Ph.D. Dissertation in Engineering

Implications of Technological Change for Human Capital at the Micro and Macro Level:

A study of skills, tasks, and labor market outcomes

미시적 및 거시적 수준에서 인적자본에 대한 기술변화의 시사점 :

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Sonja Walter

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Advisor: Jeong-Dong Lee

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Sonja Walter

Chair	Junseok Hwang	(Sign)
Vice-Chair	Jeong-Dong Lee	(Sign)
Member	Jorn Altmann	(Sign)
Member	Chulwoo Baek	(Sign)
Member	Taewon Kang	(Sign)

Abstract

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The Graduate School

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Technological advances transform labor markets by changing skill demands or even displacing jobs. Prominent studies estimating the effect of labor-replacing technology on unemployment have raised fears of adverse effects stemming from technological change. Other studies have challenged these findings, arguing that technologies create new, yet unknown, jobs. While there is no consensus on the employment effects, scholars agree that technologies increase labor productivity, making them the driving force for modern economies. Technology-driven growth would not be possible without human capital. Knowledge and skills are necessary to

leverage technology-induced productivity effects and thus must be accumulated through education or experience. However, it is unclear whether human capital acquired through formal education remains effective in increasing labor productivity.

This dissertation examines the changing role of human capital under ongoing technological change at the micro and macro levels. First, Chapter 2 offers an overview of the background literature on human capital and discusses relevant topics framing the most significant aspects of technological change and human capital to facilitate the understanding of this relationship. The following three themed chapters of the main body investigate various aspects of human capital and labor market outcomes that are particularly relevant amid technological change.

The study starts at the micro level, building around the main argument that technological change does not impact heterogeneous workers in the same way. Rather than focusing on unemployment effects, the first two chapters quantify the effects of human capital at the individual level while considering aspects of skills, tasks, and occupational routineness. Skills are a crucial aspect of human capital and are regarded as highly relevant when analyzing labor in terms of economic output. Moving away from a micro perspective, the study then adopts a macro perspective with the goal of explaining cross-country skill structures directly from micro-level labor force data. The content of the three themed main chapters is described in more detail below.

Chapter 3 examines the effects of occupational task routineness and education on wage premiums. In focus are potential differences between the productivity-enhancing effects for workers in nonroutine and routine jobs, considering differences between specific and general education. The analysis is based on a modified Mincer earnings equation estimated by a panel fixed-effects regression using German Socio-Economic Panel data for 1984–2017. The most apparent finding from this study is that the education-wage premiums increase over education levels. Temporal analysis reveals that the education-wage premiums were highest in the 1980s, which may be attributable to the skill complementing and productivity-enhancing nature of computer technologies. More importantly, the results regarding occupational task routineness indicate higher returns to education for workers in nonroutine-intensive jobs, while education proves to be less productivity-enhancing under higher levels of task routineness. Another significant finding to emerge from this study is that the routine penalty is more severe for workers with vocational education and training (VET) compared to higher skill levels, contributing to widening inequality in the labor market.

These findings facilitate the introduction of policies that target the differences in labor market outcomes for high-, medium- and low-skilled workers amid technological change. Considering changed task requirements, education and labor policies may smooth the transition from routine- to non-routine-intensive jobs and reduce inequality. This chapter adds empirical evidence to the growing body of heterogeneous returns to education. Additionally, it contributes to recent debates about the implications of technological change by analyzing the effects of skill-biased and routine-biased technological change on an occupational level, addressing specific challenges for workers of various skill levels. Specifically, it addresses the challenges of vocational education and training (VET) for workers in non-routine-intensive jobs.

Chapter 4 analyzes the link between human capital depreciation and job tasks, emphasizing potential differences between education levels. Using panel data, the study estimates Neuman and Weiss's (1995) model of human capital depreciation, extending it by a task perspective. The findings confirm that human capital depreciates faster for higher education levels. The depreciation rate is also higher for specific skills compared to general skills. The most significant finding to emerge from this study is that the productivity-enhancing value of education diminishes faster in jobs with a high share of nonroutine interactive, nonroutine manual, and routine cognitive tasks. The findings further indicate that these jobs experience frequent technology changes or have greater complementarity with technology.

The insights from this chapter provide significant implications for policymakers. A key policy priority should be equipping workers with more general skills at all education levels. With ongoing technological advances, work environments and skill demands will change, rendering previous human capital partially obsolete. This development increases the urgency to provide combined labor market, educational, and lifelong learning policies to counteract the depreciation of skills.

The present chapter appears to be the first empirical work to incorporate a task perspective based on the classification used in studies on job polarization into skill obsolescence. That understanding lays the groundwork for a holistic approach comparing human capital depreciation rates with studies on job obsolescence from labor-replacing technologies.

Chapter 5 examines various skill structures and their evolution from the perspective of capability development across European countries. This chapter links skill-occupation data from the European Skills, Competences, Qualifications, and Occupations classification (ESCO) with occupation-country data from the European Union (EU) Labour Force Survey (LFS) for the years 2011 to 2018. Building on the product space methodology, a skill space is constructed illustrating the skill sets of countries. Visualizing the skill network reveals that the European skill structure has two main clusters, one comprising mainly socio-cognitive skills and one with primarily sensory-physical skills. Further analysis unfolds remarkable differences in the skill structures among European nations. The findings from econometric analysis confirm a strong path dependence in skill development, while the current skillset determines future skill adoption possibilities.

Taken together, the findings suggest that the polarized structure of the skill space may make skill convergence unlikely. Therefore, a challenge for national and supranational policies is to reduce skill inequality between countries in Europe to achieve further economic convergence. This study is the first to combine micro-level studies on skill-relatedness with a macro perspective of national-level capability development, adding to both fields.

In sum, the main implication of this dissertation is that skills and tasks are essential determinants of economic outcomes. In particular, as the smallest factor in the labor market, skills are highly relevant for the economic outcomes of individuals and nations. Overall, the findings imply that more nuanced and granular measures considering skills and tasks are essential to provide effective policy recommendations amid ongoing technological change. The insights gained from this study may assist policymakers in addressing the implications of technological change for human capital.

Keywords: Human Capital; Labor; Skills; Tasks; Technological Change

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Chapter 1.
Introduction

1.1.Background

Human capital has become the most significant input factor in most economies, superseding physical capital. Skilled workers and the human capital embedded in them are needed to effectively and efficiently utilize physical capital to take advantage of newer, more advanced, and possibly more complex equipment. With the rise of technology in all areas of society since the 1980s, the importance of human capital has increased in modern economies over the last 50 years (G. Becker, 2002).

The fundamental driving force for modern economies is technology, which increases labor productivity. This growth, however, would not be possible without human capital. Knowledge and skills are necessary to leverage technology-induced productivity effects and thus must be accumulated through education or experience. G. Becker (2002) refers to human capital as “the fuel” (G. Becker, 2002, p.3) for this technology-driven economic growth. Investment in human capital fosters the accumulation of knowledge and skills and determines the economic outcomes of individuals or nations.

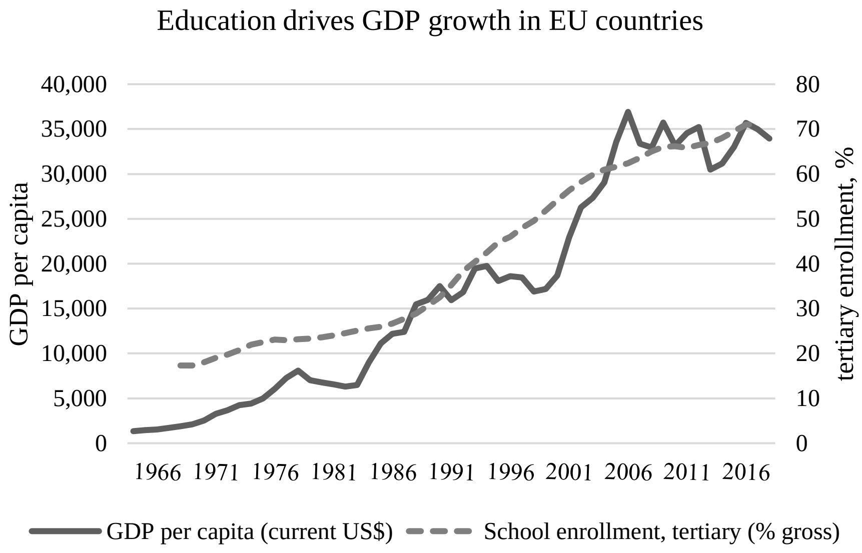
Education is vital for the formation of human capital. On an individual level, higher levels of education increase marginal labor productivity. Higher education levels on aggregate at the national level lead to faster economic growth (Goldin & Katz, 2008; Hanushek & Woessmann, 2007; Lucas Jr, 2015).

Comprehensive studies (Griliches, 1997; Mankiw, Romer, & Weil, 1992) confirm that human capital accumulation facilitates long-term growth. Griliches (1997) demonstrates that educational upgrading of the labor force has contributed significantly to growth in the United States, and Mankiw et al. (1992) provide empirical evidence for other Organisation for Economic Co-operation and Development (OECD) countries. Primary and secondary education seems to boost economic growth in developing countries, while tertiary education contributes to growth in advanced economies (Mankiw et al. (1992).

In growth accounting, scholars often label the residual as technology, but newer studies show that a substantial proportion can be explained by substituting lower- with higher-quality inputs, higher levels of skills, or human capital (Blundell, Dearden, Meghir, & Sianesi, 1999). New economic growth literature in particular developed the stance that human capital enhances a worker's ability to create and adapt to technological change. Thus, human capital is regarded as enabling factor for innovation (Aghion & Howitt, 1998; Nelson & Phelps, 1966; Redding, 1996; Romer, 1990). Contrary to previous growth economists, Lucas Jr (2015) goes a step farther and presents evidence suggesting that all growth can be solely attributed to schooling, job experience, or learning on the job.

Figure 1-1 presents the development of educational attainment and GDP per capita for countries in Europe, establishing a relationship between human capital and economic growth. EU countries have diverse economic backgrounds and schooling systems. Despite these differences, investments in education have picked up speed since the 1990s. Simultaneously, income levels in the EU continued to rise until the global financial crisis in 2008. Economic growth has subsequently slowed, and investments in education have been deferred. The EU has acknowledged that it faces a “skill crisis” due to shortages in the highly skilled labor force, which impedes growth in the EU. Restrengthening the foundation for sustainable economic growth requires improving human capital in the EU. Therefore, education and training have been emphasized as the main field of action. However, significant differences between countries remain.

Figure 1-1 Education and GDP



Source: Author’s chart based on data from the World Bank World Development Indicators (GDP) and Eurostat (schooling)

On the macro and micro levels, much evidence highlights the importance of human capital (Psacharopoulos & Patrinos, 2004, 2018). One factor evidencing the overall growing significance of human capital is the increasing individual returns to investments in human capital that reward education, training, and knowledge with better earnings. The returns are captured by the forgone earnings surrendered while spending more time in education (Mincer, 1974). On average, the returns to human capital have increased since the 2000s in most advanced countries (Psacharopoulos & Patrinos, 2018).

Tinbergen (1975) discovered that the wage gap between university graduates and unskilled workers kept growing over time while the share of highly skilled—those with tertiary education—increased. However, based on the theory of supply and demand, wage premiums should have declined with increased supply. He referred to this phenomenon as the race between technology and education. This idea gained momentum with Goldin and Katz (2008) book *The Race Between Education And Technology*, which discusses the phenomenon in detail for the United States.

While technologies can foster economic growth, they can also threaten societies. Technological advances have dramatically affected how people live and work. In particular, labor markets have been transformed due to the rise of productivity-enhancing technologies. This concept is not new, and scholars and policymakers have widely recognized the short-term effects of technology on unemployment. In 1933, economist John Maynard Keynes raised the issue of technological unemployment and possible adverse short-term effects. However, the standard view during the twentieth century was that the societal benefits outweighed these adverse effects.

However, several economists have challenged this perception when they noticed increasing unemployment rates in many industrialized economies in the 1970s and 1980s. However, it was not until a study by Frey and Osborne (2017) that academics, governments, and managers started painting a grim picture about the future of work. Frey and Osborne famously predicted that 47% of U.S. jobs are likely to be computerized, resulting in mass unemployment. Further studies followed, confirming the risk of job displacement due to technologies, although at varying degrees of severity.

Recent studies from the McKinsey Global Institute (Bughin et al., 2018; Ellingrud, Gupta, & Salguero, 2020; Smit, Tacke, Lund, Manyika, & Thiel, 2020) and the OECD (Georgieff & Milanez, 2021) predict that around 1.2 billion workers will be affected by automation and artificial intelligence (AI) and that technologies will change approximately half of all jobs. Further data shows that 5% of jobs will not exist in the future (World Economic Forum, 2020), 14% of workers will need to switch to other occupations (Georgieff & Milanez, 2021), and half of the workforce will need to retrain (Smit et al., 2020). There is no doubt that new technologies cause tremendous transformations in the world of work.

New software or machines appear to replace specific job tasks and simultaneously require new tasks to be performed. Spitz-Oener (2006) demonstrated that the transformation of jobs is more severe in rapidly computerizing occupations and that jobs demand more complex skills compared to 1979. As technological progress speeds up and penetrates all parts of the economy, the effects become more visible. Digital technologies, AI, and automation require fewer repetitive, routine skills but more cognitively complex skills that entail decision-making about issues or tasks that machines cannot accomplish (Catalano, 2018).

The demand for more technological and complex skills is expected to increase immensely over the next decade, particularly in operationally intensive sectors (Ellingrud et al., 2020). Hence, the greater fear should be the extent of the transformations rather than mass unemployment. As the transformations in the workplace continue, previously acquired skills become less valuable in the labor market. That is, one's human capital depreciates faster with ongoing technological progress and changed skill requirements. To maintain productivity, workers need to upgrade their skill sets. Continuous upskilling or further education and training may become necessary to stay productive. Despite this critical implication for individual labor market outcomes, the effect of technological change on human capital and its depreciation have gained little attention.

Recent developments such as the transformation of work caused by ongoing technological change have found their way into all parts of society, including areas of economic activity, imposing significant challenges for the future of work. This development directly implies the necessity to consider its implications for human capital on a micro and macro level. Understanding how to maintain the value of human capital through retraining, upskilling, and investing in the right skills for the future is particularly crucial. In particular, how education and technology are connected through occupational tasks and required skills should be examined in more detail. Human capital is formed through education, while technological change is indirectly reflected through the use of various tasks and skills. Analyzing these factors can foster better understanding of the role of human capital for evolutionary economic development on the macro level and for individual labor market outcomes on the micro level.

1.2. Problem statement

Investments in education increase productivity, which in turn leads to higher wages and economic growth. Empirical evidence for this is plentiful (Psacharopoulos & Patrinos, 2018). Consequently, policymakers have promoted educational upskilling to tackle the challenges imposed by technological change. Labor-replacing technologies substitute routine tasks, and workers will need to adapt to new jobs that successively entail more nonroutine tasks. These trends increase the importance of human capital and, more specifically, the role of routineness, tasks, and skills.

The role of routineness and returns to human capital

Research on the returns to human capital and the role of job tasks lags behind recent developments in the labor market. Thus, although policymakers address the skill crisis induced by technological change by promoting investments in education, these policy initiatives might not have the desired results. How well the different types of education (general and specific) can prepare workers for future jobs intensive in nonroutine tasks is poorly understood.

This thesis addresses the knowledge gap by empirically examining the routine intensity of tasks and their effects on the returns to education levels. Thus, the research objective is to explore how earnings differ for workers with varying levels of human capital and job routineness.

The research question that arises is whether all education levels prepare the workforce equally well for jobs intensive in nonroutine tasks compared to positions with repetitive, routine-intensive tasks. Specifically, this study seeks to answer how workers' wage premiums are affected by their education level and which role is played by the routine intensity of their occupational tasks. Studying the impact of technological change on the labor force can provide crucial implications for the design of future education systems and whether to promote specific or general education to maintain sustainable, inclusive growth.

The role of tasks and skill obsolescence

Current literature on human capital depreciation has begun to address some issues of technological change, highlighting the importance of task-specific human capital. However, no current study directly investigates the interplay of job tasks and the depreciation rate. To close this gap, this analysis adopts the concept of job tasks from the literature on job polarization and incorporates it into the depreciation of human capital. The research objective is to address the issue of heterogenous education and the role of job tasks in the depreciation rate.

The first research questions encompass whether workers with higher levels of education have a greater depreciation rate than workers with lower education levels, and whether the same is true for workers with specific vocational education and training (VET) versus workers with general education. Second, this study investigates whether the depreciation rate depends on how quickly or often job-related knowledge or technology change. That is, jobs exposed to changes in job-related technologies are characterized by a high share of nonroutine analytical and routine cognitive tasks. Thus, the underlying data of analysis are job tasks. This analysis facilitates the understanding of technological change and its effects on the obsolescence of human capital and provides crucial insights for the need to retrain or upskill.

The role of skills and evolutionary capability development

Future skill adoption possibilities are becoming increasingly important amid ongoing technological change. Nations need to prepare for changing skill demands and invest in the right skills to prevent falling behind. Skills embedded in a nation's workforce are crucial for productivity; thus, it is vital to understand the skill structures of countries, which skill acquisition possibilities a country has, and how to redirect its investments.

Comprehension of aggregate skill specialization on a national level is lacking. Due to the absence of data, most studies have only utilized proxied skills using educational variables or adult skill test scores. However, skills used in the workplace constitute an essential part of human capital. Furthermore, additional research is needed to explain differences in countries' human capital and why investments in human capital are successful for some countries but not others.

To close this knowledge gap, this study suggests that skill endowments and specialization can explain the differences among EU countries. This observation might explain why convergence in human capital is only partially occurring. Using actual data on the intensity of skills used in EU countries, this study aims to address why some countries grow more than others, how skills endowments are related, and how skill specialization occurs. In this work, micro and macro levels are linked to skill intensity data in occupations with aggregate employment shares. The results provide insight into the European skill structure and national skill specialization patterns, possibly explaining remaining cross-country differences despite educational investments.

1.3. Structure of the thesis

Human capital is essential on the micro and macro levels. Investments in human capital increase worker productivity and contribute to economic growth. Technological progress has increased the importance of human capital. As emphasized in previous research (Acemoglu & Autor, 2012; Goldin & Katz, 2008), the interactions between education and technology (reflected in the range of tasks in use) need further investigation to gain additional insights into the role of human capital. Thus, this dissertation examines the subject from various angles. These perspectives include the role of skills, tasks, and labor market outcomes under ongoing technological change, which is indirectly accounted for based on the assumption that it has significant implications, such as transformative developments in the labor market. Figure 1-2 provides an overview of the dissertation's structure.

Figure 1-2 Outline of the dissertation

Different aspects of human capital at the micro and macro level

- **Motivation**: Technological advances have transformed labor markets and affected workers and countries in various ways
- **Objective**: Analyzing the implications of technological change on different aspects of human capital to foster the understanding of economic outcomes at the micro and macro level

Micro level

- The role of education and routineness
- The role of tasks and skills obsolescence

Macro level

- The role of skills and capability

Studies on skills, tasks, and labor market outcomes under ongoing technological change

Chapter 3

Routineness, Education, and Wages – How Technological Change Affects Labor Market Outcomes in Germany

- **Research objective:** Analyzing the effects of routineness and education on wage premiums, focusing on the productivity-enhancing effects of education given job routineness
- **Research questions:**
  - **RQ1a:** Do higher education levels lead to higher returns regardless of the routineness of the occupation?
  - **RQ1b:** Does higher routineness render lower wages regardless of the education level?
  - **RQ2:** Is the impact of education on wages lower in routine jobs than in non-routine jobs?
- **Methodology:** Panel-fixed effects regression, Heckman 2-Stage selection model, introducing routineness to the concept of the returns to human capital investment
- **Data:** German Socio-Economic Panel (1984-2017), KldB 1992 & KldB 2010

Chapter 4

How Susceptible Are Skills to Obsolescence? A Task-based Perspective of Human Capital Depreciation

- **Research objective:** Investigating the link between human capital depreciation and job tasks, with an emphasis on potential differences between education levels
- **Research questions:**
  - **RQ1a:** How does the education level affect the depreciation rate of human capital?
  - **RQ1b:** How does the skill specificity affect the depreciation rate of human capital?
  - **RQ2a:** Do job tasks and their intensity of technology use affect the depreciation rate?
  - **RQ2b:** Do changes in job-related technology affect the depreciation rate?
- **Methodology:** Panel-fixed-effects regression, incorporating task-perspective from occupational data based on literature of job polarization
- **Data:** German Socio-Economic Panel (1984-2017); Muro et al. (2017) for data on technology use (2011-2016)

Chapter 5

The European Skill Space: A Cross-Country Analysis of the Path-Dependent Evolution of Capability

- **Research objective**: Investigating the skill structures of European countries and their evolution from the perspective of capability development
- **Research questions**:
  - **RQ1:** What does the skill structure in Europe look like?
  - **RQ2:** What are the patterns of skill specialization in European countries?
  - **RQ3:** Do national skill endowments explain cross-country differences?
  - **RQ4:** How does skill specialization take place?
- **Methodology:** Product space methodology using network analysis, OLS, Probit, and Arellano-Bond estimation), linking micro data on skills with and macro data on aggregated employment shares
- **Data:** EU-Labor Force Survey (2011-2018); European Skills, Competences, Qualifications and Occupations dataset (2020)

Finally, this thesis adopts a macro perspective and investigates the role of aggregate human capital for economic development in a broad sense. Investments in human capital are necessary for countries to succeed in today's globalized economy (G. Becker, 2002). Thus, the last main chapter analyzes existing skill endowments and checks whether differences in specialization patterns exist across countries and regions. Additionally, current skill specialization may determine future skill specialization, potentially affecting economic development in the long term. Thus, understanding the evolution of capability development and which skills countries are likely to use effectively in the future can help explain differences in economic development and enable countries to steer toward a more promising path.

The various aspects of human capital for economic development at the micro and macro levels are explored by empirical analysis in the following chapters. First, Chapter 2 describes the literature framing human capital research at the micro and macro level and establishes a connection between human capital and the influence of technological changes. Chapters 3, 4, and 5 are the main chapters of this dissertation and illuminate various aspects of human capital at the micro and macro level.

Starting at the micro level, Chapter 3 applies econometric analysis to investigate whether evidence is found for skill-biasedness or routine-biasedness in the returns to education. The chapter specifically focuses on the routine environment of the job and the implications it has for heterogenous workers using an interaction term between routineness and education. Chapter 4 considers differences between occupations based on their primary task type.

The effects of technological change on human capital are assessed, specifically, its economic obsolescence, that is, how quickly the productivity-enhancing effect of education disappears depending on the type of job tasks a worker predominantly performs. This depreciation is captured by an interaction term between education and potential experience (the time since leaving school) to capture the diminishing human capital. Chapter 5 takes a macro perspective, examining capability development across European countries and how skills are a possible driver of inequality among countries. Chapter 6 concludes with limitations and avenues for future research.

1.4. Contribution of the study

Human capital and the literature on its returns guide education policy by showing the effects of various education levels on society and the economy. This study helps gain additional insight and understanding by considering the interplay of factors related to technological change in human capital formation, its depreciation, and economic outcomes. In sum, these findings contribute to understanding the implications of technological change and human capital.

Prior research has shown that technological progress has changed the labor market, leading to skill polarization (Autor, Levy, & Murnane, 2003) and technological unemployment (Frey & Osborne, 2017). Scholars have studied the implications of task-based technological change on the possibility of becoming unemployed, and the adverse effects on routine jobs have been highlighted (Autor et al., 2003). However, it is still unclear how the routine intensity of a task affects the educational wage premiums of individuals.

The study contributes to prior research by adding empirical evidence of the heterogeneous returns to education. Unlike previous studies, this empirical analysis investigates connections between the routineness of occupational tasks, different education levels, and wages. The first study allows for heterogenous human capital and contributes to the literature on the role of technological change on occupational levels by addressing specific changes for workers of various skill levels. More specifically, this study contributes by considering the particular challenges in preparing workers for emerging non-routine-intensive jobs.

Technologies transform labor markets, rendering old human capital obsolete and requiring workers to adapt to changing skill requirements. Recent developments pressure governments to provide adequate education policies targeting the obsolescence of human capital. While many countries have realized the importance of the ongoing changes, more education measures are needed to prepare the workforce. To close the previously addressed gap in the literature, this study directly incorporates a task perspective based on the classification of job tasks adopted from the literature on job polarization while focusing on the depreciation of education. This appears to be the first study that analyzes the economic obsolescence of skills due to changes in the economic environment while incorporating factors related to technological change, that is, technology intensity and occupational tasks.

The study on human capital depreciation contributes explicitly to the field by merging the concept of job obsolescence with the concept of skill obsolescence. Thus, the research enables a comparison between the literature on skill obsolescence and works on job obsolescence. The results facilitate understanding how skill depreciation differs for various task groups. Moreover, the findings might reveal that some education levels are better at protecting workers again skill depreciation. This study may also help policymakers design effective training programs that allow professions to periodically update their qualifications to incorporate the most recently demanded skills.

Human capital formation affects workers on the micro level while also determining a nation's economic outcome in the future. Future skill adoption possibilities are increasingly critical as technologies transform occupations and skill demands. Skills used in the workplace constitute an essential part of human capital. However, skills are challenging to measure, and most studies have only used proxies such as educational variables or adult skill test scores.

To close this gap, this chapter uses a novel dataset on the intensity of skills used in EU countries and links it with employment data at an aggregate level. Analysis of path-dependent capability development in the EU applies the concept to the evolution of skills. Combining micro-level data on skills and connecting it with employment shares at the national level is a unique approach to investigate differences in skill structures across European regions. This analysis can foster understanding of why some countries grow more than others, how skills endowments are related, and how skill specialization occurs.

The findings add to the understanding of capability development and specifically the role of skills in explaining differences between countries and factors that might impair economic convergence in the long term. Skill inequality among nations should be considered when discussing policies of economic convergence in Europe and globally. To prevent falling behind, nations need to prepare and invest in the right skills. Thus, it is vital to understand which skill acquisition possibilities a country has and how to redirect its investments.

Overall, the results of this dissertation provide a more holistic picture of the implications of technological change on labor market outcomes. The three studies emphasize that capability building is essential to address the challenges of changing skills and provide evidence for the urgency of this focus. Specifically, this study may help policymakers design effective training programs that allow workers to upskill their qualifications and skills to meet labor market requirements. These findings also facilitate policy design to address challenges in the labor market. Specifically, educational policies must incorporate technological knowledge demanded by the workplace, enabling workers to quickly adapt their abilities to changing market conditions amid more rapid and disruptive technological advances. Educational investments should be redirected to foster the formation of required skills in the future.

Chapter 2.
Literature review

2.1. The concept of human capital

2.1.1. Definition

“Human capital” refers to “the knowledge, skills, competencies, and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being” (OECD, 2001, p.18). This implies that people are valuable assets that could be seen as production factors to create goods or services. Thus, human capital encompasses different aspects: First, the human aspect can be seen in the sense of a labor force that creates economic value-added through the input of human capital alongside other production factors such as physical capital and labor hours (Schultz, 1961).

Second, human capital is viewed as a process of accumulation formed through education and training (Blundell et al., 1999; De la Fuente & Ciccone, 2002). Blundell et al. (1999) define three channels through which human capital is formed. The first factor contributing to human capital is early ability, which can be innate or learned. Second, formal education is the primary channel for forming knowledge or qualifications. The last channel is on-the-job training, which enables the accumulation of skills, competencies, and expertise. Those components of human capital formation demonstrate strong complementarity. Consequently, human capital can be understood as a combination of accumulated skills, knowledge, and abilities that create economic value at the individual, firm, or national level.

Like other investment decisions, investment in human capital entails a cost. This cost can be the tuition fees for attending school or college, but it also includes the opportunity cost of forgone earnings during education or training. An economic actor, who can be an individual, firm, or country, only invests in human capital if the expected return in the future is at least as high as the related cost or the market rate of return on other alternative investments. Unlike other investments, human capital grows through its use (which leads to the accumulation of experience and the excelling of skills) and depreciates due to a lack of use and other factors (Boarini, d'Ercole, & Liu, 2012).

The widely accepted definition of human capital proposed by scholars and the OECD reflects this multifaceted nature, including various types of human capital. These types include specific human capital attained through on-the-job or vocational education and training and general human capital formed through general secondary and tertiary education. This definition comprises cognitive and non-cognitive skills, which are becoming increasingly important. Although the broader OECD definition is a helpful reference point, most ongoing statistical work measuring human capital takes a narrow approach. Formal education and the economic returns to human capital are the prevailing points of departure for most studies.

To contribute to the field, this dissertation understands human capital not only as education and its economic value. This work extends this analysis to also consider specific workplace skills as part of human capital. These skills are closely related to occupations and their associated learning as well as capability-building through experience. The consideration of concrete workplace skills is also crucial under technological change where skill demands are not static. Including applied skills allows for capturing the effects of new technologies, which directly affect the value of human capital.

2.1.2. Characteristics

The definition of human capital given above can be focused to refer to the knowledge, skills, competencies, or experience needed to produce a specific set of goods or services. Thus, the first and perhaps most distinguishing characteristic of human capital from physical capital is its intangibility. An intangible asset embedded in an individual cannot be possessed by a firm or nation or separated from its owner, which is a major difference from other economic capital. Note that both human and physical capital accumulation occur through investments and decline through use and obsolescence, though in different ways. For example, while economic capital will wear out through use, human capital typically grows through use and experience. However, human capital depreciates due to lack of use, obsolescence of knowledge, population aging, and many other factors (Boarini et al., 2012).

The nature of human capital implies a second characteristic: it is self-generating and expandable, which has often been highlighted (Kwon, 2009). Therefore, the stock of skills and knowledge can be increased by investing in education or training or by accumulating experience. This characteristic is at the center of the research on human capital as it has significant implications. The self-generating and expandable nature of human capital implies that the formation of human capital today will lead to greater accumulation in the future. Thus, contemporary growth theory sees human capital as a determining factor for economic growth because it enables cumulative growth (Hanushek & Woessmann, 2008).

The third characteristic of human capital is portability and shareability (Kwon, 2009). Knowledge, skills, or competencies lie within an individual and thus can be moved with the person, for instance, to another firm. In most cases, the knowledge holder is also the owner (unless he assigns his rights to another entity). Thus, human capital such as knowledge and skills can be shared with others. The distribution of knowledge can further facilitate human capital accumulation within an organization or nation. However, while human capital can be shared or moved, it cannot be transferred in the sense of selling it to the market.

2.1.3. Types

Human capital entails several dimensions that encompass different roles. A method of classifying human capital is by the type of knowledge or skill it comprises. Traditionally, scholars distinguish between general and specific human capital (G. Becker, 1994; Gibbons & Waldman, 2004). General human capital encompasses universally applicable skills and knowledge and is typically formed through formal education and experience. These can be moved to another firm without losing market value because they can be applied in various environments (Laroche, Mérette, & Ruggeri, 1999).

Specific human capital comprises skills, knowledge, and competencies relevant to a particular occupation or firm. Specific human capital is mainly formed through formal vocational education and training programs or informal training on the job. Thus, in contrast to general human capital, specific human capital is only somewhat portable and loses value when a worker changes his job. Many studies used this classification of human capital to explain growth differences between European countries and the United States (D. Krueger & Kumar, 2004).

However, not all specific human capital is specific to the firm but specific to the job task (Gibbons & Waldman, 2004). Already since the origin of human capital research, the idea of specialization at the task level has existed. Smith (1776) believed that specialization in fewer job tasks could increase productivity, emphasizing the role of learning-by-doing (Gibbons & Waldman, 2004). Gibbons and Waldman (2004) picked up on this idea and introduced the concept of task-specific human capital, highlighting that a large share of actual human capital stock is formed through 'task-specific learning-by-doing'. Task-specific human capital implies that this type of human capital is also valuable to other firms or even other occupations which are comprised of similar tasks. This reformed the conceptional thinking about the main characteristic of specific human capital that is not transferable to other working environments.

The idea of task-specific human capital as a third type of human capital has also been promoted through the work of Autor et al. (2003) on the effects of computerization on job tasks. The underlying concept is the same as in Gibbons and Waldman (2004) that an occupation is a combination of tasks, and workers' skills are comprised of the capability to perform different tasks (Acemoglu & Autor, 2012). With ongoing technological change, the task-based framework has been adopted by other scholars to examine the effects of automation on labor market outcomes such as unemployment (Acemoglu & Autor, 2011; Spitz-Oener, 2006).

The main advantage of the concept of task-based human capital is that it enables analyses of the effects of labor-replacing technologies such as automation, robotics, or artificial intelligence. Eventually, machines will replace some tasks that have been executed by workers (Acemoglu & Autor, 2012). However, it is unlikely that technologies will substitute entire occupations, thus analysis on a task level is a needed tool. Tasks that are more susceptible to replacement are routine. These tasks are programmable by a set of fixed rules and mostly include repetitive activities. In contrast, nonroutine tasks are difficult to be executed by machines and thus task-based human capital that is based on nonroutine tasks is less at risk of becoming invaluable in the labor market.

The task-based approach to human capital also has implications for investments in education. Due to the ongoing technological advances, not all types of education will be equally good in preparing workers for the less routine intensive task requirements in the labor market. Thus, the interplay between the different types of tasks and education is important to understand if current education systems are efficient in preparing the workforce and inducing policies that tackle the upcoming challenges. However, so far, no studies to speak of have investigated the interplay directly. Thus, the implications of task-specific human capital will be explored further in this thesis.

