Artificial Intelligence, Productivity and Performance

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Declaration

I hereby declare that except where duly acknowledged, this thesis is entirely my own work undertaken at the Warwick Business School.

It is being submitted for the degree of Doctor of Philosophy at the Warwick University of Warwick. It has not been submitted for any degree of examination in any other university.

Abstract

The thesis contributes to the field of digital economy and strategy. It links and contributes to readdressing several key economic issues, such as the AI productivity paradox, the UK productivity puzzle, EU productivity gaps, and the firm's profitability and performances from a distinct point of view. We shed light in terms of the underlying mechanisms of AI and cloud computing technologies and the role of unmeasured intangible capital and investigate the consequences of digital adoption and diffusion. All the three papers are quantitative empirical analysis leveraging multiple quantitative methods and panel data analysis. They are separate chapters but also inter-connected, bringing a complete picture to understand emerging technologies. The gaps and contributions are highlighted in the part of the introduction (the overview) and are discussed with rich details in each chapter accordingly.

1 Chapter 1: Introduction

1.1 AI: What is AI

The word "artificial intelligence" involves fundamental economic issues on what happens if AI allows the vast number of tasks previously performed by humans to become automated performed by machines. Recent progress in AI, particularly marching learning, has dramatically increased predictive power in many areas, such as speech recognition, image recognition and credit scoring (Brynjolfsson and Mitchell 2017, Agrawal et al. 2016). Other sets of AI technology systems have been developed related to processing information from external worlds, such as language and computer vision, acting on information which are computer programs conversing with humans such as robotics process automation, autonomous vehicles and virtual agents etc. It is challenging to characterize AI uniquely as the definition can change depending on the specific context of research. In some studies, what is concerned is called 'narrow AI 'to perform narrow tasks. For instance, Urban (2015) illustrate examples of narrow AI, including Google's seal-driving cars, targeted recommendations, google translations, chess playing etc. The OECD (2016) describes AI as a machine performing human-like cognitive functions such as learning, understanding, reasoning and interacting. This definition tends to embrace a broad definition of AI The broad AI is described as a system that can be applied to many context-sensitive situations where it can mimic human activity or human decision-making (Vorhies 2016). In other words, it refers to computer systems' capability to perform tasks that normally require human intelligence. In many cases, AI means specific business processes and inventions. Mckinsey (2017) surveyed firms using AI and brought real-world insight into the general use of business applications AI. They employ a narrower view of AI adoption, and it is opposite to the strict definition of 'artificial general intelligence' (AGI), which seeks to be able to perform any intellectual task belonging to the human. In their analysis with 3000 firms' senior executives interviewed, five major technology systems are categorized as the critical areas of AI development, typically including robotics and autonomous vehicles, computer vision, natural language, virtual assistants and machine learning.

1.2 The Measure of AI - automation, machine learning or other approaches

Overall, we found very little body of empirical literature surrounding AI to examine its economic impacts systematically. Having a good measure of it with the current state is difficult. Primarily, computer scientists emphasize that the feasibility of true artificial general intelligence is equal to or exceeds human intelligence (Bostom 2016). Seamans and Raj (2018) point out that no public datasets are available on the utilization or adoption of AI at either the macro/micro level. Comparably, more studies on robotics are available underneath the broad AI definition. It could be highly attributed to the physical nature of robotics, making it more convenient to be tracked over time and locations. Fuman and Seamans (2018) suggest that robotics shows clear analogies to AI and discuss the links between AI, robotics and economic outcomes regarding labour and productivity. AI components can be embedded in robotics, and for the case of productivity growth from AI Hence, we may look into empirical studies on robotics for support. Aghion et al., 2017 focus on the implications of artificial intelligence on economic growth. They define artificial intelligence as automation and model it as a process where capital replaces labour at an increasing range of tasks based on Zeira's (1998) automation model. They introduce AI (automation in their definition) into idea production functions and expect a rising productivity growth rate from a theoretical perspective. Empirically, the European Commission Report on Robotics and Employment (2016) examines industrial robots' use. The report shows that firms utilizing robotics are significantly related to higher labour productivity levels among the 3000 surveyed manufacturing firms from seven E.U. countries. By looking at national-level data from the International Federation of Robotics (IFR), Graetz and Michaels (2015) suggest robotics could be responsible for about 1/10 of the increase in annual GDP and enhance productivity growth at more than 10% between 1993 to 2007 across 17 European countries. The contribution is comparable to the effects of adopting steam engines in the 19th century. However, robotics can be informative in the manufacturing sectors and might be incomplete in revealing the situation in service industries, which constitute the bulk of modern economics. In addition, impacts from automation in robotics cannot clearly capture the nature of intelligence through an algorithm or machine learning. AI can be modelled as a drop in the costs of prediction, according to Agrawal, Gans and Goldfarb (2018). The rapid advances in prediction technology are the key driver of the current excitement of AI and believed with a profound influence in terms of AI's microeconomic impacts on enterprises. In this case, AI is defined by machine learning, a prediction technology. Although automation is a consequence of AI instead of AI per se, it is often labelled as AI and used as a more common measure in current literature.

Goolsbee (2018) interprets AI as a cluster of information technologies beyond just conventional artificial intelligence or machine learning and discusses policy tools. In my thesis, to examine AI's economic impacts concerning various components, I employ a broad definition of AI, which includes several innovative technologies and then construct a proxy for the following two chapters. We understand AI as a collective term for computing systems that can sense the external environment, think or perceive, and respond to information they have captured and their objectives. This is a broad view of intelligence as the quality that enables an entity to function appropriately and with foresight in its environment (Gillham et al., 2018, MGI report, 2017). According to this definition, this expansive view of AI includes the types of computer vision natural language processes, deep learning, robotics and automation systems, etc., and all the related applications would require investments in software and computing hardware. Empirically, the chapter follows the same approach to create a proxy for AI uptake or AI-related investments, initially adopted by the Economic Report of PwC (2018), "The macroeconomic impact of artificial intelligence". In this study, AI-related investment is measured by the capital stock on software, databases, and computing equipment of different types of emerging technologies. This approach to modelling AI is also coherent with the recent paper "Artificial Intelligence and Productivity" by Corrado, Haskel and Lasinio (2021). In the study, they treat the spending on AI as investments in productive assets as a bundle of hardware, software and databases.

It might be worth highlighting that the definition of AI employed in this chapter is different from the definition of ICT-related capital. Not all ICT technologies are included to create the proxy AI.

According to the EUKLEMS methodology guidebook (2019)[1]，standard ICT technologies cover three types of assets: computer hardware, communications equipment, software and databases. Communications equipment, for instance, which refer to the hardware used for telecommunications and networks, is not understood as part of AI-related investment in our measure. Instead, these types of ICT technology but not AI related are categorised as general tangible assets and controlled separately in the production function in my analysis. From this point of view, implications from the chapters can be different from the strands of literature that examine the relationship between general ICT technologies and productivity growth. We believe this thesis brings implications and empirical evidence on general purpose technologies which gain different characteristics from traditional ICT technologies. Compared with Haskel's paper on ICT, intangible and productivity (2014), the first chapter not merely introduce those unmeasured intangibles in the production function but, more importantly, concern AI's impacts on different product components and hence unlock relative mechanisms such as AI's impact on capital efficiency, labour substitution vs labour creation effects due to competitive prices or innovations. The relative importance of intangibles under two broad categories is compared, including innovative capital and economic competences. Although the economic competence type of intangibles generates higher contributions in enhancing general productivity growth, innovative capital helps exploit AI technologies' benefits. All these details are not addressed in previous literature.

In the final chapter, we unpack the mechanisms of how cloud computing can enhance firms' profitability gains. The U.K. e-commerce survey provides information on firms' purposes for purchasing cloud computing services, including essential Microsoft Office, file storage, hosting business's database, Finance or CRM applications and enhanced computing capacity. According to the definition of OECD (2014, 2021), cloud computing technologies are generally referred to as a set of computing resources (e.g.networks, servers, storage, applications and services) which can be accessed on-demand and flexibly. The U.S. National Institute of Standards and Technology

[1] The EUKLEMS methodology guidebook distinguished ICT and non-ICT capital. Software and databases are classified as intangible ICTs, and computer hardware, and communications equipment are classified as tangible ICTs.

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(2011) describes some essential features of cloud computing to understand where it sits within the standard product classifications. Overall, three key characteristics can be summarised regarding cloud computing services: on-demand, rapid elasticity or scalability, and low management efforts. The computing recourses from the provider are pooled and serve multiple users (multi-tenant model) through a remote internet connection. Users or firms can access the computing resources, for instance, storage, processing, memory and network bandwidth, dynamically as needed in a self-service way. Traditionally, investments in ICT technology are associated with considerable upfront suck costs in terms of purchasing hardware infrastructure, software and maintenance of the I.T. service. Now firms can obtain storage, processing capability and software applications through the "cloud computing" service as an on-demand subscription.

In terms of the relationship between the adoption of cloud computing and AI, there are some types of cloud computing services, such as enhanced computing capacity, are closely related to AI adoption, while some aspects of the cloud are only concerned with digital technology. For example, users can obtain Business Intelligence tools can be obtained, allowing organisations to analyse or mine the data, identifying underlying patterns. Business intelligence can be inserted with machine learning tools (one type of AI) to enhance predictions and forecasting for decision-making or realise an enhanced new product design. By Iaas service, users can obtain computing capability through the virtual machines (servers) to rent with the desired amounts of computing and memory/storage. Cloud providers will offer GPUs and HPCs, which are in conjunctional with traditional processors, for machine learning workloads or AI Visual recognition pictures (AI workloads) are stored in the object storage cloud and can be used to train the AI model running on the high-speed GPU servers.

1.3 The Overview

Cockburn et al., 2018 point out that scholars believe that AI and other forms of advanced automation, including robotics and sensors, have the potential as general-purpose technology to drive follow-on innovations and future productivity growth. According to Bresnahan and Trajtenberg (1995), a GPT is characterized by pervasive use in various industries and technological dynamics. However, a notable insight for past general-purpose technologies (GPTs) is that there is a significant period of readjustment, relocation, and changes in the business process (McElheran 2018). As the GPTs**,** their potential is constrained by the lack of complementary investments and notable lags between technological progress and commercialization of new ideas building on the progress (Brynjofsson et al. 2017 2018). Changes may happen relatively quickly, while the dominant result will not be promising as it is eventually subject to the firm's existing inertia. Uncertainty and constraints can be either internal or external (McElheran 2015; Gans 2016). Hence, the current **AI paradox** exists that despite the recent rapid technology process in advanced technology such as AI, corresponding increases have yet to be reflected in the productivity statistics. In other words, given rapid innovations of AI, and emerging technology, we observe surprisingly low measured productivity growth. As a fundamental starting point, Brynjolfsson, Rock and Syverson (2017) point out that current productivity will only tell more capital and labour inputs are used up in producing measured output. Inputs used to produce unmeasured capital as part of components in a complementary system will instead resemble lost potential outputs. The more relevant literature review will be discussed in each chapter. The complementary assets associated with the last wave of computerization were believed to be about ten times as large as the direct investments in computer hardware itself. Brynjolfsson, Rock and Syverson (2017) suggest the plausibility that AI-associated intangibles could be of a comparable or even greater magnitude.

The above issue of the AI productivity puzzle is the starting point of my thesis. The thesis also links and contributes to readdressing key economic issues, such as the U.K. productivity puzzle and E.U. productivity gaps, unpacking the consequences of digital adoption and diffusion from different angles. The three papers are separate but are all centred around investigating the economic impacts of emerging technologies (AI and cloud computing) and unpacking their underlying mechanisms by industry and firm-level analysis. The detailed literature review for each paper to derive the hypothesis, the gaps and contributions will be discussed in each chapter separately. The following overview briefly highlights what I did in the following three papers.

In the **first paper**, we contribute to the long-term U.K. productivity puzzle debate. Current output measures such as GDP and value-added are not adjusted for intangible capital and AI-related investments (Haskel and Westlake 2017). The study estimates AI's effects on output and productivity growth and explores the role of various previously unmeasured intangibles in the context of the AI productivity paradox. First, we systematically establish the synergies between AI uptake and different intangible components and compare the relative importance of two broad categories within the framework, innovative capital and economic competence, in enhancing AI productivity. As Seamans and Raj (2018) suggest, even though technologies may be contributing to GDP growth at the national level, it is crucial to understand how AI can affect productivity, the mechanisms and in-deep questions about the role of AI in the economy. This paper answers how AI can affect productivity growth by interacting with different productive inputs. The discussion also involves the hypotheses on AI's effect **on capital efficiency**, **redistributing** and/or **augmenting labour**, net effects on **labour substitution** vs **labour creation**, etc. Beyond the modelling of AI and different intangible investments, we analyze the channels and how AI affects other productive inputs, given the U.K.'s finer industry information.

Then the **second paper** is developed, motivated by the issue of **E.U. productivity gaps**. In the decade before the crisis, Statistics suggest the U.S. is accelerating in terms of annual labour productivity (from 1.5% to 2.3%) while a falling growth trend in Europe (from 2.4% to 1.5%), compared with the previous period. However, the productivity deterioration which happened after 2008 is a global phenomenon. It is a wider-spread productivity weakness across industries, broadening productivity gaps even among leading E.U. economies. The second paper contributes to the debate by unravelling the relationship between AI and specific intangible - human capital types. AI and human capital components (tertiary education level, vocational training and labour composition) are measured and capitalized in the model to test their synergies on labour productivity growth across countries and industries. We compare the characteristics and differences between emerging and developed economies from a regional concern of the E.U. economy. The marginal effects of AI-related investment interacting with human capital are estimated and compared between emerging and developed countries. In the end, the chapter also provides supplementary evidence and discussion on the role of AI and human capital on innovations – impacts on innovation inputs (growth in R&D capital). Innovation is concerned as a crucial indirect channel to enhance future productivity growth.

Finally, we move on to the **third paper** which is a firm-level analysis. Instead of the productivity issues that the previous two papers have heavily discussed, the last chapter further explores the impact of emerging technology on firms 'financial performances towards a complete picture of AI and emerging technologies. A vein of the literature analyzes the firm-level implications of investments in new technology and finds the consequences of investments in information technology are subject to intensive debate, as not all studies illustrate clear payoffs from new technologies. Suppose there is no effect of cost reduction or improved efficiency in production; in that case, the benefits of digital adoption will not be revealed on productivity enhancements but upon other performance indicators such as profits, market share or return of assets, capital investments etc. Overall, in the third paper, we bring some new insights on emerging cloud computing technologies as the application of the hypothesis (both adoption decision and intensity of adoption) on firms' profitability indicators. This is the first systematic firm-level analysis linking digital technology adoption, diffusion and profitability rather than productivity issues, which has gradually gained much attention in recent years. The evidence is based on the four rounds of the U.K. E-Commerce Survey and eight rounds of the Annual Business Survey. We test if adopting different cloud computing technologies is associated with positive gains on firms 'current operating profitability. The paper unpacks the mechanisms through which cloud computing potentially operates to drive profits. The discussion examines whether adopting general-purpose technology can successfully facilitate product innovations or new market shares, reduce production costs to expand existing market shares, increase profit margins, etc.

2 Chapter 2: Artificial intelligence, Intangibles, and Productivity growth

Abstract

This empirical exercise aims to contribute to the debate on the AI productivity paradox by incorporating a broader definition of intangible assets. It extends the scope of "complementary changes" in the debates on the AI productivity paradox by adopting an extended framework (CHS framework), measuring and capturing the role of intangibles in the production function. In this study, we systematically and empirically establish the synergies between AI uptake and different intangible components. We compare the relative importance of two broad categories within the framework, innovative capital and economic competence, in enhancing AI productivity. This paper emphasizes that intangible investments, which are commonly unmeasured, are, in fact, the critical missing piece of the AI productivity puzzle, according to UK evidence. In the second part, the study uncovers underlying mechanisms of how AI could affect output and productivity growth through its interaction with different productive inputs, including **capital efficiency**, **labour substitution** vs **labour augmentation**, etc. For instance, in terms of labour inputs, on the one hand, AI will take over some tasks that humans currently operate; as a result, labour employed in production will be saved. On the other hand, AI, as a multi-purpose technology, may provide more competitive prices and/or better offerings for products and services through enhanced processes and product innovations. These will expand the output and input levels of labour and capital employed with an augmenting effect. After integrating different intangibles into the growth accounting framework, this work contributes to and distinguishes AI's effect on the multiple channels of capital and labour inputs, based on the UK evidence from 1996-2018 at a detailed industry level.

Key words: Artificial intelligence; AI mechanisms; productivity growth and value-added; intangibles

2.1 Introduction

This paper focuses on the AI productivity paradox and, in particular, the role of intangibles in enhancing the productivity of AI. It is argued by the study that intangible investments, which are commonly unmeasured in most cases, are the critical missing piece of the puzzle. The lack of intangibles invested makes the benefits of AI technology invisible. The paper, therefore, extends the scope of the 'complementary changes' of AI productivity paradox by embracing the extended definition of intangible assets that Corrado (2005) initially proposed. It explains the differences in productivity or output growth attributed to the adoption of AI and the heterogeneity in the broader sets of intangible assets that a company accumulates, which have been insufficiently accounted for in traditional productivity estimations. A thorough investigation of different components of intangibles will be provided. The broader set of intangibles are measured and constructed in the growth accounting framework, falling into two categories: innovative capital and economic competence. We systematically establish their complementarities or synergies with the uptake of AI technology and compare the relative importance of the two categories in enhancing AI productivity.

Moreover, the study argues that the effects of AI productivity may operate at multiple levels. The study uncovers how AI affects production via different channels or mechanisms. Hypotheses are proposed on the relation between AI and other productive inputs, AI's effects on capital efficiency, labour substitution vs labour creation, labour augmentation (productivity) etc, are discussed. For instance, in terms of its impacts on labour inputs, on the one hand, AI will take over some tasks that humans currently undertake, hence saving labour employed in production. On the other hand, as a multi-purpose technology, AI may bring more competitive prices and/or better products and services through new innovations. The consequent increase in output would require greater inputs of labour and capital employed, with an augmenting effect. Most empirical studies examining the economic impact of AI or related technologies are based on US evidence (Brynjolfsson and McElheran 2015; Tambe 2014) or at the macro-level for multiple countries (McKinsey 2018, Graetz and Michaels 2015). The present study addresses this imbalance by examining the UK evidence concerning the role of intangible capital and unpacks AI's effects on capital and labour inputs.

This research is organised as follows: Section 2 first reviews the relevant literature and evidence that explains the productivity puzzle. We develop our hypothesis that establishes the synergies between AI uptake and different components of intangibles. The second part discusses AI's potential impacts on different productive inputs and the mechanism behind labour productivity dynamics. Section 3 describes the methodology, which begins with the theoretical frameworks of the growth accounting model and the approach to incorporating unmeasured intangibles in the production function. Then the section set out empirical economic specifications to test the central hypothesis. This section also describes the dataset used – EU KLEMS datasets. Section 4 displays some descriptive analysis of UK aggregated sectors and industry divisions to illustrate some main features of the sample. Discussions on the regression results are provided in Section 5. Finally, conclusions will be drawn on the whole story of intangibles, AI mechanisms and productivity growth.

2.2 Literature Review and Hypothesis

2.2.1 Part I. AI and Intangibles

Technology innovation has always been linked to economic growth in the literature (Romer 1990). Many studies believe that AI as a technology with great potential to disrupt economic and social outcomes of the innovations it can generate, transform the nature of work, reduce the costs of products and processes, and ultimately deliver productivity growth (Bryjolfsson and Macfee 2014; Goldfarb etc. mm 2018; Stern 2017; Mokyr 2017; Trajtenberg 2018). However, the debates on the productivity paradox show that despite recent rapid progress in related advanced technology, no noticeable corresponding gains in productivity statistics have been clearly suggested. Productivity growth remains relatively low to date (Conference Board, 2016). Very little sign indicates that AI has yet to affect aggregate productivity statistics. Labour productivity growth in a number of developed countries declined in the mid-2000s and has stayed at a relatively low level since then. As shown in the following table, the growth rates for the five leading developed economies have been roughly less than half of their 1995-2005 levels since 2005 (except Germany). Similar decelerations happen in 28 other EU countries for which the OECD has collected productivity growth data. The situation of the United Kingdom is particularly severe, with merely 0.46% per year labour productivity growth since 2005, compared with the 2.28% annual growth rate in the previous decade.

Table 2.2-1. Labour productivity slowdown and missing GDP per capita

	LP growth 1995-2005	LP growth 2005-2018	Slowdown	per capita GDP 2018	Missing per capita GDP 2018
France	1.66	0.62	1.05	$44,078	$6,341
Germany	1.69	0.83	0.86	$51,507	$5,992
Japan	1.86	0.68	1.17	$44,451	$7,225
United Kingdom	2.28	0.46	1.82	$45,466	$11,936
United States	2.51	1.01	1.50	$62,117	$13,127

Source: The Conference Board: growth of labour productivity per hour worked and GDP per capita in 2018 $ US.

