only produce quantitative results on labor demand, but also produces qualitative results. While technology establishes a complementary relationship with the high skills of human labor, it establishes a substitute relationship with its low skills. This leads to an increase in the demand for high-skilled labor (increasing labor share) and a decrease in demand for low-skilled labor (decreasing labor share), therefore it results with higher inequality (Graetz and Michaels, 2018, Hemous and Olsen, 2016, Acemoğlu and Restrepo 2015, Dauth et al 2017, Autor, 2015, Benzell et a. 2018, Sachs et al. 2015, Berg et al 2018, Chiacchio et al. 2018).

Another conceptual explanation for rising inequality between workers is *Task-Based Technological Change* (TBTC) approach. TBTC is formulated by Autor et al., (2003) with the intuition of separating the work into tasks, such as the atom splitting into molecules. Based on the measurement of task complexity, TBTC-focused studies turn their attention to how repetitive tasks a job contains. Consistent with SBTC, repetitive jobs require low skills, while more complex tasks require high skills. The main point that TBTC differs from SBTC is SBTC treats the main cause of inequality as educational differences, while TBTC claims that task content in jobs leads to inequality. Autor and Dorn, (2013) provides the finding that regarding US labor market between 1950 and 1980, while repetitive task-intensive jobs accounted for 38% of total jobs, in 2005 this rate fell to 28%, so employment in these jobs was sharp had a decline. Finding similar result for 27 EU countries in the period 1999-2010, Gregory et al., 2019 observes a rapid decline in repetitive-intensive jobs and an increase in complex task-intensive jobs, which leads a counterbalance effect by offsetting the fall in repetitive-intensive jobs.

Following Chiacchio et al. (2018) and Muro et al. (2019), in this chapter we provide evidenceconsistent with the SBTC concept, focusing on different age groups and genders. There is a close relationship between employment divergences in different age groups and genders and skill disparities. This chapter follows the hypothesis that, apart from education, experience is also a qualification included in high qualifications. The special point in this case is that experience is only obtained by the years in work; i.e. as the age gets older. Card and DiNardo (2002) supports this hypothesis by providing evidence for the periods 1980s and 1990s that the ability to use computers increases with age. In this context, young workers can compete with older i.e. experienced workers only by improving their education quality. In OECD countries, approximately one in five youth can acquire basic minimum level of skills. Besides, on average, 20% of young people end their education before completing upper secondary education (OECD, 2012).

The second focus of this chapter is to look at the inequality arising from robotization between the genders. Although there is a wide consensus on market polarization against women, robots are expected to affect men more. This prediction is explained by TBTC. Since, men work in more routine-intensive jobs (Muro et al. 2019), they face the danger of replacing robots more.

3. 3. DATA

Dynamic panel data includes 28 countries due to lack of employment data availability and has a sample period 2014-2016 with annual observations. Table 3.1.lists the countries in the dataset.

Table 3.1. List of Countries

Austria	Ireland
Belgium	Iceland
Canada	Italy
Switzerland	Lithuania
Czech Republic	Latvia
Germany	Mexico
Denmark	Netherlands
Spain	Norway
Estonia	Poland
Finland	Portugal
France	Slovakia
United Kingdom	Slovenia
Greece	Sweden
Hungary	South Africa

In chapter 2, overall employment is observed with using employment-to-population-ratio as dependent variable. In this chapter, since employment based on demographic features is analyzed, we prefer to use the number of employee data instead of employment-to-population ratio.

As a general definition, employment is defined as those from working-age populations, who are engaged in on economic activity for pay or get profit in a reference period. We used International Labor Organization (ILO) “Employment rate by sex and age” data to analyze the employment impact of robots by age ranges.ILO defines employed people as those in one of the following categories: “i) paid employment (whether at work or with a job but not at work); or ii) self-employment (whether at work or with an enterprise but not at work)”(see ILO yearly indicators, 1947-2019)

In this context, following ILO classification, we definefour age groups: (i) for those who are the beginners: 15 to 24; (ii) for those who are in their prime working lives: 25 to 34; (iii) for those who has reached the peak in their career: 35 to 44 (iv) lastly the group of workers approaching retirement: 45 to 54.

In order to smooth data, we use natural logarithms of number of employees, stock of robots, labor compensation as a % of GDP, value added as a % of GDP and GDP per capita. The average logarithmic values of number of employees according to age groups for 28 countries are documented at Appendix B. Comparing the average employment across countries, it’s clear that the youngest employee population is located in Mexico and the number of employee population decreases at a later age. As a country with a high number of employees, Germany has a higher population in the middle-agegroup.In countries other than Mexico and South Africa, an inverted U-curve representing the relationship between age and employment takes place; employment increases up to a certain age, and decreases as the age gets older since reaching the peak. In Mexico and South Africa, an age curve occurs, peaking in the 25-34 age-band and then declining;

these figures does not follow an inverted U-curve, until the age range 25-34 the increase is slow and after this age, the decrease is rapid. Therefore, in our data set Mexico and South Africa display a younger age-intensive employment feature.

3.4. METHODOLOGY AND EMPIRICAL RESULTS

In order to test the employment impact of stock of robot by age groups, we apply two-step system GMM estimator approach. For this purpose, the specification is taken to explain the relationship between employment by age and sex groups and stock of robots as follows;

$$employment_{15-24,i,t} = F(robot_{i,t}, gdppercapita_{i,t}, valueadded_{i,t}, LaborCompensation_{i,t})$$

$$employment_{25-34,i,t} = F(robot_{i,t}, gdppercapita_{i,t}, valueadded_{i,t}, LaborCompensation_{i,t})$$

$$employment_{35-44,i,t} = F(robot_{i,t}, gdppercapita_{i,t}, valueadded_{i,t}, LaborCompensation_{i,t})$$

$$employment_{45-54,i,t} == F(robot_{i,t}, gdppercapita_{i,t}, valueadded_{i,t}, LaborCompensation_{i,t})$$

where $employment_{15-24}, employment_{25-34}$, $employment_{35-44}$ and $employment_{45-54}$ indicate the employment by age groups: 15-24, 25-34, 35-44, and 45-54 respectively; i indicates countries and t indicates year.