2.1.4. Significance

Human capital is important not only for individuals but has implications at all levels of an economy. On a macro level, human capital facilitates the economic growth of nations (Romer, 1990; Schultz, 1961). Especially some earlier works have sometimes found contradicting evidence (Benhabib & Spiegel, 1994). Recent studies highlight that education does not necessarily lead to the formation of cognitive skills (Messinis & Ahmed, 2013) and thus, does not contribute to economic growth. However, most works agree on the role of human capital as a driver of growth. This means that higher levels of human capital foster future economic growth.

Human capital may even play a crucial role in regional development, but this needs further investigation (Diebolt & Hippe, 2019; Gennaioli, La Porta, Lopez-de-Silanes, & Shleifer, 2013). The results of Diebolt and Hippe (2019) show that historical human capital is an important determinant of present levels of innovation and economic development in Europe at the regional level. Thus, previous human capital accumulation may have persisting effects on economic development. Moreover, human capital also fosters firm productivity, competitiveness, and innovation activities (D'Amore, Iorio, & Lubrano Lavadera, 2017; Diebolt & Hippe, 2019).

On a micro level, human capital can increase workers’ productivity in the workplace (Griliches & Regev, 1995; Lucas Jr, 1988) which is reflected in wage growth (Schultz, 1961). Numerous studies provide empirical evidence for the positive relationship between education and earnings (Psacharopoulos & Patrinos, 2004). Thus, human capital is a means to increase the wealth of individuals. Moreover, studies have confirmed the positive effects of human capital on non-economic outcomes such as health (G. Becker, 2007). Overall, scholars seem to agree on the significance of human capital on individual outcomes, but the magnitude of the results and the topics of studies vary widely.

Furthermore, human capital does not only have direct effects on the economy and society, but it also creates externalities (Ciccone & Peri, 2006; Lange & Topel, 2006; G. McMahon & Moreira, 2014; W. W. McMahon, 2018; Moretti, 2004). There are economic and non-economic externalities from education. Economic externalities of higher levels of human capital include better investment decisions of individuals and raising personal wealth. But human capital can also spill over to other workers, thus leading to increased firm productivity or higher average regional income (Moretti, 2004). On a macro level, human capital externalities are associated with increasing economic growth rates through other indirect channels.

Non-economic externalities of human capital are associated with better health and longer life expectancy or lower crime rates in areas with higher levels of education (Moretti, 2004). Also important is the positive spillover effect of human capital on the ability to cope with changes. This is of special significance with the increasing rate of technological change and more volatile labor markets as it enables individuals to adapt to unemployment, reducing the possibility of long-term unemployment, or changed job requirements among others.

Given its importance at the macro and micro levels, it is important to measure human capital to assess the status quo of a country. Thus, the measurement of human capital serves as an assessment tool for then suggesting policies targeting the development of human resources. Specifically, studying human capital is crucial for governments and firms alike when deciding what kind of skilled workers to attract. However, it is not easy to disentangle the effects of human capital due to its complexity and wide-reaching impacts on all levels of an economy. Often proxies for human capital are used, such as productivity or income measures. Section 2.2 elaborates more on the developments of human capital investments, its measurements, and related, selected aspects.

2.2. Human capital theory

2.2.1. Avenues of human capital research

Literature on human capital is vast, and its first origins can be traced back to the English economist Sir William Petty (1623-87) and Scottish economist Adam Smith (1723-90). Petty tried estimating the national stock of human capital whereas Smith discussed the benefits of formal education over workplace training. In the 19th and 20th centuries, the concept of human capital started to emerge in various other strands of economic schools. For example, neoclassical economists Walras, Marshall, and Fisher, Austrian economist Hayek and even capability theorists gained interest in the concept.

The model of human capital sparked further interest in the 1950s and 60s, when physical capital and labor input, just measured as hours, could not explain much growth. This was especially the case for war-ridden countries like Japan and Germany which experiences rapid growth despite massive destruction of physical capital (Schultz, 1961). It was then that some economists noticed that the investment in human capital was increasing wages. Once human capital was accounted for in growth models, the explanatory power increased notably.

However, the research field did not gain in popularity until the works of Mincer (1958, 1974), Schultz (1961), and G. Becker (1994) who were among the first advocates to promote human capital as a rational choice. By investing in human capital, people gain access to a wider range of choices that allow them to increase their welfare (Schultz, 1961). Thus, the focus of these new approaches is the reason for investing in human capital, and not a nation's welfare.

Against this background, modern human capital research is predominantly measured in terms of earnings and builds upon the works of three scholars: Mincer (1958, 1974), Schultz (1961), and G. Becker (1994). Mincer (1958) introduced his infamous Mincer-type earnings equation and finds that years of education are strongly significant for earnings and human capital. In contrast, Becker introduced another approach for measuring the returns to human capital investment which uses the internal rate of return considering the benefits and the cost of education (G. Becker, 1994). (Kara, 2010) compared the two approaches to the rate of return to investment in education and finds slight differences between the two approaches. However, both approaches exhibited a declining rate of return to schooling over time in addition to higher returns for females than that for men. Due to its practicability and the more accurate results when measuring earnings differences associated with additional schooling, the Mincer approach has been adopted predominately.

The three scholars set the foundation for today's human capital research. However, over time the definition of human capital progressed. Until today, most of the work on human capital follows the traditional view of human capital where formal education is used as the main variable. Education is seen as an investment, creating an emphasis on the returns to human capital investment. In the 1970s, some scholars (Groot & Oosterbeek, 1994; E. Katz & Ziderman, 1980; Riley, 1976; Stiglitz, 1975) started to oppose this view and introduced the signaling theory. According to signaling theory, education merely functions as a mechanism to sort individuals and signal their ability to the labor market to gain higher wages. However, there is plenty of evidence that discards this view.

A decade later, economic growth scholars Romer (1986) and Lucas Jr (1988) highlighted the importance of education for economic growth instead of unexplained technical progress. In endogenous growth theory, education facilitates returns on investments in physical capital and hence spurs economic growth and innovation. Investment in human capital, along with knowledge and innovation, and knowledge are the key drivers for economic growth.

Contemporary growth theory now regards human capital as an important economic growth factor (Hanushek & Woessmann, 2008).

Since the 1990s, empirical research began to highlight the significance of other factors such as an individual's ability measured in early childhood (Blackburn & Neumark, 1993; Dearden, 1999), family background (Butcher & Case, 1994; Dearden, 1999), and the local environment (Card & Krueger, 1992). Experiments on surveys seeking to measure the skills of workers directly (in terms of literacy, numeracy, and problem-solving capacities) began in the 1990s (IALS surveys) for a pilot group of 12 countries (Folloni & Vittadini, 2010). With the same notion, other studies have begun to investigate the role of other factors. Indeed, several studies have found strong evidence that the acquired skills depreciate over time, which results in decreasing returns (Blundell et al., 1999; Lillard & Tan, 1992; Mincer & Ofek, 1982). VET thus needs to be renewed to retain its benefits.

The components of human capital proposed by the OECD reflect its multifaceted nature by including general and work-specific skills, or skills that can be tacit or explicit. This definition expands the conventional view by research in this field that only included cognitive skills to also comprise non-cognitive skills such as intra- and interpersonal skills that have assumed an increasingly important role in modern societies. Along with this, the idea of spillover effects on other parts of the economy and society emerged (Acemoglu & Angrist, 2001).

Despite the OECD’s broad definition, most of the work on measuring human capital[1] focuses on formal education and the economic returns to individuals (Boarini et al., 2012). Various empirical studies provide evidence for the positive relationship between education or schooling and earnings as well as decreasing returns to investments in human capital where the rate of return to education declines with the level of schooling (Hanoch, 1967; Kara, 2010). However, Messinis and Ahmed (2013) confirm with their empirical analysis that the level of education is not correlated with skill formation except in Asian countries (excluding Japan and Korea). While there are more critics about the use of simple measures of years of schooling as a proxy for human capital, the majority of research seems to agree on a generally positive association between human capital and wage premiums.

More recently, research on human capital has taken on diverse directions. The extensive research includes focus areas on individual, firm, and national levels. Different types of education, accounting for heterogeneous human capital, are being distinguished in some works. Messinis and Ahmed (2013) find that investments in education do not lead to the formation of cognitive skills but that investments in skills do. By comparing Japan and Korea, Lee and Wie (2017) find that the outcome of human capital is very much dependent on institutional factors such as incentive and labor contract systems. Jones (2014) used a generalized accounting approach and shows that

[1] see Folloni and Vittadini (2010) for an extensive review of the literature on human capital measurement.

differences in human capital play a greater role in explaining income differences across countries. Also, different topics about human capital investments have been examined. As the required skillset changes over time, economic development, or technological advances, other factors besides formal education become important for building and maintaining the human capital stock.

In recent years, the new concept of task-based human capital has gained momentum (Gibbons & Waldman, 2004). It considers the circumstance that human capital accumulation is very specific to the tasks on performs on the job and the required skills. In contrast to the prevailing understanding of human capital, task-specific human capital is not only accumulated through formal education but specifically through certain tasks and can be transferred to other jobs as well and that task-specific human capital contributes significantly to individual wage growth (Gathmann & Schönberg, 2007). The idea of task-specific human capital has found its way into the works on employment and job polarization (Autor & Handel, 2013; Frey & Osborne, 2017; Spitz-Oener, 2006). However, regarding the returns to human capital, task-specific human capital has not been studied yet.

Investments in human capital are a well-established concept to increase the economic outcomes of individuals and promote economic development. All major policy institutes have recognized its significance, with many having their own task force for studying the implications of human capital investments. This leads to a coinciding opinion on the topic. Some developments in the field are even pushed forward by policymakers' decisions to stress the urgency of human capital formation amid the Fourth Industrial Revolution.

2.2.2. Measurements of human capital

The motivations behind measuring human capital can be manifold and so are the approaches. Firstly, measuring human capital can provide a better understanding of the drivers of economic growth and evaluate the long-term sustainability of a country's development path. The returns to workers' skills are systematically related to prior economic growth rates. Skilled workers can adjust more rapidly to economic change (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2017).

The further motivation behind quantifying human capital is to measure the output and productivity performance of the educational sector. Education has become increasingly important, and policymakers emphasized the relevance of human capital formation. Recent discussions go beyond measuring impacts on GDP and focus on the distribution of human capital across households and individuals, including the non-monetary benefits stemming from it (Boarini et al., 2012).

Approaches to measuring human capital are plentiful and vary with different motivations (Folloni & Vittadini, 2010). The approaches can be divided into two streams including three major approaches. The first approach is the indicator approach, which attempts to quantify the human capital stock using educational attainment. The indicator approach can be further differentiated between quantity and quality assessments that measure human capital through various types of educational characteristics of the population such as standardized scholastic or adult skill aptitude tests (Fender, 2012).

The second stream utilizes monetary measures, which can be divided into direct and indirect approaches. The indirect approach indirectly measures the human capital stock as the difference between the total discounted value of each country's future consumption flows and the sum of its tangible components.

The two direct approaches can be further divided into cost-based or input-based and income-based methods. The cost-based approach treats human capital as a stream of past investments, that is, public and private expenditures for formal education and spending for on-the-job and adult training (Schultz, 1961). In addition, the cost-based approach is based on the value of the inputs needed to produce human capital (Fender, 2012). The depreciation of human capital is an essential aspect of the cost-based approach; hence, literature on the aspect of human capital depreciation is discussed in further detail in Subsection 2.2.4 of this chapter.

The income-based approach regards human capital as a stream of future earnings that human capital investment generates over the lifetime of a person (Jorgenson & Fraumeni, 1992; Le, Gibson, & Oxley, 2003; Weisbrod, 1961). It is based on the output measured as earnings that are created by the use of human capital (Fender, 2012). A major assumption of the income-based approach is that earnings reflect the marginal productivity of a worker.

These measurements also have some drawbacks that are worth mentioning. First, one might criticize that most indicators are built upon proxies such as wages or productivity. Thus, they might not measure human capital accurately. Second, when using cost-based measures, it might be difficult to isolate the cost of education from the total cost of human capital which depends on an individual’s different innate ability. In contrast, income-based measures demand that wages are separated from other income and are typically only quantifiable for employed human capital (Fender, 2012; Wolff, 2000).

Additionally, it might be difficult to isolate the effect of human capital. Factors like family background or ability are not considered and thus the results may overestimate the effects of human capital. This is also an issue when examining the effect of human capital on economic growth or other outcome variables. That is because human capital contributes to other aspects of society or individuals, such as health, that might positively influence the outcome. Thus, it is important to consider institutional and societal factors when measuring human capital (Ashton & Green, 1997; Fender, 2012).

Due to those drawbacks, contemporary literature has shifted to alternative measures of human capital. Those seek to include measures beyond the sheer quantity of education. Using only years of education does not consider differences in the education systems between countries. As a solution, many studies have started to use educational achievement, i.e., the highest educational attainment, as a variable for human capital (Vandenbussche, Aghion, & Meghir, 2006). Other scholars use the outcome of international standardized student achievement tests (such as PISA or TIMSS) to account for the quality of education (Hanushek & Kimko, 2000; Hanushek & Woessmann, 2007, 2008). Hanushek and Kimko (2000) and Hanushek and Woessmann (2007, 2008) confirm the positive effects of student achievement measured by TIMSS and PISA scores on economic growth and add that the difference between education and cognitive skills are more pronounced for developing countries. Another approach is to estimate a Mincer equation where human capital is the net effect of education, work experience, and training (Dagum & Slottje, 2000). Still others go further and use variables of health as a proxy for human capital. Jones (2014) suggests a generalized accounting approach as an alternative to traditional measures of human capital and shows that differences in human capital may fully explain the differences in GDP between rich and poor nations.

In praxis, often human capital indicators are used to express the human capital of a country or the expected human capital that an individual will likely possess at a certain age. International organizations such as the Worldbank, OECD or UN, and governments such as the EU have initiated the development of human capital indices to facilitate better education policy. These indices comprise several variables such as the years of schooling, scholastic aptitude tests (PISA or TIMSS), or the survival rate of children, and measure current outcomes. These indices are designed to compare the human capital across countries and to demonstrate how advances in education and related health positively influence the productivity or economic growth of future generations, enabling policy interventions to improve the situation (Kraay, 2018).

Overall, measurements of the human capital stock are sensitive to the chosen approach and estimates vary. Nevertheless, the available estimates attest a tremendous value to the stock of human capital which might even surpass that of physical capital (Jones, 2014). Quantifying human capital thus stays an important task for explaining growth differences between countries, firms, or labor market outcomes of individuals. The redirected focus of using other measures besides the years of schooling suggests that policies at extending the time in school do not necessarily bring the desired results of improving cognitive skills. This becomes increasingly important as developed countries experience a growth slowdown and have emphasized a shortage of skilled workers for advanced jobs that involve working with new technologies. Thus, policymakers need to design measures that specifically target the improvement of skills amid technological change to foster sustainable economic growth.

2.2.3. Returns to human capital

The relationship between education and wages has its origins in the works of Mincer (1974), G. Becker (1994), and Schultz (1961). Since then, many empirical studies have led to extensive evidence on the subject including various topics (see, e.g., Lauer and Steiner (2000) For a detailed overview, see Psacharopoulos and Patrinos (2004, 2018)). The returns to investments in education have emerged as the most popular concept of interest. The results show, that on average one year of schooling yields a return of 8% (Psacharopoulos & Patrinos, 2018). The rate of return reflects productivity increases due to the education of the worker.

Two main approaches measure the returns to human capital. The first method was initiated by G. Becker (1994) and builds on the internal rate of return. The calculation is based on the benefits and costs of education for every year of life of a person. In contrast, Mincer (1974) suggested an earnings equation where the years of schooling and experience (approximated as age minus schooling minus six) are regressed on wages. It is assumed that each year of schooling yields the same return, regardless of the level of education. The Mincer earnings equation is only used for estimating private returns to education. The internal rate of return approach can also be used for calculating social returns. Kara (2010) compares both measures and finds that although they have some differences, the use of both approaches yields similar returns to schooling. Both approaches exhibited a declining rate of return to schooling over time in addition to higher returns for females than for men (Kara, 2010). However, the Mincer earnings equation has been adopted predominantly in empirical works (Psacharopoulos & Patrinos, 2018).

The earnings premium associated with the level of education suggests that a worker's productivity increases as they acquire additional qualifications. Some scholars have argued that higher wages do not reflect higher productivity but might be a result of signaling in the labor market. For example, Card (2001) and Layard and Psacharopoulos (1974) tested the screening hypotheses and found little evidence for them. Most research also agrees with the productivity-enhancing effects of education and thus utilizes the Mincerian approach.

Traditionally, years of schooling are employed to estimate the returns to schooling. The overviews provided by Psacharopoulos and Patrinos (2004) demonstrate that between 1950 and 2014, the average rate of return lies at 8.8% per additional year of schooling and has been increasing since 2000. At the same time, school attainment has also increased; thus, those simultaneous developments could indicate a "race between education and technology." Other stylized facts include higher returns to education for females versus males, a declining rate of return with education level, and lower social returns compared to private returns.

Most studies estimate the rates of return to human capital using only the quantitative measure of years of schooling. However, they do not reflect the quality or type of education, nor the declining marginal returns to higher levels. Thus, using heterogeneous human capital, which considers different levels and types of education, is more appropriate in most cases. That is, there are noteworthy differences in human capital formation between the various types of education, which also have different economic implications.

General education is attained through formal studies such as general primary and secondary education, but it also includes education at the tertiary level. General education results in skills that are equally applicable to a variety of firms or occupations (G. Becker, 1994). Moreover, it typically prepares students for more advanced education, equipping students with the ability to acquire new skills that result in long-term relative earnings advantages (Golsteyn & Stenberg, 2017; D. Krueger & Kumar, 2004). In turn, specific education is typically formed through vocational education and training (VET) and leads to labor market-relevant vocational qualifications. Resulting in knowledge, skills, and competencies specific to a particular class of occupations that provide a short-term relative earnings advantage (Golsteyn & Stenberg, 2017).

Many studies have proven the heterogeneity of the returns, with higher education providing greater returns in form of higher wages. Nevertheless, most studies hold on to the method introduced by Mincer (1974) and estimate the returns of one additional year of schooling using a (sometimes modified) Mincer earnings equation. When allowing for heterogeneous human capital, that is the different levels of education, the wage premiums increase as people acquire additional qualifications, suggesting productivity increases (S. O. Becker, Hornung, & Woessmann, 2011; Psacharopoulos & Patrinos, 2018).

Particularly for countries with a strong vocational education system, distinguishing between vocational and general education is crucial when analyzing human capital (e.g., Alda, Friedrich, and Rohrbach-Schmidt (2020); Golsteyn and Stenberg (2017); Hampf and Woessmann (2017); Hanushek, Schwerdt, Woessmann, and Zhang (2017). Golsteyn and Stenberg (2017) use Swedish registry data to examine the short- and long-term differences between vocational and general education. Their analysis indicates that VET enhances short-term earnings whereas general skills have a stronger effect on long-term earnings. Similarly, using microdata for 11 countries from the International Adult Literacy Survey, Hanushek, Schwerdt, Woessmann, et al. (2017) demonstrate that VET provides easier entry into the labor force, but that the early short-term monetary benefits of VET diminish with age. The age pattern of early advantages and disadvantages later in a career for vocational education in countries with strong vocational systems is also confirmed by Hampf and Woessmann (2017) who use PIAAC data for the years 2012/2013.

Investments in education do not only yield returns on the individual level but also on the firm level. Training of workers has a positive impact on productivity, but the magnitude of the effect varies and productivity increases for the firm are larger than wage increases (Blundell et al., 1999). Bartel (1995) studies how firm-provided training affects wage profiles of workers and job performance scores in one large firm and finds that training has a positive effect. Moretti (2004) finds that there are plant-level productivity gains through formal education. Dearden, Reed, and Van Reenen (2006) investigate the link between training, wages, and productivity at the sectoral level using British industry data. Increasing the share of workers in an industry who receive training increases the value added per worker and wages. Moreover, workers with higher education levels and higher skills adapt more rapidly and efficiently to new tasks and technologies and can be a direct source of innovation (Blundell et al., 1999).

Returns to human capital at the macro level are measured as social returns or spillover effects. Economies benefit from investments in human capital through faster and more inclusive economic growth which is enabled through education-induced investments in physical capital and research and development (R&D,(Blundell et al., 1999). In sum, measuring the returns to human capital is vital.

2.2.4. Depreciation of human capital

Individuals acquire skills through education. Those skills depreciate over time and thus one's human capital depletes. Several studies (Lillard & Tan, 1992; Mincer, 1974) have highlighted that this may lead to decreasing returns to human capital over time. Human capital obsolescence can be divided into two types (Arrazola & Hevia, 2004; De Grip & Van Loo, 2002; Neuman & Weiss, 1995), technical and economic obsolescence. Technical skills become obsolete due to the worker's physical aging or the un-use of skills. The obsolescence of economic skills is caused by changes in the economic environment which decrease the market value of a worker’s qualifications.

Skill obsolescence has not received much attention despite its importance for human capital. Some scholars utilize Neuman and Weiss’s (1995) operationalization of the depreciation rate which focuses on vintage effects. Depreciation is indirectly measured by the interaction between education and potential experience and indicates its effect on an individual’s earning capacity following the Mincer model. It is based on the rationale that human capital depletes with the time since finishing formal education and potentially entering the labor force. This indirect measurement has the advantage that it captures the decreasing productivity effects through wages, which are the main worry for most countries (De Grip, 2006).

Murillo (2011) uses a modified version for the Spanish labor market and finds a schooling depreciation rate of 0.7% for 1995 and 0.4% for 2002, which increases with education level, and an experience depreciation rate of 3.8% and 1.8% respectively. Backes-Gellner and Janssen (2009) build upon an extended Mincer earnings equation and find that the rate of obsolescence is higher for workers in knowledge-based tasks compared to experience-based tasks. Lentini and Gimenez (2019) analyze sectoral differences in human capital depreciation in OECD countries for the period 1980 to 2005 and show that the depreciation ranges between 1% and 6% and is mainly significant in skill-intensive sectors regardless of the sector’s technological intensity.

Other scholars model human capital and its depreciation mathematically and estimate the depreciation rate directly. Groot (1998) introduces a model and finds a depreciation rate of 11-17% for Britain and the Netherlands. Arrazola and Hevia (2004) obtain depreciation rates between 1.2% and 1.5% for Spain, depending on the type of sector and periods of unemployment. Also following this approach, Weber (2014) uses data for Swiss and shows that specific skills are prone to faster depreciation (0.9-1.0%) compared to general skills (0.6-0.7%). The spread in the depreciation rates is likely attributable to differences in measurement, as well as the variation in observation periods and datasets.

2.3. Micro and macro perspectives of human capital

Human capital is not only relevant at the micro level for individuals as elaborated in the preceding subsections, but it also is important at the macro level for economies as a whole. The link between both levels is sketched in Figure 2-1. On both levels, human capital can contribute to economic growth. Human capital indirectly contributes to economic growth in that it may encourage investments in R&D and physical capital, enabling productivity growth (Blundell et al., 1999).

On a micro level, human capital improves workers' knowledge and skills, which are necessary for production. Workers apply their capabilities to perform tasks as part of their job. Workers with higher human capital levels are likely more productive and hence, receive higher wages than their low-skilled counterparts. Moreover, human capital improves the efficient use of technology and can lead to innovation activities of workers. In turn, technological change can also cause the tasks that comprise a job to change. Hence, new skills that require different human capital are demanded. New skills or knowledge need to be acquired which can happen through further education measures or on-the-job training or learning by doing. If human capital in the sense of skills is not updated and expanded, the productivity, that is, the economic value of the worker's skills decreases. This is referred to as human capital depreciation or obsolescence (Backes-Gellner & Janssen, 2009; Boarini et al., 2012; De Grip & Van Loo, 2002; Holtmann, 1972; Rosen, 1975).

At the macro level, human capital can be viewed as the aggregate stock of human capital of a country which fosters aggregate economic growth (Jia & Tomasic, 2017; Madsen, 2014; Widarni & Bawono, 2021). Therefore, investments in human capital improve the quality of the workforce, which in turn increases a country's aggregate productivity as the share of high-skilled workers increases. High-skilled are better at adapting to new technologies and performing more complex tasks. This is important because technologies complement high skilled workers through productivity increases, thus contributing to economic growth.

It is widely accepted that technological advances drive economic growth on a regional and national level. Technological progress enables efficient production processes and the production of more sophisticated products. However, human capital is essential to leverage the productivity-enhancing benefits of technology. Increasing human capital levels can induce technological change and it provides workers with the skills to adapt to it, making it a key component of economic growth (Blundell et al., 1999).

Higher levels of human capital endowments within a country can explain differences between growth rates of otherwise similar economies.

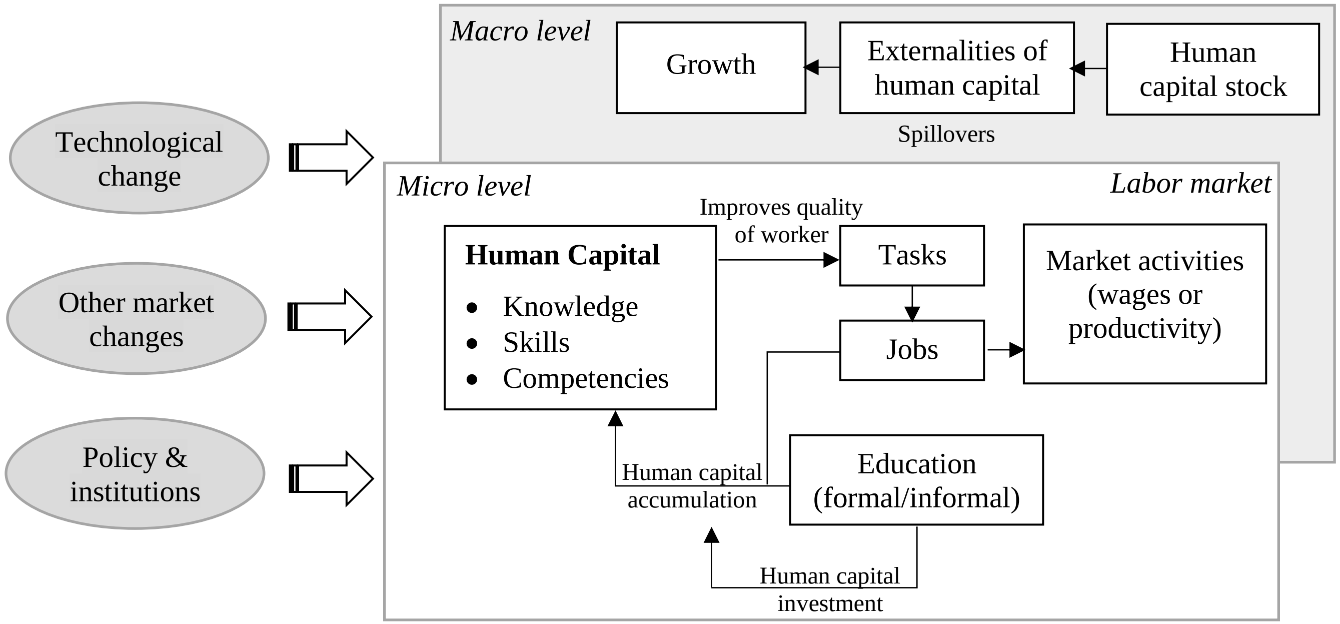
Gennaioli et al. (2013) employ a spatial model of regional and national income using cross-sectional data for 110 countries and find that human capital is the main driver of economic growth in EU countries and that different education levels are responsible for income variation within a country. Also investigating EU countries, Fagerberg, Verspagen, and Caniels (1997) explain differences between countries due to variations in technology diffusion and innovation activities. Less affluent countries lack R&D capabilities and thus cannot exploit the benefits of advanced technologies used in richer regions. While their finding does not explicitly mention human capital, advanced skills and knowledge are necessary for the formation of R&D capabilities, which can be acquired through investments in human capital.

Rodríguez-Pose and Vilalta-Bufí (2005) empirically investigate disparities in human capital endowment across EU countries and find evidence that lower human capital levels hinder economic convergence. Similarly, Funke and Strulik (2000) add evidence for the influence of a country's human capital levels on the process of catching up with technological development. Sterlacchini (2008) confirms the growth-enhancing effects of tertiary education and regional knowledge stocks measured as R&D expenditure. The GDP growth effects are more evident for countries above certain income levels. The results further show that laggard countries have been able to catch up to frontier countries if they possess a high human capital stock. (Sterlacchini, 2008)

A direct link between the micro level and the macro level can also be established through education investments and the returns to human capital. Investments in education render returns to the individual in form of higher earnings and the economy as a whole through productivity increases. At the micro level, returns to schooling reveal the productivity increases of human capital investments. At the macro level, returns to human capital investments are measured as the social returns or externalities of human capital. Several scholars (Lange & Topel, 2006; W. W. McMahon, 2006; Moretti, 2004; Winters, 2018) have looked at the social returns and provided evidence for the positive effects of education on society as a whole or specific groups of society currently and for future generations. Closely related to the concept of social returns are externalities of human capital. These are also often referred to as economy-wide spillover effects of human capital investments. Examples are for instance positive effects on health, increased participation in society, or productivity increases for the less educated. The spillovers or externalities have been studied by Ciccone and Peri (2006); Rosenthal and Strange (2008) and Wirz (2007). Thus, measuring the returns to human capital is crucial in justifying public investments in education and training.

Recapping, human capital is key to improving the economic outcomes of individuals and nations alike. Differences in human capital are responsible for variations in wages, national income levels, economic growth rates, or innovativeness among others. Understanding how human capital can help close reduce inequality among workers and cross-country differences is essential for designing policies targeting economic equality. Focusing on education and skill formation is crucial for the adaption of technologies and if a worker or a country does not possess the right skills they might risk falling behind. Under accelerating technological progress possessing the right skills and updating them continuously is necessary, and differences in skills endowments will determine future economic outcomes.

Figure 2-1 Micro and macro perspective of human capital



2.4. Technological change and labor market outcomes

2.4.1. Understanding the nature of technological change

Technological change (TC) refers to the increase in efficiency in production or process which lead to a higher level of outputs with a given level of inputs. This increase in efficiency is possible due to innovation that improves a process or product. Hence, technological progress allows for more efficient production of more and better goods and services. As a result, the production possibility frontier will shift outward, enabling economic growth. (Rousseau, 2017; Solow, 1957; Violante, 2016)

Technological change is not a recent phenomenon, it has been redefining human work throughout modern history. Technologies have induced economic transformations which changed the way humans produced goods and replaced workers in various tasks many times. The application of water and steam to mechanize production processes marked the beginning of the industrial age in the 18th century. It was then that technologies started to take over the work of human manpower in manufacturing. Innovations were mostly concentrated in the textile industry and the expansion of railroads. Later on, it led to the emergence of new industries such as steel manufacturing and petroleum refining. The Industrial Revolution transformed economies from agrarian economies to economies based on manufacturing. These developments fueled rapid economic growth in the western world, increasing income levels throughout the 18th and 19th century. They also introduced novel ways of working and living which fundamentally transformed societies. The Second Industrial Revolution was characterized by assembly line production and the use of electricity to power machinery. The application of assembly line production allowed faster and cheaper production, while it meant for workers to perform repetitive tasks.

Even then, workers were displaced due to technological inventions while new industries also emerged. In particular, the introduction of large-scale factory systems redefined the organization of work. The Second Industrial Revolution stands for labor division and specialization, which had tremendous impacts on workers and their human capital. Farmers or tradesmen who worked with hand tools started working with machines. Some workers became machine operators, requiring the acquisition of new and distinctive skills for their new tasks. These effects on the human capital of the workforce were further amplified with the beginning of the Third Industrial Revolution in the late 20th century. It is exactly those tasks that since the beginning of the Third Industrial Revolution in the 1970s are slowly being substituted by machines, further increasing the speed of production at lower cost, eventually displacing assembly workers. The further automation of production processes was enabled by the use of computers and programmable robots. The use of computers and the invention of the internet started the digitization process.

The Fourth Industrial Revolution has accelerated digitization and led to economy-wide digital transformations of industries and processes since the 2010s. Digitalization is taken to the next level where it is combined with different technologies. The automation of production processes continues and in combination with the use of information and communications technology (ICT), machines are communicating with each other, leading to the establishment of smart factories. The use of data and artificial intelligence is enabling new business models and transforming production processes. In service sectors, the use of ICT has complemented work, making labor in many white-collar jobs more efficient.

Like the preceding industrial revolutions, the Fourth Industrial Revolution has the potential to increase income levels and improve the quality of life for people worldwide. However, its speed and reach are unprecedented. The previous industrial revolutions have been transforming economies and manufacturing processes over decades, imposing changes but also allowing time to adjust. Technological advances have been accelerating, with the Fourth Industrial Revolution being the fastest yet. Its reach surpasses the first three industrial revolutions. Since the 1980s with the use of computers and the invention of the internet, many white-collar jobs have been affected by technological advances as well. The adoption of digital technology varies widely across occupations, sectors, and countries. Digital technologies and innovations have economy-wide impacts, not only on manufacturing but even on the nature of service industries. They transform entire production systems, management practices, and governance at a rapid pace, disrupting most industries globally. At the core are the worker and his human capital, representing the smallest entity to be affected by technological change.

