The impact of modern capital on skill allocation in the European Labour Market

Author: Ejoel METZ
Supervisor: Chizeng MIAO
Examiner: Dominique ANXO
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Abstract

This paper deals with the impact of "modern" capital on skill allocation in the European Union (EU) Labour Market for a period from 1996 to 2016. Applying a First-difference methodology on a panel data at the country level from Eurostat, the study finds out that as "modern" capital increases by 1%, low-skill employment decreases by -0.1%. However, the introduction of new technologies does not affect middle-skill and high-skill employment. Furthermore, "modern" capital/technology does not exhibit any statistically significant impact on working hours, suggesting that the former may affect employment at the extensive margin. The results are in line with Autor et al. (2003) and we may reject the hypothesis of Job Polarisation.
1 Introduction

The term Industry 4.0 appears more frequently in economic debates. It describes an industry where different spheres of technologies which have initially been separated merge, as described by Schwab (2017). He develops in the same paper that “velocity, scope and system impact” characterise this new form of industry which is about to grow. The importance of those technologies which are mainly computer-based is evidenced by Nordhaus (2007). He finds out that computer performance has improved “since manual computing by a factor between 1.7 trillion and 76 trillion”.

Kurz (2017) states in his paper that technological progresses do offer solutions to problems. Nevertheless, they also create new problems that challenge societies, states and economies. Regarding economies, one of the greatest challenges concerns Labour Markets. Technologies and innovations are put in to enhance productivity. However, they are in direct competition with human labour which faces the danger of technological unemployment, as described by Peters (2016). The topic of technological advances and their impacts on Labour Markets has reached the ethical sphere, because the danger of human disenchantment seems to concretise when considering technologies such as Information and Communication Technology (ICT) (Loi, 2015). From this development arises a question: "Which is the most relevant risk for human labour?".

Whereas popular or non-economic papers deal with different aspects of the life of a worker as an individual, the economists identify a process which is not new: substitution. In particular, new technologies set to replace low-skilled human labour as they gain in productivity. Previous research has shown that the task content of a particular occupation determines largely to which extent human labour is subject to substitution (Frey and Osborne, 2013; Autor and Dorn, 2013; Autor et al., 2003; Goos et al., 2009). However, new technologies are considered to profit to a certain group of human labour, namely high-skilled workers. Despite different methodologies, the results given by the four papers suggest that the adaptation of new technologies, supported by the developments of Industry 4.0, is expected to change structures in the Labour Markets.

While an occupation’s task content may be important to assess the impact of new technologies on a Labour Market, it might be interesting as well to investigate the impact on skill allocation within a Labour Market. The issue of skill allocation becomes of particular interest when one is aware of the skill levels that these tasks require. The International Standard Classification of Occupations (ISCO) provides a good orientation for this respect and allows to go further. Indeed, in order to perform some skill-related task, ISCO states that these can be done if some educational levels are met. These levels can be classified by the International Standard Classification of Education (ISCED).

Hence, the present essay tries to answer to the following question:

(see next page, please)

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1Enhancement is a set of means to improve human life, disenchantment being its opposite.
Which is the recent impact of "modern" capital on skill allocation in the European Labour Market?

The contribution of the present paper is threefold: firstly, it does not only consider employment as a Labour Market outcome but also working hours. This distinction allows to go beyond the question of employment rate in order to see if the introduction of new technologies affects occupation at the extensive or intensive margin. Secondly, the paper covers a period from 1996 to 2016 which makes it of recent actuality. Lastly and most importantly, it links directly "modern" capital to Labour Market outcomes without any deviation. Using Eurostat data and First-difference methodology, the results suggest a decline of low-skill and low-education employment induced by "modern" capital.

The present paper is structured as follows: (2) The Literature Review deals with the most recent advances in the technological sphere. A construction of a theoretical framework follows as well as a review of related studies to this paper. (3) The Methodological Framework and Results describes the technical methodology to answer the research question before a presentation of the major results and interpretation follows. (4) Afterwards, the Discussion treats the main aspects of the findings and contextualises them with respect to the Theoretical Framework. (5) Finally, the Conclusion completes the paper.
2 Literature Review

2.1 The current state of technologies

Recently, Eurofound (2018) update the reader about the current technologies and their main implications for production processes. Here shall be presented three technologies which can determine the perception of the present paper:

1. Advanced Industrial Robotics (AIR)
   New advances in sensors and dynamic programming permit to employ robots which are capable to execute tasks requiring flexibility and accuracy. What used to be unrealistic one and a half decade before (Autor et al., 2003), turns out to represent a new impact on the already impacted Labour Markets since nonroutine manual tasks seem to be at higher risk of automation than before.

2. Additive Manufacturing (AM)
   This concept aims to add products and their components into a new product instead of cutting out existing materials. AM requires that machines can model products digitally before generating them physically. The ability to turn data into things and vice versa materialises a new step of technological progress (Gershenfeld, 2012). Abstract or manual intensive tasks can be thus to a certain degree at risk of automation if machines are able to conceptualise products and to execute the construction independently.

3. Industrial Internet of Things (IIoT)
   Thanks to IIoT, cyber-physical systems implemented in a production chain communicate with each other so that the process of production becomes autonomous. Hence, any human labour used before to accompany production steps is at risk.

Estimations on possible global market outcomes illustrate the potential pervasiveness of those technologies. According to the White paper RAS 2020 (2014), AIR is estimated to represent volumes of between €1.61 and €5.42 trillion per year by 2025. Concerning AM, the global turnover may attain €423 billion (Manyika et al., 2013) while Berger (2013) estimates the industry to represent €1.44 billion. Finally, Eurofound (2018) suggest that IIoT could represent volumes from €170 and €626 billion by 2025 in the automative industry only.

Nevertheless, the following barriers to adoption shall be considered when talking about the impact of the advances mentioned above (Eurofound, 2018):

**Initial investments**: Technologies such as AIR require initial investments. Therefore, the number of companies able to integrate AIR into their production process diminishes since those initial investments require an important amount of financial and non-financial capital. On the other hand, IIoT and AM are less demanding in
terms of investment capacities, but full implementation across the entire production process requires a significant engagement.

**Energy & Raw materials**: Although there might be some differences between these technologies in terms of investment, they all require an important amount of energy. By 2050, the global demand for electricity will double of that today ([World Economic Forum, 2017](#)). Technologies allowing for more efficient use of electricity and other forms of energies will therefore play a role as important as the digital technologies themselves. Furthermore, the demand for input such as rare earth materials and other not commonly available materials will increase ([Eurofound, 2018](#)).

**Standards**: To promote the pervasion of these technologies, standards have to be set. Whereas the International Organization for Standardization (IOS) is an example of an organisation which can set standards, the latter have also to be developed by companies ([Eurofound, 2018](#)).

In any case, these three and other related advances[^I] rely on investments such as in microprocessors, internet related assets[^II] etc. ([Eurofound, 2018](#)). Companies having the necessary expertise are clearly in an advantageous position. Competing companies which do not belong to this sector will seek to access to this technology set, which could explain possible lags in adaption between industries and countries.

[^I]: Big Data, Artificial Intelligence, Cloud computing, Augmented reality, etc.
[^II]: Any infrastructure related to internet and digitalisation
2.2 Theoretical Framework

This section develops the theoretical background to understand how "modern" capital is supposed to affect skill allocation. Before we start looking at the process, it may be convenient to clarify what I exactly mean with the term "modern" capital in order to exclude vague interpretations.