We construct static and dynamic model as followsrespectively;

$$\mathrm{ln}employment_{\mathrm{j,i,t}} = \beta_0 + \beta_1 lnrobot_{i,t} + \beta_2 LaborCompensation_{i,t}$$

$$+\beta_3 lngdppercapita_{i,t} + \beta_4 lnvalueadded_{i,t} + year_t + \emptyset_i + \varepsilon_{i,t}$$

$$\ln employment_{\mathrm{j,i,t}} = \alpha \ln employment_{\mathrm{j,i,t-1}} + \beta_1 lnrobot_{i,t} + \beta_2 LaborCompensation_{i,t}$$

$$+\beta_3 lngdppercapita_{i,t} + \beta_4 lnvalueadded_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

$$j = age\ bands : 15 - 24, 25 - 34, 35 - 44, 45 - 54$$

$$i = 1,2, \dots, N$$

$$t = 1,2, \dots, T$$

where$\emptyset_{\mathrm{i}}$ is time-invariant individual fixed effect and ε is the usual error term.

First, the stationarity features of panel data are investigated. In order to avoid repetition, panel unit root test will be applied only in employment by age and sex data.

Tables 3.2 and 3.3 present the panel unit root test results for age groups and genders respectively. Unit root test results indicate that at least one of the tests show non-stationary in the employment data by age groups, whereas for the first-difference panel series stationary is provided by all the tests.

Table 3.2. Panel Unit Root Test Results for Age Groups

	$employment_{15-24}$	$employment_{25-34}$	$employment_{35-44}$	$employment_4$
	Prob.	Prob.	Prob.	Prob.
LLC	0.0000*	0.4243	0.0000*	0.0000
IPS	0.0079*	0.9987	0.7812	0.1296
Fisher	0.0001*	0.7536	0.2071	0.0008
Hadri LM	0.0000*	0.0000*	0.0000*	0.0000*
First Differences				
LLC	0.0000*	0.0000*	0.0000*	0.0000*
IPS	0.0000*	0.0010*	0.0008*	0.0012*
Fisher	0.0000*	0.0004*	0.0032*	0.0001*
Hadri LM	0.0112**	0.0001*	0.0221**	0.0072*

LLC: Levin-Lin-Chu unit-root test (H_0: Panels contain unit roots; H_1: Panels are stationary)
IPS: Im, Pesaran and Shin unit root test (H_0: All panels contain unit roots; H_1: Some panels are

stationary)
Fisher: Fisher-type unit-root test, Based on augmented Dickey-Fuller test (H_0: All panels contain unit roots; H_1: At least one panel is stationary).
Hadri LM: Hadri LM test(H_0: All panels are stationary; H_1: Some panels contain unit roots)
*, **, *** represents the significance at 1%, 5%, 10% respectively

Table 3.3. Panel Unit Root Test Results for Gender

	employment (Female)	employment (Male)
	Prob.	Prob.
LLC	0.0000*	0.0000*
IPS	0.3378	0.2473
Fisher	0.0299**	0.0910***
Hadri LM	0.0000*	0.0000*
First Differences		
LLC	0.0000*	0.0000*
IPS	0.0008*	0.0001*
Fisher	0.0000*	0.0001*
Hadri LM	0.0006*	0.0937***

LLC: Levin-Lin-Chu unit-root test (H_0: Panels contain unit roots;H_1: Panels are stationary)
IPS: Im, Pesaran and Shin unit root test (H_0: All panels contain unit roots; H_1: Some panels are stationary)Fisher: Fisher-type unit-root test, Based on augmented Dickey-Fuller test (H_0: All panels contain unit roots; H_1: At least one panel is stationary)
Hadri LM: Hadri LM test(H_0: All panels are stationary; H_1: Some panels contain unit roots)
*, **, *** represents the significance at 1%, 5%, 10% respectively

3.4.1 GMM Estimation Resultsfor Age Groups

The empirical results of the possible relationship between the number of employees aged 15-24, 25-34, 35-44, and 45-54 and stock of robots are documented in tables 3.4-3.7.

Table 3.4. System GMM Estimation Results for Age Group 15-24

	Dependent Variable: lnemployment between ages 15 and 24			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.822 (0.000)*	0.813 (0.000)**
lnrobot	0.432 0.000	-0.080 (0.000)*	-0.098 (0.044)***	-0.215 (0.086)***
lnvalueadded	-0.778 (0.001)*	0.725 (0.000)*	0.125 (0.911)	-0.420 (0.137)
lnLaborCompen.	-1.013 0.025	1.570 (0.000)*	-2.268 0.020	-4.668 (0.079)**
lngdppercapita	-0.678 (0.000)*	0.777 (0.000)*	1.488 0.038	3.001 (0.073)

First and second are coefficient levels and probability levels respectively
Number of groups: 28, Number of instruments: 23
One-Step GMM/AR(2): 0.418 Two-Step GMM/AR(2): 0.124
One-Step Hansen Test: 0.379 Two-Step Hansen test: 0.551
*, **, *** represents the significance at 1%, 5%, 10% respectively

The dynamic model for the AB two step-system GMM estimation for the dependent variable employment aged 15-24 is specified as follows;

$$lnemployment(15-24)_{i,t} = (0.813)lnemployment(15-24)_{i,t-1}$$
$$+(-0.215)lnrobot_{i,t} + (-4.668)\text{lnLaborCompen.}_{i,t} + (3.001)lngdppercapita_{i,t}$$
$$+ (-0.420)\ln ValueAdded_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

According to the AB two step-system GMM estimation (table 3.4); the first lag of the number of employees aged 15-24 is positive and significant at 1% level. The robot stock coefficient isnegative and significant according to 10% significance level. The coefficient of robot stock reveals thatevery 100 additional robot causes a decline in the number of employee between the ages of 15 and 24 by 21.5. In addition, the impact of labor compensation on the number of employeeis negative and significant at the 10%

level and GDP per capita affects significantly and negatively. And also value added has positive butnot significant impact for this young age group.