AI Productivity Paradox

Brynjolfsson, Rock and Syverson (2017) initially point out explanations for current optimism regarding the technology potential of AI, while depressing productivity performances, such as the inaccurate measure of outputs[2] and redistribution lags. In particular, they point out a notable time lag in the evolution from initially recognizing AI's potential until the measurable effects manifest. This transition process will take considerable time until the technology is sufficiently harnessed. Manifestation of impacts at the aggregate level can become apparent only when the stock of technology is built and reaches a sufficient size (Brynjolfsson 2017In addition, during the process

[2] Mismeasurements on outputs produced e.g., smart phones, social networks which potentially bring substantial utilities but mismeasured.

of implementing the technology, organisations are required to make appropriate adjustments in firms' business processes, and discover and co-invent complements to overcome the obstacles on the way towards a successful adoption. Complementary changes will accompany the diffusion of technology, and the complementary types of capital, both in tangible and intangible forms, need to be identified and prepared on site. Jovanovic and Roysseau (2005) pointed out that a general-purpose technology (GPT), with broad potential applications, will not convey productivity booming immediately on its arrival. For instance, Brynjolfsson, Hitt and Yang (2002) find evidence that combining investment in IT capital stock with a specific set of organizational practices will lead firms to become more productive and gain higher market value than those that do not invest in either, or invest in only one. However, unlike the tangible counterparts, expenditure on intangible complements is difficult to measure and is commonly not reflected on firms' balance sheets. Hence, value added due to intangible capital is not directly picked up by traditional measures for productivity or GDP. All of the discussions result in a productivity J curve, identified by Brynjolfsson (2018). The ***productivity J curve*** describes that for a general-purpose technology, measured total factor productivity may follow a J curve shape. It refers to the phenomenon of a period where measurable resources such as capital and labour are used to build new, unmeasured inputs, to complement the adoption of new technology. Because those complementary inputs are unmeasured, the total factor productivity growth will initially be underestimated. Later, the TFP will be overestimated because the measurable outputs generated by those hidden capital stocks become manifest.

UK Productivity paradox

Lessons from the digital economy productivity slowdown in recent decades may have some relevance for the AI productivity paradox, particularly in the case of the UK. Reviewing the latest evidence from the UK, US and Germany, van Ark (2016) suggests the current unprecedented pace of digitalization in the new economy still does not lead to faster productivity growth unless the economy can enter the "deployment phase". In other words, currently, we are in the 'installation phase'. It represents the period when new technologies gradually emerge and evolve, driven by newly developed infrastructure and novel ways of doing things. This involves additional installation or adjustment costs as new technologies diffuse, for instance, business process redesign. In addition, Van Ark points out that under the unsolved growth paradox of the New Digital

Economy, industries with the highest share of the value of ICT capital investments and ICT service purchases, in other words, the intensive users of digital technologies, collectively account for more than 50% of the slowdown in productivity growth in three countries since 2007. In particular, the UK even suggests a negative productivity growth in intensive ICT-using industries. This evidence indicates the difficulty of efficient absorption of emerging technologies, which could be a critical factor in explaining the current paradox.

More importantly, Corrado et al. (2016) point out that the Great Recession had a differential impact on tangible and intangible investments. Tangible capital fell massively during the financial crisis and has hardly recovered, whereas intangible investments indicate greater resilience with a faster growth rate during the recovery period. Their research points out that the UK is the only country that experienced a decreased intangible intensity during the financial crisis compared with the US and other EU countries. Countries that are more intangible-intensive before the crisis tend to be less affected by financial shocks and experience a greater economic recovery. Their analysis indicates a positive but not very strong correlation between the average ratio of intangibles over tangible investments from 2000-2007 and the value change of GDP from 2007-2013.

In addition, the mismeasurement issue in the telecom industry also aggravates the recent productivity slowdown in the UK. The flagship measures of the UK economy would be revised due to the mismeasurement of prices and real output in the telecoms sectors in the past 20 years (The *Financial Times* 2020a). Richard Heys (2018), the Chief Economist for ONS, points out a disconnect between technical performances and economic measurements, typically in the telecoms industry, and hence requires improvements to be implemented into the national accounts for the future. According to the current CPI measure (inflation series), the prices of telecoms goods and services are almost flat from 2005-2015. The real output recorded fell approximately 4% over the same period as a result, leaving it a problematic sector in productivity statistics. However, the Office of National Statistics (2020) believes that instead of a half per cent drop in prices, the prices of telecoms services actually fell by 95% between 1997-2016 in the national accounts measure. Prices are recorded improperly and fail to reflect the progress in an improved bundle of calls, texts and data offered on networks (Giles 2018). Accordingly, the volume of outputs of the telecommunications sector should have grown eight times higher than previously accounted under a revised national accounts deflator. However, the contribution from the rise in the real output and productivity growth of telecoms sectors would be partially offset by those industries that use telecoms to see a lower value-added, leaving the overall effects on GDP growth difficult to discern.

In summary, regarding the AI productivity paradox, Brynjolfsson, Rock and Syverson's 2017 study emphasizes the necessity of complementary changes, partly addressing implementation time lags and mismeasured productivity of AI. These complementary investments should be appropriately put in place, enabling true value to manifest. In addition, lessons from the digital economy productivity slow down suggest similarities with the current AI productivity paradox. For the unsolved paradox of the new digital economy, which has occurred since 2007, evidence indicates that intensive ICT industries are responsible for the largest part of productivity slowing down (Corrado et al. 2016). According to the previous discussion of slowing productivity growth, this issue could be attributed to inefficient absorption and exploitation of the new technology installed (van Ark 2016). On the other hand, the ONS (2020) recently announced that the existing flagship measures of the UK economy would be revised due to the mismeasurement of prices and real output in telecoms sectors in the past 20 years. As discussed before, the actual telecom service price fell by 95% during 1997- 2016 instead of the current estimation, falling by around 50%. The volume of outputs of the telecommunications sector should have grown eight times higher than previously accounted under a revised national accounts deflator. However, the overall impacts of UK GDP growth are still unclear.

In this paper, we argue that inadequate investments in intangibles potentially prevent the efficient absorption of AI technology and the manifestation of productivity gains. Intangibles, which have greater resilience and recovered better than tangible assets after the financial crisis, are positively linked with the value change of GDP and are expected to contribute to productivity growth in general. These investments tend to bring some spill over effects to other assets, contributing to the growth of ICT-intensive sectors (Haskel and Westlake, 2018). Hence, this study will measure the overall impact of AI on output and productivity growth, taking into account different '**hidden**' intangibles. According to the literature review, no empirical research has systematically examined the role of intangible investments in the UK productivity paradox, particularly in the context of the adoption of artificial intelligence & other emerging technologies. Although Brynjolfsson et al.

(2017 & 2018) initially brought up the theoretical possibility of '**complementary changes'** to explain the AI productivity paradox, which can be primarily attributed to unmeasured intangibles. However, their empirical evidence on intangible inputs is restricted to very limited categories, typically R&D capital, the stock of general administrative expenses (SG&A), and software and computer hardware investments. Moreover, some earlier studies emphasize tangible assets investment related to big data adoption, such as IT intensity, generic IT assets and IT infrastructure. For instance, Brynjolfsson and McElheran (2015) indicate the benefits of value-added rely on whether a firm has a robust IT infrastructure prior to its data-driven decision-making. Stronger information technology capital can reinforce data-driven decision-making or big data analytics, enhancing productivity improvement or sales performance. Müller et al. (2018) suggest that the performance effects of big data analytics require other generic IT assets, such as transactional ERP or CRM systems, which are not tailored to big data analytics solutions. Typically, the complementary elements identified at the moment for big data technology include tangible IT investments or skilled labour, such as data scientists, who can extract patterns and trends from large amounts of data.

In this study, we will develop our framework to interrogate the AI productivity paradox, measure and capitalize on a fuller range of intangibles. We use the CHS classification (Corrado, Hulten and Sichel 2005, 2009), defining intangibles into two broad categories: innovative capital and economic competencies. Innovative capital contains the components such as R&D investment, new design and other product developments; economic competencies include human capital (labour retraining), branding (marketing and advertising), and organisational capital (changes in organisational structures). This is a consistent approach to redefining intangibles, emphasised in the previous study of Corrado et al. 2014, and Haskel et al. 2013; 2017.[3] Under the framework, intangible assets are comprehensively understood as investments that enable knowledge to be commercialised, as Haskel (2019) suggested. Most of the intangible components in our study have not been incorporated into the standard national accounts. Besides R&D, a limited number of studies have discussed productivity effects attributed to other types of intangible assets, according

[3] In our study, the software and databases are not grouped into the category of intangibles as in Corrado et al. (2005). These capitals are used as a separate part to construct the proxy of AI measures – AI related capital investments. More details on the measure of AI will be provided in the methodology section.

to a literature review. R&D, typically calculated in the current national accounts, is only one facet of intangible investments and could be irrelevant in some industries, such as financial services.[4] However, only a small and imprecise figure of firms' R&D investments are reported in companies' balance sheets; this is insufficient to inform many other business activities and the total impacts of many other intangibles.

Based on the above discussion, we have the first hypothesis:

H1: Unmeasured intangible components in the framework bring synergies to AI exploitation and contribute to explaining the current AI productivity paradox.

In the following part, we review some main studies that may help further reveal the relative importance of different intangibles on productivity and potential concerns with AI. Overall, empirical studies still indicate mixed evidence on the contribution of those unmeasured intangibles to productivity issues. No highly consistent results can be found on general productivity growth. In some studies, different classifications or elements are employed when examining the importance of various intangibles.

Crass and Peters (2014) first systematically examine the productivity effects of a set of intangibles based on the conceptual framework of Corrado et al. (2009). According to the German firms' data covering the period 2006–2010, their study suggests strong positive effects on TFP from brand capital measured by market expenditure, trademark stocks and human capital proxied by share of high-skilled labour. For innovative capital, the mixed results stand out that R& D indicates a strong while in comparison, while other innovative capitals such as design and licences expenditure patent stocks show very weak productivity-enhancing effects. Results also show slightly positive long-term effects on productivity for firms investing innovative capital and brand capital. Lin and Lo (2015), in their study of Taiwanese manufacturing firms, divide the innovative property into R&D and technology buyout as two parts. According to their approach, economic competence, of which marketing and employee training are the main components, enhances output more than

[4] Financial service sectors are intangible intensive but involve no R&D actives.

innovative property does. Crass, Licht and Peters (2014) explore the role of intangibles in stimulating real gross output growth at the sector level by applying the growth accounting decomposition. The growth of the innovative property is identified as the most influential type of intangible capital for manufacturing and financial and business services, with 27% of intangibles allocated to innovative property, accounting for approximately 50% of the growth contribution of intangibles. In contrast, for all the other sectors, the growth of economic competence-related capital turns out to play a dominant role. Elnasri and Fox (2014) examine the presence and trends of intangibles in the Australian economy. One part of the study sheds some light on whether there is an excess return from intangible investments. They examine the relationship between the Australian aggregated market sector's intangible assets and multi-factor productivity (MFP). According to the regression results, intangibles of economic competence remain stronger and have robust positive effects on both the level and first difference in MFP, compared with innovative capital, which is insignificant in the first difference model.

By reviewing empirical evidence, it is ambiguous to conclude which type of intangibles play a more important role in AI productivity issues. Some intangibles tend to be more advantageous in reducing production costs, while others may promote product/service innovations, allowing firms to seize more revenue opportunities. Economic competence seems to manifest greater importance regarding general impacts on productivity.

To fill the gaps, the following part will discuss underlying theoretical grounds, push forward our hypothesis, and further suggest the relative importance of the two broad categories in AI exploitation. The study contributes towards a complete picture of the nature and characteristics of previously unmeasured intangible components in the general production function and their corresponding links with emerging technologies.

The role of innovative capital – innovative capabilities to use AI

Innovation diffuses only when complementary capabilities have been developed. Rosenberg (1979) initially points out the payoff of innovation cannot be identified in isolation, and *'It has been always happened in history that the productivity of a given invention has turned on the question of the availability of complementary innovations or technologies*. Substantial reductions in the price of IT-based equipment are considered a key driver of radical transformation happening within organisations, attributed to the sequential complementarity between technology and organisational or service innovations (Bresnahan et al. 2002). Colombo and Delmastro (2002) argue transformation within the organisations, which happens slowly but heavily influences the return of IT equipment adoption, would be an essential pre-requisite for the successful diffusion of later technological improvement. Battisti, Colombo and Rabbiosi (2005), in their study, pursue an analysis of using two allegedly complementary innovations. Firms adopt typical technological innovation – IT-based manufacturing equipment, which allows them to re-engineer products, modify the product design, and evaluate costs for different potential designs. They also jointly adopt a new business practice for innovative product offerings within the organisation, where the design team could closely collaborate between customers and suppliers. Under the joint adoption, current design activities become far more effective, as collaborations are supported by advanced IT equipment. The design team could then quickly meet clients' requirements at the early stage of design or consolidate future developments in design from suppliers in time.

According to their study, adopting technology in isolation is not enough, because firms need to develop all sorts of **capabilities** to use it. The benefits from the uptake of the same technology could be different, and it depends on the innovative way it could be exploited; for instance, by developing a new form of cooperative behaviour, illustrated in the above case, or triggering new forms of product or better service offerings. Therefore, adopting AI is not merely about implementing a new technology solution but also, at the same time, developing a new long-term capability to reap the benefits.

Taking the healthcare industry as an example, currently, drug development is dominated by hypothesis-driven discovery methods, and the rate of final approval for the new drug is less than 10%. Some firms leverage AI technology that innovatively monitors the progress of cancers, as AI can automatically follow trillions of data points from cancerous and non-cancerous cells. This AI drug discovery approach has already been used to develop new cancer-fighting drugs that are undergoing clinical trials. This application is estimated to reduce the development cost of $2.6 billion by half, and to reduce the time-to-market through a high approval rate.

Therefore, based on the analysis, AI can be built into the foundation of a firm's core operating model to unlock the benefits of productivity. It requires firms to refine certain types of capabilities to completely exploit new markets and products, or shift into new business models. The higher competitive value would be differentiated through firms' innovative activities to commercialise AI solutions. Intensive intangible investments in innovative capital are considered to be closely linked with a firm's innovative capacity, which is a long-term capability. Firms investing in innovative capital stock and AI are more likely to expand their production under greater popularity among consumers[5] and reach increased market share.

Based on the discussions in this section, I posit that:
H2: In terms of the two broad categories of intangibles, innovative capital is more important than economic competences for AI productivity.

2.2.2 Part II. AI's Cost Reduction Effects on Labour and Tangible Capital

After considering the impact of unmeasured intangibles, we now start to discuss AI's possible effects on productive inputs via different channels. Acemoglu and Restrepo (2018) initially proposed the theoretical ambiguity regarding automation on occupation or labour inputs according to the task-based model. In the production function, labour and capital are the two components that can substitute for each other. As machine productivity increases, firms' demand for humans per unit of output would explicitly decrease or displace labour. Hence, technology would reduce labour requirements as some of the occupations' tasks could be automated by adopting new equipment. On the other hand, inducing automation would also reduce production costs and the price of existing final goods accordingly. It makes firms more competitive with lower prices, resulting in increased consumer demand. This countervailing channel will offset the reduction of labour demand; hence, the overall net effects on the labour required could be ambiguous. This can be illustrated by the example of ATMs in the study by Bessen (2015). On the one hand, ATMs automate some of the tasks of bank tellers. On the other hand, they also reduce the costs of opening new bank branches. Overall, although the number of bank tellers decreased for each branch, the number of new branches that have been opened means that the total number of tellers has actually increased.

To contribute to this theoretical ambiguity, Webb (2019) empirically estimates the extent to which occupation tasks can be affected by recent technological changes in demand for those occupations. The negative effects obtained in his study suggest labour substitution effects under the two balance of forces for both robotics and software. Webb points out that these technologies are recent and also informative about how the economy will respond to AI. In his study, the text of patents contains information about what the technology can do, and he developed a new method to quantify the extent to which each occupation involves performing similar tasks. By identifying the overlap between patents and tasks, an occupations exposure score for a given technology is developed, representing the intensity of patenting activity in technology directed towards the tasks in that occupation. In their results, the overall pattern confirms the suggestive evidence that over the long run, task-level substitution leads to occupation-level decreases in employment and wages. Specifically, moving from the 25th to the 75th percentile of occupations' exposure is associated with a decline in employment of 5%–30% in the case of robots and 7–14% within-industry employment in software. Low-wage occupations/individuals with less than a high school education are most exposed to robotics technology.

However, it is worth noting that their analysis cannot rule out some other channels in which AI potentially operates, as the study focuses purely on task-level substitution for recent technologies. In fact, AI's productivity effects may operate at multiple levels. Besides the two countervailing forces, there is a richer set of ways that AI may impact production. First, AI could be a form of factor-augmenting technology change or potentially reorganise existing occupations. Second, as a typical general-purpose technology, AI will likely facilitate innovation and create new tasks from the demand side, increasing the scope of occupation and labour. The following analysis will provide more details and a complete picture of AI's underlying mechanisms.

AI – factor augmenting effects. AI may reorganise or redefine existing jobs, augmenting human capability and leading workers to be more productive. Demand for new jobs can be created. For instance, more jobs are required to build the necessary AI infrastructures, monitoring its operation

.

to ensure its full use or exploitation. Although certain activities will be taken over by machines, more workers can be freed up to engage in higher-value tasks by leveraging AI tools, eventually becoming more productive in those tasks that machines cannot perform. Besides, adopting AI may be associated with capital-augmenting effects. For instance, AI and big data signify that these technologies can provide more accurate and better decision-making in business cases. AI & IOT can also reduce capital expenditure by embedding equipment with smart monitoring and enabling preventive maintenance to increase the life span of assets, thereby reducing the need to invest in new equipment. Additional productivity gains will become evident over time as capital become more efficient as it continuously learns. A McKinsey survey (2017) points out that companies now devote approximately 10–20% of digital investment budgets to AI tools. The investments will be increased as they adopt and further absorb AI technologies, towards a higher level of annual AI investments. The increase in the investment level will eventually enhance both labour and capital employed, resulting in greater efficiency. In addition, by looking at the shape of the value-added curve of early adopters, they also point out that the next 5 to 10 years would be at an accelerating pace for adoption due to increased competition and firms' improved complementary capabilities to use advanced analytical tools.

AI – create new innovations. Apart from the efficiency through automation, firms' motivations for adopting AI relate much to a desire to develop new products and services. Innovation creates new value for an economy as new products and services for the underserved market can stimulate further consumption. MGI (2017),[6] in their survey, show ⅓ of companies invest in AI to improve sales by expanding their offerings of products and services. McKinsey Global Institute (2018)[7] surveys executive managers from over 3000 global firms across 10 countries that are the largest contributors to the world GDP, about the adoption of AI and the potential impacts of profit growth on the global economy. From micro to macro approach, they model the adoption trend of four clusters of artificial intelligence technologies, including advanced machine learning; robotics and automation; virtual assistants, and computer vision, by classifying adopters into different tiers. In particular, their simulation predicts the impact on GDP profit growth and identifies seven possible channels of drivers of productivity growth. According to their analysis, the automation of labour and new offerings from innovation are two outstanding channels that are expected to raise global GDP by 2023 by 11% and 7%, respectively. In their simulation, AI-driven automation would substitute around 10-15% of existing time worked globally by 2030 for economies. In the case of innovation gains, countries with a strong capacity to innovate can generate approximately 10% of incremental GDP by AI adoption.

Therefore, besides the effects of AI automation, we point out other potential channels of AI's impact on capital and labour dynamics. Based on the discussions in this section, I posit that:

H3: AI may positively influence labour productivity through cost reduction via:

a. Substituting existing labour and/or
b. By improving current labour efficiency (labour productivity).

The impact on labour inputs required in production is the net effect of (i) labour substitution due to automation and (ii) labour creation through more competitive prices and/or new product innovations.

H4: AI may also save tangible capital, in other words, improve the efficiency of tangible capital. Digital-based improvements in the business process due to AI may trigger tangible cost reduction via increasing the efficiency of capital utilisation (capital productivity).

2.3 Methodology

2.3.1 The Theoretical Growth Accounting Framework

We assume that an industry *j* in a country *c* at a particular point in time *t* is characterized by a production function in which inputs are fully utilized with constant returns to scale (suppressing country and time subscripts for brevity).

$$\mathrm{Y_j = f_j\left(M_j, K_j, L_j, T\right)} \quad (1.)$$

Each industry, indexed by j, purchases a number of distinct intermediate inputs, capital, and labour inputs. Y_j is the measure of output produced using inputs, including the intermediate inputs M_j, labour L_j, capital K_j and technology, indexed by time T. In this approach, it is assumed that the market is competitive where the price is equal to marginal costs, and factor price is equal to the marginal product.

Assume a Cobb-Douglas functional form for the production f_j. By taking logs and the first difference ($\Delta lnY_t = lnY_t - lnY_{t-1}$), the production function can be obtained in the translog functional form, representing the rate of growth:

$$\Delta lnY_j = \bar{v}_{K,j} \cdot \Delta lnK_j + \bar{v}_{L,j} \cdot \Delta lnL_j + \bar{v}_{M,j} \cdot \Delta lnM_j + \underbrace{\Delta lnTFP_j}_{gross\ output\ defined\ multifactor\ productivity} \quad (2.)$$

In equation 2, the growth in gross output (ΔlnY_j) can be decomposed into the growth of capital, labour, and intermediate inputs and each element is weighted by the corresponding nominal input (cost) share $\bar{\boldsymbol{v}}$ in the gross output. Any remaining output growth (Hicks-neutral technological change) is captured by the multi-factor factor productivity.

The input share $\bar{v}$ in equation (2) is calculated as the ratio of the nominal factor price of input X, $\boldsymbol{P}_{x_j}X_j$ relative to the total revenue of output $\boldsymbol{P}_{Y_j}Y_j$, as follows:

$\bar{v}_{x,j} = \frac{\boldsymbol{P}_{x_j}X_j}{\boldsymbol{P}_{Y_j}Y_j}$ for input $x_j = K_j, L_j, M_j$

$$\bar{v}_{k,j} + \bar{v}_{l,j} + \bar{v}_{m,j} = 1$$

P_{x_j} denotes factor input price, which is the cost of using input x (e.g., wage per hour).