As seen in the section The current state of technologies, we notice that many types of "modern" capital have a common ground: data. Indeed, the modern technologies are characterised by the need and by the treatment of data in order to work. The types of data which are used are as diverse as the possible fields of application. Discussing the variety of the types of data would go beyond the scope of the present essay. However, it is worth mentioning that these "modern" capitals are characterised by data processing.

A preliminary note shall also be added at this point concerning tasks. As mentioned in the previous subsection, certain types of tasks will experience changes in demand. The following will give a definition of some of them in order to follow the paper’s development. 

Routine tasks are tasks machines can perform following explicit rules. Analogously, tasks are considered nonroutine when the characteristic steps are not "well understood" (Autor et al., 2003).

Abstract or cognitive tasks require, as the designations say already, capacity of abstraction or cognition. In particular, it refers to the capacity of assessing or creating ideas. This implies also creativity.

Manual tasks require dexterity and other precise physical competences.

Having defined the main forms of tasks, we can now move forward and analyse the role of "modern" capital with respect to Labour Markets.

Throughout the literature as discussed for example in the Review of empirical studies, capital turns out to have two effects towards Labour Market outcomes: substitution and complementarity.

Substitution: As the studies suggest, capital substitutes human labour in occupations where the content of substitutable tasks is relatively high. Those "substitutable" tasks are notably routine or manual tasks. However, Frey and Osborne (2013) refer to three bottlenecks which have to be overcome so that more types of tasks are at risk of computerisation. Analogously, other "bottlenecks" which are not identified yet may have to be overcome so that they can be replaced by "modern" capital. The pace at which new innovations arise to impact human labour is without precedent (Schwab, 2017). Those innovations can endanger human labour, because they are on the one hand more productive and on the other hand cheaper than human labour. In particular, as time passes, those types of capital become at the same time more productive and cheaper.

Complementarity: The other side effect of "modern" capital is complementarity. At
the first glance, it may be not clear why capital shall complement certain types of human labour. To understand this, we need to go back to the question what capital is able to substitute. As already stated, capital substitute for human labour in occupations whose content is intensive in tasks capital can execute because of its comparative advantage. However, occupations and jobs in general do not consist in executing a single type of task. Indeed, jobs are rather characterised by a mix of different tasks a worker shall execute. If capital supplies in substitutable tasks, then it supplies at least indirectly in non-substitutable tasks, because a worker can focus more intensively on tasks capital cannot execute.

Considering this, we have to ask: "What are the theoretical implications for the Labour Markets?" Once again, only substitutable tasks such as routine or manual tasks can be executed by capital. However, not every task can be executed by everyone. Indeed, tasks require certain skills a worker has to meet with in order to perform them. Once the skill requirements are met, a worker can be employed in jobs which are intensive in the corresponding tasks. This development implies that skills are not something which is (entirely) innate. Indeed, if a worker desires to perform tasks demanding higher skills, then he can do so by accomplishing the necessary type of education. As Autor and Dorn (2013) describe in their model, a worker’s skill endowment is at the same time a factor of decision and of selection towards the skill-ranged occupations. Consequently, we expect the adaptation of "modern" capital to change skill allocations in the Labour Market. There are notably two possible outcomes which can arise:

**Job Polarisation:** Goos et al. (2009) discuss the phenomenon of Job Polarisation in the European Labour Markets. Job Polarisation is expected to occur since the adaptation of "modern" capital will mostly impact workers which are "middle-skilled" as they mostly perform tasks that "modern" capital can perform. The displaced middle-skill workers may "migrate" to low-skill or high-skill occupations which depends on several factor such as educational attainment, demand in the Labour Markets for the respective skills, individual preferences, etc. The phenomenon of Job Polarisation is depicted in figure II. While the extreme ends of skill distribution increase in share of employment with respect to total employment, there is "hollowing out" of the middle-skill group compared to figure II which illustrates in a stylised manner a possible Labour Market situation before the arrival of "modern" capital.

**Skill-biased technological change:** Goos et al. (2009) also mention the possibility of Skill-biased Technological Change (SBTC). It theorises a shift towards high-skill occupations since only high-skilled workers can operate with "modern capital" or, put differently, the emerging technologies favour high-skilled workers (Violante, 2008). A stylised outcome of this phenomenon is depicted in figure II where the frequency of people employed in high-skill occupations increases while the other two skill groups observe a decline in

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V Further definitions of skills follow in Methodological Framework and Results
employment. Nevertheless, these outcomes are subject to an important assumption: the distribution of educational attainment across the Labour Force in a country shall allow for these outcomes to occur. Whereas one can expect intuitively that there might be enough highly educated persons within a country to satisfy the Job Polarisation outcome, the SBTC outcome implies, according to figure II, that even more persons of high educational attainment are needed. Since changes in the distribution of educational attainment across the Labour Force without allowing for migration are expected to materialise slowly, factors "outside the economy" may determine the pace of any of the two outcomes. However, these two possible outcomes require assumptions which may be likely to be for certain types of countries. But these assumptions, which have to be checked beforehand, can turn out to not be for the rest of the countries. Hence, outcomes different to the two discussed above can occur. It depends among other factors on the pace at which technology substitute or complement human labour. If this pace has a "disruptive" character, then unexpected results can occur (Kurz, 2017). Hence, one shall follow the technological progresses and consider the possible impacts on Labour Markets repeatedly by taking into account geographical heterogeneity in order to predict Labour Market outcomes as reliably as possible.

2.3 Review of empirical studies

The above subparts give us some hints on how to perceive the world in terms of technological progress and their possible "disruptive impacts on Labour Markets". They have the power to destabilise whole economies (Kurz, 2017). It is therefore interesting to explore studies dealing more thoroughly with these issues, especially related to skill allocation in the Labour Markets. To give a context to the new technologies as described in Section 2.1, Eurofound (2018) examines possible shifts in skill & occupational profile demand. It concludes that those technologies yield into a new generation of manufacturing. An increased demand for high-skilled occupational profiles as well as non-technical skills is likely to be the outcome. Furthermore, social & communication skills are expected to be more and more solicited, because team work as well as clear communication are crucial conditions in order to act in a complex environment. Finally, Eurofound (2018) finds out that decentralised production processes require independent decision-making & creativity in order to deal with unforeseen events that can occur. Eurofound (2015) provides some empirical results on employment shifts. In general, the fastest-growing, large-employing jobs across the EU are well-paid service sector jobs.
such as ICT professionals and business professionals with growth rates of 10% and 9.2% respectively in the period from 2011 to 2014. On the other hand, jobs such as customer service clerks and building & related trades workers excluding electricians exhibit respectively a shrink of -5.3% and -5.2%. The growth of ICT-related occupations are in line with the expected emergence of the new technologies. Eurofound (2015) also examines long-term trends in the employment structure in six European countries\textsuperscript{IX}. Diverse forms of occupational change across those countries can be observed for the period from 1970 to 2014. It comes out that UK and Germany have experienced Job Polarisation while all countries have experienced at least growth at the top of the employment structure. This skill ”upgrade” can be explained by the requirements of new technologies and is therefore in line with the SBTC hypothesis. However, one shall be aware that deindustrialisation, emerging dominance of the service sector, the increase of the public sector as well as the ”feminisation” of the Labour Markets have taken place at this period. Thus, it cannot be excluded that these phenomena have driven to an important extent Job Polarisation and the skill upgrade.