2.4.2. Technological change and labor market outcomes: Skill-biased and routine-biased technological change

The adoption of computers into the workplace launched the digital transformation of labor markets across economies and changed the nature of work tremendously. With the gain of popularity in the 1970s and 1980s, many economies also observed an increasing demand for highly skilled workers. The increased demand raised wages for college graduates. At the same time, the number of college graduates continued to grow, increasing the supply of highly skilled workers in the labor market.

Despite the increasing supply of college graduates, however, wages continued to rise for these highly skilled workers. This observation was first made by Tinbergen (1975) for the Netherlands when he examined wage inequality and found evidence of a race between the supply and the demand for educated workers caused by technology. Goldin and Katz (2008) amplified this notion using a supply-demand-institutions framework examining the wage trends in the United States between 1890 and 2005. Their analysis unfolds that the relative supply of college graduates has started to slow down, leading to an increase in educational wage premiums since 1980. Simultaneously, the demand for low-skilled workers plummeted, increasing the wage gap between high- and low-skilled workers. Two main strands of literature have emerged to explain these developments, focusing on the skill-biasedness or routine-biasedness of technological change.

Skill-biased technological change

Technological change is skill-biased in that it favors skilled labor. Digital technologies complement the jobs of higher-skilled workers, increasing their relative productivity. Consequently, the demand for highly skilled workers increases, increasing wage premiums with education level (Alda et al., 2020; Autor, Katz, & Kearney, 2006; Goldin & Katz, 2008; L. F. Katz, 1999). That is because wage premiums reflect a worker's marginal productivity, which increased due to the complementing nature of technologies. On the contrary, lower-skilled workers do not benefit from the introduction of ICT. Rather are they penalized as those technologies tend to replace low-skilled tasks, decreasing their marginal productivity, and as a result, wages (Autor, Katz, & Krueger, 1998; Berman, Bound, & Griliches, 1994; Berman, Bound, & Machin, 1998; Card & DiNardo, 2002). Thus, skill-biased technological change (SBTC) increases the demand for highly skilled labor while simultaneously reducing the demand for less-skilled labor (Autor, Katz, & Kearney, 2008). The concept of SBTC is often used for explaining the increasing wage inequality between education groups, that is, higher wage premiums for higher education levels, and within education groups, attributing more weight to unobserved skills and experience (Antonczyk, DeLeire, & Fitzenberger, 2018).

A simple but common model of SBTC, which has been used in the majority of works (e.g., Bound and Johnson 1992; Berman, Bound, and Griliches 1994; Autor, Katz, and Krueger 1999), is summarized in Acemoglu and Autor (2011); Card and DiNardo (2002). SBTC is modeled using a production function Y which distinguishes between different types of labor, mainly between high-skilled and low-skilled labor. An economy-wide shift in the production function captures SBTC.

$$Y = f(N_H, N_L) = A\left[\alpha\left(g_H N_H\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(g_L N_L\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

That is, Y is a function of high and low-skilled labor input for the aggregate economy, determined by the elasticity of substitution between high and low-skilled workers σ, and parameters for technology (A, α, g_H, g_L). α is the distribution parameter, and $g_H, g_L$are factor-augmenting technology terms, meaning that technological change increases the productivity of high or low-skilled workers. If $\sigma > 1$, then high and low-skill workers are imperfect substitutes and an increase in g_H or g_L complements or substitutes for high or low-skill workers.

For any given value of the technical parameters, the marginal products of high and low-skilled labor give the skill unit wage under competitive labor markets. Equation 2 implies that a relative increase in the supply of high-skilled workers causes an increase in the wage of low-skilled and a decline in wages for high-skilled. An increase in technological change leads to wage growth for both skill groups.

$$w_L = \frac{\partial Y}{\partial N_L} = A g_L^{\frac{\sigma-1}{\sigma}}\left[g_L^{\frac{\sigma-1}{\sigma}} + g_H^{\frac{\sigma-1}{\sigma}}\left(\frac{N_H}{N_L}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}$$

$$w_H = \frac{\partial Y}{\partial N_H} = \mathrm{A} g_H^{\frac{\sigma-1}{\sigma}}\left[g_L^{\frac{\sigma-1}{\sigma}}\left(\frac{N_H}{N_L}\right)^{\frac{-\sigma-1}{\sigma}} + g_H^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \tag{2}$$

Equating the relative marginal product of high to low-skilled labor with the relative wage ratio, w_H/w_L, results in the relative demand for highly skilled workers, given in equation (3).

$$w = \frac{w_H}{w_L} = \left(\frac{g_H}{g_L}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{N_H}{N_L}\right)^{-\frac{1}{\sigma}} \tag{3}$$

Log transformation leads to equation (4) which captures the evolution of relative wages (Card, 2002) and establishes a link between the skill premium, the relative supply of skills, and technology. The ratio of the log wages of highly educated workers to high school graduates summarizes the relative wage premiums that high-skilled labor receives compared to low-skilled. Thus, the relative supply and demand for skills determine the wage premiums (Acemoglu & Autor, 2011).

$$\ln w = \ln\left(\frac{w_H}{w_L}\right) = \ln\left(\frac{\alpha}{1-\alpha}\right) + \frac{\sigma-1}{\sigma}\ln\left(\frac{g_H}{g_L}\right) - \frac{1}{\sigma}\ln\left(\frac{N_H}{N_L}\right) \tag{4}$$

Assuming an exogenous supply of workers, it follows that wage changes are either due to changes in technology or the relative supply of high-skilled workers, implying that a change in the relative supply of highly educated labor directly affects the skill premium *w*. The skill premium is central to empirical works studying earnings because it reflects the price of skills in the labor market. It follows from (4) that if factor-augmenting technology ($\frac{g_H}{g_L}$) capturing the skill bias of technology has stayed the same over time, then an increase in skilled labor should have reduced the skill premium *w*.

Data for the United States has shown that the supply of high-skilled workers has increased while their relative wages have also been growing (e.g., (Autor et al., 1998; Card & DiNardo, 2002; Goldin & Katz, 2008). Increases in relative wages can only arise when the supply of skills lacks behind the pace of SBTC. Therefore, it is worth noting that SBTC only occurs if there is a relative rise in g_H to g_L or an increase in α, pointing toward a race between technology and education, suggesting that new technologies complement highly skilled workers and thus increase their demand (Acemoglu & Autor, 2011; Goldin & Katz, 2008; Tinbergen, 1975).

Several approaches can test the SBTC hypothesis. Directly following the model, relative labor supply and relative wages of the different education levels or age groups can be used (Card & DiNardo, 2002). Another approach is to quantify the magnitude of technological change by computing the share of the IT sector in the economy (Jorgenson, 2001). (Jorgenson, 2001) As the use of technology in the workplace is mainly responsible for the developments in the labor market, other scholars (e.g., A. B. Krueger (1993) or Spitz-Oener (2008)) use the share of computer usage at work to measure the speed of technological change, finding that working with a computer raises wages by 8%–15%. The complementarity of ICT and human capital stems from the observations that wage inequality increased shortly after introducing computers, which more educated workers were more likely to use (Card & DiNardo, 2002; L. F. Katz, 1999; A. B. Krueger, 1993). The findings on technology-skill complementarity build on the capital-skill complementarity hypothesis formulated by Griliches (1969), where he found that skilled labor complement physical capital using U.S. manufacturing data. In contrast, Nelson and Phelps

(1966) view these effects as temporary. New technologies currently appear to be relative complements with more-skilled workers because they can cope better with technological change. However, other workers adjust their skills, which offsets wage premiums again, implying that the skill-biased advantage is temporary.

Several scholars (Acemoglu & Autor, 2011; Card & DiNardo, 2002) raised inconsistencies regarding the skill-biased change hypothesis. First, the rise in wage inequality in the United States has stagnated, despite ongoing technological progress in ICT, contradicting the main argument of SBTC. However, keeping the notion of Nelson and Phelps (1966) in mind, the catching up of low-skill workers to use computers efficiently may be responsible for the stagnating skill premiums. Second, SBTC does not account for other aspects of wage inequality such as the effect of experience or individual characteristics, and data shows that supply changes within experience or age groups affect the skill premium. Third, the model cannot explain more recent developments such as the polarization of earnings, nor does it allow for analyzing the labor-replacing effects of some occupations or tasks due to technologies. Despite the critics, the model of SBTC has proven helpful in explaining the developments in the labor market amid the skill-complementing effects of technological progress (Acemoglu, 1998; Acemoglu & Autor, 2011; Berman et al., 1994; Berman et al., 1998; Card & DiNardo, 2002; Goldin & Katz, 2008).

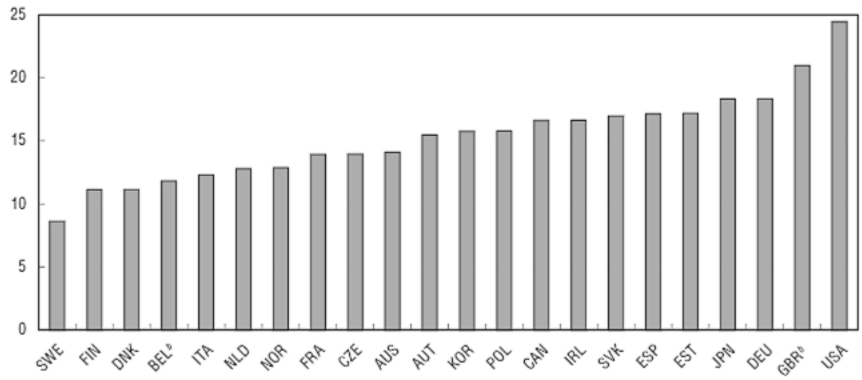
Therefore, it is not surprising that numerous studies provide evidence for the complementary effect of technologies on skilled workers. Autor et al. (1998) examine the increasing wage gap between college and high-school graduates in the United States between 1960 and 1999 and find that industries that relied heavily on computers had experienced relatively faster demand for skilled workers in the 1980s and 1990s. The authors’ framework suggests that the relative demand for more-skilled workers grew more rapidly during the past 26 years (1970–1996) than during the previous three decades (1940–1970) (Autor et al., 1998). Machin and Van Reenen (1998) add further evidence for the complementarity of computers, linking skill upgrading to R&D intensity in seven OECD countries.

Most OECD countries witnessed similar developments in the 20th century, and numerous studies have confirmed the complementary effects of skill-biased technological change on human capital since the 1960s. While most studies agree that technological change favors highly skilled workers (Acemoglu, 1998; Berman et al., 1994; Berman et al., 1998; Goldin & Katz, 2008), there is substantial variation in the skill premium across countries and regions, as Figure 2-2 depicts. European countries tend to have lower skill premiums and possible reasons are the introduction of minimum wages or the power of labor unions or employment protection legislation (OECD, 2017). Studies measuring the returns to human capital following the works of Mincer (1974) also confirm the increasing wage premiums for workers with more years of schooling or, when considering heterogeneous human capital, higher education levels (Psacharopoulos & Patrinos, 2004, 2018). More recent studies started to use actual skill measures instead, adding evidence to wage premiums for higher skills (Hanushek, Schwerdt, Wiederhold, et al., 2017).

The impact of technological change has been further accelerating since the widespread application of ICT related to the internet in the 1990s (Card & DiNardo, 2002). Several studies (e.g., Spitz-Oener (2008) or Akerman, Gaarder, and Mogstad (2015)) confirm the positive effect of computers and internet access on the wage premiums of high-skilled employees. Still, other scholars find no evidence for the productivity-enhancing effects of internet usage in several European countries (Colombo, Croce, & Grilli, 2013). In particular, the developments since the 1990s have led to inconsistencies with the SBTC hypothesis and caused the emergence of other theories that better explain the trends in the labor market in more recent years.

Figure 2-2 Cross-country differences in skill-biased wage premiums, 2012

(Percent increase in hourly wages for a standard deviation increase in numeracy)



a) The graph shows the coefficients on numeracy scores from country-specific regressions of log hourly wages (including bonuses) of wage and salary earners (in PPP adjusted USD) on proficiency scores standardised at the country level.

b) The *Survey of Adult Skills* only covered Flanders (BEL) and England/Northern Ireland (GBR).

Source: Survey of Adult Skills (PIAAC) 2012.

StatLink http://dx.doi.org/10.1787/888933239660

Source: OECD (2015)

Routine-biased technological change

The theory of routine-biased technological change emerged because the SBTC hypothesis does not suffice in fully explaining the developments in the labor market since the 1990s. In the United States and other countries alike, unemployment among middle-skilled workers increased, and their wage premiums declined. However, inequality at the lower end of the wage distribution has not increased further and the SBTC hypothesis does not explain the changes.

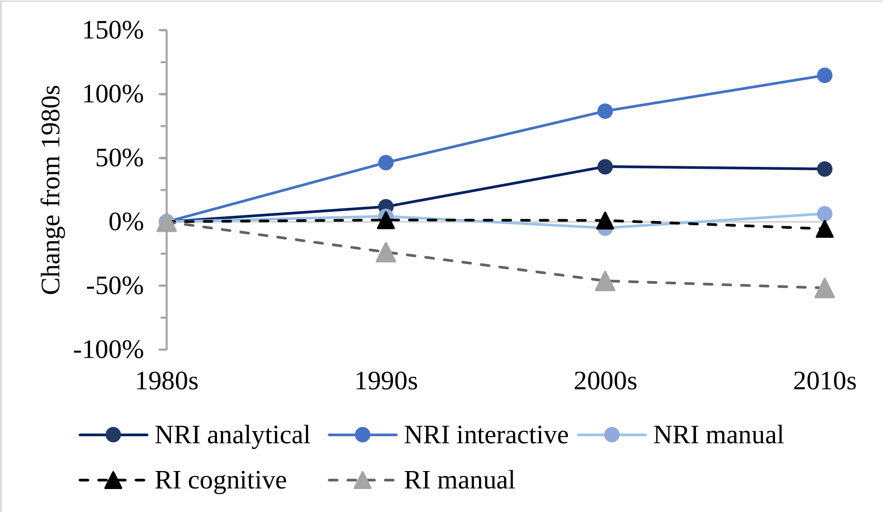
To explain these findings, Autor et al. (2003) propose a framework that considers the routine content of tasks to demonstrate how the diffusion of ICT changed skill demands in the labor market. Routine tasks are repetitive tasks that require explicit rules which can be executed by programmable machines. Nonroutine tasks often reply on tacit knowledge which cannot be translated into programmable rules. Computers complement nonroutine tasks, raising those workers' marginal productivity, while they substitute routine tasks. Industries relying heavily on routine tasks substitute human capital with computer capital as prices drop, reducing the demand and wages for workers in routine tasks and increasing the demand for nonroutine tasks in which high-skilled workers have a comparative advantage. Thus, the model serves to examine how decreasing prices of computers impact the demand for routine or nonroutine job tasks.

Acemoglu and Autor (2011) extended the framework in Autor et al. (2003) by a Ricardian model of the labor market to distinguish between skills and job tasks. Skills in this context, capture all capabilities that a worker possesses and uses for conducting job tasks. The stock of skills can be attained through investments in human capital or may be exogenously given. Workers use their skills to perform tasks in the labor market which then produces output and receives wages in return. Thus, each occupation is a set of tasks, providing a framework for interpreting patterns related to occupations.

Due to their skill-complementing nature, technologies have raised the demand for nonroutine analytical and interactive tasks that most highly skilled workers perform. On the contrary, they reduced the demand for workers in routine cognitive and manual occupations, mainly executed by middle-skilled workers. The impact on low-skilled workers employed in nonroutine manual tasks has been minimal. These tasks tend to be in jobs in the lower part of the wage distribution, while jobs with complex, nonroutine tasks in the upper part of the wage distribution. Routine tasks are typically found in occupations in the middle of the wage distribution. Thus, the technological change did not affect the demand for skills monotonously across the wage distribution but favored the upper and lower ends, implying a routine-biasedness of technological change.

Evidence for the different employment trends of routine and nonroutine tasks in Germany is provided in Figure 2-3. Since the 1980s, the employment share of workers in jobs with mostly routine tasks has been declining while employment in nonroutine jobs rises, widening polarization in the labor market. This is mostly driven by an increase in nonroutine interactive tasks and simultaneously a decline in routine manual tasks which has amplified due to improvements in technology that enable the substitution of routine cognitive tasks since the 2000s.

Figure 2-3 Trends in routine and nonroutine employment in Germany, 1984–2017



Source: author's calculation based on SOEPv34i

Goos and Manning (2003, 2007) confirm these trends of increasing employment for high and low-wage jobs using data for Great Britain since1975 while jobs for middle-skilled have been declining. They refer to this phenomenon as job polarization and show that it explains one-third of the observed increase in wage premiums. Autor et al. (2006) amplify this view by adding evidence to the continuing rise in upper wage inequality while wages at the middle and lower distribution have stopped increasing since the 1990s. At the same time, employment has increased in jobs at the higher and lower end of the wage and skill distribution. The findings show that this is consistent with an increase in non-routine-intensive jobs and a decline in routine-intensive jobs. Adermon and Gustavsson (2015) provide more evidence for job polarization in

Sweden during the years 1975–2005. Spitz-Oener (2006) adds further evidence for rising skill demands between 1979 and 1999 in former West Germany.

Dustmann, Ludsteck, and Schönberg (2009) provide evidence supporting wage polarization and compare the trends found in Germany with those of the United States. Both countries experienced an increase in the demand for highly skilled workers during the 1980s and 1990s, but the increasing wage inequality at the bottom of the wage distribution occurred later in Germany, suggesting this is not a result of technological change but due to episodic changes. Also comparing the developments in Germany and the United States, Antonczyk et al. (2018) consider cohort effects when applying quantile regression and find that wage dispersion has widened for all education groups in the United States in the 1980s and, excluding less-skilled workers, since the mid-1990s in Germany where cohort effects are important. Contrary to Dustmann et al. (2009), they attribute labor market polarization to technological change and point toward institutional differences and episodic events in explaining the different trends in the United States and Germany.

Numerous studies (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Autor et al., 2006; Autor et al., 2008; Autor et al., 2003; Berger & Frey, 2016; Dustmann et al., 2009; Goos & Manning, 2003, 2007; Goos, Manning, & Salomons, 2014; Spitz-Oener, 2006) have supported the hypothesis that technological change is routine-biased and the driver of wage inequality. Not only the use of computers but also the diffusion of broadband internet had similar effects on workers in routine and nonroutine tasks, lending further support to the RBTC hypothesis (Berger & Frey, 2016). As technologies continue to improve, the role of job tasks is becoming increasingly important in analyzing the implications for human capital and its value in the labor market. Caines, Hoffmann, and Kambourov (2017) find that the complexity of a task explains the developments in the labor market better than the routine content. They measure skill requirements by task complexity on the occupational level rather than educational attainment and show that complex tasks can be found in routine and nonroutine tasks requiring the same skill levels.

The emergence of vast literature supporting RBTC does not imply it is inconsistent with SBTC. This phenomenon can rather be viewed as an extension of the SBTC hypothesis in that it helps in explaining the effects for differently skilled workers, such as the increased demand for skilled workers and nonroutine jobs, by adding a routine perspective. Technologies complement workers in complex nonroutine jobs which require higher education levels while they replace labor in routine tasks with medium skill requirements, leading to job polarization.

Concluding, empirical works indicate that computers played a major role in the employment shifts in the labor market, away from routine and toward nonroutine tasks. Thus, the more nuanced view provided by the RBTC hypothesis appears necessary in understanding the trends in labor market polarization and increased inequality since the 1990s.

2.4.3. The implications of technological change on human capital

To gain a better understanding of more recent developments and their implications, the implications of technological change on human capital will be elaborated in detail in this subsection. The breadth and depth of the recent technological changes have also drawn the attention of scholars and sparked interest, particularly in the impact on workers and the labor market which has been transforming the structure of the whole economy. It is important to mention that technological change is mostly captured indirectly through its transformative impact on an economy or society. In the same vein, this dissertation considers technological change indirectly and focuses on the results of the implications of technological change on human capital. Scholars frequently utilize proxies such as the technological intensity of a sector or the type of occupation against the background of the transformative impact that technologies have.

Temporal analyses are used to capture how labor markets have changed with major technological developments. Until the late 1980s, technologies (mostly personal computers) are found to be skill-biased in most advanced countries, raising inequality (Acemoglu & Autor, 2011; Autor et al., 1998; Goldin & Katz, 2008). During the 1990s, labor-replacing technologies drove job polarization (Autor & Dorn, 2013). Web and e-commerce developed until the mid-2000s. This type of technological change had an impact on productivity and introduced innovations in retail and learning by using processes and is thus less skill-biased. Since the mid-2000s, technologies extended to entertainment and communication but did not concentrate on production processes which has a low impact on productivity.

Several channels link human capital and technological progress (Acemoglu & Autor, 2012). Most importantly, human capital is crucial for enabling technological progress. New technologies require the skills and knowledge to use them. A higher-skilled workforce positively affects the speed of technological change as it increases the incentives to invest in productivity-enhancing technologies which require a certain level of skill to be leveraged. Moreover, the composition of human capital, the type of education, and the level, also matter for technological advances because human capital fosters innovation and investment in physical capital (Acemoglu, 1998). In the long term, ongoing technological change continuously increases the demand for higher levels of human capital (Acemoglu & Autor, 2012; Goldin & Katz, 2008). Thus, skill upgrading of workers and continuous investment in human capital is important to manage increased pressures induced by technological change and globalization.

Technological progress is found to be capital intensive, labor-replacing, and skill-biased, enabling machines to replace human capital over time. It fuels the fear of mass unemployment, wage polarization, and greater inequality. New technologies affect workers in the workplace through technology-induced changes in work tasks. On the one hand, technologies might be labor replacing. In several works, economists like Brynjolfsson and McAfee (2014) or Frey and Osborne (2017) have emphasized that machines will replace human labor throughout the whole economy. It may result in the displacement of a large share of workers, especially in blue-collar jobs. However, others also find that new jobs may be created, resulting in a net increase in employment. Technologies can be skill-complementing and thus improve workers' productivity (Acemoglu & Autor, 2011; Autor et al., 2003).

Technological advances have reduced the cost of ICT, decreasing the relative prices of routine tasks which led to an increase in the overall routine intensity of tasks on the job. However, those are taken over by machines instead of workers, thus reducing the demand. As a result, task-based technological change can have negative effects on the wages of affected workers, while it may complement and thus benefit other workers. These recent developments have led to job polarization, demanding high and low-skilled workers in the labor market. This can also polarize wages at the lower and higher end of the wage distribution (Acemoglu & Autor, 2012).

Technological changes increased the need for higher skills. The returns to human capital reflect productivity increases and several studies indicate skill-complementary effects of technologies. For example, Lillard and Tan (1992) find that individuals working in an industry experiencing rapid technological progress experience higher returns to education. This could be because better-educated workers are more adept at responding to technological change and therefore are more productive in high-tech firms. In line with these findings, Bishop (1992) highlights higher education levels, and more advanced skills enable workers to adapt faster and better to new tasks and technologies. Using recent firm-level data for the Netherlands and Germany, Bartelsman, Dobbelaere, and Peters (2015) examined the allocation of human capital at the frontier. The results indicate that the average returns to human capital decrease with the level of technological intensity of an industry for knowledge-intensive sectors and increase with proximity to the technological frontier in low-tech sectors.

Technological change also has implications for heterogenous types of education. General education fosters technology adoption and thus leads to faster growth compared to vocational education. Some evidence for this is provided by the study of Hanushek, Schwerdt, Woessmann, et al. (2017) who compare lifetime earnings of Germany and Switzerland and find that only in Germany does general education yield higher wages. This is explained by the positive effect of general education on the ability to adopt new technologies, which is assumed to be more important in faster-growing Germany. Other studies confirm the advantages of general education over vocational education under technological change. The returns to specific educational qualifications such as VET might be smaller and decrease with technological change compared to general education, hence indicating relatively lower and declining productivity of VET.

Previous findings imply that technological change may lead to stronger obsolescence of occupation-specific skills and increase the necessity to enable people to adapt to new technologies (Hanushek, Schwerdt, Wiederhold, et al., 2017; D. Krueger & Kumar, 2004). The aspect of skill depreciation and obsolescence of human capital has become increasingly important with accelerating technological progress. Occupations change and workers need to learn new skills, rendering previously acquired human capital obsolete at a faster rate. Amid technological advances, continuous updating of skills becomes inevitable.

These findings highlight that amid rapid technological change, it is important to be able to adapt to new environments to maintain productivity. The ability to adapt to new tasks is positively shaped through human capital. Despite these trends in the labor market and the importance of the subject, the role of technological change in the returns to human capital has not been studied much yet. Some literature has incorporated the aspect of technological change into the concept of human capital, yet empirical work is still scattered. Thus, these implications of technological change on human capital will be further explored in this dissertation.

2.5. Research gap

Although the research on human capital is plentiful now, the current state is not sufficient in addressing recent developments on the micro and macro levels due to technological changes. Few scholars have directly incorporated aspects relevant to ongoing technological change into the analysis of human capital.

Returns to human capital

The returns to human capital have been studied together with some variables related to technological change. For instance, Bartelsman et al. (2015); Hanushek, Schwerdt, Wiederhold, et al. (2017), and Lillard and Tan (1992) find evidence for the benefits of general education over specific education, explaining it through the better adaptability to changing environments. These studies confirm the importance of technological change for the returns to education, however, more research is needed to fully understand the direction and effects of recent technological change.

Studies directly linking the routineness of tasks and the returns to human capital are limited. Firpo, Fortin, and Lemieux (2011) use a static Roy model to examine how changes in the price of occupation tasks have affected the distribution of wages in the United States since the 1990s. Acemoglu and Autor (2011) explore a task framework that considers comparative advantages across tasks and shows that while technological change increases the wages for one type of worker, it can lead to lower wages for another type of worker at the same time wages. This finding highlights that the effect of technological change on the returns to human capital may also depend on the type of skill or task a worker performs. In line with this, Yamaguchi (2018) uses a Roy framework to estimate the returns to skills to explain the gender wage gap. Autor and Handel (2013) measure job tasks and provide evidence that job tasks vary between occupations and that can explain wage differences between workers.

While these studies demonstrate that tasks are important for human capital and wages, they did not allow for differences in education which is a crucial source of human capital formation. More insight into the link between human capital and tasks is needed to understand the implications of technological change on the returns to human capital (Autor & Handel, 2013). Despite these developments, no studies have yet addressed the explicit link between different education levels and the routineness of job tasks when estimating returns to education. Understanding this link is highly relevant for policymakers when targeting possible adverse effects of technological change on labor market outcomes. Thus, research directly investigating the role of routineness for productivity measured as returns to human capital is needed.

Human capital depreciation

The aforementioned studies in the previous subsections lay a good foundation for the analysis of human capital obsolescence, but most works do not incorporate the effects of technological developments which have transformed most advanced economies. Occupations become more complex and skill requirements change more quickly, highly depending on technology-related factors such as the type of job tasks, or the technology intensity of a sector. Thus, previously accumulated skills may become obsolete at a faster rate. As indicated by the results in Backes-Gellner and Janssen (2009), there are differences between knowledge and experience-based tasks, providing some evidence for the importance of incorporating a task perspective into the analysis. However, their specification does not consider the depreciation of formal education, making the results hardly comparable and unsuitable for evaluating the effectiveness of current educational systems. Other studies, for example, Weber (2014) or Lentini and Gimenez (2019) do only indirectly consider differences in the depreciation by occupational segment or sector.

No study was identified incorporating a task perspective based on the classification of a job into the analysis of human capital depreciation. Thus, it is not well understood how task-based human capital depreciates. Further research is needed to fill this gap.

Macro-level skill specialization

On a macro level, human capital has been confirmed to have positive externalities on the economy and society as well as that previous human capital determines future economic outcomes. Differences in historic human capital endowment can lead to diverging economic outcomes today. Neoclassical studies see that similar countries will converge in the long run. On the contrary, endogenous growth models do not consider automatic conversion as granted. Instead, they argue that the difference between countries will persist over time, depending on previous endowments. However, traditional endogenous growth models are set in a closed economy which does not allow for international spillovers. This is highly unrealistic in today's globalized and interdependent world economy. Thus, modern models allow for international spillovers. In these models, catch-up by poor countries is possible in the long run.

Despite the acknowledged importance of human capital for economic growth and convergence, the role of skill specialization of a nation has been examined little. Human capital is an enabler of economic growth or even a direct input factor into the production function. In the past, physical capital deepening was the main driver of rising labor productivity. Since the 20th century, this has shifted toward increasing total factor productivity due to human capital deepening which enabled technological innovation. Thus, technological innovation is becoming biased which has traditionally not been recognized by neoclassical scholars and early endogenous growth models (Romer, 1990; Lucas, 1988). Due to biased technological innovation, the pressure to readjust the supply of skills and human capabilities has increased. Thus, understanding how new skills can be acquired is an important aspect to examine regarding convergence and skill specialization.

Chapter 3.
Routineness, education, and wages – How technological change affects labor market outcomes in Germany

3.1. Introduction

The introduction and use of novel technologies require a different set of skills. The adaptability of workers to changing skill demands is a challenge in today's labor markets, which are undergoing a shift toward nonroutine and more complex tasks. The use of technologies has accelerated with the COVID-19 pandemic, and education is vital to address social inequality and the future of work (ILO, 2020). Education provides workers with new skills and helps in addressing technological change. Moreover, economies with more rapid technological change reap higher returns to education (Nelson & Phelps, 1966). Thus, investments in education and technologies are necessary for economic growth and welfare.

Technologies have transformed labor markets and changed occupations throughout the last decades, sparking a debate about the skill-complementing or labor-replacing nature of technological change. Since the 1980s, the use of computers in the workplace has increased, which changed occupations and raised skill requirements. The theory of skill-biased technological change (SBTC) emphasizes that technology is skill-enhancing, and workers with higher education levels can adapt to technological changes easier. Thus, wage premiums have increased, albeit with requirements for increased educational attainment.

With the increasing adoption of information and communication technologies since the 1990s, unemployment in middle-skilled occupations increased. To explain how this affected wage inequality, Autor et al. (2003) propose a nuanced view of the skill-biased technological change hypothesis. The authors argue that computers and ICT replace routine tasks, which may cause a decline in relative wages for routine workers. Based on this, the routine-biased technological change theory (RBTC) argues that not all jobs are equal in their tasks, and technology may have adverse effects on routine intensive occupations. Goos and Manning (2007) and Autor et al. (2006) find that a decline in middle-wage routine-intensive jobs has widened inequality. More recently, Frey and Osborne (2017) predict for the United States that a large share of low-skilled jobs will dissolve due to the labor-saving effects of digitalization, while the application of ICT invites the potential for productivity increases in a wide range of nonroutine activities.

Amid these changes, it is crucial to enable workers to adapt to new tasks and occupations swiftly. University education provides general, versatile knowledge, whereas Vocational Education and Training (VET) prepares specifically for the current skill demands. The OECD (2021) acknowledged the potential of VET in equipping workers with new, digital skills and that it can represent a solution to skill shortages. Germany's 'dual system' is perceived as highly effective by multilateral organizations such as the International Labour Organization (ILO), or the World Bank and is often benchmarked (Hummelsheim & Baur, 2014). With the support of the German Federal Ministry of Education and Research (BMBF) and the GIZ, VET systems have been established in numerous countries (BMBF, 2015). While VET has many advantages, such as a smooth transition from school to labor markets, or improved economic prospects of low-skilled workers (Haasler, 2020), general knowledge might be advantageous over specific knowledge. It may lead to higher returns to human capital investments (Galor & Tsiddon, 1997; Nelson & Phelps, 1966) and faster economic growth rates under rapid technological change (D. Krueger & Kumar, 2004). Thus, the arising question is whether all types of education prepare the workforce equally well for nonroutine jobs as it has for repetitive, routine intensive occupations.

Different types of technological change affected labor markets during the last decades. On average, education and wages are positively related, however it is unclear what happens to heterogeneously skilled workers when considering the routine content of their occupational tasks. Therefore, this study attempts to analyze the returns to education considering the routineness of occupations and the different education levels. Even though SBTC and RBTC have been studied extensively, few studies have considered the implications of technological change, i.e., routineness and its impact on education and wages. There are a few studies on the technological intensity and the returns to education (Bartelsman et al., 2015; Blundell et al., 1999), or the effects of occupational and sectoral differences (Glocker & Storck, 2012). Moreover, Alda et al. (2020) considered the theory of RBTC when analyzing the returns to human capital in Germany. Graetz and Michaels (2017) explore the impact of technology on recovery after recessions but find no evidence for a hollowing-out of routine intensive, middle-skilled jobs outside the United States. Other scholars link sectoral differences with the depreciation of human capital due to changes in external environments amid technical progress (Lentini & Gimenez, 2019; Weber, 2014). These studies confirm the importance of technological change for education and wages. However, more research needs to be undertaken to understand the direction and effects of recent, routine-biased technological change fully.

To close this gap, this research examines the changing value of human capital in routine and nonroutine occupations across different periods. Learning from the German case and the impact that technological change has had on its workforce can provide important implications when designing future education systems and promoting specific or general education. Failure to adapt quickly to changed skill requirements may lead to unemployment and a lack of skilled labor.