P_{Y_j} denotes the price index of gross output and Y_j is gross output in real term.

$\bar{v}_{x,j}$ with the upper bar denoting the two-period average (Divisa index) of nominal shares, where $\bar{v}_t = 0.5\ (\bar{v}_t + \bar{v}_{t-1})$ (Mahony 2020, EU KLEMS).

To explicitly assess the contribution of industry divisions, it is more convenient to work with a value-added measure of productivity, as in many previous productivity studies. By assuming that intermediate inputs M can be separated from other inputs in equation 1, the value-added production function can be obtained in the following equation:

$$\Delta lnV_j = \bar{s}_{K,j} \cdot \Delta lnK_j + \bar{s}_{L,j} \cdot \left(\Delta lnL_j\right) + \underbrace{\Delta lnTFP_j}_{value\ added\ defined\ multifactor\ productivty} \quad (3.)$$

S represents the share of inputs costs in value added. The growth of capital and labour input is now weighted by the percentage of input costs in total value added instead of the total revenue of outputs, calculated as $\bar{s}_k = \frac{\boldsymbol{P_k k}}{\boldsymbol{P_v v}}$ and $\bar{s}_L = \frac{\boldsymbol{P_L L}}{\boldsymbol{P_v v}}$.

In addition, the theoretical framework allows for heterogeneity when differentiating diversified inputs (Inklaar et al. 2020, Crass and Peters 2014; Crass, Licht and Peters 2014).

To reflect the contribution of different types of capital or labour inputs requires a straightforward extension to equation (3), where *k = 1, …, K* types of capital inputs and *l = 1, …, L* types of labour input that each earn the marginal product as follows:

$$\Delta lnK_j = \sum_k \overline{w}_{k,j} \cdot \Delta lnK_{k,j}^{St}$$

St denotes the capital stock of asset type *k* in industry *j*. ΔlnK_j is a calculated index weighting the average growth rate for each type of capital stock.

The nominal share $\overline{w}_{k,j}$ is calculated as the proportion of the capital income of assets k, in total capital K income in industry j as follows:

$$\overline{w}_{k,j} = \frac{\boldsymbol{P}_{k_j} K_{k,j}}{\sum \boldsymbol{P}_{k_j} K_{k,j}} = \frac{\boldsymbol{P}_{k_j} K_{k,j}}{\boldsymbol{P}_{\boldsymbol{K}_j} \boldsymbol{K}_j}$$

$\boldsymbol{P}_{k_j} K_{k,j}$ denotes capital income of assets *k*, calculated as the capital stock of asset times its rental price of capital *k* (user costs of capital).

$\overline{w}_{k,j}$ with upper bar denotes the two-period average (Divisa index) of nominal shares, where $\overline{w}_t = 0.5\ (\overline{w}_t + \overline{w}_{t-1})$

The growth rate of labour input ΔlnL_j in each industry j, referred to as labour services, is specified in a similar approach:

$$\Delta lnL_j = \sum_l \overline{w}_{l,j} \cdot \Delta lnH_{l,j}$$

ΔlnL_j is a Törnqvist volume index of the growth rate of hours employed by each type of labour or alternatively, the number of employees, weighted by its nominal labour-income share $\overline{w}_{l,j}$.

Capitalizing intangibles in the production function

As emphasized in the productivity paradox, complementary changes, especially in the form of intangibles, are critical unmeasured inputs, inducing sources of mismeasurements in both output and productivity growth. According to current guidelines for national accounts (European Commission *et al.* 2009), few intangibles, including computer software, mineral exploration and the creation of artistic originals, are currently capitalized into national accounts as assets. In other words, according to the refined definition, much of the spending on intangibles hasn't been measured in conventional gross value-added data (Corrado *et al.*, 2014; Borgo, Goodridge and Pesole, 2013; Niebel and Mahony *et al.*, 2013).

Conventionally, intangible investments such as product design, market research & advertising, and changes in organizational structures or capital, are treated as firms' purchases through intermediate inputs M. As part of intermediate expenditure, these purchased intangible services are assumed to be fully used up in annual production and thus will be subtracted from gross output to obtain value added. In this study, we explicitly examine the role of intangibles in driving growth. The unmeasured intangibles are required to be distinguished separately from other capital services and reintroduce them to the production function.

Corrado and Haskel et al. (2014) developed an approach to incorporate intangibles into the production function and adjust the value added accordingly. They suggest that many intangibles can provide long-term effects on production, and hence treat the purchase of services as knowledge capital expenditure instead of spending on intermediates.

$$\boldsymbol{V_j} = P_s S_j + P_N N^{OA} - \left(P_m M_j - P_N N^{PUR}\right) = V'_j + P_N N^{OA} + P_N N^{PUR}$$
$$= P_L L_j + P_k K_j + P_R {R_j}^{OA} + P_R {R_j}^{PUR} \quad (4.)$$

On the left side, $P_N N$ is the asset value of total produced intangible goods. Part of the expenditure which was previously recorded as intermediate inputs but in fact, was used to purchase long-lived intangible assets externally, is denoted as $P_N N^{PUR}$. Besides, industries also produce, on their own account intangible assets N^{OA} such as own R&D. In traditional national account spending, own account production of intangibles is not included in the value of gross output.[8] The value of inputs used to produce those own account assets is subsumed in conventional labour or capital inputs (for instance, workers conducting R&D or producing own account software will be simply included in L rather than R&D products themselves). Including own account intangibles can directly result in additional counted output by industry and aggregated total output. The own account production leads to new output and own capital with an explicit rental payment P_R. In equation 4, V'_j is the traditional value added of industry j, which does not include intangible investment. P_R stands for the rental price and $P_R R$ is the rental payment for capitalized intangible assets. Overall, when various types of intangibles are treated as capital, the adjusted value added is higher. This is because, on the one hand, the intermediate inputs are less, and on the other hand, more output values are recognized in the production process.

With the new intangible incorporated in the value-added, equation (3) can be expanded with more disaggregation of asset types:

$$\Delta lnV_j = \bar{s}_{K,j} \cdot \Delta lnK_j + \bar{s}_{L,j} \cdot \Delta lnL_j + \bar{s}_{X,j} \cdot \Delta lnX_j + \underbrace{\Delta lnTFP_j}_{value\ added\ defined\ productivty} \quad (5.)$$

X_j contains information on different types of intangible capital services based on the definition proposed by Corrado et al. (2005, 2009, 2017, 2018). The impact of the level of technology T_j on productivity enhancement is captured by the total factor productivity $\Delta lnTFP_j$ in the theoretical framework.

[8] Statistical authorities will only take account of sales as final outputs and ignore the production of intangible assets on own account.

Measuring the capital inputs

Capital services in the production function are commonly defined by the productive inputs that flow to production from a capital asset (Dirk, Georg and Bettina, 2014). The OECD (2001), in the productivity manual, points out that although conceptually the correct measure of capital in the productivity context is the flow of capital services (e.g., Jorgenson 1967), this might induce a number of measurement issues to occur. Hence, in our model, we built the real capital stock over time via the perpetual inventory method, as in the following equation. For any capital asset K (either in the form of tangible or intangible), the stock value is accumulated according to:

$$K_{k,t} = I_{k,t} + (1 - \delta_{k,t})\ K_{k,t-1}$$

Where I is the real investment and δ is the geometric depreciation rate. The real investment I is calculated by the nominal investment (in both tangibles and intangibles) deflated by the investment index. The investment price can be converted into a rental price according to the Hall-Jorgenson relation. According to Oulton (2007), the economy-wide rate of return is such that the rental price multiplied by the capital stock equals the total economy-wide operating surplus.

2.3.2 Data

To empirically perform the growth decomposition analysis that accounts for artificial intelligence, intangible capital and other inputs, we use the production data at the industry-level disaggregation to test the hypothesis. The EU KLEMS dataset provides detailed sectoral-level measures of economic growth, productivity, capital formation and technological change for 25 individual European member states, Japan and the United States (Stehrer et al. 2019, 2021). This dataset was constructed on the basis of data from national statistical institutes and proceeded by the research consortium (wiiw[9]) to ensure cross-country harmonization for further international comparisons. The EU KLEMS Release 2019 contains sector-level estimates of outputs and capital inputs for 40 detailed industries, along with–aggregated industries (NACE Rev.2). This is the first released version (not compatible with other releases) that collects and integrates supplementary indicators on intangibles such as software and databases, organizational capital, R&D, new design,

[9] The Vienna Institute for International Economic Studies

advertising and marketing research, and training. The EU KLEMS analytical database includes broader ranges of intangible capital, as we emphasize in the literature review section, and provides a harmonized measure of intangible investments for various countries. It is also in line with the INTAN-Invest database, that recent intangible investment studies have used (Inklaar et al., 2020; Corrado et al., 2017; Corrado and Haskel et al., 2017). In addition, the EU KLEMS capital database provides the time series on assets, differentiated by computing equipment, communication equipment, computer software and database, transport equipment, other machinery and equipment, total non-residential investment, residential structure, and other intellectual property products etc. The previous section informs to identify the appropriate approach to construct each measure of the element in the production function. Using the EU KLEMS datasets, we can strictly classify our tangible, intangible and AI-related capital by each category for the UK analysis and identify the cross-country differences in other chapters.

2.3.3 Economic Specifications

2.3.3.1 AI, intangibles and productive inputs

Following the theoretical framework in the last section, we derive empirical specifications in the following way.

$$\Delta \ln(Y)_{jt} = \alpha_j + \beta_0 + \beta_1 \Delta\ln\left(K_{jt}\right) + \beta_2 \Delta\ln(L)_{jt} + \beta_3\Delta\ln\left(AI_{jt}\right) + \beta_4 \Delta\ln\left(X_{jt}\right) + \alpha_j + \gamma_t + \varepsilon jt \qquad (6.)$$

Empirically, the first difference model to remove the potential for spurious results from non-stationary residuals. In the above equation, the fixed effect method is applied to control for unobserved omitted variables. The descriptive data shows productivity gaps exist across industries over time. The unknown industry-specific intercepts denoted by α_j, are included in the regression model. They represent industry characteristics varying from one industry to another but are constant over time. The presence of business cycles or macro factors associated with overall economic growth leads to the inclusion of time effects γ_t of each observational year. The time dummies control for some unobserved variable varying over time for the whole economy, whereas not distinguished among industries. For instance, during the recession, output growth and productivity largely shrank in almost all industries. If AI investment were reduced over the same period, it could pick up the effect of declining trends, resulting in an upward bias in estimation results. Clustered standard errors are employed in the fixed effects estimator, correcting for the heteroskedasticity over time within each industry. It is worth noting that EUKLEMS databases contain detailed information on price deflators (2010 price indices) and nominal and real value (chain-linked volumes) for types of assets. To remove the effect of price inflation or deflation over the estimation period, all the variables in the specifications are in real growth rate with deflators (2010 base year) applied. Besides, as Brynjolfsson et al. (2017 & 2018) pointed out, AI's impact will not manifest until it reaches a sufficient size. To model the impact empirically, we employ capital stock growth instead of investment flows of AI and intangibles in the production function. This is consistent with the theoretical framework for measuring productive inputs.

To better capture the contribution of each productive input, we adopt the measure of output in value-added Y_j. As suggested in the previous section, the value-added measure has been adjusted by considering new intangible investments. L_{jt} denotes total labour hours worked. K_{jt} represents total tangible capital stock. The tangible capital K_{jt} is calculated as total net assets minus AI-related capital and any other intangible capital which has been counted into national accounts. X_{jt} denotes the total intangible capital stock, which comprises two broad categories as discussed in the hypothesis section, innovative property (R&D, product design and development) and economic competences (advertising and marketing research, firms' specific vocational training on employees and different forms of organizational capital). AI_{jt} stands for our measure of artificial intelligence in the study. AI technology can take effects through both embodied and disembodied forms. In our analysis, AI and related emerging technologies, as a source of technological change, are separated from the total factor productivity which is the residual term in the theoretical model.

In terms of measuring AI, since it is a relatively new phenomenon, no exact data series could be used to directly indicate the AI uptake by sectors over time. However, EU KLEMS databases provide information on aggregated data-series of capital stock, which contains AI technologies. Following the PwC (2018) approach, existing data series on emerging and AI-related technologies are leveraged to construct a proxy for AI uptake. Specifically, capital stock on computer software databases, computer hardware and relevant IT equipment cover different types of AI, discussed in the definition, and are formed together to create a proxy for the AI-related capital. In general, this estimator will be unbiased and consistent as long as it is assumed that the relationships between productivity and all the other emerging technologies in the groupings are similar.

β_3 is the parameter which captures the impact of AI uptake on output, holding constant the other covariates and unobserved industry characteristics. If the uptake of AI can bring significant impacts on productivity, it will be captured via the significance of β_3 in (I). This parameter is interpreted as the output elasticity to AI uptake, where a 1% increase in AI capital leads to a β_3 % change in value added.

To test complementarities for the intangibles, the cross-product/interaction term is derived and introduced to obtain equation (7):

$$
\begin{aligned}
ln(Y)_{jt} &= \beta_0 + \beta_1 \ln(K)_{jt} + \beta_2 \ln(L)_{jt} + \beta_3 \ln\,(AI_{jt}) + \beta_4 \ln\,(\boldsymbol{X}_{jt}) + \beta_5 \ln\,(AI_{jt}) * \ln\,(X_{jt}) \\
&\quad + \beta_5 \ln\,(AI_{jt}) * \ln\,(X_{jt}) + \sigma_{jt} \\
ln(Y)_{jt-1} &= \beta_0 + \beta_1 \ln(K)_{jt-1} + \beta_2 \ln(L)_{jt-1} + \beta_3 \ln\,(AI_{jt-1}) + \beta_4 \ln\,(\boldsymbol{X}_{jt-1}) + \beta_5 \ln\,(AI_{jt-1}) \\
&\quad * \ln\,(X_{jt-1}) + \sigma_{jt} \\
\Delta\ln(Y)_{jt} &= \beta_0 + \beta_1 \Delta \ln(K)_{jt} + \beta_2\, \Delta\ln(L)_{jt} + \beta_3 \Delta\ln\,(AI_{jt}) + \beta_4\, \Delta \ln\left(\boldsymbol{X}_{jt}\right) + \\
&\quad \beta_5 \Delta(\ln(AI_{jt}) * \ln\,(_{jt})) + \alpha_j + \gamma_t + \varepsilon jt
\end{aligned}
\tag{7.}
$$

*The validity of H2 (**The investment in intangible investments is a complementary driver of the successful exploitation of AI)** will be tested via the significance of β_5 in (II)*

Accordingly, ***H3a (AI on labour substitution) can be assessed by interacting AI with L in (8)***

$$
\begin{aligned}
\ln(Y)_{jt} = \beta_0 + \beta_1 \ln(K)_{jt} + \beta_2 \ln(L)_{jt} + \beta_3 \ln(AI)_{jt} + \beta_4\, \ln(\boldsymbol{X})_{jt} + \\
\beta_5 (\ln\,(AI_{jt}) * \ln\,(L_{jt})) + \alpha_j + \gamma_t + \varepsilon jt
\end{aligned}
\tag{8.}
$$

If we take the first derivatives of Y in respective of L to calculate the marginal impacts of the number of labour inputs used to produce the output, the negative sigh of β_5 suggest introducing additional inputs of AI- related investments will reduce the overall number of labour inputs required in the production function[10].

$$\Delta\ln(Y)_{jt} = \beta_0 + \beta_1\Delta\ln(K)_{jt} + \beta_2\,\Delta\ln(L)_{jt} + \beta_3\Delta\ln(AI)_{jt} + \beta_4\,\Delta\ln(\boldsymbol{X})_{jt} + \beta_5\Delta(\ln\,(AI_{jt}) * \ln\,(L_{jt})) + \alpha_j + \gamma_t + \varepsilon jt \tag{9.}$$

Similarly, H4 (AI on the efficiency of capital utilization) can be tested via interacting AI with K in general production function in (9)

$$\Delta\ln(Y)_{jt} = \beta_0 + \beta_1\Delta\ln(K)_{jt} + \beta_2\,\Delta\ln(L)_{jt} + \beta_3\Delta\ln(AI)_{jt} + \beta_4\,\Delta\ln(\boldsymbol{X})_{jt} + \beta_5\,\Delta(\ln\,(AI_{jt}) * \ln\,(K_{jt})) + \alpha_j + \gamma_t + \varepsilon jt \tag{10.}$$

2.3.3.2 The alternative way to test AI, intangibles complementarities

In this section, we use an alternative approach to examine the complementarity between intangible capital and AI. Rajan and Zingales (1998) propose an estimation model that includes country-industry interactions to examine the impact of financial development on economic growth. Haskel et al. (2017) adopt the same approach in their study of knowledge spillovers and ICT. In particular, they suggest the model could be advantageous for addressing reverse causality and the omitted variables bias, especially for cross-country growth regressions. Following a similar approach, we employ this difference-in-differences approach to supplement our analysis of the role of intangibles. Here, the accumulation of intangible capital is treated as a catalyst for growth by improving the competitive advantages of industries that rely more heavily on AI-related capital. The importance of AI to the industry i is measured by the industry's average AI intensity across time and then interacted with the growth in intangible capital.

[10] Our model is contemporaneous relationship based on the long run effect. More lags could be included to test reverse causality to capture more dynamic characteristics and robustness.

$$\Delta\ln(Y)_{jt} = \beta_0 + \beta_1\Delta\ln(K)_{jt} + \beta_2\Delta\ln(L)_{jt} + \beta_3\Delta\ln(AI_{jt}) + \beta_4\Delta\ln(\boldsymbol{X}_{jt}) + \beta_5\ln(\overline{AI}_j) + \beta_6\ln(\overline{AI}_j) * \Delta\ln(X_{jt}) + +\lambda_j + \lambda_t + \varepsilon jt \tag{11.}$$

λ denotes unobserved industry and time effects. $\Delta\ln(X_{jt})$ captures the growth rate of intangibles. $\ln(\overline{AI}_j)$ denotes industry i's average (log) AI intensity over time, and this term is used to capture the differential impact of intangibles on output growth in AI-intensive sectors. Haskel et al. (2017) in their empirical analysis of intangible and ICT capital, point out the best results can be obtained by using the average log level of ICT capital. This captures the underlying economic meaning that the output elasticity of intangible capital increases as the level of AI capital increases but at a diminishing rate.

Overall, *according to this approach, the validity of H1 will be tested via the significance of β_6 in (III).* If the population regression model is linear, the effect on output growth of incremental intangibles does not depend on the level of AI. Instead, if there is a non-linear effect from AI, we will find $\beta_6 > 0$. The positive sign indicates that industries that are more AI intensive would see faster growth when AI investments are complemented by higher intangible capital accumulation. A 1% increase in the level of AI intensity leads to overall (β_5 + β_6 * growth rate of intangible capital) % change in the growth of value-added.

2.3.3.3 AI and intangibles in the labour productivity function

The following specification directly addresses the issue of UK productivity slowing down and/or the AI productivity paradox, taking account of the collective contribution from AI and various types of intangibles in our framework. Apart from the arguments regarding AI's labour substitution vs labour augmentation effects, we estimate the following labour productivity function to test whether AI can increase labour productivity growth (**H4b)**, and the relative importance of different intangibles.

$$\Delta\ln(\frac{Y_{jt}}{L_{jt}}) = \alpha_j + \beta_0 + \beta_1\Delta\ln\left(\frac{K_{jt}}{L_{jt}}\right) + \beta_2\Delta\ln(\frac{AI_{jt}}{L_{jt}}) + \beta_3\Delta\ln(\frac{\boldsymbol{X}_{jt}}{L_{jt}}) + \beta_4\Delta(\ln(\frac{\boldsymbol{X}_{jt}}{L_{jt}})\ln\left(\frac{AI_{jt}}{L_{jt}}\right)) + \alpha_j + \gamma_t + \varepsilon jt \tag{12.}$$

Again, fixed effects estimation methods that capture time and industry variation are employed in the first difference form of labour productivity function. Labour productivity growth is measured by the adjusted value added per hour in industry i at time t. It can be decomposed into the same group of productive inputs as those in the output function in section 3.31. Each element is calculated as the ratio of capital stock accumulated divided by the total number of hours employed and transformed into the growth rate.

The total intangible capital $\boldsymbol{X}$ is divided into two broad categories (innovative capital and economic competences) in the following equation to identify their corresponding contribution to AI productivity. β_3 and β_4 indicate the contribution of the two broad categories to labour productivity in general. The relative importance of two types of intangibles in the context of AI (**H2**) can be compared via $\boldsymbol{\beta_5}$ in the following two equations:

$$\Delta\ln\left(\frac{Y_{jt}}{L_{jt}}\right) = \alpha_j + \beta_0 + \beta_1\,\Delta\ln\left(\frac{K_{jt}}{L_{jt}}\right) + \beta_2\Delta\ln\left(\frac{AI_{jt}}{L_{jt}}\right) + \beta_3\Delta\ln\left(\frac{\boldsymbol{X1}_{jt}}{L_{jt}}\right)$$
$$+\beta_4\Delta\ln\left(\frac{\boldsymbol{X2}_{jt}}{L_{jt}}\right) + \beta_5\Delta\,(\ln(\frac{\boldsymbol{X1}_{jt}}{L_{jt}})\ln\left(\frac{AI_{jt}}{L_{jt}}\right)) + \alpha_j + \gamma_t + \varepsilon jt \qquad (13.)$$

$$\Delta\ln\left(\frac{Y_{jt}}{L_{jt}}\right) = \alpha_j + \beta_0 + \beta_1\,\Delta\ln\left(\frac{K_{jt}}{L_{jt}}\right) + \beta_2\Delta\ln\left(\frac{AI_{jt}}{L_{jt}}\right) + \beta_3\Delta\ln\left(\frac{\boldsymbol{X1}_{jt}}{L_{jt}}\right)$$
$$+\beta_4\Delta\ln\left(\frac{\boldsymbol{X2}_{jt}}{L_{jt}}\right) + \beta_5\Delta\,(\ln(\frac{\boldsymbol{X2}_{jt}}{L_{jt}})\ln\left(\frac{AI_{jt}}{L_{jt}}\right)) + \alpha_j + \gamma_t + \varepsilon jt \qquad (14.)$$

In summary, the following table displays all the variables for the regression analysis and inputs to construct each of our measures.