Nevertheless, it shall be asked why the bottom segment of the employment structure displays opposing experiences in function of the country. It shall be recalled that we consider a period from 1970 to 2014. Different institutional settings might be more important in that period than today. Moreover, Labour Market institutions are susceptible to regulate with special caution the bottom segment. This might explain the ambiguous growth, be it positive or negative, of the bottom segment across these countries.

When looking at a more recent period, namely from 2011 to 2014, then Eurofound (2015) finds out that the diversity of structural changes in the employment across the EU countries persists. Cyprus, Greece and Ireland are examples of Job Polarisation whereas Austria, the Czech Republic, Poland, Portugal and Sweden experience an upward shift of the employment structure, i.e. skill upgrade. Nevertheless, Hungray, Italy Slovakia and Germany display signs of downward shift of the employment structure.

Obviously, the lower segment of the employment structure seems to exhibit interesting patterns. Autor and Dorn (2013) study the ”growth of low-skilled service occupation between 1980 and 2005 and the concurrent [polarisation] of US employment and wages”\textsuperscript{X}. Their model suggests a two-sector economy (goods and services) making use of four factors of production from which three are labour factors (abstract, routine and manual) and the other one is computer capital. It makes clear that there is competition between routine labour and computer. While labour is supplied in function of the workers’ skill endowment, falling prices and rising productivity through technological advances determine computer input. Autor and Dorn (2013) test the following implications of their model:

\textsuperscript{IX}Germany, Sweden, Spain, UK, Ireland and Switzerland

\textsuperscript{X}Germany, Sweden, Spain, UK, Ireland and Switzerland
Adaptation of computer capital

Thanks to falling prices, adaptation of computer capital takes place which leads to a displacement of routine task workers.

Reallocation of low-skill workers

Because of the above implication, low-skill workers will migrate from the goods to service sector, leading to employment polarisation.

Net inflow of high-skill workers

"Differential adaptation of computer capital in initially routine task-intensive [labour] markets and q-complementarity\(^X\) between computer capital and high-skill [labour]” drive net inflow of high-skill workers.

The results, focusing mainly on noncollege workers (less skilled), are in line with the implications of their model. There is significant evidence that as the share of routine-task labour increases, the adaptation of computers per employee increases by 6.9%. Routine occupation decreases for all workers by 2.5%. The trend stresses if considering only non-college workers. Finally, employment with low routine-task content rise (up to 4.3%) whereas those with high-routine-task content shrink (up to 3.8%).

Autor and Dorn (2013) therefore find evidence that the competition between computer capital and routine tasks induced by the former’s declining prices drives employment polarisation for the three labour tasks mentioned above.

However, computerisation does also affect skill demand in Labour Markets. Therefore, Autor et al. (2003) try to elucidate how computerisation affects job skill demand in the USA from 1960 to 1998. The first step of the paper consists in constructing a model to illustrate the challenges going along with computer capital. The so-called Task Model shall allow to measure changes in the composition of the job tasks (requiring certain skills).

Autor et al. (2003) distinguish between two types of tasks which are imperfect substitutes (routine and nonroutine tasks). Computer and routine tasks are perfect substitutes though. Similar to Autor and Dorn (2013), the computer price falls as time passes thanks to technological advances.

Contrary to Autor and Dorn (2013), Autor et al. (2003) consider productivity endowment as a selection factor of workers. Hence, no educational characteristics defining a worker’s skill ability are accounted for.

The results make evident that substitution of routine tasks by computer has been most likely to occur if a given industry has initially been human labour routine-task intensive. In concrete terms, computer use explains a negative in task input by labour of routine tasks (up to -23%). Furthermore, the results suggest that computerisation does not depend on the characteristics of an industry, but that the latter reallocate their workers

\(^X\)complementarity for the production of q
towards nonroutine tasks (rise of 12% in nonroutine task input). To conclude, we learn that the phenomenon of reallocation of tasks induced by the use of computers does not causally depend on an industry’s specialisation.

Distinguishing uniquely between routine and nonroutine tasks as do Autor et al. (2003) is not exhaustive enough to approach the phenomenon of computerisation. Therefore, Frey and Osborne (2013) propose a revision of the Task Model. They state that the model needs to be reviewed since important advances, especially in Machine Learning (ML), Mobile Robotics (MR) etc., have been made in the ten years between the publication of the two papers. Therefore, Frey and Osborne (2013), who try to answer the question "How susceptible are jobs to computerisation?", propose to replace the initial designation by "susceptible and nonsusceptible" labour.

To hinder vague interpretations of the new designation to compromise their work, they identify three major engineering bottlenecks which can at least dampen the pace of computerisation: perception and manipulation tasks, creative intelligence tasks and social intelligence tasks.

Frey and Osborne (2013) find out that 47% of total US employment is at high risk of computerisation. From this subset, Service, Sales and Related as well as Office and Administrative Support occupations are overrepresented. These results are, as presented in the paper, in line with the expected effects of advances in ML and MR. The pace of computerisation depends mostly on how these bottlenecks can be overcome (Frey and Osborne, 2013).

Other estimations in the paper suggest negative correlations between either wages or educational attainment and probability of computerisation, which is in line with the findings by Autor and Dorn (2013).

For the European Labour Market, (Goos et al., 2009) deals with the pervasiveness of Job Polarisation considering 16 European countries from 1993 to 2006.

This paper brings forward three hypotheses to explain why Job Polarisation might occur:

1. **Routinisation**
   This hypothesis suggests that the effects of technological advances replace jobs which tend to be routine and clerical (Autor et al., 2003).

2. **Globalisation**
   This hypothesis states that jobs which can be easily offshored are subject to change in their demand among the richest countries (Blinder, 2009). Through the higher degree of globalisation favouring the practice of outsourcing, labour becomes tradable across countries which allows firms to allocate labour inputs according to their profit-maximising logistics.
3. Wage inequality

According to Manning (2004) and Mazzolari and Ragusa (2013), the rise of income among the most richest in the USA and UK increases the demand for low-skilled labour which shall provide services.

Logged hours worked (dependent variable) are regressed on these variables described above to analyse changes in the demand for tasks. It comes out that routine task importance, offshorability, educational level and logged wages are negatively correlated with the dependent variable. Hence, the results suggest that the current technology advancements require the accomplishment of nonroutine tasks found at the extreme ends of the skill distribution. This is at the expense of routine task generally accomplished by middle-skill workers (Goos et al., 2009).

To conclude, the four papers find evidences that changes in skill allocation within Labour Markets has occurred, because routine tasks are subject of substitution by computers. These evidences, although if approached differently, are especially based on technological advances, which corresponds to the theory developed above.
3 Methodological Framework and Results

3.1 Data and Variables

To answer the research question, we use data retrieved from Eurostat (2018a,b,c), the European Union agency for statistics. Eurostat (2018a) is based on the European System of Accounts 2010 (ESA 2010) which allows to compare national accounts of different countries. This source is used to generate the variables capital and Degree of openness, which will be explained later in the essay. Eurostat (2018b) concerns the variable tertiary education and is a practical implementation of the International Standard Classification of Education. Finally, Eurostat (2018c) allows to access to the results of the European Union Labour Force Survey. This serves as the source for the dependent variables implemented in the statistical model which will be explained later in this essay.