The present study contributes in several ways. Firstly, this paper updates the empirical evidence on the heterogeneous returns to education up to the year 2017. Secondly, it differs from previous works in that it analyzes the link between the routineness of occupational tasks, education, and wages. Specifically, this study focuses on the challenges of preparing workers for emerging non-routine-intensive jobs. Additionally, the study contributes to the role of technological change on an occupational level by addressing specific changes for workers of various skill levels. Thus, the results may facilitate the introduction of policies that target the differences in labor market outcomes for high-, medium- and low-skilled workers. Considering changed task requirements in occupations when drafting education and labor market policies may help workers maintain their productivity and reduce inequality among them.

The remainder of this paper is structured into five sections. Section 2 provides an overview of the existing literature on the link between routineness, education, and wages, while this section introduces the theoretical framework. Section 3 proceeds with data and some descriptive evidence. Section 4 covers the methodology used for this analysis, and Section 5 reports the results. Finally, Section 6 discusses the results against the findings of previous studies and concludes with policy recommendations.

3.2. Routineness, education, and wages: a review of the literature

3.2.1. Education and wages

The relationship between education and wages has been studied extensively, and the annual returns to a year of schooling hover around 8.8%. Most studies rely on the method introduced by Mincer (1974), estimating the returns to one additional year of schooling using a (sometimes modified) Mincer earnings equation (Psacharopoulos & Patrinos, 2018). When allowing for heterogeneous human capital, that is, different levels of education, wage premiums increase as people acquire additional qualifications, suggesting productivity increases (S. O. Becker et al., 2011; Psacharopoulos & Patrinos, 2018).

Lauer and Steiner (2000) provide an overview of empirical estimates on the subject for Germany. The returns to education vary between 5-14% and increase with the education level. The spread in returns may stem from differences in sample definition or the empirical approach. Given the case of Germany, distinguishing between vocational and general education is important when analyzing human capital (Alda et al., 2020; Golsteyn & Stenberg, 2017; Hampf & Woessmann, 2017; Hanushek, Schwerdt, Woessmann, et al., 2017). VET equips workers with occupation-specific knowledge and skills that can be applied directly in the labor market. However, with external changes, e.g., through new technologies, their skills are not valuable anymore, and their human capital depreciates (Weber, 2014). General education forms versatile human capital, which can be applied to different occupations and industries, even under changing environments. Hence, VET leads to wage increases in the short run, whereas earnings for workers with general education peak toward the end of their careers.

General education fosters technology adoption and thus leads to faster growth compared to vocational education. When comparing the lifetime earnings in Switzerland and Germany, both apprenticeship-oriented countries, Hanushek, Schwerdt, Woessmann, et al. (2017) find that general education yields an overall advantage in earnings compared to vocational education only for Germany. One possible explanation for this is that in faster-growing economies (here Germany), where technological change is assumed to be larger, the ability to adapt to new technologies is valued more and thus benefits individuals with general education (Hanushek, Schwerdt, Woessmann, et al., 2017).

Golsteyn and Stenberg (2017) use Swedish registry data to examine the short- and long-term differences between vocational and general education. Their analysis indicates that VET enhances short-term earnings whereas general skills have a stronger effect on long-term earnings. Similarly, using microdata for 11 countries from the International Adult Literacy Survey, Hanushek, Schwerdt, Woessmann, et al. (2017) demonstrate that VET provides easier entry into the labor force but that the early short-term monetary benefits of VET diminish with age. The age pattern of early advantages and disadvantages later in a career for vocational education in countries with strong vocational systems is also confirmed by Hampf and Woessmann (2017), who use PIAAC data for 2012/2013.

These findings demonstrate differences in the returns to vocational and general education and that the ability to adapt to new tasks is essential amid rapid technological changes. The returns to specific educational qualifications such as VET might be smaller and decrease with technological change, indicating a lower and declining productivity of workers with VET. This implies that technological change may lead to stronger obsolescence of occupation-specific skills and increase the necessity to enable people to adapt to new technologies (Hanushek, Schwerdt, Wiederhold, et al., 2017; D. Krueger & Kumar, 2004). However, VET has also some advantages over general education. It conveys knowledge and skills directly applicable to a job and hence can also lead to a more productive workforce, especially in the short run.

3.2.2. Routineness, education, and technological change

With the adoption of information technologies in the 1980s, not all workers benefited from technological change, but only certain groups (Violante, 2016). SBTC theory suggests that technological change induced by new information technologies complements skilled labor. Technological progress leads to increased relative productivity and subsequently raises the relative demand for skilled workers. As a result, wage premiums rise with education levels amid continuing technological change and educational upskilling (Alda et al., 2020). The higher returns to education reflect the productivity increases for highly skilled workers. In turn, workers in low-skill jobs face the risk of labor-replacing technologies (Frey & Osborne, 2017), and thus, their marginal productivity declines with the adoption of ICT. In short, SBTC favors highly educated workers and penalizes unskilled workers (Autor et al., 1998; Berman et al., 1998; Card & DiNardo, 2002).

However, SBTC cannot fully explain the developments in the labor market of increased unemployment among middle-skilled workers since the 1990s. Autor et al. (2003) laid the foundation for the RBTC theory when they introduced the routine content of tasks. They provide evidence that in swiftly computerizing sectors the share of nonroutine tasks has increased relatively to routine tasks at all education levels and conclude that technologies replace labor in routine tasks while complementing workers in complex nonroutine jobs. Advocates of RBTC argue that technological change is routine-biased in that workers in occupations with high routine intensity experience adverse effects because ICT is substituting those jobs, while it complements jobs high in nonroutine tasks (Autor & Dorn, 2013; Autor et al., 2003; Goos et al., 2014). This results in labor market polarization.

Table 4-1 provides an overview of the most relevant empirical works that shaped the development of the hypotheses in this study. Despite extensive research linking RBTC and employment, not many studies have examined how the returns to education in routine-intensive occupations have been affected by recent technological changes. Using German data, Alda et al. (2020) test the RBTC hypothesis and find that the development of the returns differs for workers in general and specific occupational segments. While it is a first attempt to consider RBTC, their research does not consider detailed occupation groups based on the routine intensity of jobs. Glocker and Storck (2012) demonstrate that the wages of workers with VET differ from those of university graduates, depending on the professional field. VET graduates benefit the most in informatics and insurance occupations, whereas university graduates are best off when working in medical or legal professions. Similarly, Reinhold and Thomsen (2017) focus on labor market entrants and find lower returns to education when controlling for task routineness. While these studies accounted for occupational differences in the returns to human capital, they did not consider the interaction between the routineness of occupational tasks and the returns to education.

Table 3-1 Studies on routineness, education, and wages

Author(s)	**Returns to HC**	**Education level**	**Aspect of TC**	**Routine content**	**Main idea**
Psacharopolous and Patrinos (2004 & 2018)	O	O	X	X	Review shows that the average return to one year of schooling is around 8% and higher education levels yield higher returns.
Autor et al. (1998), Berman et al. (1998), Card & DiNardo (2002)	X	X	X	X	SBTC favors highly educated workers and penalizes unskilled workers. The higher returns to education reflect the productivity increases for highly skilled workers.
Yamaguchi and Godo (2003)	O	X	Patents	X	Education and new technologies are complementary, and new technologies increase the returns to education for younger workers but decrease the returns for older workers.
Lillard and Tan (1992), Krueger & Kumar (2004), Bartelsman et al. (2015), Hanushek, Schwerdt,	O	O	X (only theoretically)	X	General education is more beneficial when adapting to changes or in environments with technological change. The returns to specific educational qualifications are smaller and decrease

Wiederhold, et al. (2017)					with technological change, indicating a lower and declining productivity.
Autor et al. (2003), Autor & Dorn (2013), Goos et al. (2014)	X	X	Job tasks	O	Job polarization: Workers in occupations with a high share of routine tasks suffer adverse effects because ICT is substituting routine jobs while it complements nonroutine jobs.
Spitz-Oener (2006)	X	O	Job tasks	O	Workers with higher education levels tend to work in occupations with fewer repetitive tasks. Occupations require more complex skills today than in 1979 with the most pronounced changes in rapidly computerizing occupations.
Firpo, Fortin, and Lemieux (2011)	X	X	Occupations	X	Price changes in occupational tasks affected U.S. wage distribution since the 1990s.
Acemoglu and Autor (2011)	X	X	Job tasks	O	Task-framework shows that technological change increases the wages for one type of worker, while comparative advantages across tasks lower the wages for other workers.

Glocker and Storck (2012)	O	O	Major	X	The wages of workers with VET differ from those of university graduates, depending on the education major.
Autor and Handel (2013)	X	X	Occupations & job tasks	O	Job tasks vary by occupation, which can explain wage differences between workers.
Reinhold and Thomsen (2017)	O	O	Job tasks	O (as control)	The returns to education are lower when controlling for job tasks when examining wage growth and returns to education for labor market entrants.
Yamaguchi (2018)	O	X	Occupations & job tasks	X	Task-based Roy model in which workers possess a bundle of basic skills and occupations is characterized as a bundle of basic tasks to estimate the returns to skills to explain the gender wage gap.
Alda et al. (2020)	O	O	Occupational segments	X	The development of the returns to education differs for workers in general and specific occupational segments.
This study	O	O	Job tasks	O	Explicitly links the different education levels and the routineness of job tasks through an interaction term when estimating the returns to education.

3.2.3. VET in Germany and routineness

Germany is known for its dual education system with its university and vocational education track, which serves as a model for other countries (BMBF, 2015). The VET track has been the leading choice for workers for a long time, with 46.6%. However, the labor market has changed, and there is a reversing trend in the proportion of VET to university graduates (Destatis, 2020). Most advanced economies also experienced educational upgrading.

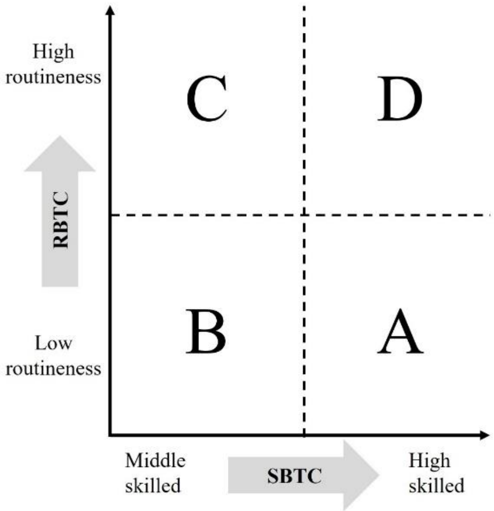
Thus, an important question that arises is whether the current education system can prepare the labor force for changing labor markets. Technologies transform work and lead to different skill requirements, reducing the productivity-enhancing efficacy of human capital. To maintain their productivity, workers must acquire the required skills, and there might be differences between the types of education. The VET track specifically prepares individuals for certain occupations, making them less versatile. Those workers may also find it challenging to adapt to new tasks, causing their human capital to depreciate faster. It might be easier to adjust the content of VET education for occupations in nonroutine jobs, providing a quick solution to equip workers with new skills needed for emerging job tasks. On the other hand, increasing university enrolment provides workers with more general content and prepares them for adapting better to new tasks. Hence, it is debatable how routineness affects a worker's human capital formed through different education levels. Answering this question helps provide the necessary tools to workers for coping with technological change.

Benefits from analyzing the German case stem from the availability and richness of data and the characteristics of Germany’s worldwide recognized dual system. The German Socio-Economic Panel (SOEP) is one of the most extensive and complex panel data sets worldwide, allowing for in-depth analysis over 34 years (Goebel et al., 2019). Moreover, Germany has its own classification of occupations (Klassifikation der Berufe KldB) with recently updated occupational descriptions. This yields the advantage that the distinctive features of the German labor market, specifically its VET system, and its occupations can be accounted for (Dengler, Matthes, & Paulus, 2014). Additionally, it allows distinguishing typically middle-skilled and high-skilled jobs, offering valuable insights for other countries with VET systems.

3.2.4. Theoretical framework and research questions

Figure 3-1 provides a sketch of the theoretical framework. The main question that this framework serves to answer is how workers’ wage premiums are affected by their education level and which role the routine intensity of their occupational tasks plays. Technological change can be skill-biased or routine-biased, leading to different effects on labor market outcomes. The horizontal axis depicts the skill-enhancing aspect under SBTC, implying a positive relationship between education and wages. The vertical axis refers to the effects under RBTC where high levels of routineness are associated with greater potential for labor-replacing technologies and lower marginal productivity, leading to a negative correlation between routineness and wage premiums.

Figure 3-1 Theoretical framework: skill-biased versus routine-biased technological change



The analysis focuses on the interplay between the two theories and their impact on the returns to education for each of the four groups. As such, this paper aims to consider the labor market effects under SBTC and RBTC separately as well as the interplay between the two. Treating them as two distinctively different dimensions allows us to examine the indirect impact of technological change on workers based on their combination of the two dimensions, education level, and the routineness of occupations. This distinction is a significant difference from previous works. Having a precise differentiation between SBTC and RBTC will benefit policymakers in finding suitable measures to deal with the effects of technological advances on labor market outcomes.

Most research on the returns to human capital examines the effects of education level without considering routineness. Based on these findings, there might be significantly large differences between the education levels within each group of task routineness due to SBTC. Higher education provides 10% higher wage premiums on average than VET (Lauer & Steiner, 2000; Psacharopoulos & Patrinos, 2018). Thus, similar effects between education levels are expected, leading to higher returns to education for groups A and D than for groups B and C.

Moreover, under RBTC, the introduction of labor-replacing technologies is likely to reduce the demand for workers in routine intensive tasks. As a result, wages will decrease in those occupations. As previous studies have demonstrated with employment effects, this applies to workers of all education levels. Subsequently, higher wages for groups A and B than groups C and D are expected. Thus, the first set of hypotheses is:

H1a: *Higher education level leads to higher returns regardless of the routineness of the occupation*.

H1b: *Higher routineness renders lower wages regardless of the education level.*

Next, this paper examines how effective the different education types are in preparing workers given the routine intensity of their jobs. Previous works provide evidence that the returns to education vary over occupational tasks and that education level is negatively correlated with routineness. Workers with higher education levels tend to work in occupations with fewer repetitive tasks (Spitz-Oener, 2006). Previous literature has also emphasized that technologies have a high substitution potential in occupations intense in repetitive tasks. One consequence is lower marginal productivity which is reflected in lower returns to education in routine intensive occupations. However, the magnitude of the routine penalty might vary for workers with different educational backgrounds.

Workers with an advanced degree might be able to leverage the productivity-enhancing effect of technologies the best and receive the highest wage premiums. Consequently, when working in routine intensive occupations, the penalizing effect may also be relatively more prominent than at other education levels. Thus, there might be a remarkable difference in the returns to tertiary education between workers in routine intensive and nonroutine intensive occupations. In contrast, middle-skilled workers with VET tend to benefit less from the skill-complementing effects of technologies. Thus, the differences between routineness might be smaller for workers with VET than for other education types. Those workers might not be able to utilize technologies as effectively, and the occupation-specific educational content of VET might prepare them relatively well for routine tasks (Alda et al., 2020).

Subsequently, the latter part of this study aims to answer how occupational routineness is related to the return to education in the case where (1) routineness is high and education level is high (group D) compared to the case where (2) routineness is high and education level is lower (group C). Based on evidence from previous research, higher task routineness may lead to lower wage premiums across all education levels. Thus, the second hypothesis is as follows:

H2: *The impact of education on wages is lower in routine jobs than in nonroutine jobs.*

3.3.Data

The analysis builds on data from the German SOEP, version 34i (doi: 10.5684/soep.v34i), which is a representative longitudinal study of private households across Germany. The major strengths of the dataset are its large sample size and its high quality of data which complies with statistical sampling strategies and representativeness (Goebel et al., 2019). The final longitudinal sample used for analysis comprises 259,779 data points for each person and year combination. All working employees with a labor income of more than 1 Euro during 1984–2017 are considered. Furthermore, the sample is restricted to workers with more than 30 hours/week and exclude outliers.

The focus of the analysis is the income and education variables as well as the routineness of occupational tasks. Besides, control variables for work experience or personal and job characteristics, including the technological intensity of the industry to control for differences in technological change, are added (see Table 3-2 for further details on the operationalization of all variables). Personal controls include an individual's age, a dummy for the marital status, and the federal state of residence. Job characteristics comprise years of job tenure, a dummy for contract maturity, a dummy for job change job, a dummy for civil servant, a dummy for leadership, and firm size. Industry characteristics refer to a categorical variable that sorts the industry of the current company based on its technology intensity for manufacturing or knowledge intensity for service sectors.

Table 3-2 Operationalization of variables

Variable	Original	Operationalization
Wage	• gross monthly wage in euros	• Hourly wages: monthly income / (4.33* weekly working hours) • Exclusion of outliers • Deflation of wages by consumer price index of the Federal Statistical Office (base year 2015) • Logarithm of deflated wages
Education level	• CASMIN classification (9 categories)	• aggregation into 5 categories • unskilled as reference group
Routineness	• 4-digit level of KldB 1992 (German classification of occupations)	• Assignment into 5 categories based on RTI-index • dummies for each category • dummy for routine / nonroutine intensive tasks
Individual level controls	• marital status • age • experience • potential experience • tenure • firm size • sector • civil • job change • maturity of contract • leader • region	• dummy for being married • survey year minus birth year • actual years of experience • age – years of schooling - 6 • length with current firm in years • dummies for core category of firm size • grouped by technological intensity (manufacturing sectors) and knowledge intensity (service sectors) on NACE 2-digit level based on Eurostat classification of industries • dummy for public sector • dummy for job change • dummy for contract worker • dummy for leadership position in current job • federal state of workplace
Year	• period (1984–2017)	• dummies for each sample year

The earnings variable, the dependent variable, is constructed as the log gross hourly earnings expressed in 2015 prices (euros). Experience is operationalized as the number of years of full-time and part-time work experience. This is a major difference from most previous studies that rely on potential experience (the difference between age and the years of schooling minus 6). However, an increasing number of papers have raised issues with using the potential experience variable in the Mincer equation (Blau & Kahn, 2013; Filer, 1993; Regan & Oaxaca, 2009). Real experience is used to capture the effect of learning through experience on the job and its effect on wages. Times of unemployment do not benefit the learning process and thus are excluded in this operationalization. Using actual experience instead of approximated experience can result in differences in the returns to experience due to possible confounding of potential experience, as Braga (2018) elaborated, and thus other controls are included to avoid an overestimation of human capital.

3.3.1. Education dummies

The education variable is coded as a categorical variable for each level of education beyond nine years of compulsory schooling. The CASMIN educational classification is used because it captures the hierarchy of educational levels in length and abilities. At the same time, it also allows to distinguish between general and vocationally-oriented (specific) professional education (Braun & Müller, 1997). The skill level is commonly proxied by education, for instance, in Acemoglu and Autor (2011). The education levels and their corresponding skill level used for the analysis are depicted in Table 3-3. The first category serves as a base group in the empirical analysis.

Table 3-3 Education dummies based on the CASMIN classification

	Variable	**Skill level**	**Skill Specificity**	**Highest education level**
1	Secondary	Unskilled	General	No further professional qualification
2	VET	Middle-skilled	Specific	Vocational education and training
3	Higher VET	High- skilled	Specific	Higher vocational education and training
4	High School	Middle-skilled	General	University entrance qualification (Abitur)
5	University	High-skilled	General	Tertiary education

Notes: VET prepares workers for jobs related to a specific trade or occupation. Higher VET is equivalent to an undergraduate university degree and is typically obtained after several years of experience and further vocational education and training after VET completion.

3.3.2. Routineness

In line with previous research (Autor et al., 2003; Dengler et al., 2014; Goos et al., 2014; Spitz-Oener, 2006), a variable representing the routine content of occupational tasks is construct. Following the method suggested by Dengler et al. (2014), each occupation is assigned one predominant task type. These task groups are adopted from Spitz-Oener (2006) and Autor et al. (2003), who differentiate between nonroutine tasks (interactive, analytical, manual) and routine tasks (cognitive, manual) and are summarized in Table 3-4. This approach is specific to the German labor market and allows for assigning almost all occupations to one of the five task types based on an occupation’s predominant task category.

First, each occupation is assigned one of the five main task types based on the German Classification of Occupations KldB2010. Then, this information is linked with the occupational variable KldB1992 available in the dataset. Each of the 3900 assigned main task types is matched with the KldB92 codes at the 3-digit level to make the two measures compatible. Due to differences in the occupational classifications between 1992 and 2010, 2470 occupations were assigned into five categories. Based on this, it was possible to construct the *routineness* variable which is a dummy variable for routine intensive tasks.

Table 3-4 Classification of routine and nonroutine tasks

	Routine tasks	**Nonroutine tasks**
Definition	Repetitive tasks that follow explicit rules and are codifiable	Complex, non-repetitive tasks that are not codifiable
Tasks	– *Manual*: equipping machines, operating machines, controlling machines – *Cognitive*: accounting, calculating, correcting text or data, measuring height, length, or temperature	– *Manual:* repairing, renovating, serving – *Analytical:* analyzing, applying, and interpreting rules, constructing, designing, planning, researching, creating, working out rules or regulations, representing interests – *Interactive:* Advertising, coordinating, negotiating, organizing, teaching, training, selling, purchasing, entertaining, managing others
Examples	Chemical laboratory workers, radio/data entry/machine operators, telecommunications mechanics, sheet metal pressers	Legislators, architects, veterinarians, interpreters, advisors, pavers, machinery or plant cleaners, train drivers
Distribution	47.6%	52.4%

Note: Based on Autor et al. (2003), Spitz-Oener (2006), and Dengler et al. (2014)

3.3.3. Descriptive evidence

This subsection portrays the distribution of education levels across time and occupations based on the routine intensity of tasks. The data demonstrate that educational upskilling occurred and that there are differences in routine intensity. The share of unskilled workers has decreased drastically from 26.3% in the 1980s to 9.7% in the 2010s. In the same vein, the share of high-skilled has increased from 7.7% in the 1980s to 24.6% in the 2010s and for higher VET from 4.9% to 9.8%. These trends align with many economies, for example, the United States, that experienced educational upgrading during this time. Analysis of the routine intensity of occupations in Figure 3-2 indicates that educational upgrading also occurred across occupation types. The share of workers with a university or higher VET qualification increased in routine intensive and nonroutine intensive tasks while the share of all other education types decreased. Interestingly, there has been a sharp decline in routine intensive occupations until 2000, driven mainly by a drop in the share of middle- and low-skill occupations.

In nonroutine intensive occupations, the share of middle-skilled did not vary much across the entire period, while there has been a sharp increase in highly skilled leading to an almost equal share of middle- and high-skilled workers in those tasks. At the same time, the declining trend of the share of unskilled and low-skilled workers has come to a halt or has even reversed in recent years. This is especially the case for occupations intense in routine tasks and middle-skilled workers in nonroutine intensive tasks, pointing toward job polarization induced by RBTC. Total employment in nonroutine tasks has been increasing while employment in routine intensive occupations has been declining, further indicating the presence of RBTC. Table 3-5 presents the summary statistics for routine and nonroutine occupations.

Table 3-5 Summary statistics by routineness for selected variables

(a) routine intensive occupations

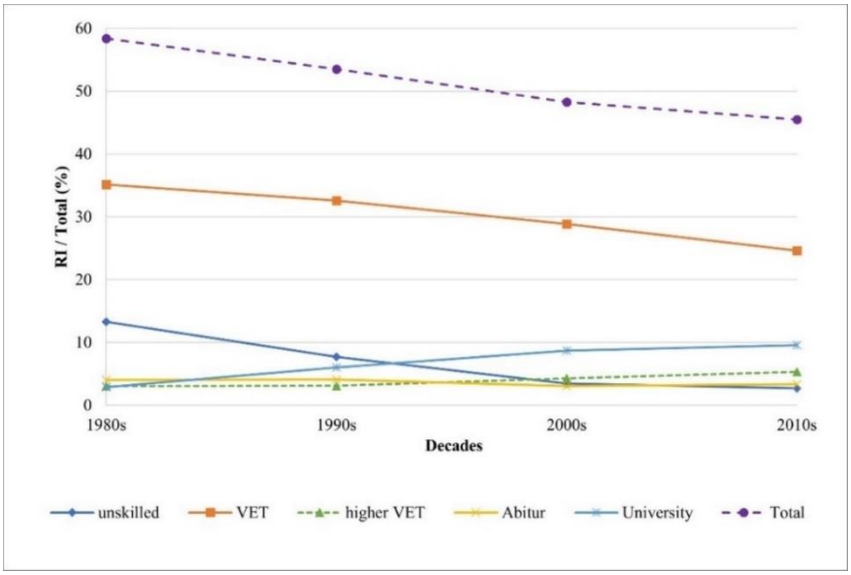
Variable	Obs.	Mean	Std. Dev.	Min.	Max.
lwage15	132,619	2.525	.638	−.728	5.330
qualification	130,495	2.593	1.238	1	5
experience	136,339	16.933	11.840	0	61.3
tenure	137,833	10.815	10.029	0	64
age	138,519	40.040	11.968	14	90

(b) nonroutine intensive occupations

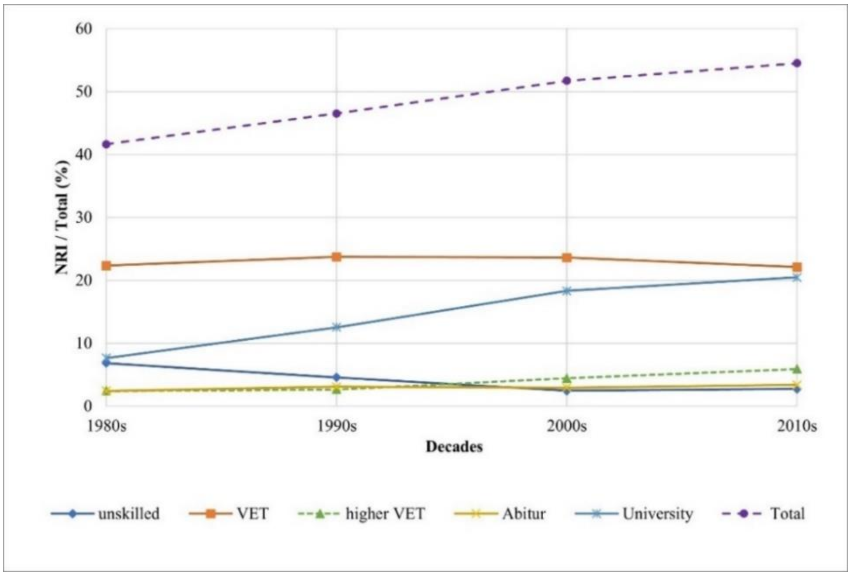
Variable	Obs.	Mean	Std. Dev.	Min.	Max.
lwage15	130,458	2.578	.662	−.728	5.316
qualification	132,809	3.128	1.447	1	5
experience	136,354	16.469	11.764	0	61
tenure	137,766	10.438	10.060	0	60.3
age	138,644	41.715	11.761	16	86

Source: SOEPv34i

Figure 3-2 Educational upskilling by routineness (full-time workers)



(a) Share of workers in routine intensive tasks by education level



(b) Share of workers in nonroutine intensive tasks by education level

Source: SOEP v34i

3.4. Econometric analysis

This section empirically examines whether the level of routineness affects the wage premiums and whether there are differences in the patterns between education levels. Technological change affects the employment growth in certain occupations and sectors due to its labor-replacing effects. This also implies considerable impacts on wage premiums. Labor-replacing technologies reduce the marginal productivity in affected occupations and lead to lower returns in routine-intensive occupations. The analysis aims to estimate the returns to different levels of education depending on the routineness of the occupational tasks.

3.4.1. Baseline model

To estimate the returns to education, this paper follows Braga (2018) and use a modified Mincer earnings equation with actual years of work experience instead of potential experience for the baseline model.

$$\ln w_{it} = \beta_0 + \beta_1 s_{it} + \beta_2 exper_{it} + \beta_3 {exper_{it}}^2 + \varepsilon_{it} \tag{1}$$

where w_{it} is the gross hourly wage in 2015 prices, s_i is the years of schooling and $exper_{it}$ refers to the work experience of individual *i* at time *t*. Subsequently, the coefficient β_1 is of primary interest and identifies the returns to education. The experience variable is included in the Mincer equation and serves as a control.

Since it is of interest how the returns vary by the type of education, the highest attained qualification instead of the years of schooling is used in the second specification. Particularly, the differences between general and vocational education and the distinction between low-, middle-, and high-skilled workers are in focus. Highly skilled refers to individuals who hold a university or higher VET degree, whereas middle-skilled are VET certificate holders. Low-skilled are those who did not pursue any professional education, namely those who have only lower or upper secondary education. The following empirical specification is estimated using a panel fixed-effects model.

$$\ln w_{it} = \beta_0 + \beta_1 Q_{it} + \beta_2 exper_{it} + \beta_3 exper_{it}{}^2 + X_{it} + Z_{it} + \varepsilon_{it} \qquad (2)$$

$\boldsymbol{Q_{it}}$ is a categorical variable indicating the highest qualification level attained, $\boldsymbol{X_{it}}$ is a vector for personal characteristics and $\boldsymbol{Z_{it}}$ refers to job characteristics of individual i at time t. These first two specifications allow testing how wage premiums are affected under SBTC.

3.4.2. Routineness

The variable *routineness* is introduced into equation (3) to analyze whether under RBTC the occupational, task-specific characteristics directly affect wage premiums.

$$\begin{aligned}\ln w_{ijt} = \beta_0 + \beta_1 Q_{it} + \beta_2 exper_{it} + \beta_3 exper_{it}{}^2 + \beta_4 routineness_{ijt} \\ + X_{it} + Z_{it} + \varepsilon_{it} \qquad (3)\end{aligned}$$

The β_4 coefficient of the dummy variable *routineness* indicates the wage effect of working in a routine intensive job.

3.4.3. Interaction between education and routineness

Last, this study simultaneously examines the interplay between education and routineness under SBTC and RBTC by interacting with the two categorical variables. This analysis provides a holistic analysis of the interplay between the returns to human capital and the impact of routineness under SBTC and RBTC, accounted for by education levels and occupational differences in the routine intensity of tasks.

$$\ln w_{ijt} = \beta_0 + \beta_1 Q_{it} + \beta_2 exper_{it} + \beta_3 exper_{it}{}^2 + \beta_4 routineness_{ijt} + \beta_5 routineness_{ijt} \times Q_{it} + X_{it} + Z_{it} + \varepsilon_{it} \quad (4)$$

Technological change is not the same over time, and subsequently, its impact on wages may differ, as postulated in Lentini and Gimenez (2019). Hence, a temporal analysis based on equation (4) is carry out by dividing the sample into three periods where technological change is expected to be different. Like Lentini and Gimenez (2019), the first period covers the 1980s, where technological change is assumed to be skill-biased. The second period covers 1991–2008, where the use of ICT accelerated and replaced repetitive job tasks. The last period covers 2009–2017, when digital technologies spread to non-technology sectors and jobs.

3.5.Results

The results of the different models are reported in Table 3-6. Personal and job controls stepwise are included stepwise when estimating the specifications from section 4 by panel fixed-effects regression using cluster robust standard errors to account for autocorrelation and heteroskedasticity of the coefficients. However, in the case of reverse causality, the fixed-effects estimator would be biased because the strict exogeneity assumption would be violated. A first-order panel vector autoregression model and a VAR-Granger causality Wald test show that routine granger causes wages, but wages do not granger cause routine. Hence, the fixed-effects model will be used. Additional *t*-tests confirm that the coefficients between the groups are significantly different from each other (Hill, Griffiths, & Lim, 2018). The results of the Heckman 2-stage selection model (Table 3-9) confirm the results qualitatively, while quantitatively, the coefficients change in magnitude when controlling for selection into the labor force.

Table 3-6 Estimates of panel fixed-effects regression

Log hourly wage in 2015 prices	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Schooling	0.061***						
	(−17.87)						
VET		0.168***	0.117***	0.108***	0.117***	0.119***	0.157***
		(−8.84)	(−6.65)	(−6.53)	(−5.74)	(−5.78)	(−6.50)
Higher VET		0.215***	0.183***	0.184***	0.180***	0.186***	0.231***
		(−8.74)	(−7.83)	(−8.35)	(−6.75)	(−6.90)	(−7.60)
High School		−0.200***	−0.202***	−0.176***	−0.187***	−0.186***	−0.151***
		(−7.66)	(−8.28)	(−7.53)	(−6.61)	(−6.50)	(−4.56)
University		0.313***	0.281***	0.275***	0.278***	0.277***	0.315***
		(−11.74)	(−10.96)	(−11.31)	(−9.79)	(−9.56)	(−10.00)
Experience	0.095***	0.091***	0.083***	0.069***	0.065***	0.065***	0.065***
	(−22.3)	(−22.54)	(−17.16)	(−13.66)	(−10.69)	(−10.52)	(−10.50)
$Experience^2$	−0.005***	−0.004***	−0.004***	−0.003***	−0.003***	−0.003***	−0.003***
	(−14.19)	(−13.58)	(−9.77)	(−8.46)	(−6.53)	(−6.44)	(−6.42)
ICT major			0.225***	0.163***	0.153***	0.153***	0.152***
			(−4.63)	(−3.53)	(−2.85)	(−2.85)	(−2.84)
Routineness						0.005	0.063***
						(−1.28)	(−3.56)
Routineness x VET							−0.060***
							(−3.29)
Routineness x Higher VET							−0.074***
							(−3.52)

Routineness x High School							−0.055*
							(−1.94)
Routineness x University							−0.060***
							(−3.17)
Constant	0.822***	1.436***	−3.777***	−3.092***	−3.028***	−3.083***	−3.117***
	(−19.02)	(−66.32)	(−15.05)	(−11.08)	(−9.15)	(−9.23)	(−9.34)
Year dummies	X	X	X	X	X	X	X
Personal controls			X	X	X	X	X
Job controls				X	X	X	X
Industry controls					X	X	X
Routineness						X	X
Interaction							X
Observations	257,171	250,108	248,551	194,970	151,849	148,272	148,272
R-squared	0.313	0.322	0.331	0.273	0.277	0.275	0.275

Notes: *t* statistics in parenthesis, cluster robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Personal controls: age, dummy for the marital status and state of residence. Job characteristics: job tenure, region of workplace, dummy for contract maturity, dummy for job change job, dummy for civil servant, dummy for leadership and firm size. Industry characteristics: categorical variable based on technology and knowledge intensity.