Table 3.5. System GMM Estimation Results for Age Group 25-34

	Dependent Variable: lnemployment between ages 25 and 34			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.819 (0.000)*	0.887 (0.000)**
lnrobot	0.468 (0.000)*	-0.034 (0.000)*	-0.088 (0.066)***	-0.122 (0.058)***
lnvalueadded	-1.136 (0.000)*	0.311 (0.001)*	0.160 (0.778)	0.219 (0.674)
lnLaborCompen.	-1.493 (0.000)*	0.906 (0.000)*	-0.292 (0.899)	-2.398 (0.004)**
lngdppercapita	-1.301 (0.000)*	0.426 (0.000)*	0.813 (0.032)**	1.355 (0.047)

First and second are coefficient levels and probability levels respectively
Number of groups: 28, Number of instruments: 23
One-Step GMM/AR(2): 0.694 Two-Step GMM/AR(2): 0.397
One-Step Hansen Test: 0.142 Two-Step Hansen test: 0.925
*, **, *** represents the significance at 1%, 5%, 10% respectively

Table 3.5 documents the empirical results for employees between the ages of 25 and 34. Robots have significant impact on this age group’s employment with a10% significance level. The coefficient of stock of robots is negative and lower than the age group 15-24; each 100 additional robots cause a decrease in the number of employees by 12.2 according to two-step system GMM. Value added has not a significant effect on age group 25-34 as it does for the age group 15-24. Moreover similar with the youngerage group, labor compensation has negative and significant impact with 1% significance level. Nevertheless 25-34 age group is more sensitive to changes in labor compensation. Likethe previous age group, GDP per capita has positive and significant impact with 5% significance level.

$$lnemployment(25-34)_{i,t} = 0.887 lnemployment(25-34)_{i,t-1} + (-0.122) lnrobot_{i,t}$$

$$+(-2.398)\text{lnLaborCompen.}_{i,t} + 1.355 lngdppercapita_{i,t} + 0.219 \ln ValueAdded_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

Table 3.6. System GMM Estimation Results for Age Group 35-44

	Dependent Variable: lnemployment between age groups 35-44			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.957 (0.000)*	0.793 (0.000)*
lnrobot	0.482 (0.000)	-0.034 (0.001)*	0.035 (0.020)**	0.447 (0.016)**
lnvalueadded	-1.271 (0.000)*	0.529 (0.000)*	0.045 (0.503)	0.108 (0.401)
lnLaborCompen.	-1.536 0.000	0.126 (0.256)	0.151 (0.170)	0.222 (0.200)
lngdppercapita	-1.211 (0.000)*	-0.218 (0.016)**	0.154 (0.004)*	0.202 (0.039)**

First and second are coefficient levels and probability levels respectively
Number of groups: 28 Number of instruments: 21
One-Step GMM/AR(2): 0.250 Two-Step GMM/AR(2): 0.341
One-Step Hansen Test: 0.352 Two-Step Hansen test: 0.530
*, **, *** represents the significance at 1%, 5%, 10% respectively

According to the empirical estimation results listed in table 3.6, the robotic impact on employees aged between 35 and 44 is positive and significant. For this age group, each 100 additional robots cause an increase in the number of employees by an amount of 44.7. In the light of this result, this group of workers, who might be considered as middle-aged group, is acting complementary to robots. Also they are vulnerable to changes inGDP per capita, which has positive and significant impact.

$$lnemployment(35-44)_{i,t} = 0.793 lnemployment(35-44)_{i,t} + 0.447 lnrobot_{i,t}$$

$$+0.222\text{lnLaborCompen.}_{i,t} + 0.202 lngdppercapita_{i,t} + 0.108 \ln ValueAdded_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

Table 3.7. System GMM Estimation Results for Age Group 45-54

	Dependent Variable: lnemployment between age groups 45-54			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.701 (0.000)*	0.460 (0.000)*
lnrobot	0.468 (0.000)*	-0.035 (0.000)*	-0.022 (0.020)**	-0.014 (0.047)**
lnvalueadded	-1.153 (0.000)*	0.429 (0.000)*	0.060 (0.258)	0.035 (0.516)
lnLaborCompen.	-1.018 (0.006)*	0.203 (0.018)	0.01 (0.994)	-0.003 (0.963)
lngdppercapita	-1.061 (0.000)*	-0.215 (0.002)**	0.052 (0.072)**	0.020 (0.519)

First and second are coefficient levels and probability levels respectively
Number of groups: 28 Number of instruments: 22
One-Step GMM/AR(2): 0.293 Two-Step GMM/AR(2): 0.306
One-Step Hansen Test: 0.501 Two-Step Hansen test: 0.352
*, **, *** represents the significance at 1%, 5%, 10% respectively

As employees get closer to retirement, the effect of robotization becomes negative again. AB two-step system GMM results show that the coefficient of stock of robots is negative and the impact of robots is significant with 5% significance level. Compared to younger ages,employment is not as vulnerable as the 15-24 and 25-34 age groups.

$$lnemployment(45-54)_{i,t} = 0.460lnemployment(45-54)_{i,t-1}$$

$$+(-0.014)lnrobot_{i,t} + (-0.003)\text{lnLaborCompen}_{i,t} + 0.0196lngdppercapita_{i,t}$$

$$+0.035\text{lnValueAdded}_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

3.4.2. Empirical Results for Gender Groups

The dynamic estimation results for the two gender groups are listed in tables 3.8 and 3.9. As listed in table 3.8, AB two-step system GMM results indicate that robots have negative and significant impact on female workers with 10% significance level. On the other hand,male workers are slightly more affected by robots. Also both gender groups are affected by GDP per capita positively and by share of labor compensation negatively, whereas they are indifferent to value added.

$$\text{lnemployment (Female)}_{\text{i,t}} = 0.937\text{lnemployment (Female)}_{\text{i,t}-1} + (-0.040)lnrobot_{i,t}$$

$$+(-1.164)\text{lnLaborCompen.}_{i,t} + (0.698)lngdp_{i,t} + (0.105)\ln VA_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

Table 3.8. System GMM Estimation Results for Female Employment

	Dependent Variable: lnemployment, Female			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.957 (0.000)*	0.937 (0.000)*
lnrobot	0.456 (0.000)*	-0.031 (0.000)*	0.091 (0.008)*	-0.040 (0.076)**
lnvalueadded	-1.270 (0.000)*	0.287 (0.000)*	0.011 (0.871)	0.105 (0.715)
lnLaborCompen.	-1.391 (0.000)*	0.451 (0.000)	-0.029 (0.685)	-1.164 (0.001)*
lngdppercapita	-1.096 (0.000)*	0.161 (0.002)**	-0.053 (0.182)**	0.698 (0.001)*