We consider the years from 1996 to 2016 (20 years) divided into five 4-year periods, because the paper seeks to investigate recent changes of the skill allocations induced by "modern" capital. We have information on all current EU members\textsuperscript{XI}, except Croatia, since this country lacks in some right-hand side variables. Therefore, we should have for each variable $5 \times 27 = 135$ observations. However, the panel data is unbalanced. The reason is that many countries accede to the EU by 2000 which means that Eurostat is missing information for some countries before 2000.

As explained in the Literature Review, the emergence of the "modern" capital is driven by two factors:

1. The prices of computer and related capital fall (Frey and Osborne, 2013; Autor et al., 2003)
2. Computers become more and more productive in certain tasks such as routine task (Eurofound, 2018; Schwab, 2017)

The literature suggests two major phenomena induced by the capital:

**Substitution:** When jobs are intensive in tasks that computers can execute, then jobs are at risk of computerisation (Frey and Osborne, 2013), because through the computers’ higher productivity and falling prices, the formers have a comparative advantage to human labour.

**Complement:** However, if jobs are characterised by tasks that cannot be executed by computers or any other capital, then there is supply of human labour to these tasks. This is, because workers can focus on these tasks. A side effect is that workers increase in productivity for these tasks.

\textsuperscript{XI} Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and UK
The independent variable of interest is *capital* which shall serve as a proxy of the new technological advances and innovations susceptible to substitute and/or supply human labour as described in the Theoretical Framework. Therefore, I propose to restrict the term *capital* to the following components I aggregate together:

- ICT\textsuperscript{XII} equipment
- Computer hardware
- Telecommunications equipment
- Transport equipment
- Intellectual property products
- Research and development
- Computer software and databases

This restriction allows to focus on recent technologies and their possible impact on skill allocation. A possible question may arise why the component *Transport equipment* appears in this development. I motivate this choice since recent technological advances do also impact the sphere of locomotion. According to Degryse (2016), the car manufacturing sector adopts the characteristics of *Industry 4.0* such as treatment of sophisticated data, autonomous driving etc. Therefore, this component is taken into consideration.

Concerning the other components, the literature also suggests that innovations such as Big Data, Artificial Intelligence etc. play a crucial role (Frey and Osborne, 2013; Eurofound, 2018). The components I have chosen fit best to the description of the technologies which are supposed to impact Labour Market outcomes.

The studies presented in the Literature Review exhibit a small but important pattern. They focus on tasks. Yet, through technological advances which can occur at a pace without precedent (Schwab, 2017), the papers redefine the tasks susceptible to substitution to fit their theory to the real world changes. I may refer to Frey and Osborne (2013) which revisit the Task Model proposed by Autor et al. (2003), because "the premises about what computers do have recently expanded". However, the literature also suggests that occupations are highly characterised by their task content. The ISCO propose to classify occupations according to skills. Hence, it is reasonable to approach the question of capital impact on Labour Markets from a "skill point of view". Therefore, two dependent variables, namely employment and working hours, are sorted by ISCO. Furthermore, as suggested in the Theoretical Framework, I check the hypothesis of SBTC presented by Goos et al. (2009) by sorting employment by educational attainment. The framework is given by ISCED.

\textsuperscript{XII}Information and communications technology
According to International Labour Organization (2013), occupations can be divided into four different ISCO skill groups:

*(See next page, please)*
• Skill Level 1 (Low-Skill)
  – Simple & routine physical or manual tasks
  – Requiring educ. Level 1 education (see later for educ. levels)

• Skill Level 2 (Middle-Skill)
  – Operating machinery & electronic equipment
  – Requiring educ. Level 2, 3 and sometimes 4 education

• Skill Level 3 (Middle-Skill)
  – Complex technical & practical tasks
  – Requiring educ. Level 5 and sometimes 6

• Skill Level 4 (High-Skill)
  – Complex problem-solving, decision-making & creativity
  – Requiring educ. Level 6-8

As we can see, the term MIDDLE SKILL is divided into two groups. According to ISCO the difference between those two groups is that the tasks executed by the "skill level 3" group are more complex than those of "skill level 2" group. More important is the fact that the two different skill groups require different educ. attainments. To my knowledge, this aspect has not been elucidated enough in the literature. Hence, instead of merging those two skill groups which can be considered as "middle-skill", it might be of interest to investigate if this middle-skill group exhibits different patterns in function of the educ. attainment.

Concerning the educational part, the following ISCED classification applies to the present paper (UNESCO, 2012):

• Level 0-2 (Low education)
  – From early childhood until Lower secondary education

• Level 3-4 (Middle education)
  – Upper secondary until post-secondary non-tertiary education

• Level 5-8 (High education)
  – Tertiary education
This yields to the following dependent variables:

1. Employment by skill
   - Skill Level 1 (Low-skill)
   - Skill Level 2 (Middle-Skill)
   - Skill Level 3 (Middle-Skill)
   - Skill Level 4 (High-Skill)

2. Weekly Actual Working Hours by Skill
   - Skill Level 1 (Low-skill)
   - Skill Level 2 (Middle-Skill)
   - Skill Level 3 (Middle-Skill)
   - Skill Level 4 (High-Skill)

3. Employment by Educ. Level
   - Level 0-2 (Low education)
   - Level 3-4 (Middle education)
   - Level 5-8 (High/tertiary education)

Finally, other control variables are introduced into the model. The goal is to control for factors which may influence the results and therefore address the problem of omitted variables.

The Degree of openness shall follow the example of OFFSHORABILITY presented by Goos et al. (2009). It is a self-calculated variable \( \frac{IM + X}{GDP} \) which takes into account the share of international trade with respect to Gross Domestic Product (GDP).

The variable Tertiary Education measures the share of people having accomplished tertiary education in a country \( i \) at time \( t \). Violante (2008) state that SBTC may favour high-skill occupation over the others. Nevertheless, Goos and Manning (2007) and Autor et al. (2006) have found evidence for Job Polarisation, relaxing the SBTC hypothesis. However, the literature suggests implicitly that tertiary education plays a central role when analysing changing patterns in Labour Markets with respect to "modern" capital. Hence, Tertiary Education is integrated into the model.

Finally, the variable female reports the employed females’ share of total employment in country \( i \) at time \( t \). It shall disentangle any gender effects from the observed pattern of the variables of interest.

\[ \text{Degree of openness} = \frac{IM + X}{GDP}, \] where \( IM \) is volume of imports and \( X \) is volume of export. Both values and the GDP value are expressed in current Euro prices.
At this point I would like to add a little precision: the variables *Capital* and *Degree of openness* of the data set limitate the possible interpretation of the study. Despite the components which construct *Capital*, we cannot be sure that all types of assets related to ”modern” capital are comprised. Obviously, there is a risk of covariance between the independent variable and the error term $\epsilon$ owing to omitted variables which would be a violation of the Gauss–Markov Condition for Best Linear Unbiased Estimator (BLUE).

The second problem deals with the *Degree of openness*. Trying to follow the example of Goos et al. (2009) where *Offshorability* has been used, it is, however, not clear if the share of international trade can reflect doubtlessly international interaction of Labour Markets. As the term openness cannot be reduced merely to trade, the ideal variable would comprise all the Labour Market component.

Although we try to address some problems which go along with statistical investigations, one problem will remain: measurement errors. Indeed, Eurostat does collect data from the different countries which may have used different systems to collect data before entering the EU. Even if the countries have unique systems to collect data, one cannot be sure of absence of errors while measuring. A consequence is that the mean of predicted values does not correspond to the true value, which is again a violation of the Gauss–Markov Condition for BLUE. Therefore, one shall be conscient that the following results may not be as accurate as they shall be.