Table 3-7 Estimates of education and routineness coefficients by time period

Log hourly wage in 2015 prices	**(1) 1984−1990**	**(2) 1991−2008**	**(3) 2009−2017**	**(4) 1984−2017**
VET	0.721***	0.108***	0.382***	0.157***
	(−5.88)	(−3.85)	(−5.63)	(−6.50)
Higher VET	0.625***	0.182***	0.272***	0.231***
	(−3.09)	(−5.22)	(−3.07)	(−7.60)
High School	0.275	−0.147***	−0.193**	−0.151***
	(−1.56)	(−3.72)	(−2.30)	(−4.56)
University	0.811***	0.220***	0.411***	0.315***
	(−2.88)	(−6.04)	(−4.71)	(−10.00)
Experience	0.086***	0.091***	0.043***	0.065***
	(−2.83)	(−12.25)	(−4.80)	(−10.50)
Experience^2	−0.006***	−0.005***	−0.003***	−0.003***
	(−3.55)	(−10.00)	(−5.00)	(−6.42)
ICT major	0	0.195***	0.147*	0.152***
	(.)	(−3.16)	(−1.74)	(−2.84)
Routineness	−0.057	0.079***	0.028	0.063***
	(−0.82)	(−3.29)	(−1.03)	(−3.56)
Routineness x VET	0.026	−0.070***	−0.028	−0.060***
	(−0.35)	(−2.86)	(−1.00)	(−3.29)
Routineness x Higher VET	0.282***	−0.097***	−0.025	−0.074***
	(−2.63)	(−3.40)	(−0.80)	(−3.52)
Routineness x High School	0.044	−0.079**	−0.005	−0.055*
	(−0.29)	(−2.07)	(−0.12)	(−1.94)

Routineness x University	0.019	−0.077***	−0.022	−0.060***
	(−0.14)	(−2.99)	(−0.79)	(−3.17)
Constant	−2.690***	−1.983***	−1.469	−3.117***
	(−2.64)	(−4.76)	(−1.49)	(−9.34)
Year dummies	X	X	X	X
Personal controls	X	X	X	X
Job controls	X	X	X	X
Industry controls	X	X	X	X
Observations	6,581	79,912	61,779	148,272
R-squared	0.344	0.164	0.158	0.275

Notes: t statistics in parenthesis, cluster robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Personal controls: age, dummy for marital status, and state of residence. Job characteristics: job tenure, region of workplace, dummy for contract maturity, dummy for job change job, dummy for civil servant, dummy for leadership and firm size. Industry characteristics: categorical variable based on technology and knowledge intensity.

3.5.1. Skill-biased wage premiums

The analysis starts with equation (3) to estimate the returns to human capital for schooling years. The results in column (1) of Table 3-6 show returns of 6.1% for an additional year of schooling. When accounting for the heterogeneity of the returns to education and estimating equation (4), the results in columns (2) – (5) confirm the positive relationship between education level and wage premiums. A university degree increases wages by 27.8%, a higher VET by 18.0%, and VET by 11.7% compared to the base level of no professional education. High school graduates have on average 18.7% lower wages. These results are within the range of returns to human capital in similar studies reported in Lauer and Steiner (2000) and Psacharopoulos and Patrinos (2018), adding evidence to the presence of skill-enhancing effects of technologies under SBTC.

3.5.2. Routine-biased wage premiums

Next, controls for the routine intensity of occupational tasks are introduced to see if wages differ by routineness. The results in column (6) of Table 3-6 show an insignificant effect of routineness on wages. Thus, routineness by itself does not appear to have any directly penalizing effects on wage premiums. However, a highly significant routineness coefficient of 0.063 is reported in column (7) when interacting with routineness and education. Interestingly, isolating the interaction effect causes the main effect to appear. This can be interpreted as that job routineness did not have the same effect for differently skilled workers, but potentially in opposite directions. Hence, the positive coefficient of routineness on wages unfolds when interacting routineness with education level.

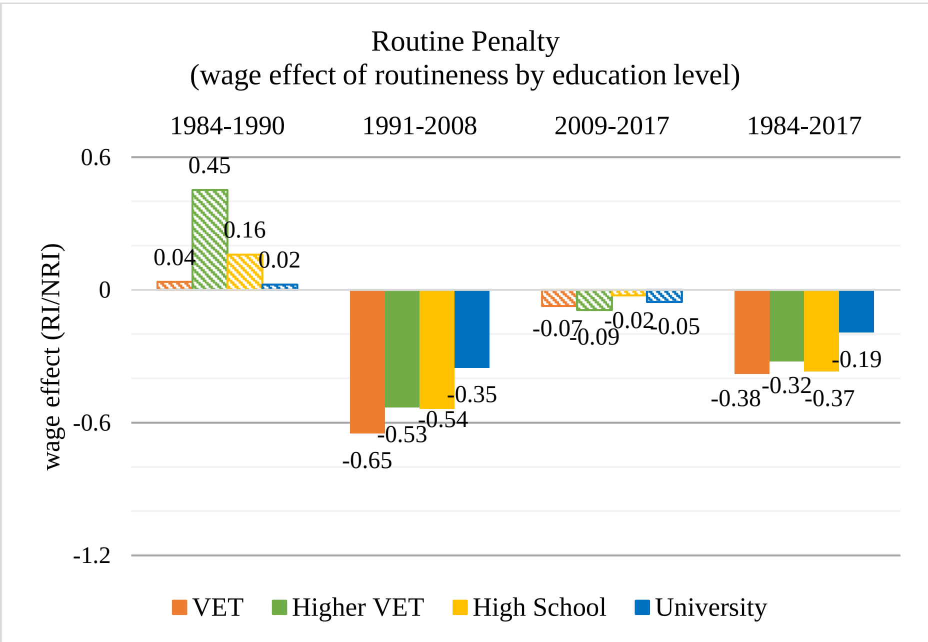
3.5.3. Routineness, education, and wage premiums

The interaction between education level and job routineness captures how wage premiums differ for workers with various skill levels in routine and nonroutine jobs, depicted in column (7) of the results Table 3-6. While the overall positive relationship between education and wage premiums holds within both routine groups, there are noteworthy differences between the returns to education in routine and nonroutine intensive occupations. First, the education wage premiums are lower for workers in routine intensive occupations across all education levels. This confirms the hypotheses that there is significant variation in the returns to education between workers in routine and nonroutine jobs. Second, the differences between routineness increase with education level, indicating greater productivity-enhancing effects of education in nonroutine intensive occupations.

Moreover, the impact of education and routineness on wages varies over the sample period, as the results of the temporal analysis in Table 3-7 show. The education coefficients are significant in all periods and were most prominent in the 1980s, before decreasing. This is in line with SBTC theory, where, in the 1980s, technologies complemented skilled labor and led to higher wages for skilled workers. The routineness coefficient and the interaction term are only significant during the subperiod 1991-2008 and the whole sample. Again, these results align with the accelerating adoption of labor-replacing technologies during that period. Additionally, the control variable for having a background in ICT-related subjects is significant, and the effect of 19.5% on wages is the strongest between 1991-2008.

To increase the interpretability of the results, the routine penalty is calculated, which refers to the ratio of the wage of workers in routine jobs over the wage in nonroutine jobs, as depicted in Figure 3-3. It unfolds that middle-skilled workers with specific education (VET) suffer the highest routine penalty with 65%. Workers with Higher VET or High school graduates earn around 54% less in routine jobs than in nonroutine jobs. In contrast, university graduates only experience a routine penalty of 35%. Hence, the results demonstrate that all workers, especially those with VET, suffer lower wages when working in routine jobs where technologies replace tasks.

Figure 3-3 Routine penalty: Wage effect of routineness by education level based on marginal effects of estimates



Notes: Routine penalty refers to the ratio of the wage of workers in routine jobs over the wage in nonroutine jobs. The coefficients for the subperiods 1984-1990 and 2009-2017 are insignificant, hence indicated differently.

3.6.Sensitivity analysis

The regression models may be susceptible to variations in the scale of the variables. Therefore, the values of the control variables used in the main analysis are restricted or relaxed to examine the effect of those differences. First, the model assumption of including only full-time workers is relaxed to test whether the results differ for the subpopulation and the entire population. Second, the experience variable is restricted to consider only full-time work experience. Third, the age of workers is limited to the core workforce, 25–65 years. Fourth, only male workers are considered. The full models of the specification with and without interaction terms are estimated including the restrictions (Table 3-8).

The results of the modified models are consistent with the results of the previous full model. The only noteworthy difference is that, for the model which includes full-time and part-time workers, the interaction term between routineness and the education level is insignificant, except for High school graduates. This might indicate that the adverse effects of routines are relevant for full-time workers only.

Furthermore, selectivity bias is often present in labor market studies due to choices of labor market participation. To check whether selection bias is present and whether it leads to different results, a two-step Heckman selection model which takes unemployment into account is estimated. In the first step, a probit model with the father’s professional education and the mother’s school education as instruments is estimated. The second step adds the inverse mills ratio from step one to the regression models as specified in the econometric section. The results of the Heckman selection model in Table 3-9 confirm the results qualitatively, while quantitatively, the coefficients change in magnitude when controlling for selection into the labor force. Selection is not present for the different regressions of the temporal analysis.

Table 3-8 Sensitivity analysis

Log hourly wage in 2015 prices	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
VET	0.102***	0.115***	0.214***	0.243***	0.038**	0.074***	0.100***	0.128***
	(−5.28)	(−5.19)	(−10.94)	(−10.91)	(−2.09)	(−3.48)	(−4.13)	(−4.32)
Higher VET	0.150***	0.169***	0.265***	0.299***	0.067***	0.116***	0.153***	0.207***
	(−5.80)	(−5.88)	(−10.77)	(−10.82)	(−2.79)	(−4.23)	(−4.58)	(−5.33)
High School	−0.139***	−0.113***	−0.154***	−0.124***	−0.091***	−0.061*	−0.199***	−0.149***
	(−5.20)	(−3.76)	(−6.50)	(−4.40)	(−3.37)	(−1.86)	(−5.16)	(−3.31)
University	0.210***	0.222***	0.345***	0.377***	0.147***	0.185***	0.250***	0.286***
	(−7.40)	(−7.31)	(−12.74)	(−12.92)	(−5.48)	(−6.32)	(−7.20)	(−7.43)
Experience	0.056***	0.056***	0.070***	0.070***	0.085***	0.085***	0.062***	0.062***
	(−11.04)	(−11.05)	(−16.53)	(−16.53)	(−16.39)	(−16.32)	(−7.19)	(−7.18)
Experience^2	−0.003***	−0.003***	−0.005***	−0.005***	−0.004***	−0.004***	−0.003***	−0.003***
	(−7.02)	(−7.01)	(−12.20)	(−12.19)	(−13.29)	(−13.24)	(−4.53)	(−4.51)
ICT major	0.136**	0.139**	0.155***	0.155***	0.151**	0.150**	0.153**	0.156**
	(−2.48)	(−2.54)	(−2.99)	(−2.98)	(−2.44)	(−2.44)	(−2.46)	(−2.52)
Routineness	0.001	0.023	0.007*	0.053***	0.004	0.061***	0.011**	0.054**
	(−0.21)	(−1.33)	(−1.73)	(−2.96)	(−1.05)	(−3.69)	(−2.19)	(−2.50)
Routineness x VET		−0.024		−0.047**		−0.057***		−0.037
		(−1.32)		(−2.53)		(−3.35)		(−1.64)
Routineness x Higher VET		−0.034		−0.056***		−0.083***		−0.085***
		(−1.61)		(−2.64)		(−4.15)		(−3.17)
Routineness x High School		−0.048*		−0.048*		−0.042		−0.074*
		(−1.81)		(−1.89)		(−1.51)		(−1.86)

Routineness x University		−0.014		−0.051***		−0.059***		−0.045*
		(−0.71)		(−2.66)		(−3.30)		(−1.94)
Constant	−2.223***	−2.227***	−2.953***	−2.985***	1.692***	1.657***	−2.765***	−2.799***
	(−5.45)	(−5.45)	(−18.61)	(−18.78)	(−49.31)	(−45.83)	(−4.75)	(−4.77)
Interaction		X		X		X		X
Workers: full-/ part−time	X	X						
Experience.: only full−time			X	X				
Age: 25–65					X	X		
Gender: only men							X	X
Observations	189771	189771	153080	153080	138682	138682	85526	85526
R-squared	0.160	0.161	0.381	0.381	0.196	0.197	0.280	0.280

Notes: *t* statistics in parenthesis, cluster robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3-9 Results of Heckman selection model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inverse Mills Ratio	−0.232***	−0.261***	−0.220***	−0.250***	−0.263***	−0.253***	−0.253***
	(−6.29)	(−6.55)	(−5.30)	(−6.27)	(−6.48)	(−6.19)	(−6.18)
Schooling	0.058***						
	(−13.26)						
VET		0.094***	0.077***	0.078***	0.094***	0.094***	0.131***
		(−3.53)	(−3.00)	(−3.40)	(−3.48)	(−3.42)	(−4.14)
Higher VET		0.145***	0.143***	0.138***	0.133***	0.136***	0.181***
		(−4.24)	(−4.33)	(−4.52)	(−3.73)	(−3.78)	(−4.56)
High School		−0.234***	−0.222***	−0.183***	−0.185***	−0.186***	−0.153***
		(−6.57)	(−6.54)	(−5.86)	(−5.00)	(−4.94)	(−3.69)
University		0.199***	0.198***	0.193***	0.196***	0.193***	0.230***
		(−5.53)	(−5.64)	(−5.93)	(−5.26)	(−5.05)	(−5.58)
Experience	0.083***	0.080***	0.077***	0.062***	0.063***	0.063***	0.062***
	(−14.04)	(−14.52)	(−12.01)	(−10.27)	(−8.85)	(−8.70)	(−8.66)
Experience^2	−0.005***	−0.004***	−0.004***	−0.003***	−0.003***	−0.003***	−0.003***
	(−12.31)	(−11.90)	(−8.50)	(−8.56)	(−7.09)	(−6.97)	(−6.94)
ICT major			0.229***	0.180***	0.188***	0.188***	0.187***
			(−4.40)	(−3.88)	(−3.56)	(−3.58)	(−3.57)
Routineness						0.007	0.068***
						(−1.60)	(−2.94)
Routineness x VET							−0.063***
							(−2.66)
Routineness x Higher VET							−0.078***
							(−2.92)

Routineness x High School							−0.054 (−1.58)
Routineness x University							−0.064*** (−2.63)
Constant	1.474*** (−20.46)	2.103*** (−43.97)	−2.215*** (−5.60)	−1.830*** (−4.78)	−1.768*** (−3.82)	−1.778*** (−3.80)	−1.801*** (−3.86)
Year dummies	X	X	X	X	X	X	X
Personal controls			X	X	X	X	X
Job characteristics				X	X	X	X
Industry characteristics					X	X	X
Routineness						X	X
Interaction							X
Observations	167753	166334	166334	153507	122932	120154	120154
R-squared	0.106	0.122	0.127	0.170	0.178	0.175	0.176

Notes: *t* statistics in parenthesis, cluster robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7. Conclusion

Amid the digital transformation, labor-replacing effects in the job market have been associated with the level of task routineness (Autor et al., 2003), while simultaneously, policymakers have emphasized the importance of education. This research aimed to provide empirical insight into this area of research by treating SBTC and RBTC as two separate dimensions and analyzing the effects of job routineness and education on wage premiums. The study adds empirical evidence for the effectiveness of formal education in environments with low routineness by extending the picture to consider the difference in the returns to human capital between routine intensive and nonroutine intensive occupations. Using individual fixed-effects estimation, the main results demonstrate that the returns to education are higher for workers in non-routine-intensive jobs, while education proves to be less productivity-enhancing under higher levels of task routineness, reflected by lower wage premiums.

First, the analysis confirms the positive relationship between education and wages as hypothesized under SBTC. The temporal analysis reveals that the education-wage premiums are highest in the 1980s, which may be attributable to the skill complementary and productivity-enhancing nature of computer technologies. This finding coincides with Lentini and Gimenez (2019), who argue that technological change differs by decade. Different technological developments have shaped the workplace during the analyzed period from 1984 to 2017. Until the late 1980s, technologies complemented skilled workers, whereas technological change from the 1990s drove job polarization due to replacing routine jobs (Autor & Dorn, 2013).

Another important finding is that routine workers of all skill groups are at risk of adverse effects under RBTC depending on the job routineness. A sizeable routine penalty for workers with VET compared to higher skill levels emerges. That further supports the intuition that VET does not seem to prepare workers sufficiently enough for the requirements of future jobs. In contrast, general university education seems to be more effective when working in nonroutine intensive occupations. Thus, this study supports evidence from previous observations on the adverse wage effects for middle-skilled workers, although the results for high-skilled differ from Alda et al. (2020). This analysis has been unable to show that highly skilled benefit under RBTC directly. However, it can confirm that highly skilled receive relatively higher wages in nonroutine intensive occupations, suggesting that education is more effective at leveraging technology-skill-complementarity effects in nonroutine work environments.

Further changes in technology will require constant adaptation to new job tasks, and thus, updating skills continuously is essential. Nevertheless, not all workers receive on-the-job training equally, and differences between training participants should be considered when designing further professional education and training programs to update workers' skills. Those who experience the highest routine penalty are also less likely to update their skills. Görlitz and Tamm (2015) find that workers in nonroutine jobs tend to participate more in training than workers with routine jobs. Thus, differences between routineness are also relevant when examining further training measures, and future studies should explore the aspects of routineness and training types in more detail.

In interpreting results, it is best to consider features of the German economy and labor market. First, Germany has a unique dual education system with a well-established VET system, which implies that a larger share of the labor force is middle-skilled workers who might be negatively affected by routineness. Second, manufacturing remains an integral part of the German economy, meaning that a larger share of jobs is still intensive in routine tasks and thus at risk (Cirillo, Evangelista, Guarascio, & Sostero, 2020). Therefore, for Germany and other countries with a dual VET system, it is more urgent to find solutions to address the ongoing challenges and prepare the workforce for more agile environments that require constant learning and adaptation. This goal can be achieved through combined education and labor market policies that target differences in labor market outcomes for high-, medium-, and low-skilled workers by addressing the changing task requirements.

This effort calls for special attention from policymakers in countries with a large share of middle-skilled workers, that is, workers who belong to the group expected to be negatively affected. While VET has its benefits, future technological changes are expected to shift employment from routine to nonroutine-intensive jobs. Thus, while effective now, the ongoing changes must be considered when designing education policy. VET can be a successful tool to provide a skilled workforce for the current labor market. However, flexibility and adaptability are becoming increasingly important in a rapidly changing work environment due to technological changes.

The relatively high routine penalty for all workers, especially those with VET, indicates that continuous education after completing formal education is necessary to adapt to new job tasks quickly. One possibility is continuing lifelong learning efforts to make further professional training programs accessible to affected workers. Another reasonable approach to tackle this issue could be to redesign the educational content and structure of VET to incorporate more general education content that enables better adaptation to the changing work environments. Either way, all efforts must be on preparing or retraining workers for the challenges in nonroutine intensive occupations.

Jobs are changing, and the demand is likely to shift toward high-skilled workers. The tension caused by the technological change of the Fourth Industrial Revolution may lead to unemployment for workers in routine intensive occupations if they cannot transfer to a nonroutine intensive job, and labor-replacing technologies may increase the gap between wages of medium-skilled and high-skilled workers. Thus, this study provides evidence for the necessity of education policy to help the transition. Consequently, there are two sides to the same coin: technologies may be labor-replacing on the one hand; on the other hand, they can be productivity-enhancing, but this is not always the case (Acemoglu, Gallego, & Robinson, 2014; Balsmeier & Woerter, 2019). Together, a policy priority should be finding solutions to address the ongoing challenges and prepare the workforce for more agile environments where constant learning and adapting will be necessary.

Chapter 4.
How susceptible are skills to obsolescence? A task-based perspective of human capital depreciation

4.1. Introduction

Education prepares workers to perform a certain set of tasks in the labor market. However, the introduction of ICT, digital technology, and robotics has changed how we work. Technologies substitute repetitive tasks and create new ones, leading to changes in skill requirements. Previously acquired skills through formal education and working experience are not applicable anymore and lose their value in the labor market, causing the depreciation of economic skills, and thus, human capital.

As the speed of technological change increases amid the Fourth Industrial Revolution, the effect of economic skill obsolescence is becoming more severe. Skill obsolescence has previously only been a concern for individuals in technology-intensive sectors or occupations. However, with the ongoing digital transformation, most occupations have changed tasks due to the skill complementing or substituting effect of technologies. Consequently, the majority of jobs are currently subject to some form of skill obsolescence. This might particularly be the case in jobs comprising complex cognitive, interactive, and analytical tasks where technology is skill-complementing and frequently used. Due to new technologies, the skills of older workers become obsolete quickly, and the economic value of human capital decreases. This effect may be further intensified when there are greater changes in technology use. To stay productive in the labor market, workers will need to upskill or even retrain to find new occupations.

Technological and organizational changes are expected to accelerate, and affect all parts of the economy, increasing the risk of and the urgency to counteract skills obsolescence. Despite these lingering effects, few studies consider factors of technological change when analyzing skill depreciation. Occupations are becoming more complex and the skill requirements to perform tasks on the job are being transformed due to the use of job-related technology. Backes-Gellner and Janssen (2009) find differences in skill obsolescence between experienced and knowledge-based tasks, providing some evidence for the importance of incorporating a task perspective into the analysis. However, the results are hardly comparable as they do not consider the depreciation of human capital acquired through different levels of education. On the contrary, this paper is interested in understanding how the tasks a worker performs affect the skill obsolescence of different levels of human capital.

To help close this gap, the study at hand attempts to examine economic skill obsolescence by incorporating different task types into the analysis. To the best of my knowledge, this is the first study that combines both aspects and distinguishes between the types of human capital and various task groups. Considering differences in the depreciation rate by job tasks contributes to the field in that it may provide novel insight into the depreciation patterns of human capital, enabling governments to design more effective education and labor market policies. This is crucial to prepare workers for changing work environments.

The main body of this paper is structured into 4 sections. Section 4.2 presents the main literature and the theoretical framework. Section 4.3 proceeds with the data and methodology. Section 4.4 summarizes the findings, and finally, Section 4.5 concludes the article.

4.2. Background literature and theoretical framework

4.2.1. Concept of skill obsolescence

The concept of human capital obsolescence has already been established in early works, such as in G. Becker (1994), Mincer (1974), and Rosen (1975). In his seminal work, G. Becker (1994) established the concept that the knowledge and skills embedded in workers can be seen as capital and thus it can also lose value. Labor income reflects the current economic value of human capital—which in terms of physical capital would be the market price—and thus a worker's productivity. Human capital acquired through formal education and learning in school as well as skills gained through work experience can increase productivity. The stock of knowledge and skills is not constant but changes over time, eventually causing one's stock of human capital to deplete.

The two types of obsolescence are technical and economic obsolescence (Arrazola & Hevia, 2004; De Grip & Van Loo, 2002; Neuman & Weiss, 1995). Technical skills become obsolete due to internal factors such as the worker's physical aging or the disuse of skills. The obsolescence of economic skills is caused by the loss in the market value of the worker's qualifications due to changes in the economic environment. Subsequently, it is often also referred to as external depreciation. Throughout the literature, the terms “depreciation” and “obsolescence” are used interchangeably, however, some scholars make a distinction between the two terms. Rosen (1975) is referring to skill depreciation what is also known as internal or technical depreciation. In turn, “skill obsolescence” refers to economic or external depreciation. The focus of this analysis will be on the external, economic aspects of human capital obsolescence or depreciation; thus, no distinction between the terms will be made in this study but instead the study uses the terms interchangeably.

“Economic obsolescence” occurs because technologies and knowledge used in society change over time. Technological or organizational changes require new skills, rendering previous skills obsolete. Especially the introduction of innovations, for instance, new production technology, and advances in research change the knowledge and skills that will be valuable in the labor market. These effects are becoming increasingly more pronounced with the advent of labor-replacing technologies that can substitute repetitive tasks.

Table 4-1 Studies on human capital depreciation

Author(s)	**Model**	**Depreciation rate**	**Country**	**Education levels**	**Sector**	**Tasks**
Johnson and Hebein (1974), Rosen (1975), Heckman (1976), Haley (1976), Mincer and Ofek (1982)	Lifetime investment models, lifecycle model, job interruption spells	1%–7%	USA	O (only years)	X	X
Neuman and Weiss (1995)	Based on Mincer (1974), added interaction term	Graphically	Israel	O (only years)	O	O
Groot (1998)	Groot (1998)	17%	UK, NL	X	X	X
Ramirez	Neuman and Weiss (1995)		Swiss	O	O	X
Arrazola and de Hevia (2004)	Extension of Groot (1998)	1.2%–1.5%	Spain	X	X	X
Janssen and Backes-Geller (2009)	Neuman and Weiss (1995)	0.7%–6%	Germany	O	X	O (experience /knowledge-based)

Murillo (2011)	Neuman and Weiss (1995)	1.8%–3.8%	Spain	X	O	X
Weber (2014)	Neuman and Weiss (1995)	0.6%–0.9%	Swiss	O	O	X
Lentini and Gimenez (2019)	Neuman and Weiss (1995)	1%–6%	OECD	X	O	X

4.2.2. Measurements of skill obsolescence

Skill obsolescence has not received much attention despite its importance for human capital. Empirical studies quantifying the rate of depreciation are still scattered and employ different approaches, as Table 4-1 summarizes. In particular, early works have used quite a broad variety of models when examining human capital obsolescence. For example, Rosen (1975) uses life-cycle earnings as a function of age and experience, finding that high school graduates have a higher rate of obsolescence than college graduates.

Similarly, Mincer and Ofek (1982) find a higher depreciation for highly educated female workers. In turn, several studies conclude that the education level is not important (Carliner, 1982; Holtmann, 1972). Others also applied the age-earnings function (G. Becker, 1994), or lifecycle investment models based on an age-earnings function (Haley, 1976; Heckman, 1976; Johnson & Hebein, 1974) or job interruption spells of women (Mincer & Ofek, 1982). Despite their differences, these works share the fact that there is no differentiation between the internal and external rate of depreciation and only one common estimate for the technical obsolescence due to the un-use of skills or physical deterioration with age (De Grip, 2006; De Grip & Van Loo, 2002).

More recently, two dominant approaches are emerging, one that estimates human capital obsolescence directly and one that uses an indirect measure. Like preceding works, Neuman and Weiss's (1995) operationalization of the depreciation rate focuses on vintage effects. However, they suggest a method to disentangle internal and external depreciation. Depreciation is indirectly measured by the interaction between education and potential experience and indicates its effect on an individual's earning capacity following the Mincer model, which already includes a squared term of experience to account for technical obsolescence. Interacting the schooling variable with the experience variable as well is based on the rationale that the economic value of knowledge and skills decreases with the time since finishing formal education and potentially entering the labor force. This indirect measure has the advantage of capturing decreasing productivity effects through wages, which are the main worry for most countries (De Grip, 2006). In their estimation, Neuman and Weiss (1995) use 1983 census data for Israel and show that the effect of interaction between workers' level of education and experience has a more negative impact on earnings in high-tech sectors, which employ more highly skilled workers.

Murillo (2011) uses a modified version for the Spanish labor market and finds a schooling depreciation rate of 0.7% for 1995 and 0.4% for 2002, which increases with education level, and an experience depreciation rate of 3.8% and 1.8%, respectively. Backes-Gellner and Janssen (2009) build upon an extended Mincer earnings equation and find that the rate of obsolescence is higher for workers in knowledge-based tasks compared to experience-based tasks. Lentini and Gimenez (2019) analyze sectoral differences of human capital depreciation in OECD countries for the period 1980 to 2005 and show that the depreciation ranges between 1% and 6% and is mainly significant in skill-intensive sectors regardless of the sector's technological intensity. Also incorporating sectoral technology intensity into the analysis, Ramirez (2002) finds a higher depreciation rate for higher education levels and that the differences increase in high-tech industries.

Other scholars model human capital and its depreciation mathematically and estimate the depreciation rate directly. For example, Groot (1998) introduces a model and finds a depreciation rate of 11%–17% for Britain and the Netherlands. Arrazola and Hevia (2004) obtain depreciation rates between 1.2% and 1.5% for Spain, depending on the type of sector and periods of unemployment. Also following this approach, Weber (2014) uses data for Swiss and shows that specific skills are prone to faster depreciation (0.9%–1.0%) compared to general skills (0.6%–0.7%). The spread in the depreciation rates is likely attributable to differences in measurement as well as the variation in observation periods and datasets.

The aforementioned studies (see Table 4-1) lay a good foundation for the analysis of human capital obsolescence, indicating that skill obsolescence might be skill biased. However, most works do not incorporate the effects of technological developments which have transformed most advanced economies. Occupations become more complex and skill requirements change more quickly (Spitz-Oener, 2006), highly depending on technology-related factors such as the type of job tasks or the technology or knowledge intensity of a sector. Thus, previously accumulated skills may become obsolete at a faster rate. As indicated by the results in Backes-Gellner and Janssen (2009), there are differences between knowledge and experience-based tasks, providing some evidence for the importance of incorporating a task perspective into the analysis. However, their specification does not consider the depreciation of formal education, making the results hardly comparable and unsuitable for evaluating the effectiveness of current educational systems. Other studies, for example, Weber (2014) or Lentini and Gimenez (2019) only indirectly consider differences in the depreciation by occupational segment or sector.

Occupations comprise a set of different tasks. Some tasks might be more likely to be substituted by labor-replacing technologies than others. Thus, this paper argues that the obsolescence of human capital may vary with the main tasks in each occupation. However, previous studies have not considered the aspect of task-specific obsolescence of heterogeneous human capital gained through various types of education. To close this gap, this study directly incorporates a task perspective based on the classification of job tasks adopted from the literature on job polarization while focusing on the depreciation of education. This enables a comparison with literature on skill obsolescence as well as works on job obsolescence.

4.2.3. Hypotheses

Based on the preceding literature review, this subsection derives the hypotheses and elaborates on the role of tasks in the depreciation of human capital. Human capital is formed through education and experience. Thus, human capital depreciation comprises two separate effects, the depreciation of the educational stock, and the depreciation of the experience stock. Those two rates, combined with investments in human capital, determine its present value. Human capital obsolescence does not occur at the same speed for everyone. Previous literature (Murillo, 2011; Neuman & Weiss, 1995) found evidence for heterogenous depreciation rates, but the results are still inconclusive. The main argument is that the economic obsolescence of human capital which is caused by changes in the external environment does not affect all individuals equally.

It may depend on the type of skills the individual possesses, and it may also vary with the type of tasks that the worker is mainly exposed to in his job.

Regarding the first point, this paper argues that more advanced skills are expected to depreciate at a faster rate compared to basic skills which do not change much over time. Advanced skills acquired through tertiary education contain state-of-the-art knowledge which might become less valuable as technologies evolve. On the contrary, basic skills are universally applicable and are still valid even when exposed to environmental changes. Concurrently, general skills which can be acquired through general secondary or tertiary education, are thought to depreciate at a lower rate because they stay valid for longer periods and can be applied even in changing economic environments. In contrast, specific skills are gained through vocational education and training (VET) or vocational tertiary education (Higher VET) which teaches specific, occupational skills and knowledge. Hence, specific skills depend on the current state of technology when acquiring the education and will decrease in value when there have been external changes. Thus, the first set of hypotheses is:

H1a: *Workers with higher education levels have a higher depreciation rate than workers with lower education levels.*

H1b: *Workers with specific, vocational education have a higher depreciation rate than workers with general education.*

The next set of hypotheses addresses the link between job tasks and skill obsolescence. A job is a combination of tasks that require certain task-related skills (Rodrigues, Fernández-Macías, & Sostero, 2021). Thus, job tasks define which skills workers use throughout their careers. However, with ongoing technological progress, job tasks and skill demands might change more quickly, rendering old knowledge obsolete. This means that the present value of human capital depends not only on knowledge acquired through formal education, but also on the technological skills demanded by the job, and the skills to use those technologies and knowledge. Consequently, the depreciation rate of human capital may depend on the main type of tasks a worker mainly performs on the job.

As previous works on job polarization have shown, manual or repetitive tasks are being replaced by machines, whereas technology is complementing complex, non-repetitive tasks (Autor & Dorn, 2013; Autor & Handel, 2013; Frey & Osborne, 2017). Human capital required to perform cognitive, analytical, or interactive tasks is more complex, and those tasks are also often complemented by the use of technologies. Examples of jobs with a high share of cognitive or analytical tasks are bookkeepers or programmers, respectively. Those individuals are also susceptible to greater changes in job-related knowledge and skill requirements. This might imply a higher human capital depreciation because the knowledge and skills acquired through formal education are for the current state of technology and lose value once technologies change. In turn, workers in jobs with a high share of manual tasks are likely to depend less on technology and human capital acquired through education is still valuable, even under the current digital transformation. Examples of occupations with a low technology content are cooks or construction workers (Muro, Liu, Whiton, & Kulkarni, 2017). Thus, a lower depreciation rate is expected for this group.