First and second are coefficient levels and probability levels respectively
Number of groups: 28 Number of instruments: 26
One-Step GMM/AR(2): 0.763 Two-Step GMM/AR(2): 0.449
One-Step Hansen Test: 0.293 Two-Step Hansen test: 0.852
*, **, *** represents the significance at 1%, 5%, 10% respectively

$$\text{lnemployment (Male)}_{\text{i,t}} = 0.887\text{lnemployment (Male)}_{\text{i,t}-1} + (-0.050)lnrobot_{i,t}$$

$$+(-1.550)\text{lnLaborCompen.}_{i,t} + (1.152)\text{lngdppercapita}_{i,t} + (-0.030)\text{lnValueAdded}_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

Table 3.9. System GMM Estimation Results for Male Employment

	Dependent Variable: lnemployment, Male			
	OLS	**FE**	**SYS GMM 1**	**SYS GMM 2**
L1.lnemployment	- -	- -	0.959 (0.000)*	0.887 (0.000)*
lnrobot	0.483 (0.000)*	-0.042 (0.000)*	-0.136 (0.023)**	-0.050 (0.097)***
lnvalueadded	-1.380 (0.000)*	0.332 (0.000)*	-0.052 (0.323)	-0.030 (0.812)
lnLaborCompen.	-1.836 (0.000)*	0.632 (0.000)*	-0.068 (0.265)	-1.550 (0.000)*
lngdppercapita	-1.205 (0.000)*	0.365 (0.000)*	-0.030 (0.271)**	1.152 (0.000)*

First and second are coefficient levels and probability levels respectively

Number of groups: 28 Number of instruments: 20

One-Step GMM/AR(2): 0.706 Two-Step GMM/AR(2): 0.685

One-Step Hansen Test: 0.292 Two-Step Hansen test: 0.328

*, **, *** represents the significance at 1%, 5%, 10% respectively

In line with vast literature, the results found for four different age groups and gender groups indicate that inequality will increase among workers as a result of the increase in the number of robots. Some groups are relatively less affected by robots, some are more vulnerable, and some employees are positively affected depending on the characteristics of their age group.

Table 3.10 summarizes the robotic impact on employment with respect to age groups and gender.

Table 3.10. Summary of the results

Responses of age groups and gender groups to each increase of robots	
Age Groups	
15-24	-21.5% (↓)
25-34	-12.2% (↓)
35-44	44.7% (↑)
45-54	-1.4% (↓)
Gender Groups	
Female	-4% (↓)
Male	-5% (↓)

Regarding the analyses based on age groups, findings support the results of Chiacchio et al. (2018)Muro et al. (2019) and Dauth et al.(2019)showing that the most negatively affected group is young people under the age of 25. As a result of every 100 robot increase, the number of employees in the 15-24 age group decreases by 21.5, while this amount in the 25-34 age group is around 12, and 1.4 in the 45-54 age group. On the other hand for the ages of 35-44, every 100 robot increase leads a reduction in a number of employees by an amount of 44.

These varying impacts, created by the rising robots, also support the SBTC hypothesis. In terms of both experience and skill, one group establishes complementary dynamics to robots, while the other group is affected negatively due to the replacement effect depending on their demographic characteristics, especially skills. SBTC highlights labor market polarization referring an employment and wage gap occurred among heterogeneous employment groups. Skill level and educational attainment play an important role in this polarization and these two key factors are closely related with experience level. This also how Caselli (2015) explains this age-related concerns on employment polarization. According to this study, skills are growing according to experience; as moving to older ages, experience and skills also accumulate. The results of our thesis also support this argument. As the age progresses, the robots' power to replace workers decreases and even turns to positive.

In terms of gender, the estimation results are in parallel with the TBTC hypothesis. As a result of the increase of 100 additional robots, the number of female employees decreased by 4, while the number of male workers decreased by 5. It has been proven that robots are more unfavorable to men. This situation is explained conceptually within TBTC; that because of male workers are more involved in routine or repetitive jobs than women, they are more exposed to the substitution of robots (Autor et al., 2003). Also this response gap our thesis indicates supports the findings of Autor and Dorn (2013).

CHAPTER 4

CONCLUSION

The concern for the technological unemployment that has existed since machines began replacing human labor continues to a larger extent today. The world economy has experienced mechanization since the first industrial revolution. In fact, every machine used in the production of goods and services naturally replaces human labor. However, machines used until about three decade ago, so-called conventional machines, cannot take over every job from people. Therefore, while they substitute human labor in limited scope of jobs, they also act as complementary to human labor in jobs they could not take over.Thus, technology-anxiety has never been as strong as it is today, and the fear that machines will cause permanent unemployment has never been so severe.

So, why is technology-anxiety so strong today?The answer to this question is closely related to what type of machines or technologies we are talking about. In general, these technologies include Information and Communication Technologies (ICT), Artificial Intelligence (AI), the Internet of Things (IoT) and smart robots. Once the necessary hardware is installed, these machines only need big data to get action, with productivity 107% above the human labor's (Ford, 2015).

Although these machines, which are attractive to firms, have not yet become widespread, experience so far is sufficient to reinforce the technological-anxiety of workers.Considering the rapid spread of industrial robots[12], robot unemployment has begun to appear in the manufacturing industry. In China, where the manufacturing industry is one of the leading industries, the number of people who lost their jobs due to

[12]see IFR'srobot stock data in chapter 2

the displacement effects of robots already reached 16 million between 1995 and 2002 (Baum, 2013).

In this thesis, the question of unemployment, which is the main center of technological-anxiety, is investigated. The possible effect of robots on employment is examined both theoretically and empirically. Therefore, first of all, the question of whether robots are substitutes or complementary is answered. The theoretical and empirical findings, which indicate that robots are not acting labor-friendly in the economies, are later extended by seeking an answer to the question of 'which labor'.So we also develop an answer to the question of whether there is a market polarization in the heterogeneous labor market in terms of different age groups and gender as a result of robots.

In the first chapter, the negative impact of robots on the labor market is explained by taking into account the dynamics between two generations through the OLG economy. Simply, we develop an OLG model, where only young individuals take part in the labor market, as well as in saving decisions. The only source of investments in the economy is these young individuals' savings. Firms are operating in single-output economy with mainly two production factors: physical capital and human labor. And all firms (in this model we use representative firm) have access to automation technology, in which they can produce robots from some part of physical capital and this decision also depends on the robot productivity rate. The novelty of this model is robots are perfect substitutes of human labor; hence in the long-run robots push wages downwards. The downward pressure on wages causes immiseration in the economy in the long run; and the main reason for this is the decrease in savings.Since our model includes the full employment economy, it does not present the impact of the downward pressure on wages on employment. But the results of the model offer us a clear comparative statics. The results, supported by the literature, point to the negative impact of robots on employment.