Table 2.3-1. List of variables

(EU KLEMS Dataset)

Y	**Value added**	- Growth rate of value added volume 2010 ref.prices, NAC mn,% log	*VA_G*	
$\frac{V}{L}$	**Value added (per hour worked)**	- Growth rate of value added per hour worked, volume 2010=100	*LP1_QI*	
L	**Total hours worked by the employee**	- Total hours worked by employees	*H_EMPE*	
M	**Intermediate inputs**	- Intermediate inputs, volume 2010 ref.prices, NAC mn	*II_Q*	
			Price indices	**Net capital stock**
K	**Tangible capital**	- Communications equipment CT - Machinery and equipment Mach - Transporting equipment TraEq - Non-residential investments oCoN	*Ip_CT* *Ip_TraEq* *Ip_OMach* *Ip_OCon*	*Kq_CT* *Kq_TraEq* *Kq_OMach* *Kq_OCon*
AI	**AI capital**	- Computing equipment IT - Computer software and databases	*Ip _IT* *Ip _Soft_DB*	*Kq_IT* *Kq_Soft_DB*
Intangibles				
1.	**Innovative capital**			
IInv1		- Research and development	*Ip_RD*	*Kq_RD*
IInv2		- Design and other product developments (Intangibles not included in the national account)	*Ip_Design*	*Kq _design*
2.	**Economic competence**			
		2.1 BRAND CAPITAL		
Ibr1		- Advertising, market research and branding (Intangibles not included in the national account)	*Ip_AdvMRes*	*Kq_AdvMRes*
		2.2 LABOUR RETRAINING		
Ihc1		- Vocational training (Own account) (Intangibles not included in the national account)	*Ip_VT*	*Kq _VT*
		2.3 ORGANIZATIONAL CAPITAL		
Ioc		- Own account organizational capital - Purchased organizational capital (Structure) (purchased management consulting services) (Intangibles are not included in the national account)	*Ip_OOCap* *Ip_POCap*	*Kq_OOCap* *Kq _POCap*

2.4 Descriptive Statistics

This section starts with a descriptive analysis of the sample. The following table lists the industries used for the regression analysis. The European National Statistical Institute produces data according to the NACE 2 industry classification. As displayed in Table 2.4.1, 19 aggregated sectors are distinguished in our sample. For some but not all time series, finer detail is available. The regression analysis in Section 5 is conducted at a finer level of aggregation, expanding the total industry size to 38.

Table 2.4-1. Industry Divisions

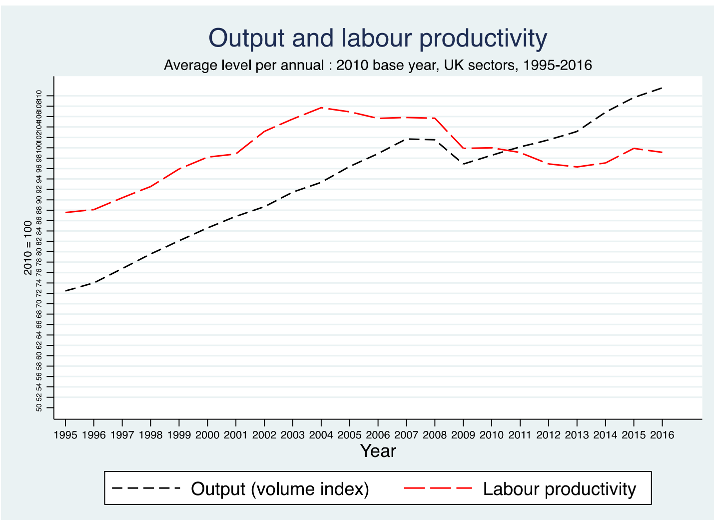
INDNR	CODE	DESC
1	A	Agriculture, forestry and fishing
2	B	Mining and quarrying
	C	TOTAL MANUFACTURING
3	…10-12	…Food products, beverages and tobacco
4	…13-15	…Textiles, wearing apparel, leather and related products
5	…16-18	…Wood and paper products; printing and reproduction of recorded media
6	…19	...Coke and refined petroleum products
7	… 20	…Chemicals and chemical products
8	… 21	…Basic pharmaceutical products and pharmaceutical preparations
9	…22-23	…Rubber and plastics products, and other non-metallic mineral products
10	…24-25	…Basic metals and fabricated metal products, except machinery and equipment
11	… 26	…Computer, electronic and optical products
12	… 27	…Electrical equipment
13	…28	…Machinery and equipment n.e.c.
14	…29-30	…Transport equipment
15	…31-33	…Other manufacturing; repair and installation of machinery and equipment
16	… D	…Electricity, gas, steam and air conditioning supply
17	… E	…Water supply; sewerage; waste management and remediation activities
18	F	Construction
	G	WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES
19	…45	…Wholesale and retail trade and repair of motor vehicles and motorcycles
20	…46	…Wholesale trade, except of motor vehicles and motorcycles
21	…47	…Retail trade, except of motor vehicles and motorcycles
	H	TRANSPORTATION AND STORAGE
22	… 49	…Land transport and transport via pipelines

23	... 50	...Water transport
24	... 51	...Air transport
25	... 52	...Warehousing and support activities for transportation
26	...53	...Postal and courier activities
27	I	Accommodation and food service activities
	J	INFORMATION AND COMMUNICATION
28	...58-60	...Publishing, audio-visual and broadcasting activities
29	...61	...Telecommunications
30	...62-63	...IT and other information services
31	K	Financial and insurance activities
32	L	Real estate activities
33	M-N	Professional, scientific, technical, administrative and support service activities
	O-Q	PUBLIC ADMINISTRATION, DEFENCE, EDUCATION, HUMAN HEALTH AND SOCIAL WORK ACTIVITIES
34	O	Public administration and defence; compulsory social security
35	P	Education
36	Q	Health and social work
	R-S	ARTS, ENTERTAINMENT, RECREATION; OTHER SERVICES AND SERVICE ACTIVITIES, etc.
37	R	Arts, entertainment and recreation
38	S	Other service activities

2.4.1 The overall trends for the UK economy

To explicitly illustrate the overall pattern of UK output, productivity growth and industry insights from the descriptive analysis, we aggregate the groups of detailed industry divisions in our sample (Table 4) into 15 aggregated market sectors for simplicity. Figure 2.4.1 shows the average level per annual output (volume index) and labour productivity across aggregated sectors from 1995 to 2017. It is the 'flatlining' of the labour productivity pattern in the decade after 2008, demonstrated by this figure, indicating that the UK productivity is slowing down. Correspondingly, in Figure 2.4.2, the UK sectoral growth performance after 2008 shows a very different pattern from the period before. After the recession years in 2008 and 2009, overall economic growth started to recover, even though at a more modest rate than before. Table 2.4-2 segments the growth of output and labour productivity for a clearer illustration. In the decade before the financial crisis, the UK sector expanded at an average real rate of 2.72 % per annum in terms of output. The value added per hour, our standard measure of labour productivity, rose by an average of 1.98% per annum over the same period.[11] Over the recovery period from 2011 to 2016, industries expanded on average by 1.59 % per annum. However, labour productivity growth remained weak even as output (value added) picked up at a growing pace during the same period. Benchmarking the sectoral performance against the decades before the recession, this shortfall of labour productivity growth after the crisis reaches up to more than 2% per annum (Table2. 4-1).

Figure 2.4.1- Figure 2.4.2



Source: Author's own calculations

Table 2.4-2. Output and Labour Productivity

Average annual growth rate (per cent), UK sectors, 1995–2016.

	Before the financial crisis (Per cent per annum)			After the financial crisis (Per cent per annum)		
	1995-2002	2003-2007	1995-2007	2008-2010	2011-2016	2008-2016
Labour productivity	2.70	0.98	1.98	-1.76	-0.18	-0.70
Value added *(Volume index)*	3.20	2.04	2.72	-1.46	1.59	0.57

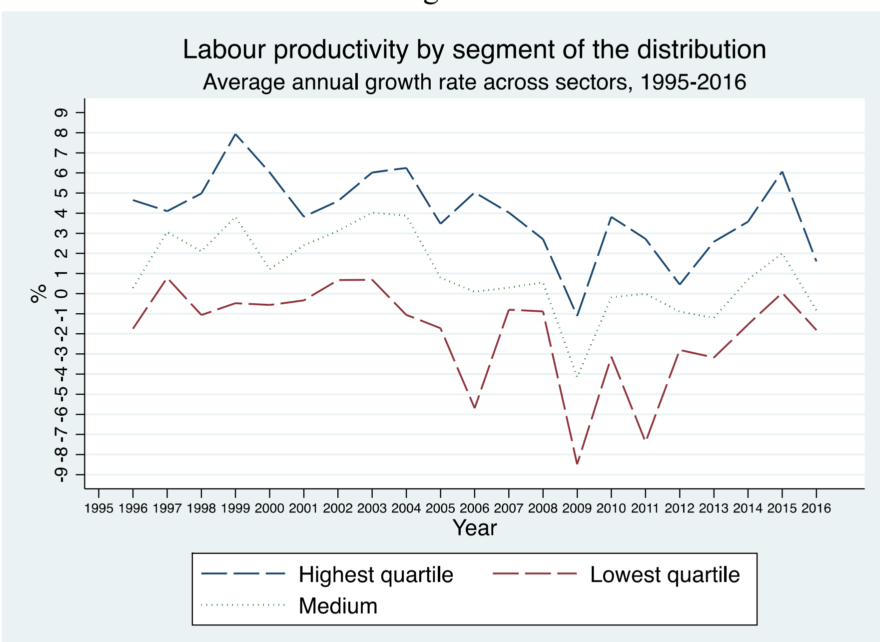
[11] The productivity growth rate decelerates in the run-up to the financial crisis from 2.7% in 1995–2002 to 0.98% in 2003–2007.

Source: Author’s own calculations

2.4.2 The distribution pattern of labour productivity growth

The following graph shows a relatively large gap between the pioneer group and the laggards within the different parts of the productivity distribution. Figure 2.4.3 displays the average productivity growth across sectors in various segments of the productivity distribution. The blue and red lines represent the trend for sectors in the top 25% (the most productive group of sectors) and the bottom 25% (the least productive group of sectors) in terms of labour productivity growth, respectively. We observe a significant gap between sectors in the upper parts of the distribution and those in the lower part, especially during the recovery period after the crisis. Between 2010 and 2016, the mean productivity growth in the upper quartile of sectors was approximately 10 percentage points more than the mean growth among industries in the lower quartile of the distribution. With the exception of the year 2009, sectors that fall into the upper quartile of the distribution can still succeed in remaining at a positive growth of labour productivity, although the overall average growth rate is close to zero.

Figure 2.4.3



Source: Author’s own calculations

2.4.3 The productivity performance of industries

The following table and graph bring some additional insights into the industry composition of productivity growth within segments. Some attention is drawn to identifying the industries' performance and corresponding characteristics, particularly within the pioneer group. A comparison of growth pre and post-financial crisis shows that all these sectors were affected by the slowdown in productivity growth, but the effect was not uniform. The Financial Services and Information & Communication sectors, which are traditionally the most productive industries, have experienced particularly unsatisfying performances in recent years. Table 4.3 and Figure 4.4 below further illustrate this point.

Table 4.3 lists the productivity ranking for market sectors and highlights their frequency of falling into different parts of the productivity distribution from 1996 to 2016. High-skilled services such as finance and insurance, information and communication, rank in the top two of the average productivity growth, do not necessarily fall into the highest quantile most frequently, but appear in fewer than half of the observation years. In most cases, their outperformance happened before the crisis, when the two sectors were experiencing the most substantial productivity growth and barely outperformed thereafter (Figure 4.4). Real estate, mining and quarrying are identified as the least productive sectors according to both productivity ranking and frequency of position in the lowest quartile. The agriculture, forestry and fishing sectors gains the highest frequency in the first quartile (10 years), but their productivity fluctuated severely, with 8 years in the lowest quartile.

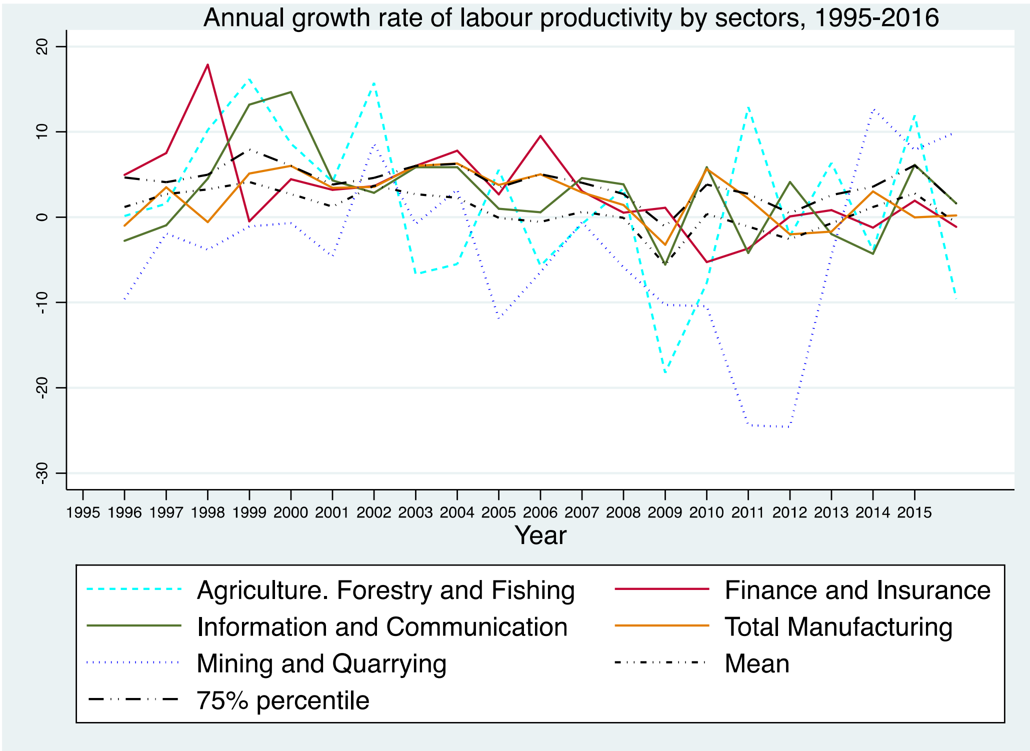
Following observations in Table 2.4-3, some illustrative sectors are selected from different quantiles and are used to visualise the overall trend of labour productivity changes from 1995 to 2017 in Figure 2.4.4 The finance industry, traditionally one of the most productive sectors, did not feature in the leading position of the upper parts of the distribution (top 25%) after 2009, and dropped below the average level several times. The information and communication sector became more unstable than in the previous decade (1998–2008), during which productivity growth was continuously above the mean. Agriculture's LP trend was unique. It follows cyclical patterns and overall instability over the two observation decades. The financial crisis initially significantly impacted its LP, with a nearly 20% decrease in 2009. However, it recovered somewhat in 2011 and did not suffer a significant slowdown in productivity afterwards.

Table 2.4-3. Labour productivity ranking and distributional segments

Sectors	**Labour Productivity Ranking (Per cent per annum)**	**Frequency** in different productivity segment		
		Highest quartile (> 75%)	**Lowest Quartile (< 25%)**	**Middle Range**
1. Financial and insurance activities	3.02	7	2	12
2. Information and communication	2.82	9	3	9
3. Total manufacturing	2.36	5	1	15
4. Professional, scientific, technical, administrative and support service activities	1.84	5	2	14
5. Agriculture, forestry and fishing	1.74	10	8	3
6. Wholesale and retail trade; repair of motor vehicles and motorcycles	1.66	6	4	11
7. Transportation and storage	1.28	6	7	8
8 Electricity, gas, steam and air conditioning supply	0.77	7	9	5
9.Construction	0.77	3	5	13
10.Water supply; Water supply; sewerage; waste management and remediation activitiessewer...	0.47	5	5	11
11.Accommodation and food service activities	0.31	3	7	11
12.Arts, entertainment, recreation; other services and service activities, etc.	0.16	3	7	11
13.Public administration, defence, education, human health and social work activities	0.06	2	4	15
14.Real estate activities	-1.00	4	11	6
15.Mining and quarrying	-3.76	4	15	2

Source: Author's own calculations

Figure 2.4.4



Source: Author's own calculations

2.4.4 The descriptives

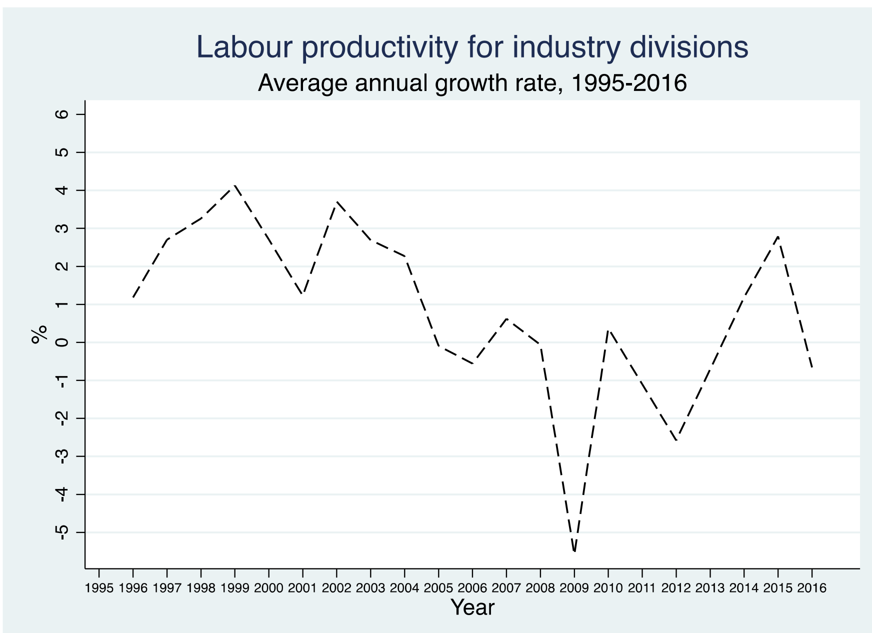
Figure 2.4.5 illustrates the labour productivity profile by averaging detailed industries in our sample across 1995 and 2017. Again, we observe a similar pattern of productivity slowing down, as suggested in the higher level of aggregation. Table 2.4-4 reports some characteristics for detailed industry divisions in the different parts of the productivity growth distribution between 1996-2008 and 2009-2016 respectively. Both output and capital are in real value, which is the chain-linked volume series with the reference year 2010. According to the following table, industries in the top 25% percentile of labour productivity growth are also associated with the highest average growth in total output (value added in volume index); in other words, expanding production at a faster rate. Their average accumulation of total AI-related capital (-0.35%) and the average of intangible capital per year (0.92%) of the highest quantile are not growing faster than other groups. It is also worth noting that the descriptive statistics on labour inputs show the upper decile of industries continuously reduces the total number of hours employed in the production process across observational years. As a result, they experience stronger growth in the accumulation of AI and intangibles per labour hour worked. For instance, between 2009-2016, on average, the annual growth rate of intangibles for industries in the highest quartile (top 25%) was 3.94%, compared with 1.64% for industries in the middle range and 0.54% in the lowest quartile (bottom 25%). This difference in intangible investments per hour between industries in the upper and other parts is accelerated in the post-crisis period.