H2a: *The depreciation rate is higher in jobs with a high share of interactive, analytical, and cognitive tasks where technology is frequently used and task-complementing.*

Moreover, this paper argues that the differences in human capital depreciation depend on how much the use of technology has changed. As technology advances, machines can perform a wider range of tasks, slowly taking on nonroutine tasks that have previously been classified as safe. Thus, nonroutine occupations that have been exposed to changes in job-related technology use, e.g., that adopted more technologies into the job, are also more likely to demand the acquisition of new knowledge and skills. Thus, human capital might become obsolete at a faster rate if the change in technology use is high.

H2b: *The depreciation rate is higher in jobs that experienced greater changes in job-related technology use compared to other jobs.*

This study aims to answer the presented research questions by incorporating the role of job tasks and the impact of technology into the empirical analysis of human capital obsolescence. The results will provide workers, firms, and policymakers alike with a better understanding of the implications of technological change on the value and validity of human capital. This is crucial amid the further anticipated transformation of labor markets.

4.3. Data and methodology

To examine the depreciation rate and potential influencing factors, the German Socio-Economic Panel (doi: 10.5684/soep.v34i) for the years 1984-

2017 is used for the relationship between educational attainment and wages as well as other control variables for personal or job-related characteristics.

As presented in subsection 2, the prevailing measurement of skill obsolescence is the indirect estimation of the depreciation rate. The depreciation rate of human capital depends on the decreasing effect of schooling on wages with time in the labor force and is modeled using an extended earning function based on Neuman and Weiss (1995) and Mincer and Ofek (1982). The model accounts for the productivity-enhancing effect of education, the marginally decreasing effect of experience, and the depreciation of human capital related to the obsolescence of the worker's skills from formal education due to changes in the market environment. The education-specific depreciation is indirectly estimated in equation (1) as the interaction between the highest education level and potential years of experience, i.e., time since completing formal education *(Edu_i X $pexper_{it}$)*. The coefficient of β_2 indicates how skill obsolescence affects the worker's earnings.

$$\ln w_{it} = \beta_0 + \beta_1 Edu_i + \beta_2 (Edu_i \times pexper_{it}) + \beta_3 pexper_{it} + \beta_4 {pexper_{it}}^2 + X_{it} + \varepsilon_{it} \quad (1)$$

A panel fixed-effects estimation with cluster robust standard errors is used to account for autocorrelation and heteroskedasticity of the error terms. Controls for personal or job-related characteristics are included stepwise.

Next, this paper investigates whether skill obsolescence depends on the main type of task a worker performs. To incorporate different occupational tasks, a categorical variable from the German classification of occupations (KldB 1992) is constructed. Following the method suggested by Dengler et al.

(2014), each occupation is assigned one predominant task type. These task groups are adopted from Spitz-Oener (2006) and Autor et al. (2003) and differentiate between nonroutine tasks (interactive, analytical, manual) and routine tasks (cognitive, manual). Data on the change in job-rated technology use comes from Muro et al. (2017) who provide information on the use of technology for 545 occupations between 2001 and 2016.

The categorical variable *tasks* is introduced to differentiate between the different types of occupational tasks. This variable is first simply added to equation (1) to control for possible task-related wage effects. Finally, equation (1) is estimated for each of the 5 task groups to see how the depreciation rate varies for different types of job tasks. Table 4-2 summarizes the main variables used in the analysis.

Table 4-2 Descriptive statistics (full-time workers >30 hours/week)

Variable		Observations	Mean	Std. Dev.	Min	Max
Earnings (deflated base year 2015)						
lwage15	Log gross hourly wages	266,234	2.546	0.654	−0.728	5.330
Education level (base group: only secondary education)						
2	VET	488,577	0.512	0.500	0	1
3	Higher VET	488,577	0.072	0.259	0	1
4	High school (Abitur)	488,577	0.083	0.276	0	1
5	University	488,577	0.193	0.395	0	1
Potential experience (years)						
pexper	age – years in education – 6	510,724	35.479	17.800	1	93
Tasks						
1	Nonroutine analytical	266,537	0.233	0.423	0	1
2	Nonroutine interactive	266,537	0.087	0.281	0	1
3	Nonroutine manual	266,537	0.175	0.380	0	1
4	Routine cognitive	266,537	0.326	0.469	0	1
5	Routine manual	266,537	0.180	0.384	0	1

Source: SOEP v34i (doi: 10.5684/soep.v34i)

Table 4-3 Results of fixed-effects regression with deflated log hourly wages as dependent variable

Log hourly wages	(1)	(2)	(3)	(4)	(5)
Education level					
VET	0.718***	0.497***	0.509***	0.488***	0.495***
	(27.04)	(18.20)	(18.35)	(14.54)	(14.59)
Higher VET	0.696***	0.597***	0.581***	0.555***	0.567***
	(19.98)	(15.95)	(15.69)	(12.67)	(12.89)
High school (Abitur)	−0.302***	−0.280***	−0.218***	−0.231***	−0.223***
	(−9.50)	(−9.41)	(−7.13)	(−6.21)	(−5.93)
University	0.649***	0.613***	0.635***	0.602***	0.609***
	(16.47)	(12.95)	(13.97)	(11.34)	(11.38)
Depreciation of education					
VET*pexper	−0.015***	−0.010***	−0.012***	−0.011***	−0.011***
	(−17.40)	(−11.51)	(−14.35)	(−11.18)	(−11.13)
Higher VET*pexper	−0.016***	−0.013***	−0.014***	−0.014***	−0.014***
	(−13.81)	(−10.25)	(−11.52)	(−9.70)	(−9.71)
High school*pexper	0.013***	0.011***	0.009***	0.009***	0.008***
	(9.22)	(8.01)	(6.68)	(5.43)	(5.21)
University*pexper	−0.010***	−0.010***	−0.012***	−0.012***	−0.012***
	(−9.43)	(−6.25)	(−8.78)	(−6.87)	(−6.82)
Experience					
pexper	0.040***	0.070***	0.070***	0.063***	0.064***
	(7.71)	(9.57)	(10.38)	(8.05)	(8.10)

Depreciation of experience					
pexper-squared	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(−41.64)	(−12.55)	(−13.70)	(−10.90)	(−10.68)
Constant	0.881***	−3.248***	−2.347***	−2.382***	−2.347***
	(14.36)	(−24.00)	(−16.19)	(−14.07)	(−13.69)
Controls	none	+ personal	+ job	+ industry	+ tasks
Observations	262.7780	261.101	204.689	158.561	154.792
R-squared	0.407	0.425	0.388	0.386	0.385

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, t statistics in parentheses, cluster robust standard errors

Table 4-4 Results – Human capital depreciation by task group

Log hourly wages	**Nonroutine tasks**			**Routine tasks**	
	analytical	interactive	manual	cognitive	manual
Education level					
VET	0.394**	0.677***	0.541***	0.635***	0.503***
	(−3.07)	(−7.62)	(−8.56)	(−10.84)	(−8.07)
Higher VET	0.462***	0.803***	0.572***	0.792***	0.563***
	(−3.4)	(−6.49)	(−5.73)	(−11.08)	(−5.27)
High school (Abitur)	−0.244	−0.181	−0.15	−0.08	−0.316***
	(−1.83)	(−1.69)	(−1.87)	(−1.36)	(−4.24)
University	0.393**	0.931***	0.646***	0.869***	0.411*
	(−2.68)	(−6.01)	(−4.04)	(−10.14)	(−2.07)
Depreciation of education					
VET*pexper	−0.010**	−0.019***	−0.015***	−0.016***	−0.012***
	(−2.98)	(−4.54)	(−8.42)	(−9.48)	(−7.42)
Higher VET*pexper	−0.012***	−0.023***	−0.019***	−0.021***	−0.015***
	(−3.30)	(−4.51)	(−6.27)	(−8.62)	(−5.27)
High school*pexper	0.008*	0.008	0.000	0.003	0.011***
	(−1.97)	(−1.12)	(−0.01)	(−1.63)	(−3.48)
University*pexper	−0.009*	−0.020***	−0.016***	−0.019***	−0.011*
	(−2.36)	(−3.97)	(−4.76)	(−6.36)	(−2.46)
Experience					

pexper	0.031*	0.091***	0.075***	0.091***	0.072***
	(−2.43)	(−3.58)	(−3.94)	(−7.44)	(−3.34)
Depreciation of experience					
pexper-squared	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(−3.85)	(−5.22)	(−6.05)	(−6.81)	(−5.66)
Constant	−1.798***	−1.655***	−3.561***	−1.620***	−3.077***
	(−3.70)	(−3.52)	(−10.00)	(−6.68)	(−7.26)
Observations	46,523	17,716	30,927	62,462	28,791
R-squared	0.366	0.320	0.283	0.449	0.369

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, t statistics in parentheses, cluster robust standard errors

4.4. Results

This section presents the results of the different specifications of the panel fixed-effects regression, summarized in Table 4-3. In the preferred specification, column (4), the coefficient of the interaction term is negative for all types of human capital except high school education, indicating the depreciation of human capital. The annual depreciation rate of education is the lowest (1.1%) for workers with VET degrees, followed by workers with a university degree (1.2%) and highest for workers with higher VET (1.4%). These values are in line with previous studies (Lentini & Gimenez, 2019; Neuman & Weiss, 1995) and add additional evidence to the higher depreciation rates for higher education levels. Higher education levels contain state-of-the-art knowledge which depends on the state of technology and knowledge at the time of education and it might be outdated more quickly when technological changes occur. Moreover, these estimates indicate that skills from specific education – VET compared to high school and higher VET compared to university – deplete relatively faster, which has also been found by Weber (2014) for Switzerland. This finding can be explained in that specific human capital is only limitedly transferable to other tasks and thus depreciates when there are changes in the economic environment. The depreciation rate for one additional year of potential experience is relatively low (0.01%) compared to other studies (Murillo, 2011). This could be due to the newer period examined because previous works already indicated a declining trend of the depreciation of experience.

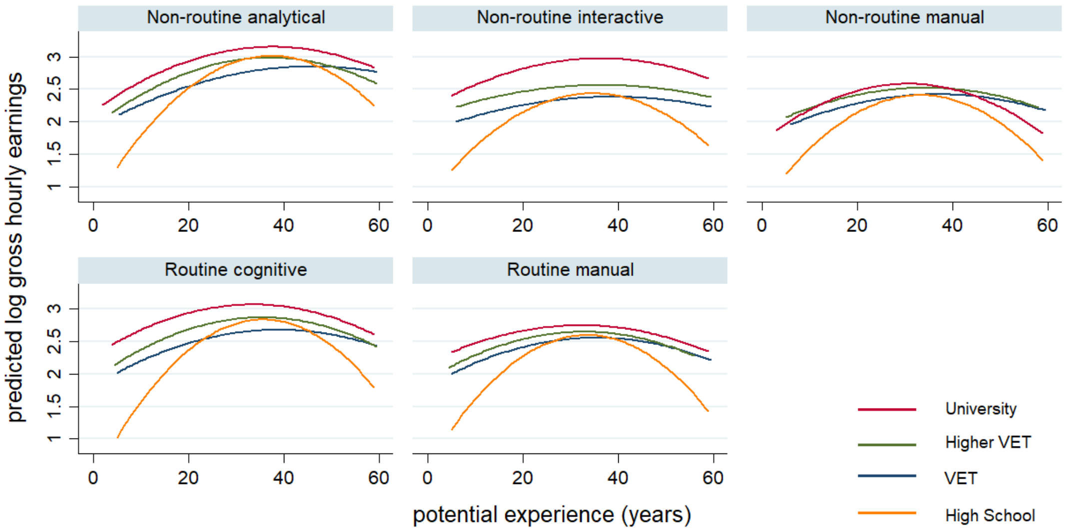
Next, the results of the regression by predominating task-type are displayed in Table 4-4. The results show that the depreciation rate varies by education level and job tasks, confirming empirically that both factors are important for determining skill obsolescence. Especially in nonroutine interactive tasks, nonroutine manual tasks, and routine cognitive tasks, skills are at higher risk of depreciating. The annual depreciation rate is highest in nonroutine interactive tasks with 2.0% for human capital acquired through tertiary education and 1.9% for VET. Skill obsolescence is even higher for specific human capital formed through higher VET (2.3%). On the contrary, workers' human capital does only depreciate at half the speed in jobs with mostly nonroutine analytical tasks. Another interesting finding is that the return to experience is also significantly higher in those tasks that experience higher depreciation rates, as the variable for potential experience *pexper* indicates.

To gain a better understanding of the implications of the differences in depreciation, the predicted earnings-experience profiles are plotted across tasks using the results of model specification 5. Figure 4-1 shows that variations in earnings profiles are quite pronounced, with noticeable differences between task groups and education levels. Earning levels and educational wage premiums are overall lower in manual tasks and higher in analytical, interactive, and cognitive tasks. The graphs reveal that the earnings of workers with VET will exceed those of workers with higher VET toward the end of their careers. In nonroutine manual tasks, VET and higher VET lead to even higher earnings than tertiary education. Moreover, it unfolds that earnings peak early for high school graduates, temporarily surpassing those of workers with VET and higher VET, and then depreciate rapidly. These findings highlight the importance of human capital depreciation. Despite lower education levels, differences in depreciation rates can in some cases compensate for earnings differences toward the beginning of a career. Thus, even for university graduates, continuous learning efforts and investments in training are necessary to maintain the economic value of their human capital.

A detailed look at occupations with a high share of interactive or cognitive tasks reveals that those jobs have experienced greater changes in job-related technology. As summarized in Table 4-5, digital, task-complementing technology has already been extensively used in occupations with mostly cognitive and analytical tasks, but this has also been changing moderately. Thus, this finding might explain why workers performing jobs that are mostly comprised of those tasks are facing a high depreciation rate.

On the contrary, the use of job-related technology has increased dramatically for nonroutine manual occupations. For instance, occupations in construction, accommodation and food services, or transportation and warehousing are mainly comprised of nonroutine manual tasks which had a low use of digital technology in 2001 (Muro et al., 2017). By 2016, the use of job-related technology doubled, rendering previous knowledge obsolete at a high rate. Thus, the average skill obsolescence for the entire period is moderate, although it might be higher for recent periods. Nonetheless, the use of technology is still relatively low compared to other occupations, possibly implying more changes that may lead to further skill obsolescence in the future.

Figure 4-1 Predicted earnings–experience profiles by task groups for heterogeneous levels of human capital.



Note: *t*-tests confirm significant differences between task groups and education levels, except between VET and Higher VET. To check for significance in the peaks, a pooled regression is first employed over all task groups, and then the turning point and its standard errors are calculated using nlcom. *t*-tests indicate no significant differences in the peaks within task groups.

Table 4-5 The link between job tasks and human capital obsolescence

Task type	Task example	Use of task-complementing technology	Change in job-related technology use	Human capital obsolescence
Nonroutine analytical	Researching, designing	medium	low	low
Nonroutine interactive	Managing, entertaining	high	high	high
Nonroutine manual	Repairing, serving	low	high	medium
Routine cognitive	Bookkeeping, calculating	high	medium	medium
Routine manual	Operating machines	low	low	low

Source: author’s elaboration based on Muro et al. (2017) for data on technology use. The task groups are adopted from Spitz-Oener (2006)

4.5. Conclusion

New technologies change working environments and skill demands, rendering human capital acquired through formal education obsolete. Especially digital technologies are changing occupational tasks and the skills needed to be productive in the labor force, which may create opportunities for some and impose risks for others. Getting a better understanding of its effects on human capital depreciation is crucial for workers, firms, and policymakers alike.

The present study analyzed the economic obsolescence of skills due to changes in the economic environment and incorporated factors related to technological change, that is, technology intensity and occupational tasks. The results bring forth that human capital in nonroutine interactive, nonroutine manual, and routine cognitive tasks depreciates faster than human capital in other tasks. This finding may be attributable to two factors, as summarized in Table *4-5*. First, technology complements nonroutine interactive and routine cognitive tasks. Jobs with a high share of those tasks also use digital technologies more than other jobs. With the increased use of technology, job-related knowledge will also change, and human capital gained through formal education cannot be applied anymore, increasing obsolescence. Second, some occupations experienced greater changes in the use of digital technologies. This is especially the case for jobs with a large share of nonroutine manual tasks where the use of digital technology has been relatively low in the past but is constantly rising. The increasing digitalization of those occupations is rendering older knowledge and skills obsolete.

With the ongoing digital transformation, more dramatic changes in work environments are likely, possibly increasing the rate of skill obsolescence further. While the results of the current study indicate that human capital depreciation will be smaller in routine tasks, this should not be interpreted as positive news. As studies on job polarization have demonstrated, routine cognitive tasks are in the process of being substituted by technologies. Routine-intensive occupations are likely to gradually disappear in their current form, increasing skill obsolescence. In turn, nonroutine tasks have been considered non-substitutable by technologies. However, the findings unfold a relatively high depreciation rate for workers in nonroutine tasks, while the demand for those job tasks is increasing.

Most policymakers have emphasized upskilling of the workforce and increasing tertiary education enrolment as a solution. However, the results show that tertiary education does not protect workers against skill obsolescence. This needs further elaboration. Tertiary education leads to the formation of general human capital which can be transferred to other tasks with common properties as well. Thus, the knowledge acquired through general education is also more likely to apply to other tasks. However, if knowledge related to an entire task group is expected to become obsolete due to external changes, then even general, higher education cannot protect workers. This finding is important because it indicates that simply increasing the education level of the workforce is not enough. Across all task groups, human capital gained through tertiary education depreciates annually at a substantial rate. The findings show that this can even lead to a disadvantage in earnings-experience profiles in the case of workers in mostly nonroutine manual tasks compared to other education levels which have a lower depreciation rate. Consequently, the initial investment in tertiary education could dissolve if no further training is undertaken. Thus, changes in educational content and continuous investments are inevitable to avert serious problems, and considering human capital depreciation is crucial.

Creating an inclusive labor market that provides opportunities for all workers will require significant efforts to prepare workers for tasks in the digital age. It will be important to provide the most vulnerable groups with the digital skills necessary to participate in a digital economy. For other groups, it will be crucial to be able to adapt and specialize in new skills that cannot be performed by machines. These developments put pressure on governments to provide combined labor market and education policies targeting the obsolescence of human capital. While many countries have realized the importance, more education measures are needed to prepare the workforce for the ongoing changes. This study may help policymakers to design effective training programs that allow professionals to update their qualifications periodically to incorporate the most recently demanded skills. Most importantly, educational policies need to incorporate technological knowledge demanded by the workplace and enable workers to adapt their abilities to changing market conditions quickly amid more rapid and disruptive technological advances. In the same notion, firms need to provide more training opportunities for their employees if they do want to have a more productive workforce. Individuals need to be aware of the current developments and prepare to participate in training frequently. If all efforts are toward acquiring new and updated skills, further technological changes can bring many benefits and opportunities as well.

Chapter 5.
The European skill space: A cross-country analysis of path-dependent capability development

5.1. Introduction

This study constructs a European skill space, a network space illustrating the skill structures of European countries, to investigate the structural differences among the countries and their evolutionary paths. Human capital is a significant determinant of economic growth, as seen in many cases worldwide (Gennaioli et al., 2013). Therefore, with the convergence of schooling rates and educational attainment, the economic growth rates or GDP per capita should also converge. However, global economic inequality has increased. This trend can be observed not only in developing countries, but also in developed countries. One such example is the European Union (EU), where a north-south divergence pattern can be observed. Policies such as the Lisbon Strategy or Europe2020 aimed to achieve inclusive growth by reducing the economic gap between EU countries through investments in education and research and development (R&D). However, since 2010, convergence has slowed despite all efforts, and major differences remain between member states (Fulvimari, Bontout, Salanauskaite, & Vaalavuo, 2016).

Previous studies indicate that differences in human capital specialization determine future economic outcomes (Madsen, 2008). Using historical literacy rates, Diebolt and Hippe (2019) show that previous human capital endowments can explain regional differences in economic development and innovation activities. Rodríguez-Pose and Vilalta-Bufí (2005) find that cross-country differences in human capital influence the convergence process of EU countries that have lower human capital levels. Moreover, a nation's human capital can also shape the catching-up process of technological development (Funke & Strulik, 2000). Many scholars have accepted that human capital is as important as other input factors (e.g., physical capital and labor hours) and there is ample evidence that human capital has a positive impact on economic development and growth in the EU (Badinger & Tondl, 2003; Fagerberg et al., 1997; Gennaioli et al., 2013; Rodríguez-Pose & Crescenzi, 2008).

However, it is still unclear why some countries are able to upgrade their human capital through investments in human capital or R&D and why others are unable to do so. According to a number of studies, simply upgrading education levels is insufficient to accelerate human capital growth and may not result in equal growth in all countries (Sterlacchini, 2008). The factors causing these differences are yet to be completely understood, and human capital levels continue to vary significantly between countries despite their efforts in education policies.

One way to explain these differences is through skill. Human capital is formed through not only education, but also experience and so-called workplace or job skills. Education sets the early path for one's development, as most educational measures occur during childhood and youth. After entering the labor force, the main drivers of human capital formation are experience and on-the-job training. Recently, the role of job tasks and skills in explaining economic differences has gained attention. For example, Hanushek, Schwerdt, Wiederhold, et al. (2017) examine the disparities in growth between countries and show that skills (measured as Programme for International Student Assessment (PISA) and Trends in International Mathematics and Science Study (TIMSS) test scores) are the primary determinants for economic well-being. However, their results also indicate that the results of skill improvements can only be seen in the long term. Countries with higher skills tend to benefit more in the long term. The findings of Martinaitis (2014) suggest that the quality of the employment domain (tasks, technologies, work organization, etc.) could be as important as formal education systems in upgrading the skills of the labor force. Valente, Salavisa, and Lagoa (2016) provide evidence of the role of work-based skills as a contributing factor to economic growth in the EU. Moreover, skills embedded in a nation's workforce are crucial for productivity, and further research is needed on the skill structures of countries to fully understand their human capital.

Another way to explain the different levels of human capital among countries is through the path-dependence of human capital development. The factors influencing human capital development, such as knowledge and skills, are highly dependent on the current level of human capital (Dai, Yan, & Jianping, 2021; Ruttan, 1997). This paper argues that a country's historical and current skill structure of the labor market might also determine its future growth paths, and attainment of new skills that are far from the current skill structure is less likely. In other words, countries cannot easily change their skill specialization and are likely to stick to related skills even when they acquire new skills. Thus, the existing skill sets determine future possibilities of skill adoption and serve as a source of different levels of human capital. Skill polarization, as demonstrated in metro areas of the United States, can prevent workers from upgrading to more complex jobs with higher wages (Alabdulkareem et al., 2018). This study examines whether this is also the case at the national level.

Future skill adoption possibilities are becoming increasingly important amid ongoing changes in technology. Technologies are transforming occupations and, as a result, skill demands. The ability to acquire new skills is more critical than ever in a digital knowledge economy. To prevent falling behind, nations need to prepare for and invest in the right skills. Thus, it is vital to understand which skill acquisition possibilities of a country, and redirect its investments accordingly. This study suggests that skills endowments and specialization can explain the differences in capability between EU countries and why convergence in human capital is only occurring in part. Due to lack of data, most studies have only utilized proxied skills using educational variables or adult skill test scores. However, skills used in the workplace constitute an essential part of human capital. Using actual data on the intensity of skills used in EU countries, this study fosters an understanding of countries' skill endowments, and how they are related to the future development of skills.

The remainder of this study is aligned as follows. Section 5.2 reviews previous studies on human capital, namely, skills and path-dependence. Section 5.3 describes the data used for the construction of the skill space, and the statistical and econometric analyses. Section 5.4 explains the methodology of the skill space, based mainly on the product space method and econometric model. Section 5.5 presents the results of the skill space and the statistical. Section 5.6 discusses the findings and their implications and limitations, and Section 5.7 concludes the study.

5.2. Literature review

Human capital - the skills and knowledge embedded in individuals - has become the main driver of growth since the 20th century, emphasizing the increasing role of human capital accumulation (Eicher & Garcıa-Penalosa, 2001; Williamson, 1991). Skill inequality between countries and among workers within a country has been increasing with trends of technological change. Technologies are constantly emerging and transforming the nature of work, resulting in new job tasks or occupations. Workers must adapt to the new skills demanded by new tasks. This is also important for the aggregate labor force of a country to remain competitive. Disparities between countries can occur because of a country's economic specialization (e.g., product specialization, manufacturing or service intensity, the complexity of goods and services), determinants of human capital (e.g., educational investments, years of schooling, the share of university graduates) or institutional factors (e.g., quality of schooling system, policies, economic stability). However, a combination of these factors is often responsible for cross-country differences, with many studies attributing significant differences to human capital endowments (Acemoglu & Dell, 2010; Gennaioli et al., 2013; Glaeser, La Porta, Lopez-de-Silanes, & Shleifer, 2004). Investigating the link between skills, technology, and education, Eicher and Garcıa-Penalosa (2001) argue that skill accumulation can reduce or widen inequality in an economy. The country's trajectory is shaped by the cost of education, education externalities and the substitutability of high and low skilled workers.

Skills are an underlying aspect of economic specialization, human capital endowments, and institutional factors and allow for capturing national capabilities that are important for economic development. Acquired capabilities or skills are necessary to successfully transform economies (Eriksson & Hansen, 2013), and the composition of different skills throughout a country's economy, especially the acquisition of related skills, is beneficial (Boschma, Eriksson, & Lindgren, 2009). Previous studies (e.g., Autor et al., 2003; Autor and Dorn , 2009) have investigated the effects of automation and labor-replacing technologies on the labor market and have confirmed job polarization due to a relative decline in middle-wage occupations. The polarization hypothesis discusses labor market polarization along the skill distribution. This implies a strong connection to skills; however, most studies do not directly use the concept of skills. Rather, they classify occupations into task groups to examine the effect of technological change on occupations. However, this may be too aggregated to understand how workers adopt new skills or countries adopt new specializations.

Recent works (e.g., Hanushek and Woessmann, 2012) demonstrate that acquired skills can explain cross-country differences better than schooling variables as a proxy of human capital. Skills are linked to occupations through tasks. Occupations are composed of a set of tasks, and each task requires specific skills for its execution (Rodrigues et al., 2021). Hence, each occupation can be expressed directly through its related set of skills. Using skills, the smallest unit of analysis, provides a better insight into the labor market structure because the results remain valid even if occupations change due to technological transformations.

The concept of skill complementarity has emerged in recent studies to explain trends in the labor market. For example, Gathmann and Schönberg (2010) analyze workers' transitions between occupations and find that the similarity of workers' skill sets and the requirements of each occupation were the dominant movements. They argue that attaining new skills through education requires investment of money and time, and thus constrains the movement between different skill categories. This argument also explains skill and labor market polarization in that it may hinder workers from moving upwards in the skill distribution, preventing them from escaping skill polarization. Table 5-1 summarizes additional studies that utilize network analysis to examine complementarity or relatedness with respect to skills and occupations.

Table 5-1 Studies on occupation and skill relatedness using network analysis

Author(s)	**Country**	**Year**	**Network**	**Main idea**
Farinha et al. (2019)	US	2005-2016	Occupation	Jobs differ in 3 dimensions of relatedness; density represents the complexity of jobs.
Muneepeerakul et al. (2013)	US	2010	Occupation	Occupations are not industry-based so existing skills may be converted into occupations and create new occupations with different skills.
Shutters et al. (2016)	US	2005-2013	Occupation	Transition to the creative economy by occupational interdependencies; urban areas follow a general trajectory that requires specialization in create and non-creative occupations.
Shutters and Waters (2020)	US	2018	Skill	Network of city’s prevalent labor skills to calculate economic tightness using skill-based measure; cities with higher tightness have higher income levels; resilience of a city depends on network.
Alabdulkareem et al. (2018)	US	2014-2015	Skill	Skill polarization into two clusters; network constraints career mobility.
Levy Yeyati and Montané (2020)	Argentina	2003, 2019	Occupation / Industry	Transitions (after employment/ unemployment) between some jobs are widespread compared to others; reveals preference of workers to stay in same industry or occupation.

Neffke & Henning (2013)	Sweden	2004-2007	Industry	Skill relatedness is measured indirectly through labor flows among industries; firms are more likely to diversify into industries that have related skills.
Neffke (2019)	Sweden	2001-2010	Occupation / industry	The interconnectedness of human capital through educational synergy, substitutability, and complementarity between workers' skills (education).
This study	EU countries	2011-2018	Skill	Cross-country analysis of skill complementarity; regional specialization tendency; diversification (entry and exit of new skill) more likely to adopt close by skills to current skill set/structure; previous specialization defines future paths.

The overview reveals that most works focus on the US labor market and that the application to occupations is prevalent. Most studies rely on proxies, such as occupations, because it is difficult to quantify workers' skills. Alabdulkareem et al. (2018) take the first step toward a more granular analysis by approximating workers' skill sets from the skill requirements of occupations. The main argument is that skills close to an existing skill set in terms of the network topology are more attainable. The results confirm that skill polarization is the underlying driver of job and wage polarization in the US labor market, demonstrating the necessity of a more detailed analysis that considers job-related skills. Shutters and Waters (2020) examine a city's resilience to shocks by relying on measures of interconnectedness and economic tightness. These measures build on the distribution of workers by occupations to understand structural elements of an urban economy, which are also implemented by other scholars (Farinha, Balland, Morrison, & Boschma, 2019; Muneepeerakul, Lobo, Shutters, Goméz-Liévano, & Qubbaj, 2013) who use network analysis in this context. This allows for the computation of a network of pairwise skill interdependencies, which highlights a city's latent economic structure. The analysis reveals that cities with higher economic tightness have higher income levels but are less resilient to shocks.

While the aforementioned studies emphasize the role of skills at the micro-level, skills and occupations may also affect economic outcomes at the macro level. Understanding how countries specialize in skills and the factors that constrain them from adopting new skills to their portfolios can help explain inequality and slowed-down convergence, albeit increasing investments in education and R&D. Innovation and regional studies have provided empirical evidence to support the significance of path dependence in capability development. Path dependence is the result of the cumulative concentration of activities in certain places over time” (Fujita, Krugman, & Venables, 1999; Krugman, 1991). At the individual or firm level, concepts such as tacit knowledge (Nonaka, 1991) and sticky local information (Von Hippel, 1998) suggest that there is strong path dependence in capability development, as knowledge or know-how cannot be transferred easily or readily to another. Moreover, at the macro-level, recent studies in the field of economic geography have demonstrated that regions and countries also show regional path dependence in industrial development (Boschma, Minondo, & Navarro, 2013; Hidalgo, Klinger, Barabási, & Hausmann, 2007), knowledge creation (Colombelli, Krafft, & Quatraro, 2014; Eum & Lee, 2019; Kogler, Essletzbichler, & Rigby, 2017; Lis & Rozkwitalska, 2020), and occupational distributions (Botticini & Eckstein, 2006). These studies commonly suggest strong evidence that regions tend to diversify into new industries or technologies that use capabilities similar to those of current industrial or technological structures.

However, the previous studies at both micro-level and macro-level have limitations because they depend on the aggregated results of capabilities, such as export and patent, which can be affected by various factors such as capital, infrastructure, and knowledge. Therefore, they cannot represent the dynamic skill structures of individuals, who are directly involved in the capability development process. To fill this gap, a few studies, such as Alabdulkareem et al. (2018), have examined individuals and their jobs to study the path-dependent diversification paths in skills and occupations. However, the importance of path dependence in skill development at the national level remains unclear. To provide policy implications for human resource management, this study utilizes national-level data on skills and jobs, which are directly related to the capability of individuals. This provides another approach for linking the skill space to current studies on path-dependent capability development.

Synthesizing the arguments from works on the micro and macro level, this study proposes that a country's future skill specialization is determined by its current skill structure. Countries are endowed with certain skills and capabilities embedded in their labor force. These skill endowments that are closely linked to occupations may depend on historical and institutional factors that create differences in the economic structure. Hence, not all countries utilize the same skills with the same intensity, which leads to a certain level of skill specialization within an economy. This study expects that skills closely related to a country's labor market are more likely to be obtained by the workforce in that country (following the logic of Hidalgo et al., 2007; Alabdulkareem et al., 2018; Shutters et al., 2020). Moreover, this expected skill relatedness may cause differences in specialization patterns between countries and regions, which will be explored throughout this study to add insight into the role of skills in explaining cross-country differences.

5.3.Data

This section describes the data construction process used to analyze the differences between European countries using skill endowments. This study uses upon two different types of datasets to capture the underlying skill structure, specialization patterns, and skill relatedness at the national level with the objective of shedding light on the disparities between European countries. The first data set is related to skills, and the second refers to occupations, which are linked to receive skills data across countries. Thus, it is necessary to understand the link between skills and professions. Occupations, defined as a group of jobs with similar competencies, comprise a set of specific tasks. Each task requires related skills to be executed. Skills are the ability to perform tasks. Hence, it can be said that each job task has complementary skills. Consequently, each occupation consists of a set of job tasks, which in turn requires specific skills (see Rodrigues et al., 2021 or Autor and Dorn, 2013 for further elaboration).