### 3.2 Statistical Model

As mentioned in the Introduction, the main objective of this paper is to test whether ”modern” capital impacts skill allocation significantly in the European Labour Markets. The literature suggests to adopt an Ordinary Least Squares (OLS) model. This paper follows this method and applies an OLS model to the variables as described in Data and Variables. This yields to construct the following equation:

$$Y_{i,t} = \alpha + \beta \times X_{i,t} + \gamma \times \Omega_{i,t} + \delta \times \Gamma_{i,t} + \eta \times \Theta_{i,t} + \sum_{t=2}^{4} I_t + \varepsilon_{i,t}$$

(1)

where

- $Y$ is the 4-year period growth rate of one of the three outcome variables as described in Data and Variables, calculated as follows: $%\Delta Y = \frac{Y_{i,t+4} - Y_{i,t}}{Y_{i,t}}$ where $Y_{i,t}$ is the number of people being employed or the average working hours at year $t$ and in country $i$. The same formula applies to the following variables

- $X$ is *Capital* growth rate

- $\Omega$ is the growth rate of people having accomplished tertiary education,

- $\Gamma$ is the growth rate of the *degree of openness*,

- $I_t$ is the growth rate of people having accomplished tertiary education,
$\Theta$ is the growth rate of the females’ share of total employment,

$I$ is a time dummy for the periods 2000-2004, 2004-2008, 2008-2012 and 2012-2016, the period 1996-2000 being the reference,

$\varepsilon$ is the error term.

Since all variables are expressed as percentage changes within a period of 4 years, the model specification takes country fixed effect into account.

Time based studies often face the same problem: autocorrelation. Autocorrelation occurs when an observation $x$ at time $T_{t+1}$ depends on observation $y$ at time $T_t$ while $(x, y) \subset D$ (D: set). It is a serious problem since the variance will be underestimated and we are thus more likely to reject $H_0$ although it is true. Therefore, the present model will be robust regressed.

Nevertheless, it shall be mentioned that the model itself might not be perfect. Indeed, endogeneity problems such as reverse causality or omitted variables can bias the results. However, this paper is restricted to the impact of ”modern” capital on the skill allocation in the European Labour Markets. Therefore, only variables related to this issue are considered.
3.3 Summary Statistics

Table 1: Eurostat (2018a,b,c)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment Skill group 1</td>
<td>91</td>
<td>0.0254</td>
<td>0.165</td>
<td>-0.318</td>
<td>0.549</td>
</tr>
<tr>
<td>Employment Skill group 2</td>
<td>91</td>
<td>-0.00143</td>
<td>0.0817</td>
<td>-0.244</td>
<td>0.305</td>
</tr>
<tr>
<td>Employment Skill group 3</td>
<td>91</td>
<td>0.0581</td>
<td>0.184</td>
<td>-0.360</td>
<td>0.705</td>
</tr>
<tr>
<td>Employment Skill group 4</td>
<td>91</td>
<td>0.0939</td>
<td>0.125</td>
<td>-0.262</td>
<td>0.536</td>
</tr>
<tr>
<td>Employment Educ. Level 0-2</td>
<td>91</td>
<td>-0.101</td>
<td>0.148</td>
<td>-0.438</td>
<td>0.394</td>
</tr>
<tr>
<td>Employment Educ. Level 3-4</td>
<td>91</td>
<td>0.0400</td>
<td>0.142</td>
<td>-0.213</td>
<td>0.619</td>
</tr>
<tr>
<td>Employment Educ. Level 5-8</td>
<td>91</td>
<td>0.170</td>
<td>0.174</td>
<td>-0.375</td>
<td>1.136</td>
</tr>
<tr>
<td>Working hours Skill group 1</td>
<td>91</td>
<td>-0.00561</td>
<td>0.0239</td>
<td>-0.0604</td>
<td>0.0691</td>
</tr>
<tr>
<td>Working hours Skill group 2</td>
<td>91</td>
<td>-0.00533</td>
<td>0.0304</td>
<td>-0.121</td>
<td>0.134</td>
</tr>
<tr>
<td>Working hours Skill group 3</td>
<td>91</td>
<td>-0.00301</td>
<td>0.0242</td>
<td>-0.0821</td>
<td>0.0556</td>
</tr>
<tr>
<td>Working hours Skill group 4</td>
<td>91</td>
<td>-0.00867</td>
<td>0.0325</td>
<td>-0.131</td>
<td>0.129</td>
</tr>
<tr>
<td>Capital</td>
<td>91</td>
<td>0.224</td>
<td>0.370</td>
<td>-0.578</td>
<td>1.624</td>
</tr>
<tr>
<td>Degree of openness</td>
<td>91</td>
<td>0.0465</td>
<td>0.104</td>
<td>-0.307</td>
<td>0.445</td>
</tr>
<tr>
<td>Tertiary education (× 100)</td>
<td>91</td>
<td>2.703</td>
<td>2.685</td>
<td>-13.70</td>
<td>12</td>
</tr>
<tr>
<td>Female (× 100)</td>
<td>91</td>
<td>1.814</td>
<td>3.410</td>
<td>-6.900</td>
<td>10.40</td>
</tr>
</tbody>
</table>

The first impression to get from the Table 1 is indeed that many observations are missing. The maximum number of observations is 91 out of possible 135 (< 70%). Given the unbalanced panel data, the regression can only take into account 91 observations. Therefore, table 1 considers only these 91 observations.

Except for the first middle-skill group, the variable employment by skill has positive means. The Standard Deviations (SDs) are large compared to the means. Both the low- and high-skill occupations exhibit an increase in employment (2.5% and 9.4% respectively). The middle-skill occupations do have means of opposing signs. However, the statistics include every country and every period. Whereas geographical heterogeneity may explain high SD values, we cannot draw any inference for the different periods from the statistics. These are controlled for in a second step when presenting the regression results.

The variable employment by education shows an interesting pattern, because those with the lowest educational attainment seem to experience, in average, displacement across the EU during the 20 years of observation (-10.1%). Similar to the previous variable, employment by education has large SD which can also be explained by geographic heterogeneity. The fact that employment by education increases for the highest-educated, whereas the least-educated experience a decline, gives rise to the supposition that SBTC may play a role within the EU. This would favour employment of those which are highly educated.
The last outcome variable, *working hours by skill*, exhibits a general decline across all skill groups, countries and periods. Although the means are close to zero, SD are large which proves again heterogeneity within this variable. Two possible reasons may explain the general decline. Firstly, productivity of low- and high-skill workers augments with increasing *capital*, because it complements for tasks within a job/employment that it cannot execute. This can lead to a more efficient allocation of time for the workers. In other terms, one may need less time to do the same work.

On the other hand, declining working hours can also be a sign for an ongoing substitution process in the EU since some skill requirements may face declining demand. However, this consideration, except for the first middle-skill group, contrasts with the rise of *employment by skill* insofar as more workers are employed for tasks with these skill requirements.

The variable *capital* displays a mean of 22.4% which indicates a higher use of capital. The high value of the SD allows to statistically investigate the impact of *capital* on skill allocation on employment, but is again a sign of geographical heterogeneity.

When considering the period of the study (1996-2016) and the countries constituting the data set (EU members), then one shall not be surprised of the general rise of the *Degree of openness*. Through the EU, the countries develop more interacting trade on an international scale. The introduction of the *Euro* in the period 1999 and 2002 (within the study period) strengthens this aspect.