Table 2.4-4. Characteristics of industry divisions in different segments of the labour productivity growth
(Percentage change per annum)

Variables	All	Highest Quartile (Top 25%)	Middle	Lowest Quartile (Lowest 25%)
Average 1996-2008				
Labour productivity	2.61%	8.36%	2.40%	-2.74%
AI capital per labour	5.76%	7.79%	5.70%	3.89%
Tangibles per labour	3.05%	6.15%	2.55%	0.95%
Intangibles per labour	0.23%	1.75%	0.38%	-1.75%
Intangibles (economic competences) per labour	0.89%	2.61%	0.76%	-0.57%
Intangibles (innovative capital) per labour	1.62%	3.09%	1.93%	-0.44%
Value added	1.87%	4.63%	1.50%	-0.20%
AI capital	5.12%	4.31%	4.86%	6.39%
Level of AI capital (log)	6.94	6.71	7.05	6.95
Total labour hours employed	-0.67%	-3.51%	-0.78%	2.38%
Tangibles	2.40%	2.68%	1.72%	3.45%
Intangibles	-0.55%	-1.76%	-0.51%	0.70%
Intangibles (innovative capital)	0.95%	-0.42%	1.15%	1.95%
Intangibles (economic competences)	-1.60%	-2.57%	-1.76%	-0.18%
Average 2009-2016				
Labour productivity	-0.16%	7.02%	-0.15%	-7.35%
AI capital per labour	0.91%	2.84%	1.04%	-1.29%
Tangibles per labour	0.55%	3.02%	0.39%	-1.64%
Intangibles per labour	1.70%	3.94%	1.64%	-0.54%

Intangibles (economic competences) per labour	0.52%	2.62%	0.49%	-1.56%
Intangibles (innovative capital) per labour	1.00%	3.26%	0.97%	-1.17%
Value added	0.22%	4.04%	0.35%	-3.85%
AI capital	1.01%	0.14%	1.50%	0.95%
Level of AI capital (log)	6.94	6.68	7.31	6.49
Total labour hours employed	0.09%	-2.71%	0.46%	2.21%
Tangibles	0.65%	0.31%	0.85%	0.60%
Intangibles	1.70%	1.25%	2.01%	1.58%
Intangibles (innovative capital)	1.10%	0.55%	1.43%	1.03%
Intangibles (economic competences)	2.43%	2.10%	2.68%	2.29%
Observations	635	168	315	168

Figure 2.4.5



Source: Author's own calculation

2.5 Results Analysis

The following results illustrate the relationship between AI and other productive inputs, including tangible capital, labour and integrated categories of total intangibles, based on the specifications. In column 2, regarding the efficiency of tangible capital, for the average growth rate of AI capital

(3.2%), 1% growth in tangible capital inputs affects the value-added growth by 0.28 percentage point. The interaction term between AI and tangibles has a negative and significant sign. This indicates that more AI capital employed substitutes for the amount of tangible capital engaged and, at the same time, makes existing tangibles more productive. It is consistent with **H3** that the digital-based business process through AI helps to reduce the cost of capital and increase the efficiency of existing capital employed. Regarding the net effects on labour inputs, our empirical results from column 3 do not support the net labour displacement argument **(H4a)** as in the case of robots and software (Webb 2019). Within the multiple levels that AI potentially operates on, we observe a positive interaction between AI and labour inputs, collectively augmenting labour to enhance general output growth. More detailed evidence of AI and labour-augmenting effects will be discused in the following table.

Columns (4) and (5) reveal the role of those previously unmeasured intangibles on the general production function. Total intangible capital stock accumulated, which contains information on R&D, product design and development, branding capital, labour retraining, organisational process, etc., positively and significantly contributes to the growth in value added at the 5% level by approximately 0.14% as shown in column 4. By introducing interaction between AI and total intangibles in the framework in column 5, results suggest complementarities (**H1)** between AI capital and intangibles. The value added of additional capital stock of AI is greater, by 0.0334 percentage points, for each additional 1% increase in the intangible capital accumulated.

Table 2.5-1. Impact of AI on output growth

Dependent variable: Growth rate of value added						
Variables		**Estimation techniques: FE**				
AI capital stock	$\Delta\ln(AI)$	0.0795^{*}	0.0795^{*}	0.0795^{*}	0.0795^{*}	0.0795^{*}
		(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Tangible capital stock	$\Delta\ln(K)$	0.107^{**}	0.107^{**}	0.107^{**}	0.107^{**}	0.107^{**}
		(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Total hours worked by employees	$\Delta\ln(L)$	0.119^{**}	0.119^{**}	0.119^{**}	0.119^{**}	0.119^{**}
		(0.039)	(0.039)	(0.039)	(0.039)	(0.039)

Intangible capital stock	$\Delta\ln(X)$				0.145**	-0.0872
					(0.030)	(0.555)
Interaction1	$\Delta(\ln(L)\ln(AI))$			0.0220*		
				(0.071)		
Interaction2	$\Delta(\ln(K)\ln(AI))$		-0.0239*			
			(0.063)			
Interaction3	$\Delta(\ln(X)\ln(AI))$					0.0315*
						(0.076)
N		805	805	805	805	805
adj. R-sq		0.260	0.260	0.260	0.260	0.260
P-value in parentheses * p<0.1 ** p<0.05*p<0.01**						

Table 2.5-2 directly addresses the issue of AI productivity, considering different categories of intangibles and the mechanism behind the labour productivity dynamics. According to our results, AI its-self does not enhance labour productivity growth directly. Its role becomes clear when the interaction with intangibles (column 3) is taken into account. The marginal effect of AI uptake depends on the sum of its main effects and the interaction term. If AI per labour hours were to rise by 1%, labour productivity would be expected to increase by **0.3%,** given the average level of intangible invested. This is consistent with **H4b** that instead of labour substitution effects, AI positively augments labour employed via improving their efficiency as a way of cost reduction. Our estimation shows the incremental effect of AI on productivity is 0.046 percentage points for each unit increase in intangible capital accumulation.

Compared to tangible capital, intangibles suggest relatively higher productivity enhancement in the size of magnitude. The source of influence can be decomposed into two aspects: first, intangibles themselves are crucial components to accelerate the overall general level of labour productivity, similar to what we found in the value-added production function. Second, intangibles raise the quality of AI-related capital investments by exploiting synergies.

In Panel B, we distinguished the two broad categories to further identify the source of complementarities within the broad intangibles. In columns 4–7, intangible investments are divided into innovative capital and economic competences. Innovative capital includes R&D investments, new designs and other product developments. These components are intimately linked to enhancing an organisation's long-term innovative capability. Economic competences constitute a larger group of elements, including branding capital measured by advertising and marketing expenditure, organisational capital from purchased management consulting, and own-account organisational change. Both categories suggest a positive contribution in the first difference function and are essential to incorporate into the production function. In particular, economic competences indicate a more significant and positive effect on general labour productivity compared with innovative capital.

It is worth noting that economic competence tends to be more effective at enhancing general labour productivity. However, in the context of AI, the interaction term with innovative capital shows a greater persistence to enhance AI productivity at a 5 % significance level (column 5), while no significant effects are suggested by interacting with economic competences. This is consistent with the H2 that innovative capital undertakes a more important role in exploiting AI. Firms that invest in AI need to develop their long-term capabilities to use it. Investments in innovative capital are closely linked to improving firms'' innovative capacity, in other words, complemented by a series of innovative activities to commercialise AI solutions. Given the average growth of innovative capital (1.3%), a 1% increase in AI-related capital stock per hour can lead to a 0.3589 % increase in labour productivity growth.

Table 2.5-2. AI, intangibles and labour productivity growth

Dependent variable: Growth rate of value added per hour							
Variables		*Estimation technique: FE*					
		Panel A			Panel B		
AI capital stock per hour	$\Delta\ln\left(\frac{AI}{L}\right)$	0.0794	0.2799**	0.0669	0.2605	0.2761***	0.3220**
		(0.171)	(0.014)	(0.205)	(0.107)	(0.003)	(0.046)
Tangible capital stock per labour	$\Delta\ln\left(\frac{K}{L}\right)$	0.2549***	0.2513***	0.2390***	0.2376***	0.2341***	0.2342***

		(0.000)		(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
Total intangible capital stock per hour	$\Delta\ln\left(\frac{X}{L}\right)$	0.3367***		0.6228***				
		(0.000)		(0.000)				
Complementarities with total intangible capital per hour	$\Delta(\ln\left(\frac{X}{L}\right)\ln\left(\frac{AI}{L}\right))$			0.0460**				
				(0.020)				
Innovative capital stock per hour	$\Delta\ln\left(\frac{X1}{L}\right)$				0.1023	0.0956	0.3575***	0.2995*
					(0.145)	(0.188)	(0.003)	(0.069)
Economic competence capital stock per hour	$\Delta\ln\left(\frac{X2}{L}\right)$				0.2834***	0.5122**	0.2721***	0.3810
					(0.000)	(0.011)	(0.001)	(0.117)
Complementarities with innovative capital	$\Delta(\ln\left(\frac{X1}{L}\right)*\ln\left(\frac{AI}{L}\right))$						0.0393**	0.0310
							(0.013)	(0.118)
Complementarities with economic competences	$\Delta(\ln\left(\frac{X1}{L}\right)*\ln\left(\frac{AI}{L}\right))$					0.0360		0.0168
						(0.121)		(0.586)
Controls								
Complementarities between different intangible assets	$\Delta\ln\left(\frac{X1}{L}\right)*\Delta\ln\left(\frac{X2}{L}\right)$							0.1172
								(0.826)
Year dummy		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N		658	625	625	646	646	646	646
adj. R-sq		0.315	0.351	0.353	0.348	0.349	0.351	0.349

P-values in parentheses * p<0.1 ** p<0.05*p<0.01**

In Table 5.3, following the alternative approach in Corrado and Haskel (2017), we further examine the complementarity between intangibles and AI in the general production function. It is also a way of signaling robustness on our earlier results. This model is believed to be more advantageous in addressing reverse causality and omitted variables bias. In the following table, we find out whether AI-intensive sectors that accumulated intangible capital at a relatively faster rate could experience stronger productivity growth. An affirmative answer would be expected if investments in additional capital, such as new organisational processes, marketing expenditures, etc., are necessary elements of complementary changes.

From our results, AI-intensive industries, which simultaneously accumulate intangible assets at a relatively faster pace, would gain an additional 0.094 points in general output from each unit of increase in intangible capital. Hence, for multi-purpose technologies, intangibles help resolve the inefficient absorption of AI technology installed and generate higher output growth. Consequently, industries that have more AI capital invested and jointly accumulate intangible assets faster tend to be the most productive.

Similar to Table 2.5-1, after incorporating intangibles in the general production function, we include AI interaction with labour and capital inputs in columns 3 and 4, respectively. A consistent result is obtained, which is a net effect on labour creation and capital saving. Column 2 also indicates the magnitude of unmeasured intangibles in the total value added. The positive interaction term shows that the impact of changes in intangible investments on output growth is non-linear, and the size of effects intimately depends on the intensity of AI uptake. In our sample, given the average level of AI, 1% growth in intangibles would contribute about 0.38 percentage points to the growth of value-added.

Table 2.5-3. Complementarities between AI and intangible capital

Dependent variable: Growth rate of value added

AI capital stock	$\Delta\ln\,(AI)$	0.0726	0.0747*	-0.1726	0.3352***
		(0.116)	(0.098)	(0.290)	(0.007)
Total hours worked by the employees	$\Delta\ln\,(L)$	0.1035*	0.1099*	-0.0252	0.1131*
		(0.095)	(0.071)	(0.805)	(0.057)
Tangible capital stock	$\Delta\ln\,(K)$	0.0794*	0.0824*	0.0949**	0.2420***
		(0.089)	(0.075)	(0.045)	(0.004)
Total intangible capital stock	$\Delta\ln\,(X)$	0.1454**	-0.0256	-0.3739	-0.2707
		(0.027)	(0.239)	(0.196)	(0.233)

Industry AI capital stock level	$\ln(\overline{AI_\iota})$		0.0233***	0.0221***	0.0245***
			(0.000)	(0.000)	(0.000)
Complementarities between AI and intangibles	$\ln(\overline{AI_\iota}) * \Delta\ln(X)$		0.0561*	0.0685*	0.0564*
			(0.059)	(0.073)	(0.057)
Complementarities between AI and labour	$\Delta(\ln(L)\ln(AI))$			0.0195*	
				(0.099)	
Complementarities between AI and capital	$\Delta(\ln(K)\ln(AI))$				-0.0252*
					(0.067)
Other controls					
Complementarities between intangibles and capital	$\Delta\ln(X) * \Delta\ln(K)$				0.5377
					(0.653)
Complementarities between intangibles and labour	$\Delta\ln(X) * \Delta\ln(L)$			-1.6718*	
				(0.093)	
Year dummies		Yes	Yes	Yes	Yes
_cons		772	772	772	772
P-values in parentheses * p<0.1 ** p<0.05*p<0.01**					

2.6 Conclusion

Overall, in this study, we start with the theoretical suggestions by Brynjolfsson et al.'s (2018) and extend the scope of 'complementary changes' to tackle the AI productivity paradox. This 'study develops its own framework, synthesises and measures intangibles by taking categories identified in the literature to unpack the mechanism of AI within the production function, and estimate corresponding effects on productivity growth. Our evidence confirms that those intangibles, whose contributions are not fully measured in traditional estimations, are crucial in production and productivity growth. The more substantial growth of intangibles accumulated drives greater productivity growth of AI and related emerging technologies. Investments in a broad range of intangibles help adapt and better absorb AI technology and in total generate a more significant impact on labour productivity growth than other fixed capital. In particular, the innovative intangible assets suggest greater importance in complementing AI productivity growth. The innovative capital is associated with developing the long-term capability/innovative capacity to commercialise AI and emerging technologies through new business practices and offerings.

Within the production channels, we observe that the uptake of AI and related emerging technologies can effectively substitute ordinary tangible capital. This is a process innovation with digitally embedded equipment or smart technology with AI capabilities, which maintains the output of goods and services but reduce the fixed capital investments. For instance, deploying AI solutions can increase the life span of assets and thus reduces purchasing new equipment in the future. In terms of impacts on labour inputs, though, according to current literature, AI can automate human activities or, in other words, replace labour in production. It does not ultimately lead to the reduction of labour inputs required. In this paper, empirical evidence do not confirm the net effects of labour substitution, but instead the increased use of labour. The labour creation can be attributed to improved competitiveness of products and services and/or new product innovations provided in the market by AI. However, this empirical study cannot explicitly distinguish the direct and indirect channels for labour creation, as it requires additional profitability indicators. The mechanisms behind labour productivity dynamics tend to support some labour augmentation effects after considering different intangibles. New jobs or labour might be needed to build AI infrastructure and monitor its operations during the technology adoption. At the same time, AI may advance some types of labour over others. Adopting AI and related emerging technologies may reorganise existing jobs towards non-routine tasks requiring digital skills, accompanied by rising productivity gains. For instance, higher skilled workers are needed to extract patterns or transfer insights from AI technologies or work consistently with the capabilities of AI. Overall, our empirical evidence suggests AI improves the efficiency of labour employed by augmenting human capabilities, thus enabling current labour to become more productive. Finally, it is worth noting that innovations in AI will not be captured by productivity growth, as innovation does not stimulate gains in efficiency. It can only be reflected by other measures, such as current profits and return on assets or capital invested. Given this limitation, the third chapter will investigate more evidence on technology adoption and firms' financial performance indicators.

Appendix

The following table excludes the mining industry, whose labour productivity performance differs from the other sectors. Similarly, AI uptake tends to generate a more significant impact on labour productivity for those industries that are intangible intensive. Coefficients of AI and intangibles show more substantial significance while the sign and size remain similar, as in Table A1 By excluding the mining industry, economic competences become greater regarding both main effects and complementarities.

Table A1. Impact of AI on labour productivity

Dependent variable: Growth rate of value added per hour

Variables		*Estimation technique:*				
AI capital stock per hour	$\Delta\ln\left(\frac{AI}{L}\right)$	0.1345***	0.3802***	0.1149***	0.3316***	0.4309***
		(0.0487)	(0.0543)	(0.0399)	(0.0500)	(0.0449)
Tangible capital stock per labour	$\Delta\ln\left(\frac{K}{L}\right)$	0.2261***	0.2196***	0.1986***	0.1917***	0.1922***
		(0.0351)	(0.0346)	(0.0322)	(0.0315)	(0.0316)
Total intangible capital stock per hour	$\Delta\ln\left(\frac{X}{L}\right)$	0.3041***	0.6517***			
		(0.0403)	(0.0537)			
Complementarities with total intangible capital per hour	$\Delta\left(\ln\left(\frac{X}{L}\right)\ln\left(\frac{AI}{L}\right)\right)$		0.0557***			
			(0.0322)			
Innovative capital stock per hour	$\Delta\ln\left(\frac{X1}{L}\right)$			0.0629	0.3265***	0.0508
				(0.0121)	(0.0314)	(0.0098)
Economic competence capital stock per hour	$\Delta\ln\left(\frac{X2}{L}\right)$			0.3188***	0.3087***	0.6890***
				(0.0487)	(0.0490)	(0.0543)
Complementarities with innovative capital	$\Delta\left(\ln\left(\frac{X1}{L}\right)*\ln\left(\frac{AI}{L}\right)\right)$				0.0405***	
					(0.0296)	
Complementarities with economic competence	$\Delta\left(\ln\left(\frac{X1}{L}\right)*\ln\left(\frac{AI}{L}\right)\right)$					0.0578***
						(0.0330)

Complementarities between different intangible assets	$\Delta \ln\left(\frac{X1}{L}\right) * \Delta\ln\left(\frac{X2}{L}\right)$						
Year dummy		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N		604	604	625	625	625	625
adj. R-sq		0.350	0.355	0.350	0.357	0.354	0.356

Se in parentheses * p<0.1 ** p<0.05*p<0.01**

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3 Chapter 3: Artificial Intelligence, Human Capital and Productivity growth

Abstract

This empirical study, motivated by the issue of a slowdown in EU productivity, establishes the link between investments in AI technology and a specific type of intangible asset – investments in human capital. Based on the sectoral level analysis for multiple countries, our study affirms the robust complementary effects of human capital in terms of AI productivity gains across different estimation methods. The paper constructs the framework by splitting human capital into two aspects: general labour quality and specific training. Relations between AI and various human capital components are unpacked, examined and compared in our framework, including vocational training, tertiary education and labour composition. The marginal effects of AI, enhancing labour productivity, are quantified under different scenarios. In addition, the study also extends the analysis into the context of emerging EU economies. Although it is widely considered that AI technology poses threats to the development of developing economies due to job displacements, our empirical evidence tends to support the positive side, consistent with the part of the sub-hypothesis. Given each level of growth in human capital, we observe more considerable benefits from an additional increase in AI capital investments in terms of the case of emerging economies.

Key words: Artificial intelligence; Labour productivity growth; Intangibles and human capital

3.1 Introduction

Since 1995, statistics have suggested a slowing down of productivity has manifested in many European countries. In the decade before the 2009 financial crisis, annual labour productivity in the US was accelerating (from 1.5% to 2.3%), yet there was a falling growth trend in Europe (from 2.4% to 1.5%). According to the OECD statistics (1995–2019), the productivity growth of the EU-28 has been slowing steadily in recent decades. The ongoing stagnation is not primarily accounted for by the legacy of the Great Recession but reveals a long-term trend. The gap between the pre-downturn trend rate of productivity growth and its actual post-downturn performance is known as the 'productivity puzzle'. For instance, the collapse in growth has been particularly pronounced in the UK, where labour productivity growth disappeared during the recession and remained stubbornly low in the following eight years. Figure 3.1.1 illustrates the difference between the actual and the projected productivity growth. We can observe that the equivalent productivity gap among the average of the other G7 countries (US, Japan, Canada, Italy, Germany, France) is much smaller than that of the UK. Figure 2 displays the difference in productivity trajectories (constant price GDP per hour) among G7 leading economies, where Italy and the UK have ranked at the lowest and second lowest in GDP per hour since 2008. The deterioration in the post-recession period is a global phenomenon, further broadening the productivity gaps even among leading economies. According to recent records from the Office of National Statistics, the productivity growth in 2016 continues to be below the average real growth in terms of GDP and GDP per worker compared with the G7 developed countries and is broadly unchanged in the nominal GDP gap. In contrast, Germany's statistics suggest an entirely different pattern in some key industries (ICT, finance, etc.) from that in most EU countries, with much more substantial growth in TFP and outperforming others post-crisis.

Figure 3.1.1

Constant price GDP per hour worked, G7 countries （1997–2016）

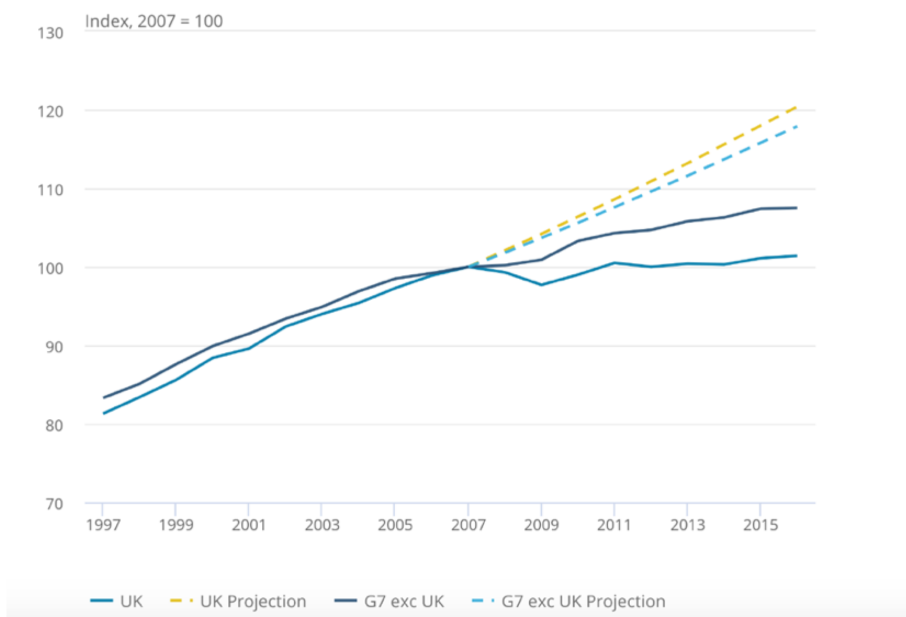
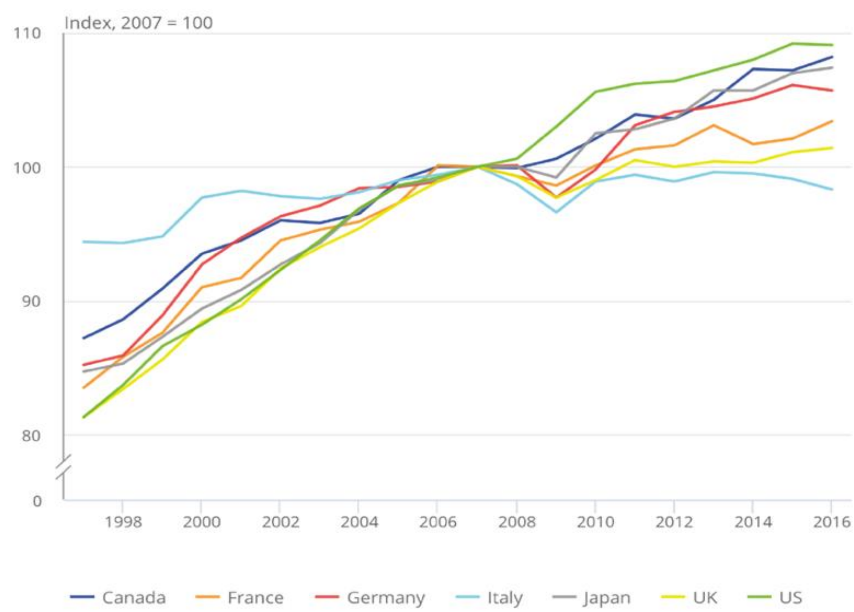


Figure 3.1.2

Constant price GDP per hour worked, actual and projections (1997–2016)



Source: OECD, Eurostat and ONS

Based on the slowing down of productivity and variability across countries, this research contributes to resolving the issue by considering the relation between AI and human capital on productivity gains. We see the effects of transformative AI technologies everywhere except in productivity statistics.[12] It is argued in this paper that labour productivity can effectively be enhanced when AI and appropriate human capital inputs are used together.