First, this study utilizes the novel European Skills, Competences, Qualifications and Occupations (ESCO) database provided by the European Commission and EU member states to retrieve information on the intensity of skill usage in occupations. The ESCO database comprises a dictionary of 13,485 skills linked to 2,942 occupations in the EU. It is similar to the O*Net for the US labor market, which has been used by many studies to analyze occupations, skills, and tasks concerning labor market outcomes.

However, the US and European labor markets differ in several aspects. For example, many European countries have strong vocational-oriented education systems, which are also reflected in their occupational structures, leading to differences in occupations and corresponding tasks. Consequently, a major benefit of using the ESCO database is that it accounts for the peculiarities of the EU labor market and its education systems. Another advantage is that it reflects the current state of skill use in the labor market. However, owing to its novelty, the ESCO dataset does not provide information on the changes in skill importance over time. Acknowledging that it is not possible to track within-occupational skill changes, the focus is on the current state of occupational skill specialization. The most recent ESCO Skill-Occupation Matrix Table (290 × 125 matrix) from 2021 links 290 ESCO skills groups with 125 ISCO-08 occupation groups at the 3-digit level.

Furthermore, this study relies on the EU Labour Force Survey (LFS) data, a random sample survey of private households in the EU provided by Eurostat, while constructing data that reflects skill specialization. The data are delivered quarterly, with a large sample size of 0.3% of the total population, which corresponds to 1.7 million persons. The large sample size provides stable population estimates of the labor market and socio-demographic characteristics. Generally, the quality and accuracy of the EU LFS are high. However, because the data are based on a population sample, they are subject to the typical sample and selection errors associated with survey data. (Eurostat, 2021).

To account for errors associated with survey data, several measures are enforced. All countries rely on probability sampling, mostly multi-staged stratified random sample design. Moreover, the use of weights corrects for sample selection and adjustments for non-response are applied. Another advantage of using the EU LFS data is its high cross-country comparability which is a major argument for using this dataset in the current analysis. (Eurostat, 2021)

Data on the number of people working in each occupation in each country and year were retrieved from the EU LFS data for a total of 27 countries for the period 2011-18. This includes all EU member states plus EFTA countries (Iceland, Norway, and Switzerland). However, owing to data unavailability Bulgaria, Malta, and Poland were excluded. The yearly data used are based on the annual average of quarterly data. The use of population weights allows for the calculation of representative employment shares for each country.

Using employment shares for each country and year, yearly occupation-country matrices are created first. This step provides eight 125 × 27 matrices that link each of the 27 countries with the employment shares of the 125 3-digit ISCO-08 occupations. The same occupation codes were used in ESCO, smoothing the matching process. Next, the ESCO Skill-Occupation Matrix was multiplied by each year's occupation-country matrix of equal size. The resulting skill-country matrix, used for all further calculations, is 290x27 in size and represents how much of each skill is used by each country to represent country-specific skill specialization.

5.4. Methodology

In order to analyze how countries evolved through different skills, this study adopts the concept of product space by Hidalgo et al. (2007). Product space, a network space of products or industries based on the relatedness among the products, illustrates the current industrial structures and suggests potential paths for the industrial development of countries. The main argument of path-dependent industrial diversification is that capabilities lie behind the diversification process, and countries are likely to diversify to industries that require capabilities shared with the current industrial structures. Adopting the product space methodology based on the comparative advantages of skills at the national level, this study introduces the concept of a skill space that illustrates the structures of skills possessed by each country.

To measure a country's possession of a skill, this study uses the concept of comparative advantage and considers that a country has the skill if it has a comparative advantage of that skill. The measurement of comparative advantage follows Balassa's (1965) revealed comparative advantage (RCA), which calculates the country's relative share of the industry compared to the world's share of that industry. If the RCA value is larger than 1, then the country has a comparative advantage in that industry, and vice versa. Adopting this approach, this study measures the comparative advantage in skills using the skill dataset explained in the previous section instead of the industrial volume in the original calculation of RCA.

$$RCA_{c,s} = \frac{x(c,s)}{\sum_s x(c,s)} \bigg/ \frac{\sum_c x(c,s)}{\sum_{c,s} x(c,s)} \tag{1}$$

where c stands for country, s stands for skill classification, and x represents the amount of skills used in country c.

To construct the skill space, it is necessary to measure complementarity (Alabdulkareem et al., 2018) or the similarity between two skills. If two skills are closely linked with each other, they are likely to require the same capabilities, and it is predictable that a country that already has a comparative advantage in one skill is likely to show a comparative advantage in the other.

Mathematically, this concept can be expressed as the conditional probability of whether country *c*, which has a comparative advantage in skill s_1 is likely to have advantage in skill s_2, which is $(\mathrm{P}(\mathrm{RCA}x_{s_1} \geq 1 | \mathrm{RCA}x_{s_2} \geq 1))$, and vice versa $(\mathrm{P}(\mathrm{RCA}x_{s_2} \geq 1 | \mathrm{RCA}x_{s_1} \geq 1))$. As there are two different conditional probabilities for each pair of skills, this study considers skill complementarity between two skills as the minimum of the pairwise conditional probability, following Hidalgo et al. (2007). The complementarity φ_{s_1,s_2} between skills s_1 and s_2 can be expressed as

$$\varphi_{s_1,s_2} = \min\{\mathrm{P}(\mathrm{RCA}x_{s_1} \geq 1 | \mathrm{RCA}x_{s_2} \geq 1), \mathrm{P}(\mathrm{RCA}x_{s_2} \geq 1 | \mathrm{RCA}x_{s_1} \geq 1)\}. \quad (2)$$

As such, complementarity between two skills can indicate relatedness between them. Based on the complementarity between two skills, a correlation matrix of 290 × 290 skills can be constructed. The following step calculates the skill's degree of relatedness with the current skill structure, or the skills in which a country currently has an advantage. This relatedness with the existing skill structure, density, differs by country, skill, and year. Conceptually, it is the average complementarity with other skills, calculated by the sum of complementarities between one skill and other skills with RCA, divided by the sum of complementarities with the skill and all other skills. In the mathematical representation, ω_{s_2}, the density around skill s_2, is defined as

$$\omega_{s_2} = \frac{\sum_{s_1} x_{s_1} \varphi_{s_1,s_2}}{\sum_{s_1} \varphi_{s_1,s_2}} \quad (3)$$

where x_{s_1} is 1 if s_1 has RCA larger than 1 and 0 otherwise, and φ_{s_1,s_2} is the complementarity between skills s_1 and s_2.

This study estimates how the current advantage of a country in terms of related skills influences the country's future skills. Therefore, the analysis regresses the comparative advantage of skills at time t+1 against the skill density at time t. The econometric estimation can be written as follows:

$$\begin{aligned} SkillRCA_{c,s,t+1} = \beta_1 SkillRCA_{c,s,t} + \beta_2 SkillDensity_{c,s,t} + \beta_3 pop_{c,t} \\ +\beta_4 gdppc_{c,t} + \beta_5 capital_{\ c,t} + \beta_6 hc_{c,t} \\ +\beta_7 eduexp_{c,t} + \beta_8 teredu_{c,t} + \alpha_t + \varepsilon_{c,p,t} \end{aligned} \tag{4}$$

where the dependent variable $SkillRCA_{c,s,t+1}$ is 1 if country c has a comparative advantage in skill s at time $t+1$, and 0 otherwise. Similarly, independent variable $SkillRCA_{c,s,t}$ is 1 if country c has a comparative advantage in skill s at time t, and 0 otherwise. The key independent variable $SkillDensity_{s,t}$ measures the density around skill s at time t. The model also includes country-level control variables from Penn World Table 10.0 (Feenstra, Inklaar, & Timmer, 2015), such as log of population, log of GDP per capita, capital stock, human capital index, educational expenditure, and tertiary education enrolment rate. α_t is the time-fixed effect, and $\varepsilon_{c,i,t}$ is the error term.

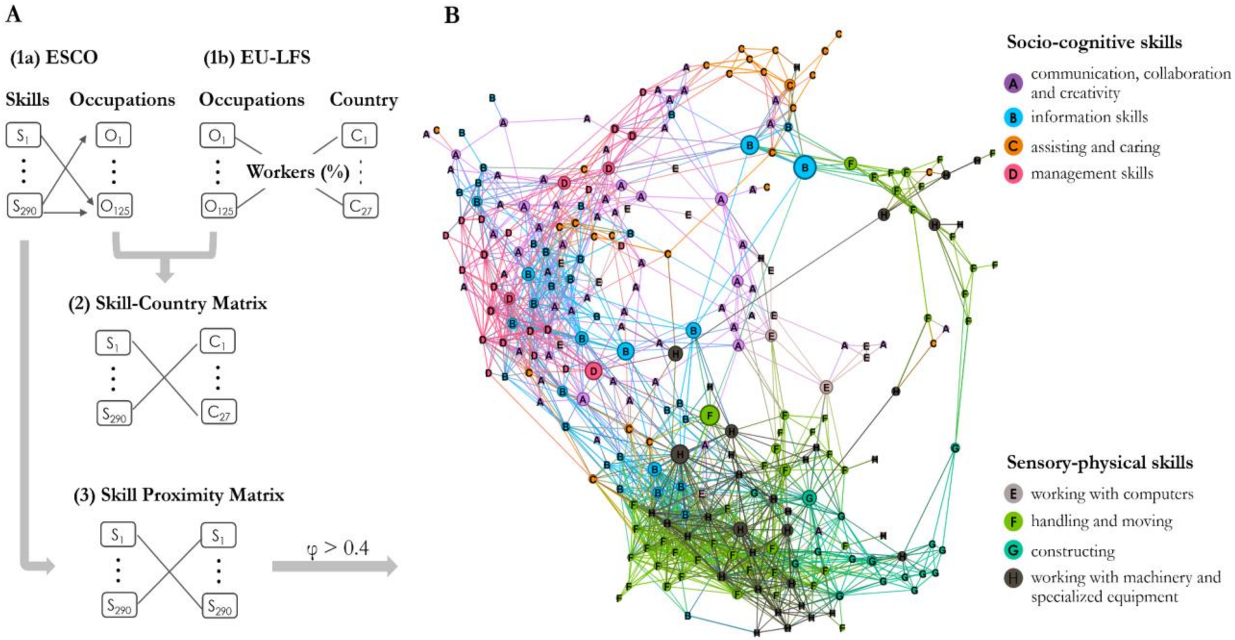
5.5.Results

5.5.1. The structure of the European skill space

This section begins by visualizing the full skill complementarity matrix representing the EU skill structure. The illustrated network builds on a hierarchically clustered matrix of the skill space with 290 nodes representing each skill and 33,054 edges. To uncover relevant ties between skills in the network, the graph in Figure 5-1 includes only links (1,630 edges) between skills with a skill complementarity $\varphi > 0.4$ (edge weights > 0.4). As skill complementarity or skill relatedness captures the co-occurrence of skills across EU countries, two highly complementary skills tend to be close to each other in the skill network, while skill pairs with weaker relatedness are farther away. Using the Louvain community detection algorithm (LCD), this study observes that the EU skill structure has two distinct clusters and two smaller communities located at the periphery of the network. The two large clusters can be interpreted as socio-cognitive skills and sensory-physical skills. Subsequently, the results confirm the polarization of the skill space in Europe, which could be the underlying cause of job polarization, as noted by Alabdulkareem et al. (2018) in the US.

As the network representation reveals, the skill space has dense and sparse parts. Using a measure of centrality provides insights into the skills in each of the two main lobes of the skill space. The centrality measure is computed based on the skill complementarity matrix to show the relation between skills with RCA to all skills. Table 5-2 shows that strong heterogeneity of the pattern of relatedness of skills exists, where skill categories do not determine the location in the skill space. Information skills dominate the densest part. Skills in the sparest part are in the disconnected peripheral area of the skill space and not visible in Figure 1 at $\varphi > 0.4$. This heterogeneity in the skill space suggests that its structure and where a country is oriented within it become important for its development path (Hidalgo et al., 2007).

Figure 5-1 The EU skill space and its construction



Note: A) The data for the skill space is constructed by matching the ESCO and EU-LFS, resulting in a skill-complementarity matrix. B) The skill space is visualized as network structure based on the skill complementarity φ using only edge weights greater than 0.4.

Table 5-2 The centrality of the skill space

a) Top 10 skills in the *densest* part of the skill space

Code	Skill	Group	Paths
84	measuring dimensions and related properties	B	0.2021762
283	using precision measuring equipment	H	0.2016886
83	measuring physical properties	B	0.1978871
98	monitoring, inspecting, and testing	B	0.1958799
89	estimating resource needs	B	0.1954115
70	interpreting technical documentation and diagrams	B	0.1927094
164	making decisions	D	0.1906456
286	maintaining mechanical equipment	H	0.1882897
146	developing contingency and emergency response plans	D	0.1882621
96	evaluating systems, programs, equipment, and products	B	0.1874835

** B – information skills, D – management skills, H – working with machinery and specialized equipment

b) Top 10 skills in the *sparsest* part of the skill space

Code	Skill	Group	Paths
130	preparing and serving food and drinks	C	0.0132432
173	using digital tools for collaboration, content creation, problem solving	E	0.0132618
2	negotiating	A	0.0194425
107	counselling	C	0.0230058
225	handling animals	F	0.0240738
154	performing administrative activities	D	0.0283299
180	sorting and packaging goods and materials	F	0.033479
200	tending plants and crops	F	0.0346276
212	fabricating tobacco products	F	0.0385133
63	solving problems	A	0.0400621

** A – communication, collaboration and creativity, C – assisting and caring, E-working with computers, F – handling and moving

5.5.2. Specialization patterns

It is not only essential to understand the skill structure of the skill space and which skills are in dense areas, but it is also important to investigate the location of different countries within the skill space. Using representative country examples, Figure 5-2 and Figure 5-3 show that a nation's skill specialization can take on three different patterns. The first group of countries use socio-cognitive skills effectively, while sensory-physical skills are used below average. In stark contrast, the second group of countries specialize above average in sensory-physical skills, while socio-cognitive skills play a subordinate role. The last group comprises countries that have strong specialization across the entire skill space. This grouping appears to be related to income levels. Countries with higher income levels tend to use socio-cognitive skills above average, whereas economically less developed countries in Europe have above-average use of sensory-physical skills.

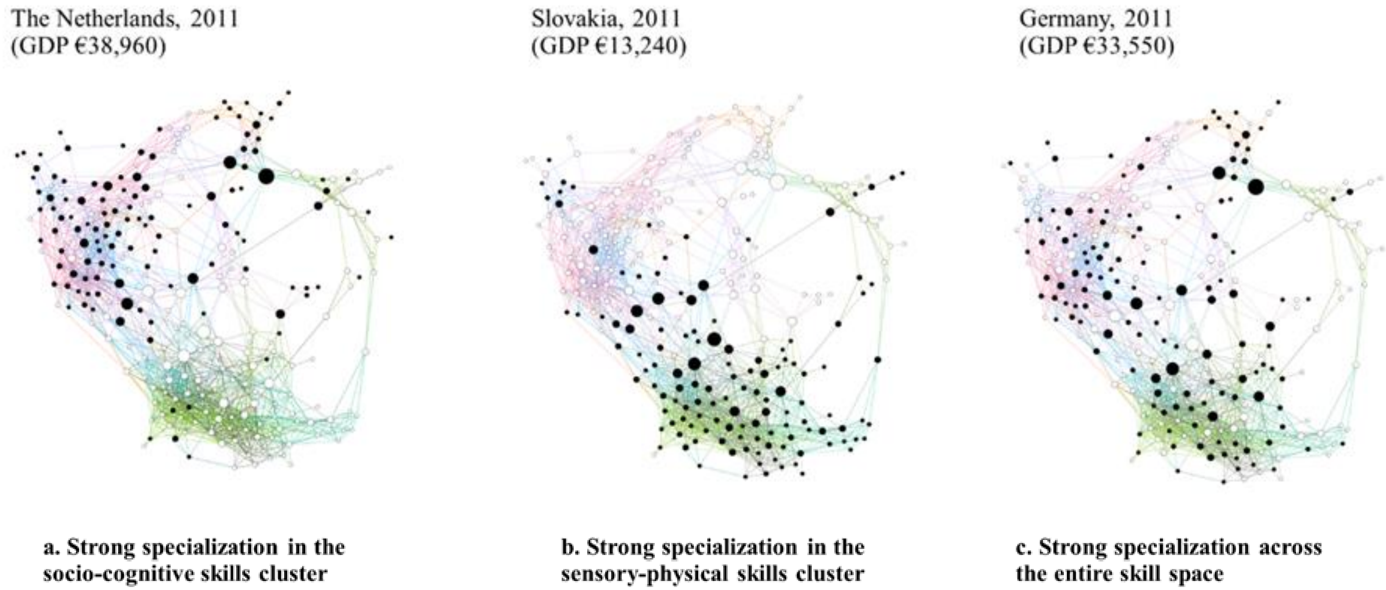
Comparing specialization patterns in the three sample countries (the Netherlands, Slovakia, and Germany) between 2011 and 2018 yields two observations.. First, changing skill specialization and transitioning to other parts of the skill space appears to be a slow process. Second, transitions tend to happen toward the stronger established position, such as a concentration in socio-cognitive skill specialization for the Netherlands and a shift to denser parts of the sensory-physical skill cluster for Slovakia. For Germany, only a barely perceptible shift toward denser parts of the socio-cognitive skills cluster can be observed.

Given the polarized skill space and different specialization patterns between countries, this study further investigates whether there are regional differences in skill specialization based on the quantity of comparative advantages in each region, using the skill-country matrix. As shown in Table 6-3, as of 2018, countries in west and north Europe specialize in different skills than countries in east and central Europe. Countries with above-average skill use from groups A-D tend to use skills from groups F-H below average. The more affluent west and north Europe have mostly relative comparative advantages in socio-cognitive skills, A-D. In contrast, the newer EU countries in east and central Europe have more comparative advantages in skill groups F-H, hence sensory-physical skills. Countries in the south of Europe are relatively diversified across all skill groups, except for working with computers and management. These findings indicate a regional polarization of skills that are used effectively across Europe.

With a measure of average centrality of all skills in which the country has a comparative advantage, Figure 5-2 and Figure 5-3 reveal that the two clusters have different specialization patterns. A location in the dense part of the skill space means that skills related to the current skill specialization are nearby, making it easier to adapt to new skill demands. Surprisingly, countries in central and east Europe, which have, on average, lower GDP per capita, specialize in the denser parts of the skill space, with most comparative advantages in the sensory-physical skills cluster. In turn, more prosperous countries in the west and north of Europe tend to specialize in socio-cognitive skills and less dense areas of the skill space. This finding is partially contrary to the expectations and the findings of Hidalgo et al. (2007) in the product space, where richer countries specialize in the dense part of the product space.

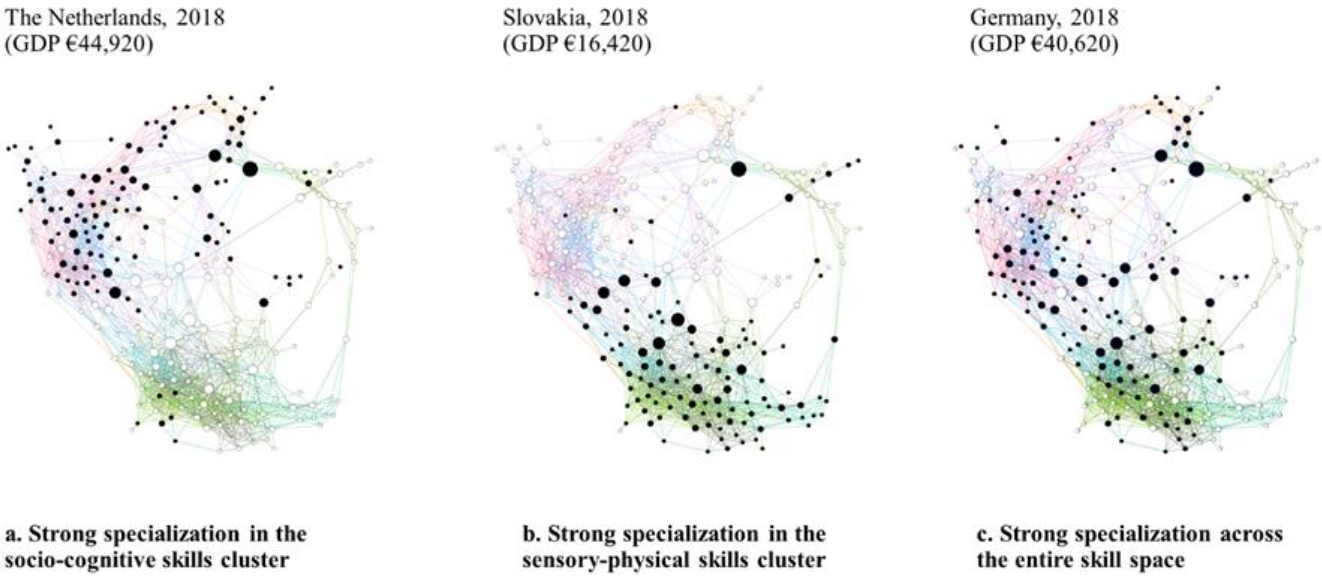
A comparison of 2011 and 2018's average centrality in Figure 5-4 shows that countries transition slowly through the skill space, implying that changing skill specialization is a relatively slow process. However, most countries move toward denser parts of each cluster. Regions tend to grow their efficient use of skills in skill groups that are already strong compared to less-developed skill groups. These evolutionary patterns suggest that skill specialization might be subject to path dependency. Thus, the following subsection empirically explores the existence of path dependency.

Figure 5-2 Different patterns of skill specialization, 2011



Notes: Skill specialization can take three different shapes, with strong specialization in a. socio-cognitive skills (Belgium, Switzerland, Denmark, Ireland, Iceland, Luxemburg, Norway, The Netherlands, Sweden, UK), b. sensory-physical skills (Czech, Spain, Italy, Croatia, Hungary, Portugal, Romania, Slovakia), c. the entire skill space (Austria, Cypress, Germany, Estonia, Finland, France, Greece, Lithuania, Latvia)

Figure 5-3 Different patterns of skill specialization, 2018

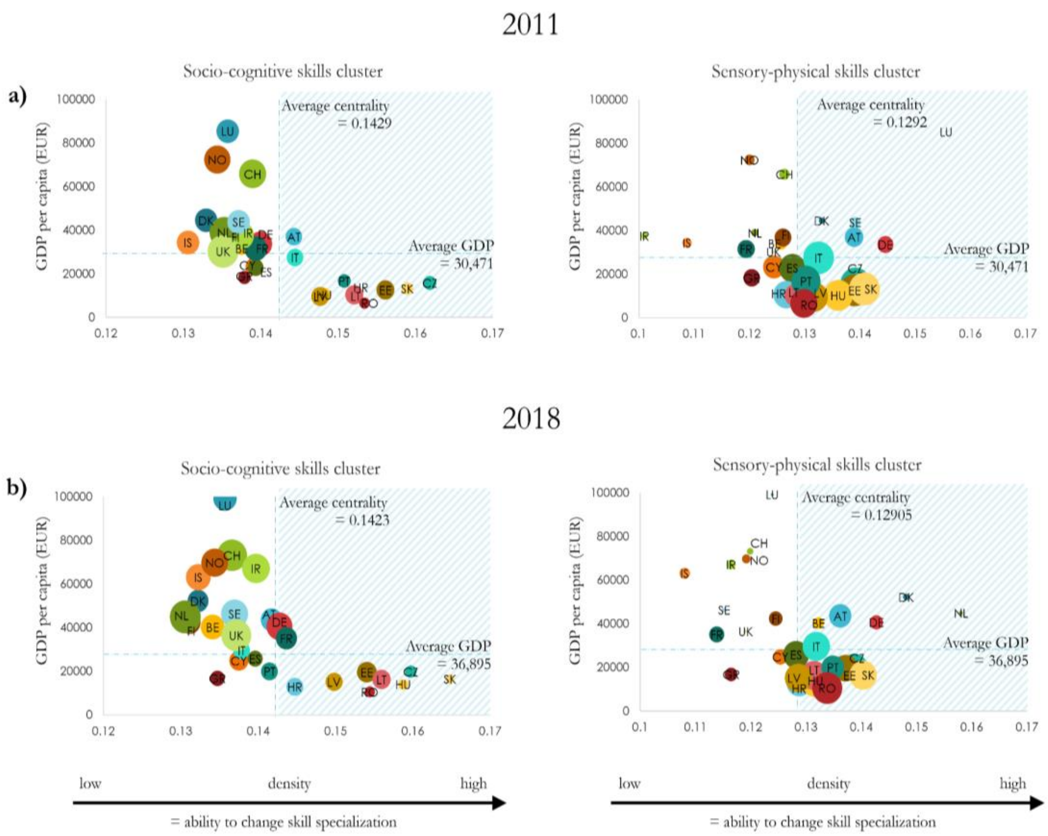


Notes: Skill specialization can take three different shapes, with strong specialization in a. socio-cognitive skills (Belgium, Switzerland, Denmark, Ireland, Iceland, Luxemburg, Norway, The Netherlands, Sweden, UK), b. sensory-physical skills (Czech, Spain, Italy, Croatia, Hungary, Portugal, Romania, Slovakia), c. the entire skill space (Austria, Cypress, Germany, Estonia, Finland, France, Greece, Lithuania, Latvia)

Table 5-3 Regional skill specialization based on the quantity of comparative advantages in 2018

2018		West		East		Central		North		South	
A	communication, collaboration, and creativity	44	(36.1%)	17	(11.6%)	13	(9.6%)	43	(32.8%)	24	(18.2%)
B	information skills	23	(18.9%)	17	(11.6%)	19	(14.1%)	19	(14.5%)	13	(9.8%)
C	assisting and caring	21	(17.2%)	6	(4.1%)	6	(4.4%)	19	(14.5%)	13	(9.8%)
D	management skills	20	(16.4%)	8	(5.4%)	4	(3.0%)	16	(12.2%)	5	(3.8%)
E	working with computers	10	(8.2%)	2	(1.4%)	3	(2.2%)	9	(6.9%)	2	(1.5%)
F	handling and moving	3	(2.5%)	45	(30.6%)	35	(25.9%)	9	(6.9%)	39	(29.5%)
G	constructing	0	(0.0%)	18	(12.2%)	17	(12.6%)	7	(5.3%)	16	(12.1%)
H	working with machinery and specialized equipment	1	(0.8%)	34	(23.1%)	38	(28.1%)	9	(6.9%)	20	(15.2%)
	Number countries	9		5		3		5		5	
	Total RCAs	122		147		135		131		132	

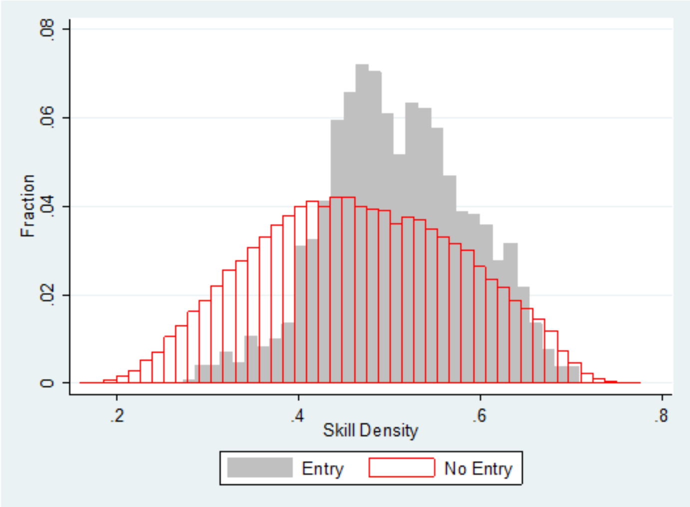
Figure 5-4 Average centrality of all skills in which the country has a comparative advantage



5.5.3. Path dependency

The statistical evidence from this study further supports the claim that countries are more likely to diversify into a new skill if the skill has a higher relatedness with the current skill structure. Figure 5-5 shows a histogram of the probability of diversification in the following period based on the current skill density level. The histogram reveals that the emergence patterns of new skills differ according to their relatedness to the existing skill structures. To test whether there were differences in the skills that were newly acquired by the countries, this study divided the skills into two groups. The first group comprised skills that experienced entry, which means that the country did not have a comparative advantage at time t but developed a comparative advantage at time t+1. The second group refers to skills that did not experience entry. Figure 5-5 shows that newly acquired (entry) skills show higher relatedness with the current skill structure than the skills that are not used efficiently (no entry) by a country in t+1.

Figure 5-5 Probability of diversifying into a new skill at t+1 based on the skill density at t



Lastly, econometric analysis tests whether there is a causal relationship between the current skill structure and the emergence of new skills. The dependent variable, $SkillRCA_{c,s,t+1}$, is the comparative advantage at time t+1. The key independent variables are $SkillRCA_{c,s,t}$ which captures the relationship with the new skill structure at time t, and $SkillDensity_{c,s,t}$, which represents the skill density at time t. Columns (1) and (2) in Table 5-4 show the regression results of the basic model using OLS and probit models with both independent variable. Columns (3) and (4) report the results of the full model, including control variables but without year dummy variables, and columns (5) and (6) include year dummy variables. As robustness check, an Arellano-Bond dynamic panel model using additional time lags confirms the results (see Table 5-5).

The results are consistent across the different models. The current presence of comparative advantage in skills has a significant and positive effect on the development of future comparative advantages in skills. In addition, the results show that lagged skill density has both significant and positive effects on $SkillRCA_{c,s,t+1}$. This suggests that the emergence of new skills is path-dependent, and that countries are more likely to acquire new skills if they are closely related to the skills in which they already have an advantage. Considering that developing new skills is a learning process, new skill emergence can be interpreted as learning by utilizing current knowledge or experience.

Table *5-6* shows the estimation results for the two skill types: socio-cognitive and physical skills. To analyze whether there is a difference in the path-dependent relationship by skill type, the estimation divided the sample into two groups of skills. The independent variable $SkillDensity_{c,s,t}$ was also divided into two types of densities: $CogSkillDensity_{c,s,t}$ representing the density of cognitive skills around skill s, and $PhySkillDensity_{c,s,t}$ for the density of physical skills around skill s.

As in the previous analysis, $SkillRCA_{c,s,t}$ has a positive and significant effect on the next period's comparative advantage in skills. Among the two types of density, $CogSkillDensity_{c,s,t}$ also showed a positive and significant effect on the comparative advantage of the next period across the two subsamples by skill type. However, the notable result is that $PhySkillDensity_{c,s,t}$ is significant and positive only for the physical skill subsample but insignificant for the socio-cognitive skill subsample. This means future physical skills' emergence depends on both the socio-cognitive and physical skill structures that countries currently have, but the adaption of socio-cognitive skills only depends on the current socio-cognitive skill structures.