The second chapter empirically analyzes the effect of robots on employment. According to dynamic panel study results, we arrive to the empirical evidence that is consistent with theoretical analysis. According to the results, each robot increase causes a 0.7% drop in employment-to-population ratio for 47 selected countries in a period of 2004-2016. Two-step system GMM estimation is preferred in order to control potential endogeneity among all independent variables and also to avoid any problems that may arise from country-specific effects. Since the AR(2) and Hansen Test results provide more significant results in two-step system GMM, two-step system GMM is preferred instead of one step-system GMM estimator.

The limited data set due to the availability of robot stock data, doesn’t allow sufficient analysis for all the country income groups; for this reason, analysis is made only on high-income countries. Results show that negative robotic impact on employment is slightly higher in high-income countries (-3.1%), which hold a large part of the global robot stock.

Although the direction of impact on employment provides an important data, the world we live in today has a heterogeneous labor market. Therefore, it is expected that each form of labor will be affected by robots in different intensities and directions. In this regard, an empirical analysis is developed over labor classifications based on age and gender groups in the labor market. Chapter 3, which is devoted to the estimate that takes into account this heterogeneity, presents results that fit the concepts of SBTC and TBTC.In line with SBTC, young workers are predicted to be more negatively affected by robotization. Moreover, men are more involved in routine jobs than women workers. Therefore, compatible with the TBTC hypothesis, male workers are anticipated to be more negatively affected by the robot increase. According to dynamic panel data estimation results, it is found that every 100 increase in the number of robots decreases the number of male workersby 5, whereas it decreases the number of female workers by4.

The above results also shed light on some suggestions and needs for future studies.

As the findings in the first chapter point out, the increase in robot productivity allows countries with lower capital stocks to enter robot technology. Therefore, analyzes to be made on developing countries, which are known to have more routine work, will make a significant contribution to the literature.However, in order for such a study to be performed through panel data analysis, sufficient robot stock data is required. Once this problem is resolved, a comparison between different country income groups also stands as an opportunity for future studies.

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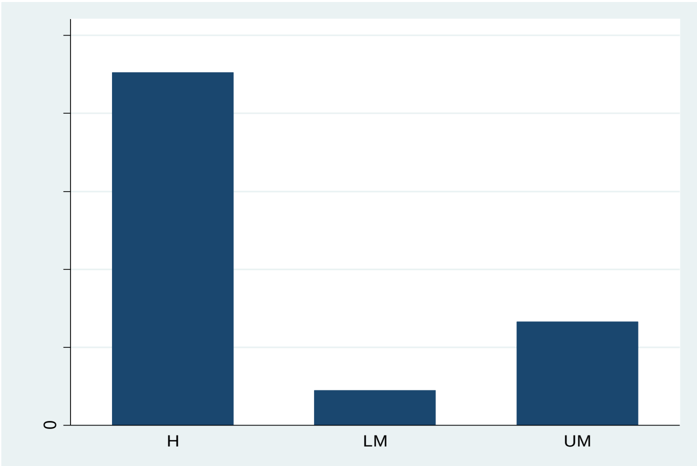
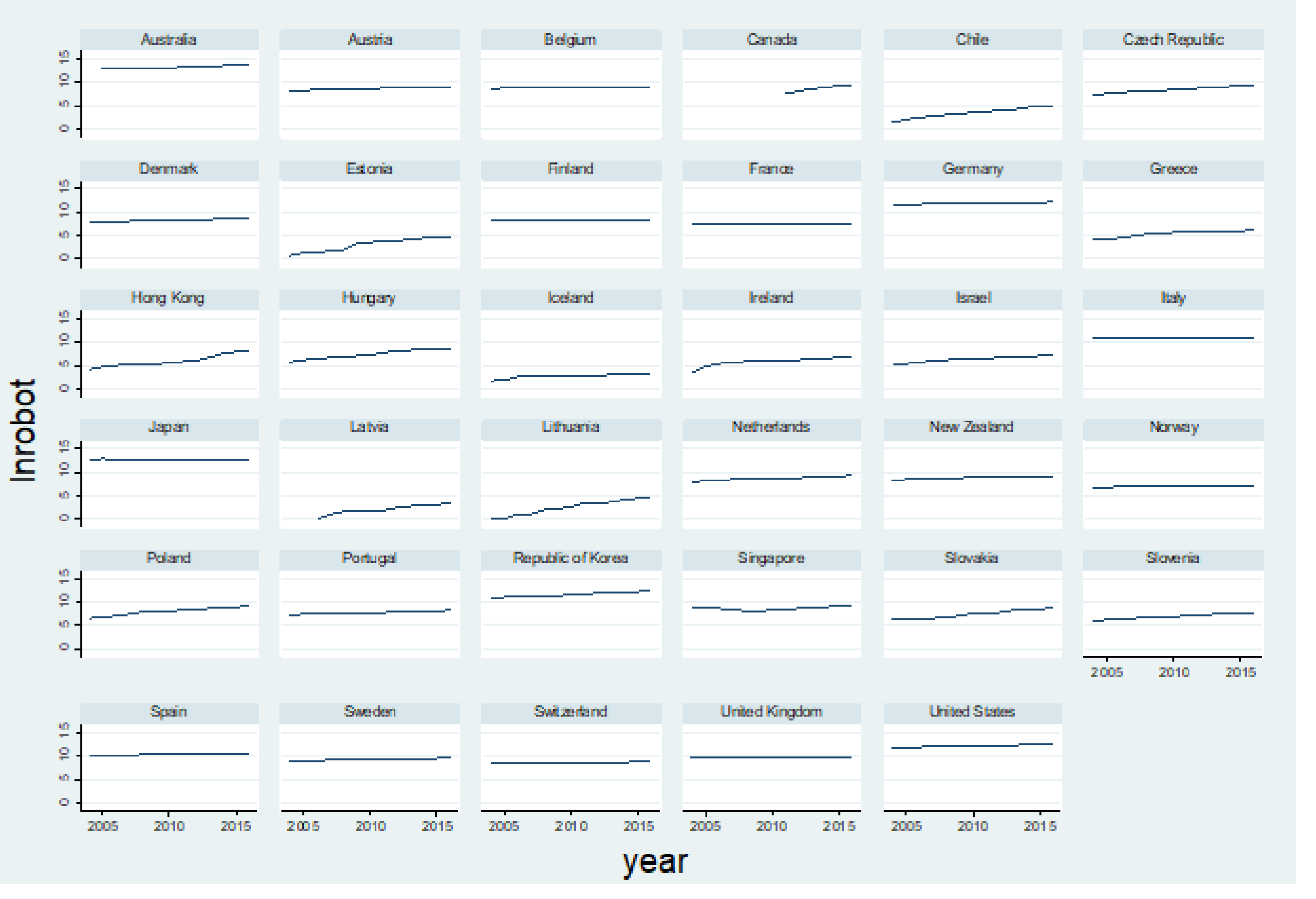
APPENDIX A.