Besides, this chapter also contributes to answering a more precise question: Can AI - related investment be a solution for countries with a limited amount of skilled labour? For example, one way to measure generic human capital is to link it with investment in tertiary education, which is one of the mechanisms directly associated with the policy level[13]. Overall, we consider different measures of human capital that policymakers can intervene in and employ a framework that divides human capital investments into two aspects: upskilling through general labour quality and uncertified vocational training in the workplace. We employ the framework on human capital and enhance it by including AI-related capital investments. Our study estimates the marginal effects of AI technology on labour productivity, conditioned on various human capital components, including labour composition, education, and specific training. We allow for a better measure of labour quality (labour composition) and then have better inferences in terms of the importance of AI. In particular, the results emphasize the importance of investing in specific vocational trainings to enhance labour productivity growth rather than simply expanding general higher education. AI productivity is coupled with stronger vocational training and new business models to better use workforce skills and move up the value chain. The Institute of Public Policy (2014) criticized that the growth in university graduates has far outstripped the number of high-skilled jobs available in Britain, hence leading to a significant mismatch in the labour market. This appeals to the government to take action to reform vocational qualifications to be rigorous and responsive to employers' needs particularly under the digital technology adoption and transformation process.

[12] The facts describe the phenomenon of the AI productivity paradox, which refers to the fact that the technology expectations of AI and the associated economic statistics are in conflict with one another (Brynjolfsson et al. 2018).
[13] In the first paper, we focus more on private dimension such as private R&D and other diverse types of intangibles.

Besides the central issue of the slowdown in EU productivity, it is also worth noting that Eastern Europe may experience a different development trajectory from Western Europe. We would like to explore the impact of AI and human capital on productivity growth within reginal concerns. Under our observational period (1995–2015), some countries from Eastern Europe were classified as developing economies or low-middle income countries. By taking benefits from the multi-country database, this study extends the analysis of AI, human capital and productivity into the context of emerging economies. Traditionally, developing economies utilise abundant semi-skilled but lower-paid workers to attract foreign manufacturing companies and outsourced services. As a result, they acquire competitive advantages in export-oriented industries (IFC 2020). Following this view, AI poses new threats and may especially affect the growth of developing countries, as the new technology could displace millions of jobs in the future. Embedding cognitive abilities mobilised by the labour force, AI will potentially block the traditional development ladder. For instance, AI systems are leading to massive job losses in the back office administrative functions in finance and health (Goldin 2019). These roles have been outsourced in recent years to many developing economies such as India, Vietnam, South Africa, etc. However, a distinct view is concerned in this study regarding the impacts of AI on less developed countries. It is argued that AI may offer new opportunities that reduce the costs and barriers to entry for enterprises in emerging economies. Innovative business models that apply AI technology could be delivered to help those developing countries leapfrog some issues on infrastructure, education, etc. The ambiguity motivates this study to unlock the main research question by providing additional supplementing insights on AI, human capital and labour productivity growth across groups in our sample. The two groups are further defined and distinguished in comparison, representing the developed (high-income countries) and emerging economies (low-middle income countries).

Structure

The format of this paper is as follows. Section two starts by reviewing some key research in terms of intangibles, technology and productivity. It highlights research gaps and the contributions that this study has made in comparison with other work. The section also discusses the role of human capital components, AI technology and corresponding productivity effects under different scenarios, and then develops hypotheses and sub-hypotheses from the author's point of view. The Methods section details various human capital components in our framework. This section derives the economic models of productivity that we will estimate, and describes the econometric strategy. The datasets are described in the following section separately, containing the measure of variables and preliminary results by statistical analysis. Regression analysis and further evidence are presented in the Results section with robustness checks, and then concluding remarks are offered in the final section.

3.2 Background literature and gaps

A range of studies has investigated the impact of IT technologies on productivity growth. Amongst these studies, a small strand of literature focuses on the additional channel through which intangible investments can affect labour productivity growth. This literature emphasises the claims initially pointed out by Brynjolfsson, Hitt and Yang (2002) that the existence of complementary intangibles (organisational assets as intangibles) can affect the effectiveness of ICT adoption or better exploitation of ICT technologies. The argument was brought up based on some firm level evidence, but there is no actual data on measuring intangibles in Brynjolfsson et al. (2002). Specifically, it is found in their study with a relatively higher output elasticity for ICT technologies than its income share. This finding is rationalised as the omitted variables bias effect from intangibles. Furthermore, Boom, Sadun and Reenen (2007) focus on the US 'productivity miracle' debates that have raged since the mid-1990s. Their study notes that, compared with non-US multinationals, a better organisational structure or organisational design feature is developed, allowing US multinationals to use technologies more efficiently and thereby increase their IT capital's productivity. The importance of intangible capital is initially highlighted according to firm-level evidence.

Following this early hypothesis by Brynjolfsson et al., Chen, Niebel and Saam (2016) first unpack the definition of intangibles based on the CHS framework (2005, 2009) and identify the differential impacts of intangibles across varying levels of ICT intensity sectors. Their empirical analysis suggests that intangible capital can provide a higher return on value-added growth in those ICT-intensive sectors than in non-ICT intensive sectors. Tackling similar questions, Corrado et al. (2017) filled the gap at the industry level by analysing 10 EU countries from 1997 to 2007. This empirical work further corroborates intangibles' complementarities with the stock level of ICT technology. Additionally, it points out the indirect productivity spill-over as a result of the diffusion of knowledge initiated from intangibles. Given the recent availability of sectoral breakdown in the INTAN-invest database, these two empirical studies proceed a step further in uncovering new insights on ICT and intangibles, as some data on all intangible asset types are introduced into the estimations.

Moving to the context of artificial intelligence, similarly, Brynjolfsson (2017) first points out the parallels between the previous ICT technologies and AI. It is argued the impact of AI has yet been reflected in productivity statistics as AI requires a large stock of complementary capital, both tangible and intangible, to be built and put in place at the same time. Their 2018 study derives a theoretical model that illustrates how these unmeasured intangibles can initially lead to the underestimation of the aggregated output growth in the early years of AI adoption, and then the overestimation of aggregated output growth later on. This phenomenon is referred to as the ***J curve*** effect. However, given the empirical firm level illustrations in the study, it is R&D and capitalised general administrative expenses that are used as the proxies to illustrate the role of intangibles. Hence, in this case, we only know that, in theory, intangibles are hidden, unmeasured and possibly involve a range of diverse factors, such as human capital, business process redesign, new management practices, or other co-inventions, etc. Very few studies from the literature systematically investigate the relationship between AI technology and the composition of intangible investments. In other words, current empirical evidence is still insufficient to affirm which components of intangibles are particularly effective in terms of AI technology and the associated magnitudes. This issue is partly attributed to the data unavailability and techniques that can precisely measure both AI technology and intangible capital. Although the discussion that we mentioned can bring us some understanding of the role of intangible capital in the general ICT technology adoption, lessons cannot be fully applied to the case of AI and big data. It is because different types of complementary capital might be specifically required depending on the nature of the technology. At the same time, the related deployments will be associated with different prices and adjustment costs accordingly. AI is considered a general-purpose technology that can be transformative and continuously improved over time (Brynjolfsson et al. 2018). Adopting AI & big data related technologies may be unpacked with a range of applications, which help organisations make better marketing and business decisions, detect fraud, conduct predictive analysis and forecast, etc. Thus, investing in AI technology could be vastly different from other previous ICT technologies, in which many new business opportunities or even the entire business model could be driven with AI adoption over time.

Following the analysis, this research will fill this gap by linking the AI technology invested with a specific type of intangible – investment in human capital. Human capital is a broad concept that includes ‘education, training, medical care and additions related with knowledge and health’ as defined by Becker (1992). Distinctively, this paper considers the complementarity of human capital in AI investments, and formalises its framework by splitting human capital into two aspects: general labour quality and specific training. Precise AI-related human capital components are identified in our framework, including vocational training, tertiary education and labour composition. If we compare similar studies that focus on AI and intangibles, clearer contributions and differences of this study can then be identified. A very recent study by Corrado, Haskel and Lasinio (2021) uses the CHS (2005; 2009) framework and calculates the total amount of plenty of previously unmeasured intangibles. It aims to directly assess the productivity ‘J-curve’ hypothesis according to Brynjolfsson et al. (2018, 2021). However, the estimation does not fully support the above hypothesis. In their cross-country industry level estimations (1995–2017), the trend of miss-measured intangibles is not sufficiently significant to bring a J curve effect. There are some hints found in the US but no evidence in the Western European economies, suggesting that intangibles could be sufficient to explain the magnitude of the decreasing trend in the TFP growth after the financial crisis. Hence, in Western EU economics, it is ambiguous to conclude the complementarity between the total intangible assets and AI technology. Besides, our first chapter examines the AI productivity puzzle from an intangible approach based only on UK industry-level statistics. It uncovers some underlying mechanisms of how AI could affect labour productivity growth through production channels, and measure a wide range of intangible assets, broadly classified into innovative capital and economic competence. Results in this chapter confirm the complementary effects between AI and total intangible assets in terms of labour productivity growth, while the complementarity is more attributed to innovative capital according to the two-type classifications. Overall, both of the above papers consider the role of intangibles in a relatively broad range, whereas it is not all types of intangibles confirmed as necessities to enhance AI productivity. Instead, this study argues that the contribution of AI and productivity can be partly accounted for by a particular type of intangibles – investments in human capital, given panel data analysis in European countries. A recent study by Tambe et al. (2019) includes human capital in the analysis and realises skills matter for US AI firms. They measure AI adoption through the technology skillsets of labour. To be more specific, IT employment measures[14] are constructed based on the employment histories of US IT workers on LinkedIn. Labour with different skills in AI, data science, cloud computing, digital literacy, management and advertising skills can be captured, given their occupations. In their study, human capital is augmented in one of the production functions. It is measured by the level of degrees achieved (Bachelor's degree, Master's degree and JD, etc.) and has been found with a positive effect on the productivity of IT employment. However, instead of applying a generalised view of human capital based on years of education, age, etc., our study pushes forward the discussion of their roles explicitly linked to AI. A precise framework is offered to unpack how various elements of human capital, together with AI technology, take effect to enhance labour productivity. It should be noted that the range of economic competence can be relatively widespread within an organisation; however, the link with AI investments is still yet to be established on different types of skills.

3.3 Hypothesis

3.3.1 Part I. AI and Human Capital

First, why does this study pay particular attention to the investment in human capital instead of other intangible assets? If we consider the related AI strategy through a global lens, some essential leading practices can be learned from those countries with a solid competitive advantage in AI adoption. Compared with other global rivals, the US and Germany rank as the top 2 countries in terms of the number of firms classified as 'seasoned' AI adopters.[15] Germany stands out uniquely, in that it that outpaces the other six countries (US, China, UK, Canada, Australia and France) for AI training. Respondent companies from Germany are more likely to develop and train existing workforces to fill the AI talent gap. They put strong efforts into employees' educational backgrounds through a holistic approach, train staff to use AI in their work, train developers to

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[14] The IT employment measures (either in quantities or capital accumulation) are referred as the IT related intangible assets in their study.
[15] The 'seasoned' in their survey refers to the most experienced adopters at the leading edge of AI adoption maturity.

innovate in new solutions, and upskill existing IT staff to use those new solutions. A similar path is also happening in the US, with the most significant percentage of seasoned AI adopters, and has always been leading in public and private AI research in the world. Many US companies are employing internal training programmes in response to the pressure of talent. Recent reports point to three major concerns early AI adopters face: AI's potential cybersecurity vulnerabilities, AI risks and AI skill gaps. The lack of skills seems to be a pervasive one. Around 68% of the global respondents in *Deloitte's State of AI in the Enterprise* (2021) indicated moderate to extreme concern about the AI skills gap.

The practical evidence reveals that first movers now feel increasing pressure on the talent gap issue. As more firms put AI into operation and products, the right talents are crucial to support their large-scale initiatives. Organisations can seek the best talents externally, as the government can address the demand, and develop and support graduates of the national education system. However, the talent pool might be somewhat fixed or inelastic, simply relying on the national education system. Hence, some adopters have now turned to investing in internal training programmes and utilising existing employees, as in the two illustrations, to ensure the entire organisation works effectively with new capabilities.

From a theoretical viewpoint, labour inputs can be associated with the impact of AI technology on productivity. Abis and Veldkamp (2020) model the factor input of skilled labour, data and machine learning technology through the knowledge production function. They estimate how much the production function has changed due to the use of big data and AI technology compared with classical data analysis.[16] It is found that machine learning technology will change the ratio of data and labour (analogous to the Industrial Revolution in goods production), allowing humans to be more efficient at knowledge production. Three types of labour are distinguished in the framework: data managers, artificial intelligence analysts, and classical data analysts. Data managers take the

[16] In their study, they use labour market data from the financial sector and estimate two production functions – one for classical data analysis and one for machine learning. The classical data analysis refers to the old statistical techniques in financial analysis such as ANOVA, Stochastic Optimisation, GLM, Bootstrapping, Markov, Monte Carlo Simulation, Black-Scholes, etc. The AI data analysis is identified by the key word in the job postings, such as Machine Learning, Natural Language Processing, Neural Network, Automatic Speech Recognitions, CNN, SGD, etc.

roles in creating the information, for instance, selecting, purchasing and processing raw data into usable data stock. They create structured datasets, which along with analysts, are the inputs into the knowledge production function. In other words, the knowledge is produced by a mixed combination of processed data stock and analysts with either relevant big data, AI, machine learning skills, or traditional statistical techniques. The processed data input is the same for both types of analysts. Their results indicate a decline in the diminishing return to data, which shows up as an exponent on data input in the knowledge production function. The estimated data exponent increases from 0.56, using old statistical techniques, to 0.734 due to the use of new big data or machine learning technology. Hence, the old technology has a greater declining return to data in comparison. AI technology could significantly increase the productivity of analysing more extensive data sets by approximately 31%.

In sum, their analysis indicates machine learning technology could use a broader array of data types, including some data stock challenging to be used by traditional analysis. As a result, a higher marginal value (less declining return) is obtained for an additional piece of data compared with previous technology, improving productivity accordingly. At the same time, under the increasing size of data stock in the digital age, those firms with more accumulated data are prone to employ more analysts with data-related skills, or data managers in general. The more those workers work with data, the higher the marginal value of data and the more valuable data stock is. Overall, we can refer from the discussion to the increasing importance of skills in complementing AI productivity. The supply of skilled labour relies on the accumulation of human capital that consists of investments in general knowledge to enhance labour quality as well as training of specific skills required. From the experience of the leading global AI adopters, as we discussed previously, hints suggest both aspects of these investments matter in the competition and help advance AI efforts. Abis et al. (2020)'s study only estimates a change in the knowledge production parameters of firms within the financial industry. Our study pushes forward and focuses on the role of human capital for various detailed industry divisions in multiple countries.

In addition, Mahoney (2012) first employs a growth accounting decomposition to show the impact on output growth of an extended measure of human capital. In their work, human capital, as intangible investments, is embodied in individuals; it is unable to transfer to others and does not appear in the national accounts. Their study distinguishes two types of human capital: 1. investment in formal education, which is assumed to be primarily general, and occurs before individuals join the workforce; 2. Continued training that firms invest in their employees to reap some benefits, or on-the-job training. Their study points out that failure to consider continuous training will lead to severe underestimates of the magnitude of human capital accumulation or changes in the average skills of the workforce. In Mahoney's study, the cross-country correlation for the average share of continuous training between general education tends to be positively significant. This piece of evidence brings us some indications that continuous training and general education are plausible complements rather than substitutes. Hence in this research, we unpack the definition of AI-linked human capital and employ a framework that contains two aspects of human capital with various measures[17] (vocational training, tertiary education and labour composition). We arrive at the first hypothesis on the relationship between human capital and AI on productivity growth:

H1: Investment in human capital, measured by vocational training, tertiary education and labour composition, can generate a positive complementary effect with AI uptake on productivity growth.

3.3.2 Part II. Two sub-hypotheses

General vs specific human capital investment. CEDEFOP (2014) points out that assessing types of skills or human capital best suited to AI is complicated, as skills required for rapid technology adoption may subsequently differ for effective exploitation. This section supplements the main hypothesis **H1** and further distinguishes the relative importance between specific training and general labour quality in the case of AI technology. According to the review, there is a lack of enough theoretical concerns for different components of human capital investments linked with emerging technologies.

[17] Detailed explanations of the measures and construction of the framework will be placed in the methodology section.

The study by O'Mahoney et al. (2008) suggests that ICT-related demand for labour holding a university degree in the US has been particularly strong since the 1980s, the period of early adoption of ICT technologies. In other words, the initial adoption of ICT technology in the US is supported by greater availability of tertiary education labour compared with European countries. As a result of the initial rapid pace of ICT innovations, in the following decade the US economy experienced accelerated growth in productivity. Since 1995, industries that produce ICT equipment have experienced higher productivity growth. There is also a capital-deepening effect from the investments in ICT technology across the whole economy in the US. During this period, rather than requiring university graduates, ICT-related demand for labour with intermediate qualifications began to increase in the US. In addition, German apprentice training is another example of intermediate qualifications, updated regularly to concern the advances in ICT technology and software. The training would equip apprentices with routine operations or maintenance, quickly adapting to firm-specific requirements.

Therefore, given those facts in the US, we may distinguish the importance of different human capital investments in the context of AI productivity. We may expect university graduates or up-skills arising from general education to be crucially important in the initial stage; in other words, it is the stage where new technology is developed or adopted. Later, as the new technology becomes established, vocational skills gradually reveal a more important role in adapting firms' specific requirements and exploiting the benefits in depth accordingly.

AI productivity in developing economies. *Some* arguments suggest that AI-driven technical change may not necessarily be as strong skill-biased as the previous wave of digital technologies. From this perspective, Ernst, Merola and Samaan (2019) in their work point out the importance of social, interpersonal, and emotional skills or learning capacities for workers to be able to use new technologies. The requirement of technological skills is mainly in the area of product or service development. Since more and more applications of AI come on to the market, a certain generic understanding of availability and use cases for new technology is becoming essential, just as reading and basic mathematical skills are essential for today's low-skilled workforce. As intelligent machines are taking over routine tasks such as compliances, verification or other rules-based tasks, employees will shift to work on sales, marketing or consulting, etc.

Following this view, we infer that the gains in productivity from AI technology may not happen merely in developed economies. AI-based applications can, in particular, play a productive role in those countries faced with challenges in education or infrastructure. The generation of expert systems initially relies on hardwired expertise gathered from countries and in different contexts. The learning capacity of AI would then allow the system to be amenable and deployed on various occasions without much prior knowledge of the local environment. Local users of the applications are not required to understand the underlying technology in depth, or provide complex inputs into the devices. Intelligent day-to-day usage can generate advice based on overall best practices combined with local situations. For instance, an AI expert system in Africa is used to help farmers get more information on selecting and planting a suitable variety of seeds to improve agriculture (Saiz-Rubio and Rovira-Más 2020). Hence, AI-based applications are more productive by providing customer-tailored or production-characterised solutions, and creating low entry barriers for diffusion. It would be especially promising for developing countries, as most developing or low-income countries do not possess adequate resources to build higher education systems under a similar scope and breadth as developed countries. The issue leads to disadvantages in the supply of labour with the right technical skills to develop new technology. Instead, using AI applications or AI-based tools on a broader scale relies on diverse and non-technical skill sets, as discussed, allowing developing countries to overcome existing gaps more quickly.