The statistics suggest an average rise of 2.78% of people having accomplished tertiary education while SD is large. There might be several reasons for this outcome: firstly, the access to tertiary education may have become less difficult over the years. Although the aspect of ”difficulty” is a vague term allowing for large and perhaps even contradictory interpretations, it implies a preference of the population to study. Secondly, the rise of this variable may be the result of migration. Owing to the *Schengen Area* within the EU, people are able to study more easily abroad what they want, but which may not be proposed in their home country. Lastly, it is also possible that the salary of jobs requiring tertiary education has increased over time. This implies that people initially meditate on whether to study or to enter Labour Markets prematurely. The rise of the variable *tertiary education* can thus be explained by a rise of returns to education incentivising people to study. This corresponds to the *Schooling Model* proposed by Chiswick (1974).

The last variable, *Female*, shows an average rise of 2.25% of the share of employment occupied by female persons. This can be explained, among other things, by more flexible working days allowing females to combine family and professional life. However, the heterogeneity within the EU does not exclude that there might be countries which ”support” female employment which are less occupied by them in other countries.
3.4 Regression estimates

3.4.1 Employment by skill

Table 2: Impact of Capital on skill allocations in employments (Eurostat, 2018a,b,c)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Low-Skill</th>
<th>Middle-Skill 1</th>
<th>Middle-Skill 2</th>
<th>High-Skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>-0.109**</td>
<td>0.0111</td>
<td>0.0986</td>
<td>0.0485</td>
</tr>
<tr>
<td></td>
<td>(0.0526)</td>
<td>(0.0219)</td>
<td>(0.0840)</td>
<td>(0.0406)</td>
</tr>
<tr>
<td>Tertiary education</td>
<td>-0.00668*</td>
<td>-0.00255</td>
<td>0.00746</td>
<td>0.0108**</td>
</tr>
<tr>
<td></td>
<td>(0.00371)</td>
<td>(0.00221)</td>
<td>(0.00557)</td>
<td>(0.00465)</td>
</tr>
<tr>
<td>Degree of openness</td>
<td>-0.265**</td>
<td>-0.0763</td>
<td>0.0783</td>
<td>0.0364</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.0606)</td>
<td>(0.164)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Female</td>
<td>0.0252***</td>
<td>0.0141***</td>
<td>0.0177*</td>
<td>0.0186***</td>
</tr>
<tr>
<td></td>
<td>(0.00582)</td>
<td>(0.00325)</td>
<td>(0.00934)</td>
<td>(0.00543)</td>
</tr>
<tr>
<td>Time dummy Period 2</td>
<td>-0.128*</td>
<td>0.00492</td>
<td>-0.0163</td>
<td>0.0675</td>
</tr>
<tr>
<td></td>
<td>(0.0711)</td>
<td>(0.0267)</td>
<td>(0.0832)</td>
<td>(0.0515)</td>
</tr>
<tr>
<td>Time dummy Period 3</td>
<td>-0.120**</td>
<td>0.0324</td>
<td>-0.0553</td>
<td>0.00739</td>
</tr>
<tr>
<td></td>
<td>(0.0542)</td>
<td>(0.0300)</td>
<td>(0.0770)</td>
<td>(0.0460)</td>
</tr>
<tr>
<td>Time dummy Period 4</td>
<td>-0.231***</td>
<td>-0.0148</td>
<td>-0.126</td>
<td>0.0633</td>
</tr>
<tr>
<td></td>
<td>(0.0691)</td>
<td>(0.0280)</td>
<td>(0.0784)</td>
<td>(0.0487)</td>
</tr>
<tr>
<td>Time dummy Period 5</td>
<td>-0.169***</td>
<td>0.00408</td>
<td>-0.113</td>
<td>-0.00622</td>
</tr>
<tr>
<td></td>
<td>(0.0625)</td>
<td>(0.0243)</td>
<td>(0.0749)</td>
<td>(0.0458)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.188***</td>
<td>-0.0236</td>
<td>0.0541</td>
<td>-0.0150</td>
</tr>
<tr>
<td></td>
<td>(0.0673)</td>
<td>(0.0271)</td>
<td>(0.0802)</td>
<td>(0.0495)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>91</th>
<th>91</th>
<th>91</th>
<th>91</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.522</td>
<td>0.557</td>
<td>0.384</td>
<td>0.282</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table proposes an overview of the regression results based on the equation 1 where $Y$ is employment by skill. All estimates are to be interpreted ceteris paribus.

We notice that an one percentage point increase of capital impact low-skill employment by -0.109 percentage points at 5% significance level whereas the other groups exhibits a rise of up to 0.1%. However, the positive estimates are statistically insignificant. Thus, we have reliable evidence that capital substitutes for workers employed in occupations with low-skill requirements. The results suggest though that capital promotes employment with middle-skill and high-skill task requirements, but that other factors are likely to play a more important role.

Tertiary Education correlates negatively with the low-skill and the first middle-skill groups (-0.07% and -0.02% respectively) and the latter group’s estimate is not significant, the
being significant at 10% level. On the other hand, second middle-skill and the high-skill groups exhibit an increase in employment (>0.01% and 0.01%) and the estimate for the latter group is significant at 5% level while the other is not significant. This suggests at least tertiary education selects positively persons with respect to their educational attainment. The middle-skill groups exhibit ambiguous pattern. Regarding the signs, the estimates for the degree of openness is the same as for tertiary education. While the first two skill groups have respectively -0.23% and -0.08% estimate values, the last two do have 0.08% and 0.04% respectively. The low-skill group’s estimate is significant at 5% level whereas the other groups’ estimates are not.

The variable Female is positively correlated with employment by skill across all skill groups (up to 0.03%). Except for the second middle-skill group, the estimates are all statistically significant at a 1% level. This shows that female employment is a good proxy to explain changing patterns in the skill allocations of employment.

The estimates for the time dummies are all negative for the most recent period except for the first middle-skill group. Except for the high-skill group, the fourth period exhibits negatives estimates as well. Only the estimates for the low-skill and the second middle-skill groups are negative across all periods while the former group is the only group to have significant estimates.
3.4.2 Employment by educational attainment