Table 5-4 Econometric results for the estimation of the skill density based on the skill space

Dependent variable $\boldsymbol{SkillRCA_{c,s,t+1}}$	**OLS (1)**	**OLS (1)**	**OLS (3)**	**Probit (4)**	**OLS (5)**	**Probit (6)**
$SkillRCA_{c,s,t}$	0.822*** (0.003)	2.739*** (0.019)	0.820*** (0.003)	2.724*** (0.020)	0.819*** (0.003)	2.724*** (0.020)
$SkillDensity_{c,s,t}$	0.393*** (0.012)	3.343*** (0.104)	0.410*** (0.012)	3.521*** (0.108)	0.411*** (0.012)	3.531*** (0.108)
Population (log)			-0.017*** (0.004)	-0.156*** (0.033)	-0.018*** (0.004)	-0.160*** (0.033)
GDPPC (log)			0.021*** (0.006)	0.190*** (0.055)	0.022*** (0.006)	0.196*** (0.057)
Capital Stock (log)			-0.006 (0.006)	-0.044 (0.049)	-0.006 (0.006)	-0.048 (0.050)
Human capital			-0.013*** (0.004)	-0.134*** (0.036)	-0.013*** (0.004)	-0.136*** (0.037)
Edu. Expenditure			-0.002* (0.001)	-0.012 (0.012)	-0.002 (0.001)	-0.012 (0.013)
Tertiary Edu.			0.0001 (0.0002)	0.001 (0.002)	-0.0001 (0.0002)	0.001 (0.002)
Constant	-0.101*** (0.005)	-2.991*** (0.047)	-0.204*** (0.040)	-4.025*** (0.353)	-0.210*** (0.040)	-4.080*** (0.354)
Year dummy	No	No	No	No	Yes	Yes
Observations	54,810	54,810	54,810	54,810	54,810	54,810
R-squared	0.774		0.774		0.774	
Log-likelihood		-12032.1		-12008.1		-12002.8

* p<0.05, ** p<0.01, *** p<0.001, t statistics in parentheses, cluster robust standard errors

Table 5-5 Econometric results for the estimation of the skill density based on the skill space using Arellano-Bond model

Dependent variable $\boldsymbol{SkillRCA_{c,s,t+1}}$	**Lag 1 (1)**	**Lag 1 (2)**	**Lag 1 (3)**	**Lag 2 (4)**	**Lag 2 (5)**	**Lag 3 (6)**	**Lag 3 (7)**
$SkillRCA_{c,s,t}$	0.276***	0.278***	0.261***	0.367***	0.338***	0.353***	0.331***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.026)	(0.026)
$SkillRCA_{c,s,t-1}$				0.115***	0.097***	0.118***	0.105***
				(0.014)	(0.014)	(0.017)	(0.017)
$SkillRCA_{c,s,t-2}$						0.020	0.018
						(0.015)	(0.015)
$SkillDensity_{c,s,t}$	1.724***	2.016***	2.079***	1.444***	1.589***	1.421***	1.535***
	(0.052)	(0.058)	(0.056)	(0.079)	(0.078)	(0.130)	(0.134)
Population (log)		-0.083***	-0.097***	-0.067***	-0.077***	-0.067***	-0.074***
		(0.009)	(0.009)	(0.007)	(0.007)	(0.008)	(0.009)
GDPPC (log)		0.077***	0.090***	0.062***	0.071***	0.062***	0.068***
		(0.008)	(0.009)	(0.006)	(0.007)	(0.008)	(0.008)
Human capital		-0.044***	-0.042***	-0.032***	-0.034***	-0.029***	-0.030***
		(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.008)
Edu. Expenditure		-0.002	-0.007*	-0.003	-0.005**	-0.005**	-0.006**
		(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.475***	-1.261***	-1.405***	-0.961***	-1.088***	-0.958***	-1.039***
	(0.017)	(0.089)	(0.096)	(0.079)	(0.085)	(0.106)	(0.112)
Year dummy	No	No	Yes	No	Yes	No	Yes
Observations	54,810	54,810	54,810	46,980	46,980	39,150	39,150
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.000	0.000	0.000	0.779	0.312	0.575	0.975

Notes: Standard errors are shown in parentheses. * p<0.10, ** p <0.05, *** p<0.01.
AR(#) gives the p-value of the Arellano-Bond test for AR(#) in first differences

Table 5-6 Econometric results for the estimation from skill density based on skill space, by skill groups (physical / socio-cognitive)

	Socio-cognitive Skills (A, B, C, D)		Physical Skills (E, F, G, H)	
Dependent variable $\boldsymbol{SkillRCA_{c,s,t+1}}$	**OLS (1)**	**Probit (2)**	**OLS (3)**	**Probit (4)**
$SkillRCA_{c,s,t}$	0.820***	2.733***	0.802***	2.676***
	(0.004)	(0.026)	(0.004)	(0.030)
$CogSkillDensity_{c,s,t}$	0.471***	4.216***	0.167***	0.924***
	(0.020)	(0.176)	(0.028)	(0.234)
$PhySkillDensity_{c,s,t}$	0.013	0.263	0.435***	3.902***
	(0.029)	(0.252)	(0.020)	(0.018)
Population (log)	-0.017***	-0.168***	0.027***	0.316***
	(0.005)	(0.043)	(0.006)	(0.058)
GDPPC (log)	0.026***	0.194**	0.006	0.011
	(0.009)	(0.077)	(0.010)	(0.090)
Capital Stock (log)	-0.013*	-0.051	-0.038***	-0.359***
	(0.008)	(0.071)	(0.008)	(0.076)
Human capital	-0.016***	-0.144***	-0.041***	-0.415***
	(0.006)	(0.050)	(0.007)	(0.060)
Edu. Expenditure	-0.006***	-0.048***	-0.009***	-0.090***
	(0.002)	(0.017)	(0.002)	(0.021)
Tertiary Edu.	-0.0008***	-0.005**	0.001***	-0.011***
	(0.0003)	(0.002)	(0.0003)	(0.003)
Constant	-0.132**	-3.946***	0.510***	3.244***
	(0.055)	(0.486)	(0.074)	(0.659)

Year dummy	Yes	Yes	Yes	Yes
Observations	30,996	30,996	23,814	23,814
R-squared	0.775		0.778	
Log-likelihood		-6711.3		-5028.4

* p<0.05, ** p<0.01, *** p<0.001, t statistics in parentheses, cluster robust standard errors

5.6. Discussion

5.6.1. Skill specialization in Europe

This study set out to explore how the European skill structure looks like, what the patterns of specialization are for European countries and how skill specialization takes place with the goal to fosters an understanding of countries' skill endowments, and how they are related to the future development of skills.

This study shows that different countries specialize in different parts of the polarized skill space. Over time, most countries tend to move to the core and expand their specialization in the cluster in which they are already strong. The exploratory analysis also suggests that countries with higher GDP per capita tend to be located in the socio-cognitive lobe of the skill space, and that a shift away from the physical-skills cluster might occur as countries' economies develop. This observation is in line with Shutters and Waters (2020), who find that cities with more prosperous economies transition from sensory-physical areas of the skill network to socio-cognitive areas. One possible explanation is that, as countries develop and transition into knowledge/service economies, globalization trends (particularly outsourcing) and advances in production technology (e.g., the use of robots or AI) may drive the shift away from sensory-physical and toward socio-cognitive skills. Thus, exploring how regional specialization patterns are linked to economic development, outsourcing, or technology adoption would be a lucrative area for future studies to investigate.

Contrary to the expectations and previous findings from the product space (Hidalgo et al., 2007), less affluent countries in east, central, and south Europe tend to specialize in the denser part of the sensory-physical skill cluster (see subsection 5.5.2). The results of skill relatedness confirm that countries can diversify fairly easily into and acquire nearby related skills. The ability to adapt to new skill demands is important amid constantly changing skill demands in the labor market and enables countries to maintain a competitive workforce. Digital technologies have gradually replaced physical and routine-intensive tasks (Aubert-Tarby, Escobar, & Rayna, 2018; Frey & Osborne, 2017; McGuinness, Pouliakas, & Redmond, 2021). Thus, while these countries are likely to adopt new skills related to their current skill portfolio, the polarized skill structure, as visualized in Figure 5-1, might lead to a lock-in in the sensory-physical skills cluster, making it difficult for them to specialize in newly emerging socio-cognitive skills. This difficulty is amplified because diversification into new skills is a slow process. In turn, countries in western and northern Europe tend to specialize in socio-cognitive skills and less dense areas of the skill space, which means they are less likely to specialize in new skills due to their lower skill relatedness. Consequently, a skill trap can occur if they cannot adopt skills farther away in the skill space. However, considering the developments in the labor market, a shift toward socio-cognitive skills is occurring, possibly giving countries with stronger socio-cognitive skill structures an overall competitive advantage over other countries if they can make larger jumps in the skill space. These trends may further drive the wedge in the economic outcomes of European countries. Policymakers must address this issue to achieve further convergence and reduce inequality.

In addition, countries show a strong path dependence during skill acquirement processes, as future skills heavily depend on the skill structures currently possessed by the country (see subsection 5.5.3). The two skill types showed different patterns of path dependence, as having related socio-cognitive skills heavily influences both socio-cognitive and physical skills in the future, whereas having related physical skills has only an impact on future physical skills. This result points toward the possibility of a country getting trapped in the physical cluster, as physical skills do not provide a strong path to future socio-cognitive skills. In other words, only countries with socio-cognitive skills now are likely to have socio-cognitive skills in the future. These patterns answer the postulated questions and show that path dependence in skill development can explain why countries do not experience convergence in their skill structures.

5.6.2. Implications

Theoretical implications

Several studies have examines the industrial diversification patterns of countries through the path-dependent evolution of capabilities (Boschma et al., 2013; Hidalgo et al., 2007), yet only a limited number of studies analyze the actual people that possess the capabilities. Recently, studies have begun to explore the diversification of jobs at the regional level (Alabdulkareem et al., 2018; Farinha et al., 2019). Considering that industrial structures and jobs are the results of capabilities rather than the capabilities themselves, taking a step further, this study suggests another skill-based perspective to understand the dynamic structural changes of countries' capabilities. The results support the implicit assumptions of previous studies that the skills of individuals also evolve path dependently, and people are more likely to acquire new skills if they are more related to their current skill sets.

The impact of cross-country differences in human capital in explaining convergence between EU countries is further elaborated by the proven path-dependency of skills. The results indicate that a country's underlying skill structure might condition its future economic outcomes, thus adding to the literature on human capital by providing some evidence on the direct role of skills. Previous studies proxied skills using educational variables or adult skill test scores (Diebolt & Hippe, 2019; Hanushek, Schwerdt, Wiederhold, et al., 2017; Rodríguez-Pose & Vilalta-Bufí, 2005). Thus, this study adds to the literature by using actual data on the intensity of skills used in EU countries. This research enhances the understanding of the relationship between workplace skills and labor market outcomes.

Policy implications

The findings of this study suggest substantial implications for human resources policies aimed at repositioning countries' labor forces. Considering the rapid and challenging technological changes that are forecasted to displace jobs and cause fluctuations in the job market (Aubert-Tarby et al., 2018; Frey & Osborne, 2017; McGuinness et al., 2021), more countries are eager to provide new skills to their citizens to prepare for new types of work. In doing so, educational and labor policies should consider the current skill sets of the local labor force in addition to the potential of new skills, keeping in mind that strong path dependence occurs during the learning process. The transformation or acquisition of skills is less challenging if they are more related to the current skill sets, and the assessment of the current skill specialization should precede educational programs.

5.6.3. Limitations and future research

This study has some limitations that require further research. First, it covers only a short period between 2010 and 2018 due to the data consistency. However, many job displacements and transitions to jobs requiring different skill sets occur mainly during economic crises (Krebs, 2007), including the recent difficulties stemming from the COVID-19 pandemic (von Wachter, 2020). As this study does not cover enough time periods to evaluate the effects of crises on changes in skill structures, some results may have been influenced by socioeconomic changes. Further studies with a more extended time period would be able to assess the effects of external environments, such as economic crises, on skill diversification and restructuring. Second, ESCO data is currently only available for one year and thus does not capture skill changes in occupations. However, the skill content of occupations is not static, and changes over time. Future studies should consider this and analyze intra-occupational skill changes within the context of this research. Third, this study did not include differences in institutional factors (Boschma & Capone, 2015) in the analysis. Previous studies have pointed out that institutions, specifically labor market institutions, can affect workers' skill shifts and acquisitions (Filippetti & Guy, 2020; Howell & Huebler, 2001; Tang, 2012). Although this study found significant path dependence in skill diversification across countries, there can be differences between the countries with different institutional backgrounds, such as different degrees of labor market rigidity or education and labor policies.

5.7. Conclusion

This study constructed a European skill space based on the product space methodology (Hidalgo et al., 2007) using data from the EU LFS and ESCO. The main goal was to analyze the different skill structures of European regions and the path dependence of structural changes. The European skill space is based on aggregated skill data at the national level, where labor skills are measured directly through their link with occupations. This addresses the limitations of previous studies on national-level capability development, which relied on indirect proxies for capability, such as export or patent data. In contrast, studies on skill-relatedness, such as Alabdulkareem et al. (2018) or Shutters and Waters (2020), used direct skills measures but did not adopt a macro-perspective. Thus, this research adds to both fields by combining micro-level skills data with a macro-perspective of national-level capability development.

This study shows that there are significant differences in the skill structures of European countries. While countries in northern and western Europe tend to possess more socio-cognitive skills, those in southern and eastern Europe show comparative advantages in physical skills. In addition, regardless of region, European countries showed path dependence during their past structural changes in skills. These results indicate that there is little evidence to argue that the skill sets of European countries are becoming convergent, and that skill inequality among nations should be a serious policy issue in discussion of economic convergence in Europe.

Chapter 6.
Conclusion

6.1. Summary of the dissertation

This study set out to illuminate various aspects of human capital, focusing on the impact of technological change on labor markets. Technological advances have been transforming labor markets and affected workers and countries in various ways, increasing the relevance of human capital for economic outcomes at the micro and macro level. Most advanced countries have observed employment shifts away from routine jobs toward nonroutine jobs, and a fear of technological mass employment has emerged. However, as history has shown, technological changes tend to destroy jobs but also create new jobs. Those new jobs comprise a mix of novel job tasks that demand different skills, thereby transforming occupations. Therefore, rather than focusing on unemployment, it is crucial to understand how workers and nations in the aggregate can maintain productivity amid these trends.

Previous studies on human capital are inadequate to appropriately consider these developments. A comprehensive perspective of human capital from various angles to understand the implications of trends induced by technological change has not been sufficiently studied, and many works on human capital have limitations to address an evolving environment. To close this gap and supplement previous research, this dissertation analyzed different aspects of human capital and considered the implications of technological change. The results foster the understanding of the role of (1) education and routineness, (2) tasks and skill obsolescence, and (3) skills and capability development. Chapters 3–5 focused on these different aspects, respectively.

Chapter 3 analyzed the effects of routineness and education on wage premiums, focusing on the productivity-enhancing effects of education given job routineness. A variable for job routineness is introduced to the concept of the returns to human capital and employs panel fixed-effect regression and Heckman's 2-stage model to account for selection. Specifically, the chapter aimed to answer three questions to increase the understanding of routineness and education. First, this chapter examined whether higher education levels lead to improved returns regardless of the routineness of the occupation. Second, the chapter investigated whether higher routineness renders lower wages regardless of the education level. Third, the question of whether routineness has a more substantial impact on the wage premium than the education level was addressed.

The results indicate that education-wage premiums increase over education levels, which is consistent with the prevailing evidence in the field. Introducing routineness and interacting it with education confirms that the productivity-enhancing effects of education differ by routineness. This finding can be interpreted as more evidence for routine-biased technological change that affects employment and the effectiveness of education, implying productivity penalties in routine-intensive jobs.

Chapter 4 investigated the susceptibility of skills to obsolescence, emphasizing potential differences between education levels. The empirical analysis applied fixed-effects panel regressions to estimate an extended Mincer equation based on Neumann and Weiss's (1995) model. This chapter incorporated a task perspective based on the literature on job polarization to answer two sets of research questions. First, the study examined how the depreciation rate of human capital differs by education level and by the specificity of skills. Next, the task perspective was included to identify the possible effects of job-related technology on skill obsolescence.

The findings confirm that human capital gained from higher education levels depreciates faster than other human capital. The depreciation rate is also higher for specific skills compared to general skills. Moreover, the productivity-enhancing value of education diminishes faster in jobs with a high share of nonroutine interactive, nonroutine manual, and routine cognitive tasks. These jobs are characterized by greater technology complementarity or more frequent changes in core-skill or technology-skill requirements.

Chapter 5 investigated the skill structures of European countries and the evolution of skills from a capability development perspective. Specifically, the analysis first focused on understanding the skill structure in Europe and the patterns of skill specialization for European countries. The research then aimed to answer whether aggregate skill endowments explain cross-country differences and how skill specialization occurs.

The network visualization demonstrated evidence of a polarized European skill space. Major differences were evidenced among European countries regarding their skill structure and endowments. Countries in north and west Europe are strong in socio-cognitive skills, while the south and east of Europe show more comparative advantages in the physical skills cluster.

Moreover, the study confirms path dependence when acquiring new skills across all regions. The adoption of future skills heavily depends on a country's current skill structure. Notably, currently possessed sensory-physical skills only influence the adoption of related sensory-physical skills, possibly explaining barriers to further convergence.

In sum, the chapters in this study argue that the productivity-enhancing effects of human capital are closely linked to technology-induced changes that affect the labor market. Empirical evidence in the main chapters reveals various aspects of human capital. First, the effectiveness of human capital varies by the routineness of an occupation's tasks. Second, job tasks are significant influencing factors for skill obsolescence. Third, national-level skill specialization is an evolutionary process. These findings provide unique insights into the importance of skills and job tasks, implying to policymakers that the use of more granular measures such as skills and tasks is essential to consider amid ongoing technological change.

6.2. Implications

6.2.1. Theoretical

This study has several implications for theory, as already discussed in detail in the preceding chapters. Technologies transform labor markets, meaning that educational variables as a single avenue to guide education policy are insufficient. The results provide evidence that factors related to actual workplace skills and job tasks are crucial determinants of economic outcomes. This finding addresses the limitations of previous works on human capital, which mainly relied on educational measures or aptitude test scores measuring adult skills as a proxy for labor skills. This study highlights the significance of considering various, more nuanced factors to better understand the effects on heterogenous workers' labor market outcomes.

Specifically, the results showed that considering the routineness of occupations when analyzing the economic effects of human capital can lead to different conclusions, adding further evidence to the heterogeneous economic outcomes of workers. The findings of this investigation complement those of earlier studies on adverse wage effects for middle-skilled workers (e.g., Alda et al. (2020)). However, they differ from Alda et al. (2020) for high-skilled laborers. Although more research is needed to obtain a clear understanding, accounting for the effects of skill- and routine-biased technological change at the occupational level deepens the understanding of the specific implications of technological progress.

In addition, the study is the first to incorporate a task perspective into the analysis of human capital depreciation based on the classification used in works on job polarization and highlights the importance of accounting for job tasks. Most earlier works have focused on the effects of technological change on employment but fell short in considering the income opportunities of workers. Adding a task perspective allows for comparisons of monetary implications directly with studies on job obsolescence due to labor-replacing technologies. This analysis will facilitate a more holistic understanding of the effects of technological changes on the job market.

This thesis also offers a method to directly measure labor skills at the macro level through their connection with occupations. This approach addresses the limitations of previous studies on national-level capability development that have relied on indirect proxies of capability such as exports or patent data.

The results indicate that a country's underlying skill structure might condition its future economic outcomes, thus adding to the literature on human capital by providing some evidence for the direct role of skills. Previous studies have proxied skills using educational variables or adult skill test scores (Diebolt & Hippe, 2019; Hanushek, Schwerdt, Wiederhold, et al., 2017; Rodríguez-Pose & Vilalta-Bufí, 2005). Skills are perceived as highly relevant yet quantifying skills has been challenging and data availability remains limited (Shutters & Waters, 2020). Although there are emerging studies at the micro level that use a direct measure of skills using skill-relatedness (e.g., Alabdulkareem et al. (2018) Shutters and Waters (2020)), these works did not adopt a macro perspective. Therefore, this research added to both fields by combining micro-level skills data with a macro perspective of national-level capability development using real data on the intensity of skills used in EU countries.

6.2.2. Practical

This dissertation provides stark evidence for necessary action to address the possible adverse effects of technological changes on human capital and productivity. Considering aspects of skill-biased and routine-biased technological change at the occupational level deepens understanding of the specific challenges for workers with various skill and routine levels, allowing policymakers to address these challenges more effectively. The results have implications on a micro and macro level.

At the micro level, the results of the current study facilitate the introduction of policies targeting differences in labor market outcomes for high-, medium-, and low-skilled workers amid technological change. Considering the changing task and skill requirements, educational content and on-the-job training may smooth the transition from routine to non-routine-intensive jobs and reduce inequality. Another significant practical implication is that a redesign of educational measures is recommended focusing on equipping workers with more general skills at all education levels. With ongoing technological advances, work environments, and with-it, skill demands will change, rendering previous human capital obsolete. This development increases the urgency to provide combined labor market, educational, and lifelong learning policies to counteract the depreciation of skills. Therefore, a key policy priority should be to provide adequate education policies targeting the obsolescence of human capital.

Increasing the education level of the workforce is not enough. Changes in educational content and investments are inevitable. Policymakers and companies should design effective training programs that allow professionals to periodically update qualifications considering the workplace's technological knowledge requirements. Such programs should enable workers to quickly adapt their abilities to changing market conditions. Taken together, policies acting at the micro level must address ongoing challenges and prepare the workforce for more agile environments in which constant learning and adapting will be necessary.

At the macro level, the results indicate no convergence among the skill sets of European countries, implying that economic convergence might be difficult to attain unless governments target skill differences among countries. Consequently, targeting skill inequality among nations should be a serious policy issue regarding economic convergence in Europe.

The findings across the three studies suggest substantial policy implications for human resources policies aiming to reposition countries' labor forces. The rapid transformation of labor markets and work environments has caused the displacement of some jobs (Frey & Osborne, 2017) and led to the obsolescence of certain skills and tasks. Thus, government actions are necessary to prepare the labor force for new skills, tasks, and occupations. This can be achieved through government or firm interventions that facilitate upskilling of the labor force, helping workers at risk of adverse effects to adapt better to changing environments. Such skill sets could be attained differently, such as itemized skill sets to ensure a targeted adoption and retention of skills with high demand in the labor market. When implementing such programs, countries must consider the skills currently needed as well as those in the future labor market, improving the match quality of the worker's skills with skills needed in the labor market (OECD, 2017).

An alarming finding of this research is that education seems to be less effective in increasing worker productivity in jobs mainly composed of routine tasks. The skill premium might widen under low levels of routineness, increasing inequality in the labor market. This is a worrisome finding considering trends in the labor market. The effects of skill-biasedness, which has caused inequality, are magnified with the shift to nonroutine tasks in the labor market, thus suggesting that technological change drives a wedge between skill levels and the routine content of the job.

A key implication of this study is that educational and labor policies should consider the local labor force's current skill sets and the potential of the new skills, keeping in mind that strong path-dependence takes place during the learning process. The transformation or acquisition of skills is less challenging if they are more related to current skill sets. Moreover, an assessment of workers' current skill specialization should precede the implementation of educational programs.

When applying the findings from this research to other environments where technological change might be different, for example, at a sectoral level, the methodology and structure of the research may be maintained. However, case-specific differences must be carefully considered. In less rapid environments, the effects would probably be less pronounced, whereas in rapidly changing environments, the differences between routine and nonroutine jobs as well as skill obsolescence could be stronger. When considering those differences, the findings can provide useful insights into the transformation of workplaces and can serve as a guideline for policies in less-advanced countries that are yet to go through this transformation. Moreover, future transformations might have similar effects; hence, this study can serve as a starting point for analysis of future transformations and adjustments in educational policies.

Although the studies in this dissertation are based on data from the past decades, the findings provide crucial insights related to these developments. The findings can be applied to better adapt to future changes imposed by various types of technological changes. The three studies showed that the demanded skills and human capital are not static but change over time, implying that in 10 or 20 years, the required skill set can be quite different from the one needed today. Thus, the main challenge of education is that it needs to prepare workers for as-yet-unknown jobs.

Given the transformative changes due to novel technologies, retraining is essential, and optimal timing is crucial in designing effective policies. The optimal point for retraining to maintain human capital must be at the turning point of the experience-earnings profiles, which appears to be after approximately 20 years in the labor force. However, the intervals will likely shorten due to an accelerating pace of technological development.

While the outlooks for workers in the labor market may seem less promising with the increasing use of labor-replacing technologies such as robots or AI, there is little doubt that human labor will still be needed. Nonroutine, intensive interactive tasks, such as managing, or activities that entail creativity or originality remain necessary to create innovation and use emerging technologies. In the end, the current changes are merely a transitionary process that is shifting or creating new skill demands. If complemented by effective educational and labor market policies, these changes can invite new opportunities for workers, firms, and countries alike.

6.3.Limitations and future research

Some limitations suggest possible avenues for future research. First, Chapters 4 and 5 use data on Germany when analyzing implications at the micro level. The German labor market and education system have quite distinct features with a strong dual system where many workers choose specific over general education. Thus, it is unclear whether the results can be applied to countries with different institutional settings. Future studies should explore the relationship between education and skill obsolescence with a task perspective for other countries to generalize the findings. Nevertheless, the studies contribute to the literature by extending the mostly U.S.-focused empirical evidence. Germany is a significant economic power, renowned for its innovations and technological skills, and is often referred to for its tuition-free but quality education system. Learning how the country addresses the challenges of technological change and advances in capability building is important for other countries. Hence, the results of this study can serve as a valid benchmark for other nations with similar characteristics.

Second, the studies in this manuscript did not explicitly account for institutional factors. However, previous scholars have highlighted that institutions in general and labor market institutions specifically (Boschma & Capone, 2015) possibly influence economic outcomes, particularly regarding skill shifts and acquisitions (Filippetti & Guy, 2020; Howell & Huebler, 2001; Tang, 2012). Considering institutional differences can provide further insights into the link between economic outcomes and skills.

Third, the study on the European skill space covers only a short period of eight years. However, change is a slow process, and it may be necessary to cover more extended periods to fully understand the structural transformations in the skill space. Due to inconsistencies, the process of matching occupational classifications from ISCO-08 and ISCO-88 has imposed challenges for many researchers, and it would have been too time-consuming to conduct the task appropriately.

Finally, to add another piece to the puzzle regarding the implications of technology-induced labor market transformations, future works might want to consider using ESCO data on workplace skills and examine how the returns to specific workplace skills differ and which skills suffer a greater risk of obsolescence. Alternatively, the European skill space also lends itself to deeper analysis of educational or technological factors such as the routineness of skills or by considering sectoral differences.

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Abstract (Korean)

초 록

미시적 및 거시적 수준에서 인적자본에 대한 기술변화의 시사점 : 기술, 작업 및 노동 시장 결과에 대한 연구

Sonja Walter
Technology Management, Economics, and Policy Program
The Graduate School
Seoul National University

기술 발전은 기술 요구 사항을 변경하거나 일자리를 대체함으로써 노동 시장을 변화시킨다. 노동 대체 기술이 실업에 미치는 영향을 추정한 저명한 연구는 기술 변화로 인한 부작용에 대한 두려움을 불러일으켰다. 다른 연구에서는 기술이 아직 알려지지 않은 새로운 일자리를 창출한다고 주장하면서 이러한 발견에 이의를 제기한다. 고용 효과에 대한 합의는 없지만 학자들은 기술이 노동 생산성을 증가시켜 현대 경제의 근간이 되는 원동력이 된다는 데 동의한다. 기술 중심의

성장은 인적 자본 없이는 불가능하다. 기술에 의한 생산성 효과를 활용하기 위해서는 지식과 기술이 필요하므로 교육이나 경험을 통해 축적되어야 한다. 그러나 정규 교육을 통해 획득한 인적 자본이 노동 생산성을 높이는 데 여전히 효과적인지 여부는 불분명하다.

이 논문은 미시적 차원과 거시적 차원에서 지속적인 기술 변화에 따라 변화하는 인적 자본의 역할을 살펴보고자 한다. 먼저 2 장에서는 인적 자본에 대한 배경 문헌의 개요를 제공하고 기술 변화와 인적 자본의 관계를 쉽게 이해할 수 있도록 가장 중요한 측면을 구성하는 몇 가지 관련 주제를 논의한다. 그런 다음 본문의 주요한 세개의 장은 기술 변화 속에서 특히 관련이 있는 인적 자본 및 노동 시장 결과의 다양한 측면을 조사한다.

이 연구는 기술 변화가 서로 다른 근로자에게 같은 방식으로 영향을 미치지 않는다는 주요 주장을 바탕으로 미시적 수준에서 시작한다. 실업 효과에 초점을 맞추기보다는 처음 두 장은 기술, 작업 및 직업의 일상적인 측면을 고려하면서 개인 수준에서 인적 자본의 효과를 수량화하는 것을 목표로 한다. 기술은 인적 자본의 중요한 측면이며 경제적 산출 측면에서 노동을 분석할 때 매우 관련성이 높은 것으로 간주된다. 미시적 관점에서 벗어나 이 연구는 미시적 수준의 노동력 데이터에서 직접 국가 간 기술 구조를 설명하는 것을 목표로 거시적 관점을 채택한다. 본문의 주요한 세개의 장의 내용은 아래에 더 자세히 기술되어 있다.

3 장에서는 일상적인 직업과 교육이 임금 프리미엄에 미치는 영향을 조사한다. 초점은 특정 교육과 일반 교육 간의 차이를 고려하여

비일상 및 일상 작업 근로자의 생산성 향상 효과 간의 잠재적 차이 이다. 분석은 1984-2017 년 동안 독일 사회경제 패널(GSOEP)의 데이터를 사용하여 패널 고정 효과 회귀에 의해 추정된 수정된 Mincer 수익 방정식을 기반으로 한다. 이 연구에서 가장 분명한 발견은 교육 수준에 따라 교육 급여 프리미엄이 증가한다는 것이다. 시간적 분석에 따르면 1980 년대에 교육 임금 프리미엄이 가장 높았으며, 이는 컴퓨터 기술의 기술 보완 및 생산성 향상 특성에 기인할 수 있다. 더 중요한 것은, 직업적 업무 일과성에 관한 결과는 비일상적인 집약적 업무에 종사하는 근로자의 교육에 대한 더 높은 수익을 나타내는 반면 교육은 더 높은 수준의 업무 일과성의 수준에서 생산성 향상이 덜한 것으로 판명되었다. 이 연구에서 나오는 또 다른 중요한 발견은 기술 프리미엄이 일상적인 수준이 낮을 때 확대되어 노동 시장의 불평등을 증가시킨다는 것이다. 이 연구에서 나오는 또 다른 중요한 발견은 VET 를 가진 근로자의 일상적인 처벌이 숙련도가 높은 근로자에 비해 더 심하여 노동 시장의 불평등을 확대하는 데 기여한다는 것이다.

이러한 결과는 기술 변화 속에서 고, 중, 저숙련 근로자의 노동 시장 결과의 차이를 목표로 하는 정책의 도입을 용이하게 한다. 변경된 작업 요구 사항을 고려할 때 교육 및 노동 정책은 일상적인 작업에서 비일상적이고 집약적인 작업으로의 전환을 원활하게 하고 불평등을 줄일 수 있다. 이 장은 교육에 대한 서로 다른 수익의 증가에 대한 경험적 증거를 추가한다. 또한, 다양한 기술 수준의 근로자가 직면한 특정 문제를 해결하고, 기술 편향 및 일상 편향 기술 변화가 직업 수준에 미치는 영향을 분석하여 기술 변화의 의미에 대한 최근 토론에 기여한다. 특히,

비일상적인 집약적 작업에 종사하는 근로자를 위한 직업 교육 및 훈련(VET) 문제를 다룬다.

4 장에서는 인적 자본 감가상각과 직무 간의 연관성을 분석하여 교육 수준 간의 잠재적인 차이를 강조한다. 패널 데이터를 사용하여 이 연구는 Neuman 과 Weiss(1995)의 인적 자본 감가상각 모델을 작업 관점으로 확장하여 추정한다. 연구 결과에 따르면 교육 수준이 높을수록 인적 자본이 더 빨리 감가상각된다. 일반 스킬에 비해 특정 스킬의 감가상각률도 높다. 이 연구에서 나온 가장 중요한 발견은 교육의 생산성 향상 가치가 일상적이지 않은 대화형, 비일상적인 수동 작업 및 일상적인 인지 작업의 비중이 높은 직업에서 더 빨리 감소한다는 것이다. 연구 결과는 추가적으로 이러한 직업이 기술 변화를 자주 겪거나 기술과의 상호 보완성이 더 크다는 것을 의미한다.

이 장에서 획득할 수 있는 통찰력은 정책 입안자들에게 중요한 의미를 제공한다. 주요 정책 우선 순위는 모든 교육 수준에서 근로자에게 보다 일반적인 기술을 제공하는 것이다. 지속적인 기술 발전, 작업 환경 및 그로 인해 기술 요구 사항이 변경되어 이전의 인적 자본이 쓸모 없게 될 것이다. 이것은 기술의 가치 하락에 대응하기 위해 통합 노동 시장, 교육 및 평생 학습 정책을 제공해야 하는 시급성을 증가시킨다. 이 장은 직업 양극화에 관한 저작에서 사용하는 분류에 기초한 과업관점을 기술노화화로 통합한 최초의 실증적 연구라고 볼 수 있다. 이는 인적 자본의 감가상각률을 노동 대체 기술로 인한 고용 노후화에 대한 연구와 비교할 수 있는 전체론적 접근의 토대를 마련한다.

5 장에서는 유럽 국가 전반에 걸친 능력 개발의 관점에서 다양한 기술 구조와 진화를 조사하기 시작했다. 2011 년부터 2018 년까지 유럽 기술, 역량, 자격 및 직업 분류(ESCO)의 기술 직업 데이터와 EU 노동력 조사(LFS)의 직업 국가 데이터를 연결하여 이 장에서는 스킬 스페이스 구성하기 위해 제품 공간 방법론에 기반한 국가 스킬군을 제시한다. 스킬 네트워크의 시각화는 유럽의 스킬 구조가 주로 사회인지 스킬로 구성된 클러스터와 주로 감각-물리 기술로 구성된 두 가지 주요 클러스터를 가지고 있음을 보여준다. 추가 분석은 유럽 국가 간의 기술 구조에서 현저한 차이를 보여준다. 계량 경제학 분석의 결과는 현재 스킬군이 미래 기술 채택 가능성을 결정하는 기술 개발의 강력한 경로 의존성을 확인한다.

종합하면, 연구 결과는 기술 공간의 양극화 구조가 기술 측면에서 수렴을 불가능하게 만들 수 있음을 시사한다. 따라서 국가 및 초국가적 정책의 과제는 더 많은 경제적 수렴을 달성하기 위해 유럽 국가 간의 기술 불평등을 줄이는 것이다. 본 연구는 기술연관성에 대한 미시적 연구와 국가적 역량개발의 거시적 관점을 결합한 최초의 연구이다.

요약하면, 이 논문의 주요 의미는 기술과 작업이 경제적 결과의 중요한 결정 요인이라는 것입니다. 특히 노동시장에서 가장 작은 존재로서의 기술은 개인관 국가의 경제적 성과와 밀접한 관련이 있다. 전반적으로, 연구 결과는 지속적인 기술 변화 속에서 효과적인 정책 권장 사항을 제공하기 위해 기술 및 작업과 같은 보다 미묘하고 세분화된 조치가 필수적임을 시사한다. 이 연구에서 얻은 통찰력은 정책 입안자가 인적 자본에 대한 기술 변화의 의미를 다루는 데 도움이 될 수 있다.

주요어: 인적 자본; 노동 시장; 스킬; 작업; 기술 변화

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