Robot average distribution of robots, country income groups



H: High income countries; LM: Lower-middle income economies; UM: Upper-middle income countries

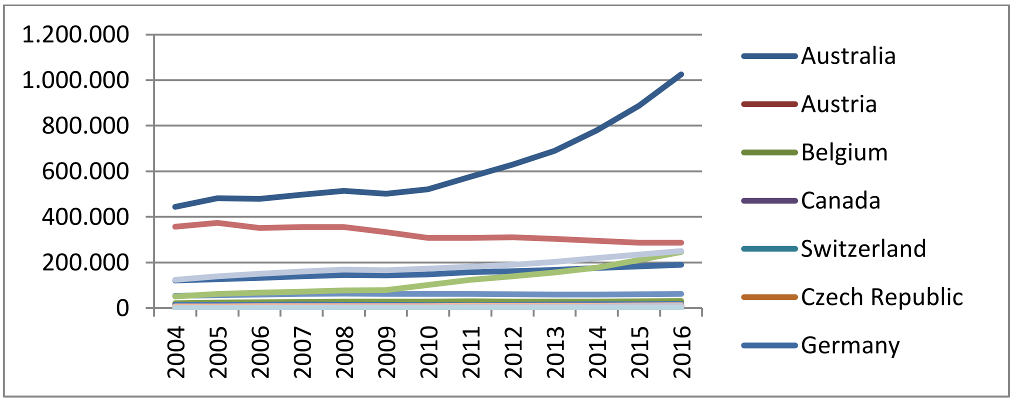
Stock of Robots At High Income Countries, 2004-2016



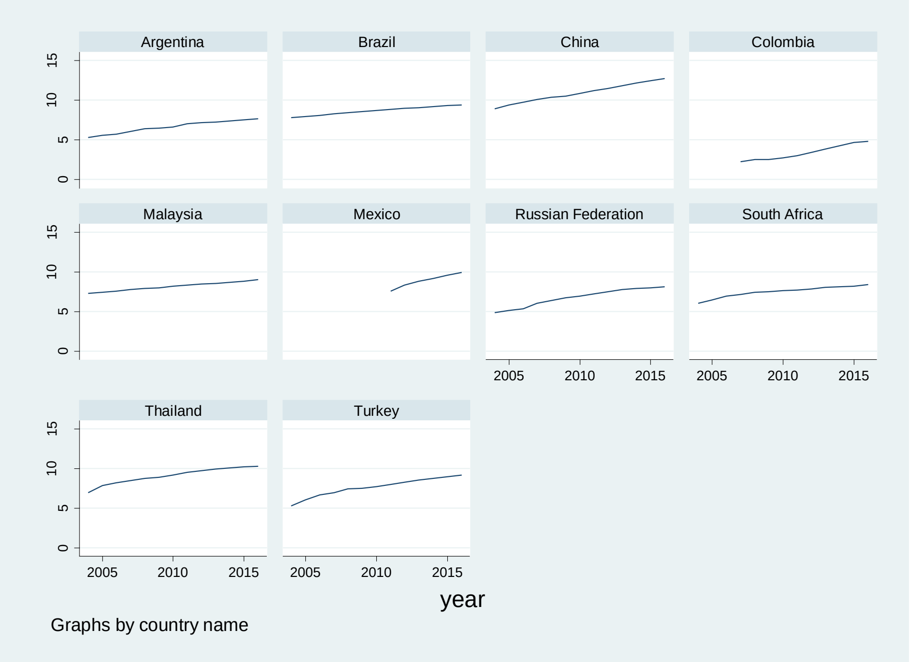
Average ln(Stock Of Robots), High Income Countries

Country Name	Avg. ln(stock of robots)	Country Name	Avg. ln(stock of robots)
Australia	13.2991	Denmark	8.2984
Japan	12.6876	Poland	7.9901
United States	12.0908	Portugal	7.7252
Germany	11.9301	France	7.6059
Republic of Korea	11.5789	Slovakia	7.3567
Italy	11.0047	Hungary	7.3561
Spain	10.2282	Slovenia	6.9383
United Kingdom	9.633	Norway	6.8914
Sweden	9.166	Argentina	6.5962
New Zealand	8.8443	Israel	6.3041
Belgium	8.8279	Hong Kong	5.9437
Canada	8.717	Ireland	5.8169
Austria	8.6598	Greece	5.3754
Netherlands	8.6367	Chile	3.5097
Singapore	8.6038	Estonia	3.0792
Czech Republic	8.4865	Iceland	2.6594
Switzerland	8.4586	Lithuania	2.5162
Finland	8.3749	Latvia	2.0787