Table 3: Impact of Capital on educ. selection in employment (Eurostat, 2018a,b,c)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Level 0-2</th>
<th>Level 3-4</th>
<th>Level 5-8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>-0.0745**</td>
<td>0.0614*</td>
<td>0.0323</td>
</tr>
<tr>
<td></td>
<td>(0.0308)</td>
<td>(0.0326)</td>
<td>(0.0264)</td>
</tr>
<tr>
<td>Tertiary education</td>
<td>-0.0152***</td>
<td>-0.0152***</td>
<td>0.0504***</td>
</tr>
<tr>
<td></td>
<td>(0.00469)</td>
<td>(0.00431)</td>
<td>(0.00687)</td>
</tr>
<tr>
<td>Degree of openness</td>
<td>-0.261**</td>
<td>0.153</td>
<td>-0.167</td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>(0.164)</td>
<td>(0.197)</td>
</tr>
<tr>
<td>Female</td>
<td>0.0250***</td>
<td>0.0195***</td>
<td>0.00487</td>
</tr>
<tr>
<td></td>
<td>(0.00374)</td>
<td>(0.00471)</td>
<td>(0.00523)</td>
</tr>
<tr>
<td>Time dummy Period 2</td>
<td>-0.0164</td>
<td>0.00195</td>
<td>0.0911*</td>
</tr>
<tr>
<td></td>
<td>(0.0459)</td>
<td>(0.0644)</td>
<td>(0.0459)</td>
</tr>
<tr>
<td>Time dummy Period 3</td>
<td>0.0291</td>
<td>-0.0539</td>
<td>0.0247</td>
</tr>
<tr>
<td></td>
<td>(0.0465)</td>
<td>(0.0627)</td>
<td>(0.0358)</td>
</tr>
<tr>
<td>Time dummy Period 4</td>
<td>-0.0687</td>
<td>-0.0406</td>
<td>-0.0576</td>
</tr>
<tr>
<td></td>
<td>(0.0446)</td>
<td>(0.0625)</td>
<td>(0.0733)</td>
</tr>
<tr>
<td>Time dummy Period 5</td>
<td>-0.000564</td>
<td>-0.0665</td>
<td>-0.0487</td>
</tr>
<tr>
<td></td>
<td>(0.0450)</td>
<td>(0.0600)</td>
<td>(0.0589)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0592</td>
<td>0.0606</td>
<td>0.0277</td>
</tr>
<tr>
<td></td>
<td>(0.0419)</td>
<td>(0.0630)</td>
<td>(0.0631)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>91</th>
<th>91</th>
<th>91</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.534</td>
<td>0.540</td>
<td>0.648</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table proposes an overview of the regression results based on the equation 1 where \( Y \) is employment by education.

We notice that capital correlates negatively with employment growth rates of the least educated (-0.07%) whereas the other two groups exhibit positive correlations (up to 0.06%). The high-education group’s estimate is not statistically significant while the other two’s are (at 5% and 10% significance level respectively). This suggests that capital has a selective character since it substitute for workers with low educ. attainment and supply for those who have middle educ. attainment.

A rise of tertiary education attainment seems to explain a rise in employment for the highest educated only (0.05%) while the other two groups are negatively correlated with it (> -0.02%). All estimates are statistically significant at 1% level.

The growth rates of the degree of openness seem to correlate negatively to employment
growth rates of the low- and high-education groups (up to -0.6%) while the middle-
education group displays an estimate of 0.15%. Only the estimate for the least-educated
group is statistically significant at 5% level while the other two are not.

Growth rates of female employment is in positive correlation with *employment by education* across all education groups (up to 0.03%). Yet the high-education group estimate is insignificant whereas the estimate for the other two groups is significant at 1% level.

The time dummy results show that across all the education groups the estimates for the two recent periods are negative. Only one of the twelve time-dummy estimates are significant (5%).
3.4.3 Working Hours by skill

Table 4: Impact of Capital on skill allocation in working hours (Eurostat, 2018a,b,c)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Low-Skill</th>
<th>Middle-Skill 1</th>
<th>Middle-Skill 2</th>
<th>High-Skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>-0.00450</td>
<td>0.00155</td>
<td>0.00459</td>
<td>0.0150</td>
</tr>
<tr>
<td></td>
<td>(0.00872)</td>
<td>(0.00995)</td>
<td>(0.00711)</td>
<td>(0.0105)</td>
</tr>
<tr>
<td>Tertiary education</td>
<td>0.000449</td>
<td>0.00150</td>
<td>0.00142</td>
<td>0.000111</td>
</tr>
<tr>
<td></td>
<td>(0.000906)</td>
<td>(0.00117)</td>
<td>(0.00116)</td>
<td>(0.00120)</td>
</tr>
<tr>
<td>Degree of openness</td>
<td>-0.0238</td>
<td>-0.00442</td>
<td>-0.0237</td>
<td>0.00233</td>
</tr>
<tr>
<td></td>
<td>(0.0266)</td>
<td>(0.0293)</td>
<td>(0.0219)</td>
<td>(0.0271)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.00172*</td>
<td>-0.00162</td>
<td>-0.00188**</td>
<td>-0.00263**</td>
</tr>
<tr>
<td></td>
<td>(0.000984)</td>
<td>(0.00104)</td>
<td>(0.000902)</td>
<td>(0.00119)</td>
</tr>
<tr>
<td>Time dummy Period 2</td>
<td>-0.00189</td>
<td>0.0155</td>
<td>-0.0150</td>
<td>-0.0128</td>
</tr>
<tr>
<td></td>
<td>(0.0134)</td>
<td>(0.0183)</td>
<td>(0.0132)</td>
<td>(0.0219)</td>
</tr>
<tr>
<td>Time dummy Period 3</td>
<td>0.0147</td>
<td>0.0196</td>
<td>0.00842</td>
<td>-0.00513</td>
</tr>
<tr>
<td></td>
<td>(0.0116)</td>
<td>(0.0174)</td>
<td>(0.0121)</td>
<td>(0.0208)</td>
</tr>
<tr>
<td>Time dummy Period 4</td>
<td>-0.00768</td>
<td>0.0158</td>
<td>0.00107</td>
<td>-0.0126</td>
</tr>
<tr>
<td></td>
<td>(0.0125)</td>
<td>(0.0181)</td>
<td>(0.0134)</td>
<td>(0.0207)</td>
</tr>
<tr>
<td>Time dummy Period 5</td>
<td>0.0124</td>
<td>0.0238</td>
<td>0.000790</td>
<td>-0.00544</td>
</tr>
<tr>
<td></td>
<td>(0.0107)</td>
<td>(0.0168)</td>
<td>(0.0118)</td>
<td>(0.0208)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.00446</td>
<td>-0.0233</td>
<td>-0.00255</td>
<td>0.000891</td>
</tr>
<tr>
<td></td>
<td>(0.0117)</td>
<td>(0.0167)</td>
<td>(0.0123)</td>
<td>(0.0204)</td>
</tr>
</tbody>
</table>

Observations 91 91 91 91
R^2 0.141 0.112 0.172 0.046

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table proposes an overview of the regression results based on the equation 1 where Y is working hours by skill growth rate at week-level. Capital results are negative for the low-skill group (> -0.01%). On the other hand, all the other groups show positive results (up to 0.02%). Nevertheless, all estimates are not statistically significant. This means that capital is likely to not have any impact on working hours.

For tertiary education, the estimates are positive across all skill groups (> 0.01%). However, none of the estimates is statistically significant.

Degree of openness seems to profit for the high skill group only in terms of employment (0.02%) while the other groups respond negatively (up to -0.02%). Similar to the two previous variables, all estimates are statistically insignificant.

Female shows negative estimates across all skill groups (up to -0.004%). Only the first middle-skill group’s estimate is not significant while the others’ are.
For the high-skill group, all four dummies have negative estimates (up to -0.01%). Only the first middle-skill group exhibits positive estimates across all time dummies (up to 0.02%). The other two skill groups display unclear patterns. In general, the majority of the extreme-skill groups has negative estimates (six out of eight) while the majority of the middle-skill groups has positive estimates (seven out of eight). However, none of the time dummies is statistically significant.
4 Discussion

According to the results presented in the section Regression estimates, we can disentangle three findings of interest.

The first finding deals with working hours. The variable of interest capital does not significantly impact actual weekly working hours in EU countries. Considering that capital has significant estimates for the low-skill employment variables, we can state that capital exert influence at the extensive level rather than the intensive level. However, impetuous conclusions may lead to an imprecise image concerning this relationship. As I have explained in Section 3.1, the problem of measurement errors could lead to inexact estimations. Furthermore, the data for working hours retrieved from Eurostat are based on averages. Even if there is not any measurement errors, much information still gets lost through averaging, evidenced by high SD. Therefore, investigating the relationship capital-working hours should be approached differently to get at least significant estimates.