In sum, the above discussions point out the gaps, and bring us to consider the role of different components of human capital, which will be investigated further in the regression analysis. Investment in higher education, which often focuses strongly on advanced technological skills, will be primarily required in areas where new AI-related products or services are being developed. These investments are crucial to improve firms' innovations and potential to affect productivity growth in the future. There are other human capital investments that can provide more specific knowledge in the workplace, or diverse skills, more important in the effective uses of new technology and hence gains in productivity. These types of human capital are not necessarily acquired through the formal education system or possessed by highly skilled workers with university degrees. In addition, since using AI-based tools or applications requires little or no prior technical knowledge, AI helps improve productivity even for low-skilled workers, by offering expert knowledge to them as non-specialists. For those developing countries with limited resources, AI-based tools can provide new ways and allow them to leapfrog traditional developments, skipping the need to set up expensive infrastructure or long process education challenges.

Ha: Investments in in-firm training are more effective than investments in higher education to enhance AI productivity growth.

Hb: The productivity growth of AI is especially promising for currently low-income or developing countries.

3.4 Methods

3.4.1 The Estimation models

According to the neoclassical model, only exogenous technical progress drives long-run productivity growth, and capital suffers diminishing returns. In contrast, the new growth theory intends to provide an endogenous mechanism for long-run productivity growth. Firms may face constant or increasing returns to scale to all private inputs. The level of technology can be determined by the stock of some private inputs such as R&D, human capital and spillover effects from heterogeneous capital investments, etc., delivering long-run change in productivity growth (Mankiw, Romer and Weil 1992; Griliches 1995).

The starting point in this study is based on Griffith and Reenen (2004 & 2020), who investigated the impact of R&D capital on productivity growth at the firm and industry levels. In their model, the TFP growth rate depends on the knowledge stock's growth rate, measured by R&D capital. It is believed that resources devoted to R&D are also essential resources and should be devoted to information technology and highly educated workers. Human capital, as one of the categories of intangible investments in the definition in CHS (2005), is similar to the way of measuring the impact of intangibles. The standard growth accounting framework is adopted, incorporating the variation in human capital accumulation and AI uptake. It is assumed that an industry j in country c, at a particular point in time *t*, is characterised by a Cobb-Douglas production function exhibiting a constant return to scale.

$$Y_{cjt} = \theta_{cjt} f\left(K_{cjt}, L_{cjt} AI_{cjt} H_{cjt}\right) \tag{1}$$

The production function is written in value-added form. The value-added depends on the inputs of labour *L*, tangible capital *K*, AI technology *AI*, accumulation of human capital *H*, and total factor productivity θ. Using the first-order approximation of the function $f(.)$ and the assumption that marginal products of the four inputs are equivalent to their factor prices, the log of output is expressed as in equation (2).

$$ln(Y)_{cjt} = \alpha \ln(K_{tan_{cjt}}) + \beta \ln(L_{cjt}) + \gamma \ln\,(AI_{cjt}) + \delta \ln\left(H_{hum_{cjt}}\right) + \epsilon_{c,j,t} \tag{2}$$

To eliminate the differences in productivity levels across industries and countries, the productivity function is expressed by the growth rate, approximated in the form of the first difference. In addition, the first difference is specified to ensure the stationarity of the data, and to prevent the potential possibility of spurious results.

$$\Delta\, ln(Y)_{cjt} = \beta_1 \Delta \ln(K_{tan_{cjt}}) + \beta_2 \Delta \ln(L_{cjt}) + \beta_3 \Delta\ln\,(AI_{cjt}) + \beta_4\, \Delta\ln\,(H_{hum_{cjt}}) + \varepsilon_{c,j,t} \tag{3}$$

The estimation model we employed tends to indicate a long-run relationship between AI uptake, knowledge capital and productivity growth. In particular, emerging technologies are still relatively new, and may require time before those technologies can fundamentally transform the production process and lead to faster economic growth (Stiroh 2000; Brynjolfsson et al. 2017). However, from the literature review, current studies do not explicitly identify the implementation or restructuring lags between the initial invention of AI and its measurable impacts on the economy.

The additional interaction term is introduced into equation (3) concerning the endogenous relationship between the growth rate in AI technology and human capital. We now have the following equation (4) as the primary empirical model to apply the fixed effect estimation method. We have the fixed effect estimation on the growth rate equation, assuming the specific time trend for each sector per country in terms of the productivity level. In other words, a time trend is applied separately to each sector in different countries.

Choudhry (2009) suggests the validity of using a fixed effect approach to estimate the productivity relationship empirically. In their study, Choudhry applied the dynamic panel GMM model to capture the impact of any endogeneity and measurement error in the model and obtain similar results.

$$\begin{aligned}\Delta\, ln(Y)_{cjt} = \beta_1 \Delta \ln(K_{tan_{cjt}}) + \beta_2\, \Delta\ln(\, L_{cjt}) + \beta_3 \Delta\ln\, (AI_{cjt}) + \beta_4\, \Delta\ln\, (H_{hum_{cjt}}) \\ + \beta_5 \Delta\ln\, (AI_{cjt}) * \Delta\ln\, (H_{hum_{cjt}}) + \mu_t + \mu_{c,j} + e_{c,j,t}\end{aligned} \tag{4}$$

In equation (4), the value-added growth, here augmented by intangible inputs, is decomposed into the following components. K_{cjt} represents other fixed capital. It is calculated as total net assets deducted by AI capital and the other intangible capital counted into national accounts. Part of ICT capital, for instance, communication equipment, is separated from AI and included in $K_{cjt}. L_{cjt}$ denotes employed labour hours worked. H_{hum} represents total accumulated human capital, which will be discussed in detail later in this section. AI_{cjt} stands for the capital stock of broad AI-related technologies invested.[18]

It is worth noting that one challenge of this study is to employ an appropriate variable as the proxy of AI uptake. AI components can be embedded in both computer software and hardware. Evidence presented in Stiroh's (2001) Federal Reserve Bank of New York Economic Policy Review supports the use of measuring AI adoption through the quantity of emerging technologies, for instance, AI-related types of capital. Goolsbee (2018) discusses the role of policy in an AI-insensitive economy, and interprets AI to include a cluster of information technology beyond just

[18] The way we creates a proxy for AI uptake or AI related investments is the same approach employed in the Economic Report of PwC (2018) 'The macroeconomic impact of artificial intelligence'. The study creates a proxy for AI uptake that covers different types of AI discussed in the definition, including software, databases, and computing equipment of new technologies.

conventional AI or machine learning. For instance, Furman and Seamans (2018) suggest robotics shows clear analogies to AI and discuss the links between AI (robotics) and economic outcomes, including labour and productivity. Scholars believe that AI and other forms of advanced automation, including robotics and sensors, can be considered as general-purpose technology to drive follow-on innovations and future productivity growth (Cockburn et al., 2018). Particularly as the GPTs, their potential is constrained by the lack of complementary investments and notable lags between technological progress and the commercialisation of new ideas building on the progress (Brynjofsson et al. 2018).

The EU KLEM database contains aggregated data series of capital stock groupings, including AI technologies. If assuming the impact of AI-related capital stock is similar to the other emerging technologies in the grouping, in other words, a similar relationship between emerging technologies and productivity within the sub-groups, our variable should provide an unbiased and consistent estimator to capture the potential effects of AI on the productivity growth.

The time dummies μ_t represent the non-constant components in technical change or macro-economic shocks that affect the growth rate in all countries. It is likely the unobserved country-industry characteristics will be correlated with explanatory variables. These unobserved characteristics are controlled by including country-industry specific fixed effects represented by $\mu_{c,j}$ in equation (3). It is tempting to assume that the estimated coefficients may only reflect a period of simultaneous AI or human capital growth on labour productivity growth over the same period, and thus simply represent a spurious correlation instead of causality. However, this overlooks the fact that the model specified in the first difference can remove some possibility of spurious regression due to the non-stationarity of residuals, and contains linear heterogeneity time trends for each industry. Therefore, even if there were persistent and simultaneous growth in AI-uptake or human capital investment and labour productivity over time, the coefficients of interest would only be related to the residual movements around the deterministic growth trend.

In this model, there could be some concerns that the effect of investments on human capital, such as training, is overestimated. For instance, firms may invest heavily in labour retraining during the years when output is growing more quickly. This concern should not be overstated, as investments in human capital are not generally pro-cyclical. The key assumption to interpret the coefficients on human capital as causal is $E\left(H_{hum_{cjt}} e_{c,j,t}\right) = 0$. It is reasonable to allow the weaker assumption where $E\left(H_{hum_{cjt+s}} e_{c,j,t}\right) \neq 0, s > 0$. This condition means that current variables are predetermined in the production function, while the current shock can only feed back to future investment in human capital (Reenen 2004). Given the relatively long time series (like ours 1995–2016), the bias on the coefficient is likely to be very small (Nickell 1981)~~.~~ However, the above assumption may still be violated; for instance, firms could already know current shocks by predictions and then adjust their investments in the same period accordingly. If this were the case, we believe the residuals in the production function to be serially correlated. The violation of key assumptions, in turn, depends on the absence of serial correlation in the error term. Hence some formal testing for autocorrelation will be conducted before starting the fixed effect estimation. A causal interpretation from AI and human capital to production is justified only when the present growth in AI and human capital is predetermined.

3.4.2 Two components of human capital

In this exercise, human capital investments are divided into two parts: vocational training to improve the specific skills required by companies, and labour quality from external higher education to improve general skills. The cross-country correlation between the average share of continuous training and general education tends to be positively significant (Mahoney 2012). It brings some indications to us that continuous training and general education are plausible complements rather than substitutes. Therefore, we may expect different impacts on AI productivity attributed to these two ways of investing in human capital.

Given that human capital contains two separate components, the production function equation 1 becomes the following. $H_{hum_{cjt1}}$ are split into two parts, where $H_{\boldsymbol{hum1}_{cjt1}}$ picks up the effect from **training** while $H_{\boldsymbol{hum2}_{cjt1}}$ picks up the effect of general **labour quality**. Conceptually, we hope to separate out the part of skills that firms invest as part of market sector intangible investments and the part invested by the state.

The equation (4) with the additional interaction terms becomes the following equation

.

$$\begin{aligned}\Delta\, ln(Y)_{cjt} = \beta_0 + \beta_1 \Delta \ln(K_{tan_{cjt}}) + \beta_2\, \Delta\ln(\, L_{cjt}) + \beta_3 \Delta\ln\, (AI_{cjt}) + \beta_4\, \Delta \ln\left(H_{\boldsymbol{hum}1_{cjt}}\right) \\ + \beta_5\, \Delta \ln\left(H_{\boldsymbol{hum2}_{cjt}}\right) + \beta_6 \Delta\ln\, (AI_{cjt}) * \Delta\ln\left(H_{\boldsymbol{hum1}_{cjt}}\right) + \beta_7 \Delta\ln\, (AI_{cjt}) \\ * \Delta\ln\left(H_{\boldsymbol{hum2}_{cjt}}\right) + \mu_t + \mu_{c,j} + e_{c,j,t}\end{aligned} \tag{5}$$

By dividing the total labour hours employed on both sides of equation (5), we get the labour productivity function,

$$\begin{aligned}\Delta \ln\left(\frac{Y_{cjt}}{L_{cjt}}\right) = \beta_1 \Delta \ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + \beta_2 \Delta\ln\left(\frac{K_{tan_{cjt}}}{L_{cjt}}\right) + \beta_3 \Delta\ln\left(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}}\right) + \beta_4\, \Delta\ln(\frac{H_{\boldsymbol{hum2}_{cjt}}}{L_{cjt}}) \\ + \beta_5\, \Delta \ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}}\right) + \beta_6 \Delta\ln\left(\frac{H_{\boldsymbol{hum2}_{cjt}}}{L_{cjt}}\right) * \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) \\ + \beta_7 \Delta\ln\left(\frac{H_{\boldsymbol{hum2}_{cjt}}}{L_{cjt}}\right) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}}\right) + controls + \mu_t + \mu_{c,j} + e_{c,j,t}\end{aligned} \tag{6}$$

In the labour productivity function, the growth in value-added (augmented by intangible inputs) per hour can be decomposed into human capital per hour, AI capital per hour, and tangible and intangible capital per hour, with additional terms capturing interaction effects. β_1 represents the elasticity of productivity with respect to AI by industry and country (0.1 denotes a 1% growth in AI-uptake (per hour employed), enhancing labour productivity by 0.1%). The significance of β_5 and β_6 indicate the relative importance of labour retraining and general labour quality on AI's labour productivity effects accordingly. Interaction between two components of human capital is included only as additional controls to get more precise estimates for β_5 and β_6. It is also worth noting that the first chapter emphasises the importance of different categories of intangible capital, e.g., R&D, design of new products, organisational capital, etc. Together, this capital appears as control variables in our labour productivity function to overcome some omitted variable bias. The estimation method and other endogeneity issues have been discussed in the production function (equation 3).

Empirically, some literature points out that rather than the first difference, the level of human capital, especially education, should be included in the growth accounting model. The effect of changes in human capital on economic growth is generally found to be insignificant in late empirical studies. In contrast, the current level of human capital can, in fact, better explain the relationship between human capital and growth (Ali et al. 2018). Hence, the percentage of tertiary education is included in the empirical regression analysis.

3.4.3 The alternative measure for labour quality

Some studies point out that the input of labour, divided by the number of hours worked, also stands for a measure of labour quality (LQ). Labour input, in this case, is a composition of adjusted labour hours, where the adjustment uses wage bill shares for compositional groups. It is computed by weighting each type of labour hours worked by the share each type of labour occupies in the total labour compensation. This measure relies on the assumption of a perfectly competitive market where firms employ additional labour until their marginal productivity is equivalent to its marginal cost (CEDEFOP 2014). It corresponds to the difference in the marginal product of workers by type with different levels of skills. For instance, in the study of Mahoney (2012), the combined labour composition and training together forms an expanded measure of human capital in growth accounting. Labour composition is believed to be mainly driven by the up-skills of the overall labour force arising from general education. They pointed part of investments that adds to the returns to workers is captured by the labour composition, whereas the part that corresponds to firms' expenditure is estimated by the contribution of intangible in-firm training stock.

Issue of double counting

There might be some concerns about double-counting when including firm-specific human capital and labour composition at the same time. Corrado, Haskel and Lasinio (2017) suggest that both the return to schooling and the return to 'learning by doing' through experience are embodied in this labour composition via a higher wage return. The increase in the labour composition multiplied by labour shares in the production function is a direct channel to capture the contribution from general skill changes or human capital accumulation to economic growth. Conceptually, it is best to separate the part of skills invested by firms (as a part of market intangible investment) and the other part invested by the state. Under the Becker-type assumptions (1962), the investments by firms, which are the specific in-firm training, will not raise workers' wages, since it is hard to use these skills outside the firms (Marrano, Haskel and Wallis 2009; Borgo, Goodridge and Haskel 2012). In other words, if firms are only funding firm-specific training, as the market wage is unaffected, including both will not double count the contribution of skills. However, if the effect of experience, which can be captured by their salaries, and at the same time in part attributed to the firm-specific training that a worker has received earlier, there would be some issues in double-counting for the part of experience effects by including both measures.

Computation for labour composition

This part explains how we define labour composition in our regression analysis. A vital feature of the EU KLEMS database is that both labour and capital inputs are not homogeneous (M). It contains various types of labour, such as low-skilled and high-skilled workers, earning at their marginal products. Labour service input represented by L_j in the following is a composition-adjusted - labour hours, where the adjustment uses wage bill shares for composition groups by EU Labour Force Survey data.

This measure assumes a perfectly competitive market where firms employ additional labour until their marginal productivity is equivalent to its marginal cost. Labour input is computed by weighting each type of labour hours worked by the share that each type of labour occupies in the total labour compensation, as suggested in the following equation. In EU KLEMS, working hours H_j are cross-classified into 18 labour categories (k =18) according to educational attainment, age (as a proxy for work experience or on-the-job training), and gender as the three dimensions, which are 3×3×2 types accordingly. In terms of educational attainment, EU KLEMS identified three main qualification groups: university degree, including technical-level qualifications or short-cycle higher education qualifications, intermediate-level qualifications (diplomas or certificates), and no formal qualifications. The age groups are 15–29, 30–49 and 50+, respectively.

$$\Delta lnL_j = \sum_l \bar{w}_{l,j} \cdot \Delta lnH_{l,j}$$

The growth in labour service ΔlnL_j is calculated by a Törnqvist volume index of the growth of hours worked $H_{l,j}$ by each labour type l, weighted by its nominal input shares $\bar{w}_{l,j}$.

$$\overline{w}_{l,j} = \frac{P_{l,j} H_{l,j}}{\sum_k P_{k,j} H_{k,j}}$$

$P_{l,j}$ is the nominal factor price or marginal product of labour input *l* in industry j (i.e. the hourly wage). The nominal share $\overline{w}_{l,j}$ for each type of labour *l* is calculated as the two-period average of each type in the value of labour compensation. In other words, it is a two-period average share of labour type *l* in total labour cost (hourly wage) in industry j.

Then, with slight manipulation, labour inputs can be decomposed into labour composition and total hours.

$$\Delta lnL_j = \sum_l \overline{w}_{l,j} \cdot \Delta lnH_{l,j} - \Delta lnH_j + \Delta lnH_j$$

$$= \sum_l \overline{w}_{l,j} \cdot \Delta lnH_{l,j} - \sum_l \overline{w}_{l,j} \cdot \Delta lnH_j + \Delta lnH_j$$

$$= \underbrace{\sum_l \overline{w}_{l,j} \cdot \Delta ln \frac{H_{l,j}}{H_j}}_{\boldsymbol{chnage\ in\ labour\ composition}\ (\boldsymbol{\Delta lnLC_j})} + \underbrace{\Delta lnH_j}_{\boldsymbol{chnage\ in\ total\ hours\ worked}\ (\boldsymbol{\Delta lnH_j})} \qquad (a)$$

(a) Resulting in (b):

$$\Delta lnLC_j = \Delta lnL_j - \Delta lnH_j \qquad \text{(b)}$$

The above decomposition indicates that the input of labour can be influenced by other sources. Changes in the proportion of each labour type in the workforce can affect labour input growth beyond any change in the total hours worked. For instance, an increase in the hours worked of labour with a relatively higher share of income, such as high-skilled jobs, will increase labour inputs. In contrast, a compositional shift towards women or lower-paid jobs will bring a negative labour composition effect. Additionally, changes in the relative factor price (wage) can also affect the shares, and thus growth, on labour inputs.

The first term $\Delta lnLC_j$ is known as the 'labour quality' in the growth accounting literature (e.g. Jorgenson et al. 2005). It corresponds to the difference in the marginal product of workers by type with different levels of skills. Therefore, changes in LC_j multiplied by labour shares can directly reflect how accumulated human capital (or skills changes) on economic growth.

Similar to equation (5), by introducing the calculated labour composition into the production function, we have the LC_{cjt} that replaces the $\frac{H_{\boldsymbol{hum2}cjt}}{L_{cjt}}$ as the measure for general labour quality. β_5 in equation (6) directly captures the relation between AI and overall skills on productivity growth. Investments in vocational training still appear in the equation, given the Becker-type assumption discussed before.

$$\begin{aligned}\Delta\ln(\frac{Y_{cjt}}{L_{cjt}}) = \beta_1 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + \beta_2\Delta\ln\left(\frac{K_{tan\,cjt}}{L_{cjt}}\right) + \beta_3 \Delta\ln\left(\frac{H_{\boldsymbol{hum1}cjt}}{L_{cjt}}\right) + \beta_4\Delta\ln\left(lnLC_{cjt}\right) \\ + \beta_5\Delta\ln\left(lnLC_{cjt}\right) * \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + \beta_6\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}cjt}}{L_{cjt}}\right) \\ + \beta_7\Delta\ln\left(lnLC_{cjt}\right) * \Delta\ln(\frac{H_{\boldsymbol{hum1}cjt}}{L_{cjt}}) + controls + \mu_t + \mu_{c,j} + e_{c,j,t}\end{aligned} \quad (7)$$

3.4.4 Identifying emerging European countries

To further examine some cross-country differences in AI, human capital and productivity, as well as the robustness of the complementary effects, the World Bank's country classification is applied to distinguish two groups across European countries. For analytical purposes, the World Bank (2020) assigns the world's economies to four groups by the gross national income (GNI) per capita estimates. GNI is converted from local currency into the US dollar, calculated using the World Bank Atlas method. For the current 2022 fiscal year, the World Bank's income classifications are as follows: Low-income economies ($1,045 or less), Lower middle-income economies (between $1,045 and $4,095), upper-middle income economies (between $ 4,096 and $12,695), and high-income economies ($12,696 or more). These low-income and middle-income economies are usually referred to as 'developing countries' (WDI 2009). The term 'developing' is used for convenience but does not intend to imply the economy has reached a preferred or final stage of development (WDI 2009). In our sample,[19] two countries (Estonia and Lithuania) can be identified as developing countries. They have experienced the stage where GNI per capita was initially

[19] The sample available only contains information on multiple European countries and no information on the leading developing countries, i.e. China and India.

located in the low or lower middle-income level range during the sample observation period from 1995 to 2016.