Trends In Robot Stock In High Income Countries



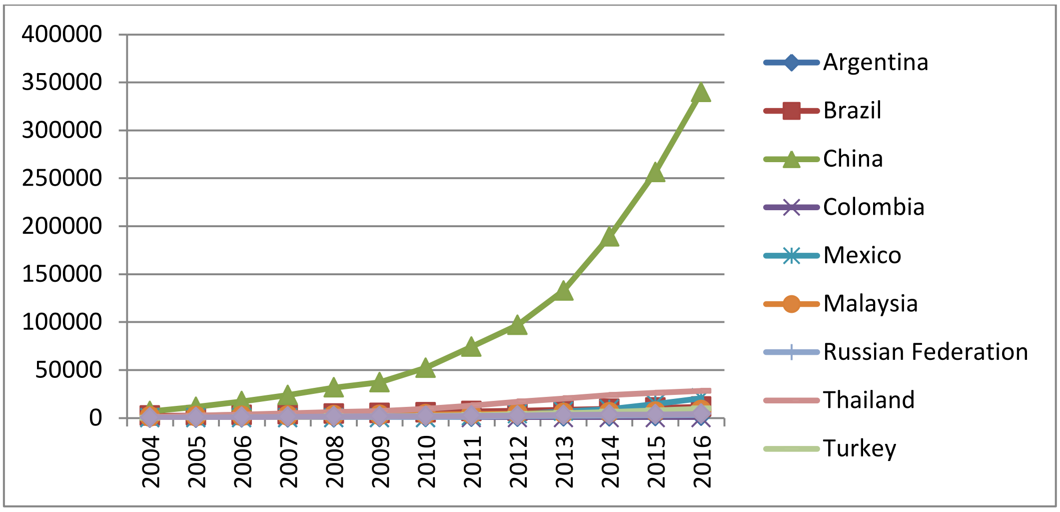
Stock of Robots AtUpper-Middle Income, 2004-2016



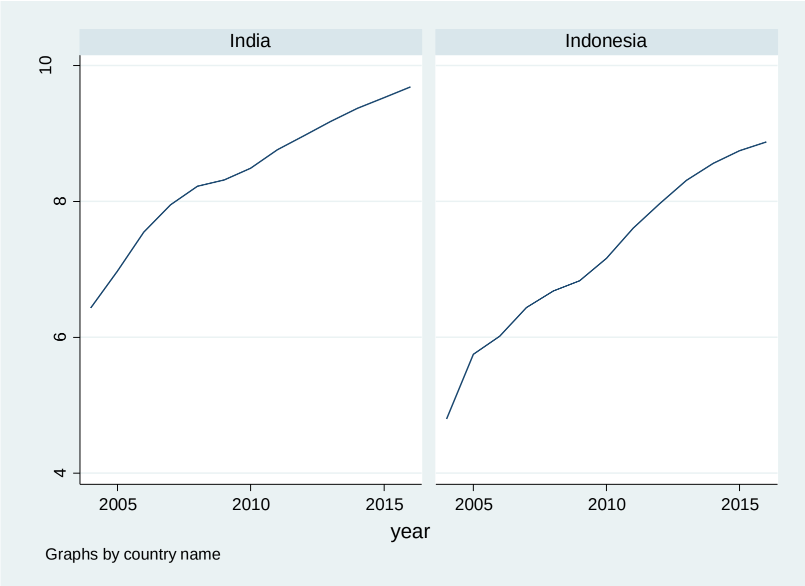
Average ln(stock of robots), Upper-Middle Income

Country Name	Avg. ln(stock of robots)
China	10.8969
Thailand	9.0668
Mexico	8.8945
Brazil	8.6313
Malaysia	8.1556
Turkey	7.6302
South Africa	7.5653
Russian Federation	6.7637
Colombia	3.3679

Trends In Robot Stock In Upper-Middle Income Countries



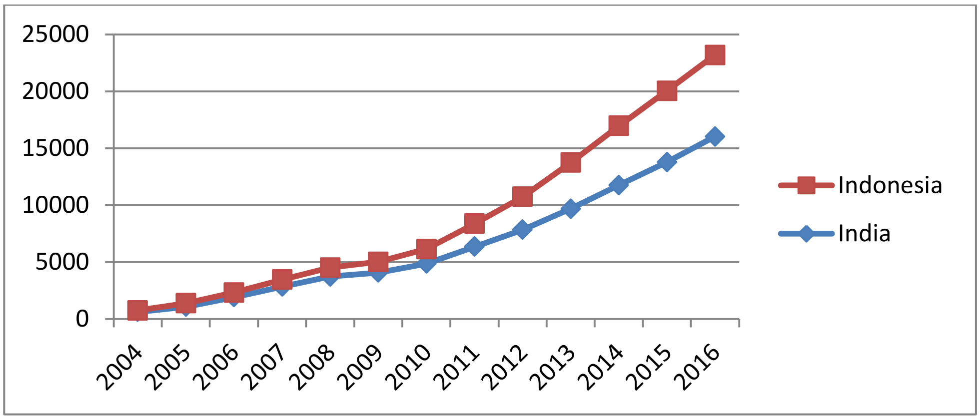
Stock of robots at lower-middle income countries, 2004-2016



Average ln(stock of robots), Lower-Middle Income

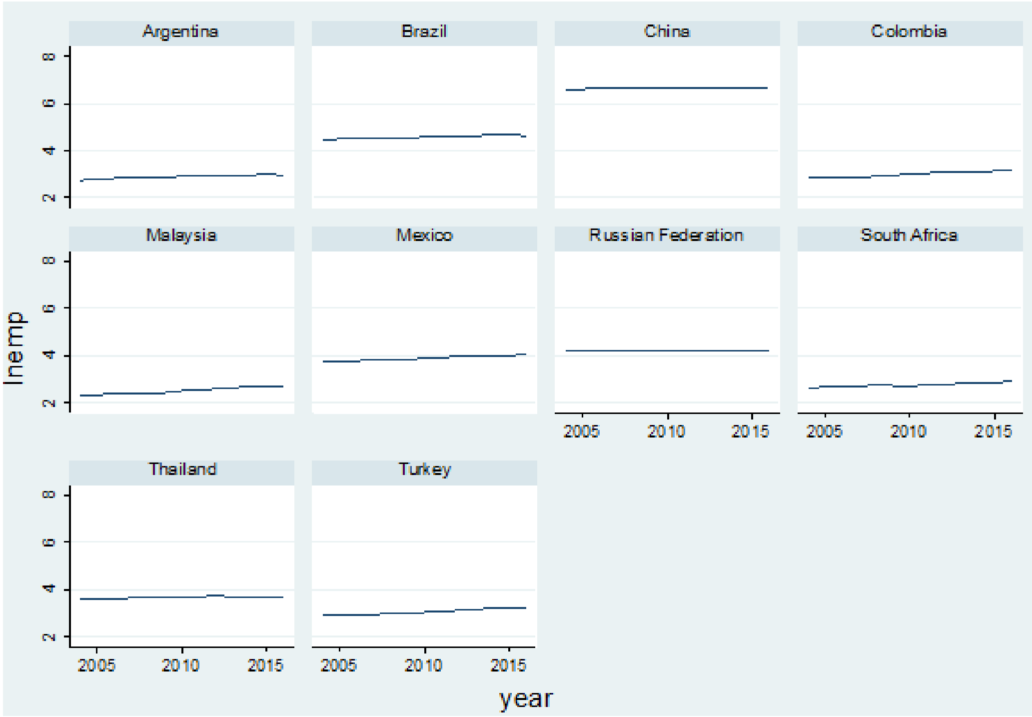
Country Name	Avg. ln(stock of robots)
India	8.4162
Indonesia	7.21