Following the example of Goos et al. (2009), the importance of different tasks may be a better explanator whose results would be in line with the present essay’s if the latter’s were significant.

The question of alternative approaches also arises when considering the estimates for the middle-skill group although divided into two subgroups. Indeed, they do not exhibit any significant correlations with capital. Nevertheless, the latter correlates significantly with the middle-education group. Considering the ISCO classification for occupations at page 15, we notice a mismatch between middle-skill and middle-education group. This implies that middle-educated workers have qualities that middle-skilled workers do not have and vice versa. Therefore, phenomena such as Job Polarisation or SBTC impacting skill allocation have to be approached by a ”skill point of view” rather than education. The results suggest that the first phenomenon predicting a ”hollowing-out” of the middle-skill occupationa is not likely to occur.

Another interesting observation is that capital seems to impact significantly the low-skill & low-education groups while the high-skill & high-education groups yield to inconclusive results. Despite the fact that the latter groups’ signs can be explained by the Theoretical Framework presented earlier in the paper, we are not able to understand from the Regression estimates why there is a significance-related difference between these two groups. A possible explanation can be found in one of the many underlying assumptions of the presented model, namely equal Labour Market opportunities. In particular, we assume with the Statistical Model that the three skill and education groups face equal Labour Market opportunities, i.e. same wage, same working hours and especially similar contracts etc. Yet, this is an unrealistic assumption since not every task can be done by everyone because of their different skill and education requirements. According to the developments of Massey et al. (1993) concerning the Dual Labour Market Theory,

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XIV Except for Working hours

XV see: Literature Review
high-skilled workers are less likely to be displaced as their skills require employers to invest in those workers able to operate with new and sophisticated capital. Consequently, high-skilled workers become like capital whose costs of unemployment must be bared by the employers. Although this theory may explain the signs of the high-skill estimates, the aspect of duality has not been well-integrated in the model. However, it is not guaranteed that more sensitivity towards this issue leads to significant results for the high-skill and high-education groups. Despite these facts, the low-skill estimates correspond with the findings of Autor et al. (2003) while the works of Autor and Dorn (2013) confirm the present paper’s result regarding the low-education group.

The above development implies that capital impacts low-skill and low-education groups rather than the other groups although theoretically concerned by ”modern” capital. It may be therefore convenient to explore more thoroughly the different aspects of ”modern” capital and its relationship to different Labour Markets to fit theories to real world changes. Throughout the literature, we have seen that different models are picked up and revisited (Frey and Osborne, 2013) since technological advances occur in an increasing pace. Despite recent data on which the present paper is based, its weaknesses are undeniable such as missing observations or omitted variables. Furthermore, as mentioned earlier in the paper, we cannot be sure that the components constructing the variable capital is exhaustive. Other technologies such sensor equipment, Augmented Reality Systems, etc. are also related to Industry 4.0, but Eurostat does not provide data. Hence, the present paper cannot fully answer to the question whether ”modern” capital impacts skill allocation in Labour Markets. The results suggest only a decline of low-skill & low-education employment/working hours. The other two groups’ results being insignificant, more investigation would enrich the topic with evidences. In particular, it may be interesting to know if sensitivity towards different Labour Markets’ characteristics influences the present paper’s findings. The variable female gives a hint, because it has significant statistics for the middle- and high-skill groups as well as significant estimates for the middle-education group. These estimates suggest that gender-related questions may be of interest when discussing about skill-based employment. The variable degree of freedom is as inconclusive as capital.

5 Conclusion

Recent breakthroughs in the technological sphere and the emerging debate about Industry 4.0 stress the importance of the former upon the economic world. Several reflections are made regarding their possible impact on Labour Market structures. A careful emphasis is dedicated towards task allocation. The literature as presented earlier in this paper does not, however, link the technological advances with skills upon which tasks are dependent. Therefore, the present essay tries to investigate the impact of ”modern” capital on skill allocation at the example of EU countries.
"Modern" capital, defined as an aggregation of assets treating data, has been OLS regressed on three outcome variables, namely employment by skill, by education and working hours by education.

It comes out that the extreme skill estimates are in line with Job Polarisation and Skill-biased technological change theory. The Regression estimates show a decline of low-skill and low-education employment induced by "modern" capital which is in line with the works of Autor et al. (2003) and Autor and Dorn (2013).

However, the middle-skill estimates do not allow to make further conclusion concerning which of the two outcome theory is the most likely to occur. Moreover, only the low-skill and low-education estimates, except for working hours, are significant while the other groups’ estimates are inconclusive. The estimates for worknings hours across all skill groups are not significant as well.

This observation questions the ability of the results to assess accurately any changes in skill allocation in the European Labour Market induced by "modern" capital. The results are subject to some limitations such as the assumption of equal Labour Market opportunities, measurement errors or missing observations. While the first two limitations have statistical impacts on the results, missing observations impact the image we get from the results of lack of information. Therefore we have to be conscient that the estimates might have been different if those observation were not missing.

The results suggest negative impact of capital upon low-skill and low-education employment. According to Kurz (2017), this can lead to a stress testing and legitimation crises for whole societies if the effects of "modern" capital become disruptive. To prevent any negative shocks for countries, important investments in education (especially in the research sector) are needed. These investments may permit low-skilled and low-educated persons to keep pace with the changes triggered by new technologies.

To improve understanding of Labour Market effects of "modern" capital, the first limitation (equal opportunities) can be an incentive for further research as it is not realistic that persons of different skill and education endowments face equal Labour Market opportunities. The most important Labour Market outcomes such as probability of employment, wage, type of employment contract etc. are function of these endowment.

It may be also convenient to study if "modern" capital impacts employment differently depending on industry, skill and education groups, countries etc. In any case, outcomes other than Job Polarisation or SBTC can occur since both theories rely on the assumption that "modern" capital selects workers in function of different tasks to be done and yet, defining tasks content can only be subjective although an international known framework is given by ISCO.
A Appendix

I Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>ML</td>
<td>Machine Learning</td>
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<tr>
<td>MR</td>
<td>Mobile Robotics</td>
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<tr>
<td>SBTC</td>
<td>Skill-biased Technological Change</td>
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<tr>
<td>ISCO</td>
<td>International Standard Classification of Occupations</td>
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<tr>
<td>ISCED</td>
<td>International Standard Classification of Education</td>
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<tr>
<td>AIR</td>
<td>Advanced Industrial Robotics</td>
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<tr>
<td>AM</td>
<td>Additive Manufacturing</td>
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<tr>
<td>IIoT</td>
<td>Industrial Internet of Things</td>
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<tr>
<td>EU</td>
<td>European Union</td>
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<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
</tr>
<tr>
<td>BLUE</td>
<td>Best Linear Unbiased Estimator</td>
</tr>
<tr>
<td>SD</td>
<td>Standard Deviation</td>
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<tr>
<td>IOS</td>
<td>International Organization for Standardization</td>
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<tr>
<td>OLS</td>
<td>Ordinary Least Squares</td>
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<tr>
<td>ICT</td>
<td>Information and Communication Technology</td>
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<tr>
<td>ESA 2010</td>
<td>European System of Accounts 2010</td>
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II Figures

Figure 1: SBTC

Figure 2: Job Polarisation

Figure 3: Before adaptation of "modern" capital
B References