Trends in robot stock in lower-middle income countries



Stock of robots at high income countries, 2004-2016

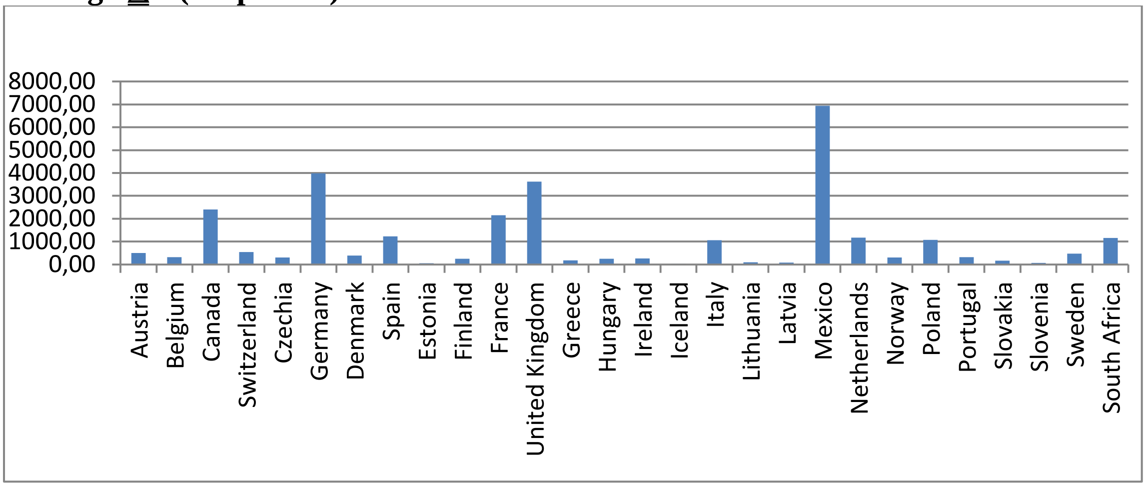
Stock of robots at upper-middle incomecountries, 2004-2016



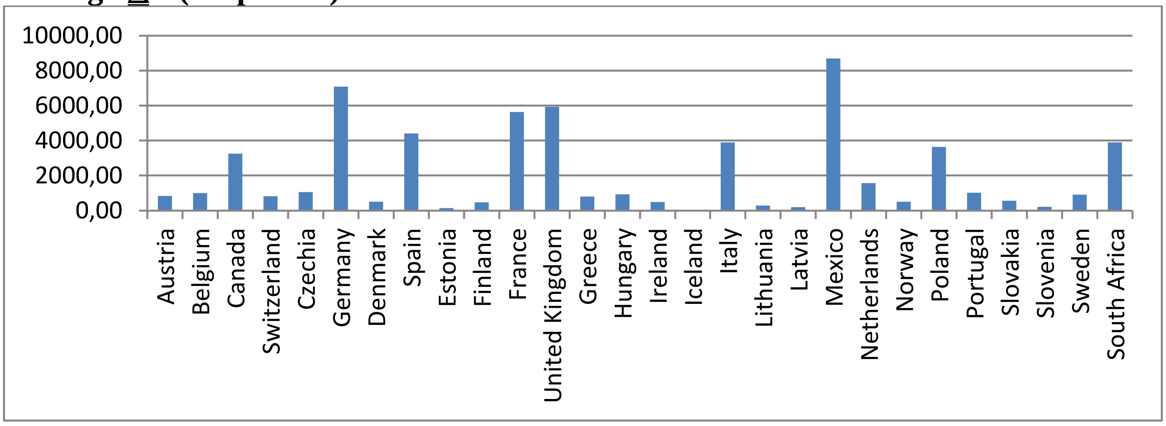
Lower-middle income

APPENDIX B.

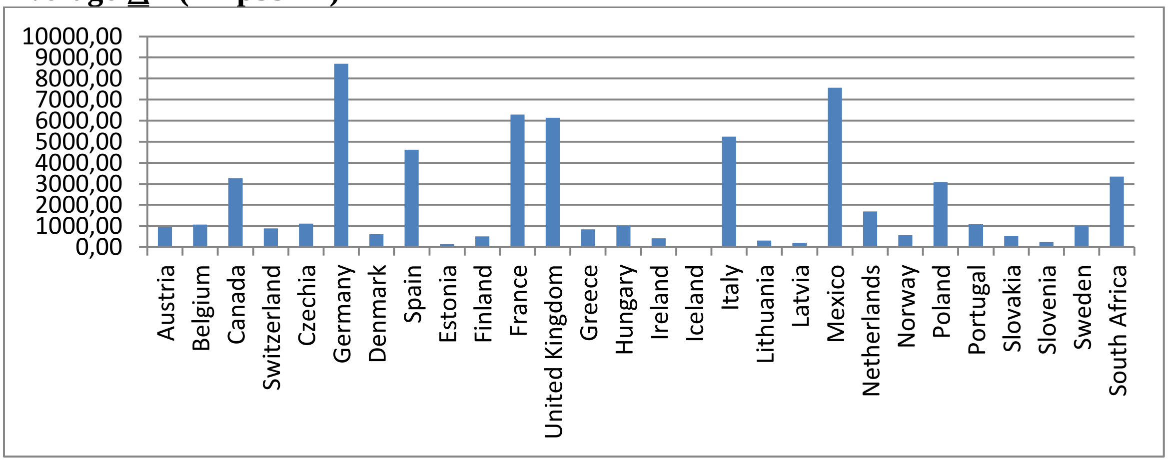
Average Δln(Emp15-24)



Average Δln(Emp25-34)



Average Δln(Emp35-44)



Average Δln(Emp45-54)