The terms ‘emerging’ and ‘developing’ economies are often used interchangeably. In contrast, emerging economies refer to countries from the middle-income group, distinguished from the low-income developing countries (IMF working paper 2011). The term ‘emerging market economy’ is initially attributed to Van Agtmael (1984), who defines countries with lower absolute, but rapidly growing per capita income, and their authorities favour economic liberalisations and free-market systems. Essentially, it describes countries gradually migrating or emerging from developing to developed status**.** In our sample, Slovenia and the Czech Republic were in the range of higher middle income at the beginning of the period, and then joined advanced countries in 2007 and 2009 respectively. These two countries experienced the transitional stage during the observational period and were also selected into the same group as Estonia and Lithuania to compare with other developed economies since the early years, e.g. Germany, France, North Europe, etc. Furthermore, it is worth noting that Greece joined the developed countries earlier than 1995, but was downgraded to an emerging market in 2013, according to the MSCI annual market classification review. The main reason for reclassification is that the debt in Greece reached an unsustainable level since 2009 and did not meet the risk criteria for developed market status. Thus, in the analysis, Greece is still treated as a developed or high-income country instead of an emerging economy in the middle-income group. It is believed Greece shares similar trajectories with other advanced members and is notably different in many key characteristics from other emerging markets in our sample.

Following the above discussion, a dummy variable $Developing_i$ representing the group of low-middle income countries is defined as developing economies. Both the dummy variable ($Developing_i$) and the interaction term with AI ($Developing_i * \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right)$) are introduced into the labour productivity function (equation 6 or equation 7). If the β_8 is positively significant, it suggests that growth in AI constantly brings more substantial effects on productivity growth for developing countries compared with the developed economies. The marginal effect for the two groups can be computed to examine if AI’s productivity growth is more promising for lower-income countries (**Hb**). As the dummy variable is time-invariant in this equation, the pooled OLS is used for analysis with additional time and industry controls.

$$\begin{aligned}\Delta\ln\left(\frac{Y_{cjt}}{L_{cjt}}\right) = {} & \beta_1 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + \beta_2\Delta\ln\left(\frac{K_{tan\,cjt}}{L_{cjt}}\right) + \beta_3 \Delta\ln\left(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}}\right) + \beta_4 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}}\right) \\ & + \beta_5 \Delta\ln(lnLC_{cjt}) + \beta_6 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) * \Delta\ln\left(LC_{cjt}\right) + \beta_7 Developing_c + \beta_8 Developing_c \\ & * \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + controls + \alpha_t + \alpha_{c,j} + e_{c,j,t}\end{aligned} \tag{8}$$

$$\begin{aligned}\Delta\ln\left(\frac{Y_{cjt}}{L_{cjt}}\right) = {} & \beta_1 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + \beta_2\Delta\ln\left(\frac{K_{tan\,cjt}}{L_{cjt}}\right) + \beta_3 \Delta\ln\left(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}}\right) + \beta_4 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}}\right) \\ & + \beta_5 \Delta\ln\left(\frac{H_{\boldsymbol{hum2}\,cjt}}{L_{cjt}}\right) + \beta_6 \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) * \Delta\ln\left(\frac{H_{\boldsymbol{hum2}\,cjt}}{L_{cjt}}\right) + \beta_7 Developing_c \\ & + \beta_8 Developing_c * \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right) + controls + \alpha_t + \alpha_{c,j} + e_{c,j,t}\end{aligned} \tag{9}$$

3.5 Data

3.5.1 Dataset

This research is conducted at country-industry level analysis to unlock some mechanisms of AI competition from a multiple-country perspective. The data used in this study is the EU KLEMS, which provides two datasets – a statistical database and an analytical database. The former includes detailed information on economic growth, productivity and capital formation, entirely in line with national accounts data provided by the national statistical institutes to Eurostat. The analytical database includes supplementary data on those investments not capitalised in the national accounts. The EU KLEMS Release 2019 covers all 28 EU member states, Japan and the United States under a long-time panel from 1995 to 2017, collecting data at industry level according to the ISIC Rev. 4 industry classification. In the EU KLEMS, capital inputs are distinguished into various categories, allowing us to strictly define our tangible and intangible assets, labour inputs and AI by using categories. Since AI is a relatively new phenomenon, there is no exact data series available at the industry level for multiple countries directly measuring the investment in AI technology. Instead, the capital input data contains the real value of various AI-related capital investments, e.g., software, databases, computing equipment, etc. These capital form the basis for the proxy of AI uptake and together cover different types of AI. For the measure of human capital, the EU KLEMS analytical database contains information on the stock of vocational training and the wage-adjusted labour service at industry level. By dividing the total hours employed, we compute the measure of $\frac{H_{\boldsymbol{hum1}cjt}}{L_{cjt}}$ and $lnLC_j$ respectively. In addition, the OECD dataset also provides information on the employment rates of the population according to their education levels. This is directly linked with the measure of $\frac{H_{\boldsymbol{hum2}cjt}}{L_{cjt}}$. Therefore, we proceed mainly to work with the EU KLEMS database, and additionally introduce the measure of general education level from the OECD database, forming the matched dataset. Table 3.5-1 lists all actual measures in the dataset of variables in the methodology section.

TABLE 3.5-1. LIST OF VARIABLES

(EU KLEMS AND OECD DATASET)			
Y	**Value-added**	- The growth rate of value-added volume 2010 ref.prices, NAC mn,% log	*VA_G*
$\frac{\boldsymbol{V}}{\boldsymbol{L}}$	**Value-added (per hour worked)**	- The growth rate of value-added per hour worked, volume 2010=100	*LP1_QI*
L	**Total hours worked by employees**	- Total hours worked by employees	*H_EMPE*
$\boldsymbol{K_{tan}}$	**Tangible capital (Net capital stock)**	- Total assets (Deducted by AI and intangible capital) - Communications equipment CT - Machinery and equipment Mach - Transporting equipment TraEq	*Kq_GFCF* *Kq_CT* *Kq_TraEq*

		- Non-residential investments oCoN	*Kq_OMach* *Kq_OCon*
$\boldsymbol{K_{intan}}$	**Other intangible capital (Net capital stock)**	- Research and development - Design and other product developments - Advertising, market research and branding capital	*Kq_RD* *Kq_Design* *Kq_AdvMRes*
AI	**AI capital (Net capital stock)**	- Computing equipment - Computer software and databases	*Kq_IT* *Kq_Soft_DB*
HUMAN CAPITAL			
IN-FIRM HUMAN CAPITAL INVESTMENT			
$\mathbf{H_{hum1}}$	**Vocational training (Net capital stock)**	- Vocational training	*Kq _VT*
GENERAL LABOUR QUALITY			
$\mathbf{H_{hum2}}$	**Edu**	- Educational level: The percentage of the workforce with tertiary education[20]	*OECD data (national level)*
	Alternative measure	- Labour composition (Labour service / Total hours worked by employees)	*LAB_QI/H_EMPE*

3.5.2 Descriptive analysis

The following figures provide some primary insights by calculating time average values at the country level in our sample. The period covered by annual growth rates of AI, human capital and labour productivity is 1996–2016. Figure 3.5.1 shows the primary relation between the growth of AI technology (not per labour hours) and the growth of human capital components, indicating some complementarities. Figure 3.5.2 includes three panels, each plotting industry labour productivity growth on the Y-axis. The X-axis of the panel shows the growth rates for the three variables of our interest in the labour productivity function (AI, $\boldsymbol{H_{hum1}}$ and $\boldsymbol{H_{hum2}}$). The growth of training capital ($\boldsymbol{H_{hum1}}$) increases substantially with labour productivity, although the average growth value in the sample is relatively small. It should be noted that the graph does not indicate

[20] The employment rate in OECD dataset refers to the number of persons in employment as a percentage of the population of working age (25–64).

causality. For instance, the relationship may be due to some common factors boosting all independent and dependent variables.

Table 3.5-2 reports summary statistics for the variables used in the labour productivity function.[21] The sample available involves 38 detailed industries across 17 European countries in total. According to the World Bank classifications discussed in the methodology section, these European countries are divided into two main groups. The first group consists of the developed members that have achieved above the threshold of the high-income group before 1990, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Spain, Sweden and The United Kingdom. The second group comprises the other four countries (the Czech Republic Estonia, Lithuania and Slovenia), initially low or middle-income. Table 3.5-2 also displays the mean comparison test between groups. Overall, the developing economies suggest relatively faster growth in AI, tangibles and controlled intangible capital. In contrast, the developed countries remain at a more substantial advantage in terms of tertiary education and skilled labour among the working population.

[21] Variables in the summary statistics table are in decimal value, not in percentage value.

Figure 3.5.1

Growth of AI and human capital components in 17 EU Countries

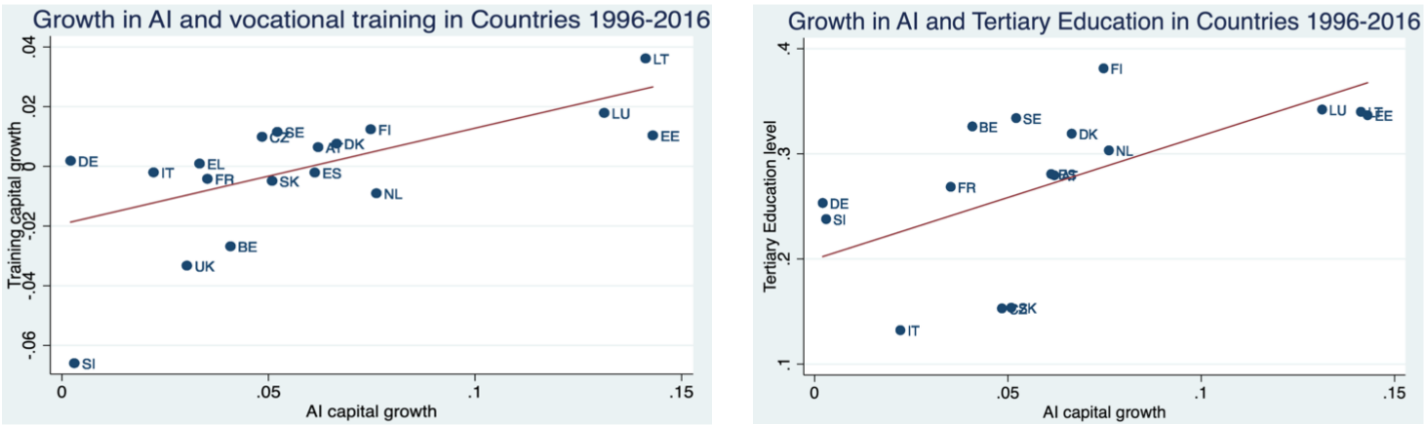

Figure 3.5.2

Industry labour productivity growth in17 EU countries 1996–2016

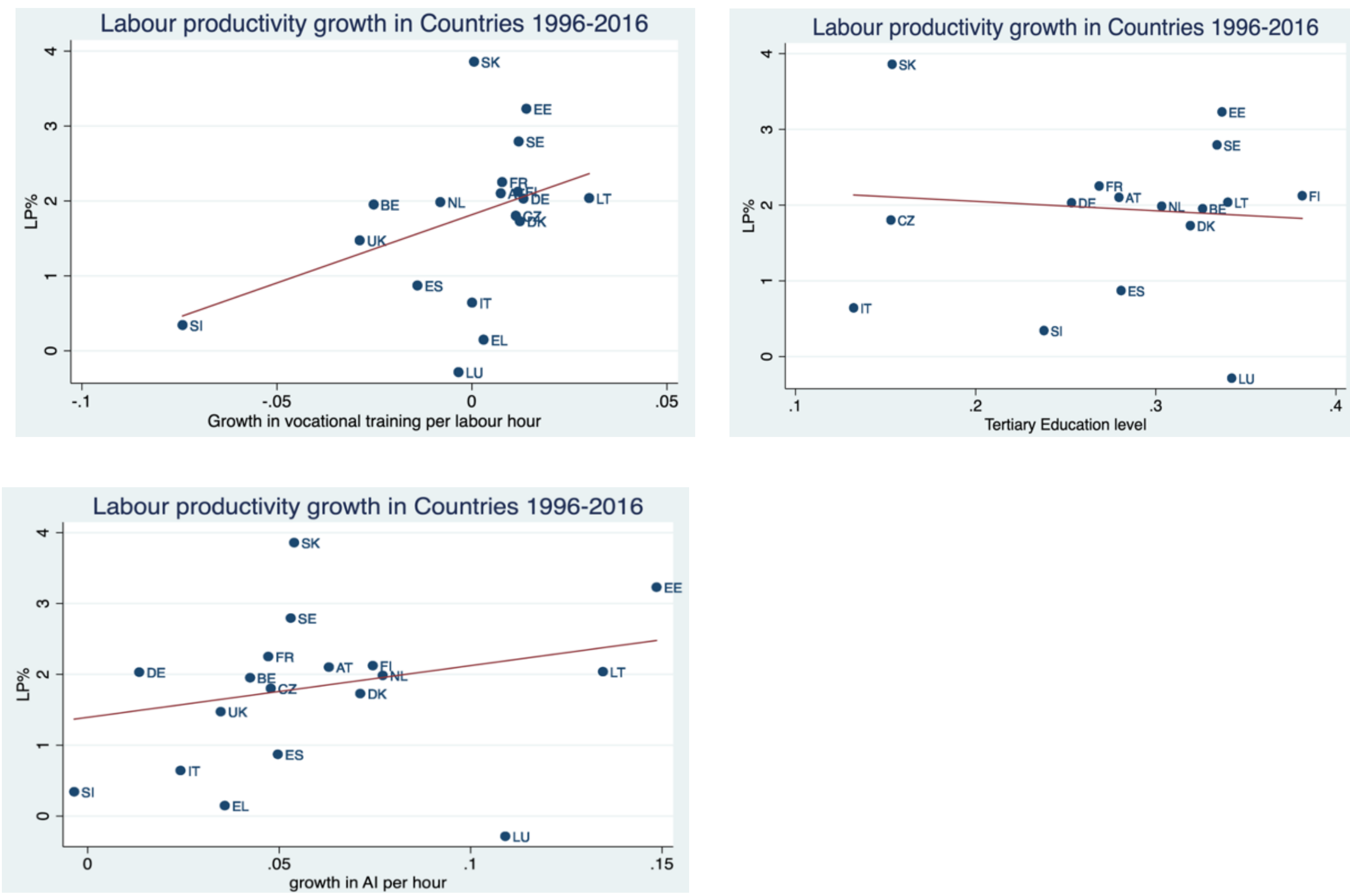

TABLE 3.5-2 SUMMARY STATISTICS

		Mean	Median	SD	(1)	(2)	(1)-(2)	(1)-(2)
		TOTAL SAMPLE			DEVELOPED	DEVELOPING	DIFF	P-VALUE
DEPENDENT VARIABLE								
V/L	Growth in value added per hour	0.0181	0.0149	0.1477	0.0180	0.0186	-0.0005	0.8846
INDEPENDENT VARIABLE								
K_{tan}/L	Growth in tangible capital per hour	0.0171	0.0118	0.0894	0.0143	0.0320	-0.0177	0.0000
AI/L	Growth in AI capital per hour	0.0566	0.0456	0.1871	0.0540	0.0704	-0.0163	0.0054
	Growth in AI capital	0.0559	0.0433	0.1835				
IN-FIRM TRAINING								
H_{hum1}/L	Growth in vocational training per hour	-0.0003	0.0038	0.0844	-0.0005	0.0005	-0.0009	0.7388
	Growth in vocational training	-0.0011	0.0047	0.0744				
LABOUR QUALITY								
H_{hum2}/L	Tertiary education level	0.2652	0.2795	0.0902	0.2754	0.2237	0.0518	0.0000
	Change in labour composition	-0.0019	0.0014	0.0598	-0.0011	-0.0074	0.0063	0.0291
OTHER CONTROL VARIABLES								
K_{intan}/L	Growth in intangible capital per hour	0.0231	0.0262	0.0924	0.0251	0.0321	-0.0070	0.0513

3.6 Results

Table 3.6-1 illustrates how human capital and AI can jointly affect labour productivity growth. Column 1 suggests that the coefficient on AI technology is insignificant when labour productivity is regressed on AI capital alone. However, when the measure of AI variable interacts with one component of human capital, the coefficient on interaction term become significantly positive, according to the results in columns 2 and 4. This points out the potential complementary effects of human capital (**H**) to facilitate the exploitation of AI's benefits, and suggests very limited or no benefits from AI investment directly when lacking enough relevant vocational skills in the labour force to support the decision at the same time. Based on the estimated coefficient of the interaction term, the impact on productivity growth for an additional percentage increase in AI uptake is greater by an amount of approximately 0.26 percentage points for each one-unit increase in vocational training. Labour productivity growth is much faster in industries that can invest heavily in their training alongside, hence making use of AI technology in a more effective way. In terms of the two components of human capital, vocational training positively and significantly affects labour productivity growth both on its own and in interactions. This is estimated to be appx 0.11–0.12 percentage points on improving labour productivity growth at a 1% level of significance, given the average growth of AI capital. Regression 4 contains the interaction term with both human capital components: labour quality by general education and vocational training. However, general education as the second component of human capital in our definition does not suggest strong complementary effects on labour productivity for AI investment.

Part II reveals more detail on changes in the marginal effect of AI, interpreted conditionally on the interaction with training. The sample used for regression analysis contains a series of finer industry divisions, and the growth of the firm's training capital per labour varies markedly across industries, from –0.6 % (min) to 0.68 % (max) during observation years. Marginal effects in this table are evaluated at the distribution of training capital starting from its fifth percentile, under each unit (0.1) increase to the maximum value. By the following pattern, it can be observed that growth in vocational training significantly enhances AI productivity, which ranges from negative to 0.15. The positive effects of AI investment can be ensured only for some industries that provide enough relevant training in time to support the use of new technology.

TABLE 3.6-1. IMPACTS OF AI AND HUMAN CAPITAL ON LABOUR PRODUCTIVITY

PART I					
		(1)	(2)	(3)	(4)
COUNTRY-INDUSTRY FIXED EFFECT		FEa	FEb	FEc	FEd
AI	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$	-0.00	0.00	-0.021	-0.026
		(0.019)	(0.019)	(0.046)	(0.044)
TANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{\boldsymbol{tan}\,cjt}}{L_{cjt}}\right)$	0.135***	0.128***	0.134***	0.124**
		(0.047)	(0.047)	(0.047)	(0.048)
HUM1: TRAINING VOCATIONAL TRAINING	$\Delta\ln(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}})$	0.114***	0.098***	0.114***	0.199**
		(0.037)	(0.036)	(0.037)	(0.091)
HUM2: LABOUR QUALITY (WORKFORCE WITH TERTIARY EDUCATION (%))	Edu_{ct}	0.0167	0.0213	-0.001	0.002
		(0.069)	(0.069)	(0.079)	(0.079)
COMPLEMENTARITIES					
AI AND HUM1	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}}\right)$		0.256*		0.264*
			(0.147)		(0.145)
AI AND HUM2	$Edu_{ct} * \Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$			0.082	0.101
				(0.145)	(0.140)
CONTROLS					
OTHER INTANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{\boldsymbol{intan}\,cjt}}{L_{cjt}}\right)$	0.097***	0.096**	0.096***	0.093**
		(0.037)	(0.038)	(0.037)	(0.038)
HUM1 AND HUM2	$Edu_{ct} * \Delta\ln(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}})$				-0.347
					(0.302)
YEAR DUMMIES		Yes	Yes	Yes	Yes
N		7053	7053	7053	7053
STANDARD ERROR IN PARENTHESES * P<0.1 ** P<0.05***P<0.01					

PART II

PANEL A. MARGINAL EFFECTS OF AI ON LABOUR PRODUCTIVITY AT LEVELS OF VOCATIONAL TRAINING						
	ME in (2)			ME in (4)		
GROWTH OF VOCATIONAL TRAINING $\Delta\ln(\frac{H_{hum1cjt}}{L_{cjt}})$	dy/dx	Delta-method Std. Err.	P>z	dy/dx	Delta-method Std. Err.	P>z
-0.11	-0.028	0.025	0.266	-0.028	0.024	0.257
-0.01	-0.002	0.019	0.897	-0.001	0.019	0.944
0.09	0.023	0.023	0.323	0.025	0.023	0.280
0.19	0.049	0.034	0.151	0.052	0.034	0.128
0.29	0.074 *	0.047	0.100	0.078*	0.047	0.094
0.39	0.100 *	0.060	0.099	0.104*	0.060	0.083
0.49	0.125 *	0.075	0.092	0.131*	0.074	0.077
0.59	0.151 *	0.089	0.089	0.157*	0.088	0.075

PANEL B. MARGINAL EFFECTS OF VOCATIONAL TRAINING ON LABOUR PRODUCTIVITY AT MEAN VALUE (50%) OF AI						
	ME in (2)			ME in (4)		
AVERAGE GROWTH OF AI CAPITAL $\Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$	dy/dx	Delta-method Std. Err.	P>z	dy/dx	Delta-method Std. Err.	P>z
0.057	0.11***	0.037	0.001	0.12***	0.036	0.001

Table 3.6-2 again investigates the impact of AI and human capital on labour productivity, but uses the alternative measure for $H_{\boldsymbol{hum2}}$ (labour quality). The table also demonstrates if I allow for a better measure for labour quality, we have better inference in terms of the importance of AI. **H1** can still be confirmed by including the interaction terms of two components in the regressions. However, in terms of the relative importance, results in column 4 suggest a greater complementary effect between growth in AI technology and growth in labour composition, compared with the complementarity of vocational training. While the primary effect of vocational training is positively significant across specifications, the interaction between vocational training and AI becomes less significant when AI interacts with both measures. Note that the complementary effect from training is diluted, and it could be attributed to the issue of double counting. As mentioned in the previous section, it is argued that labour composition, as a wage-based measure of relative labour quality, may reflect the possession of both uncertified skills gained through informal training or experience and certified skills through education attainments between group members. Overall empirical results in Table 3 are confirmed with a robust complementary effect between upgrading the level of skills and AI investments on labour productivity, while the relevant importance for the two components ($H_{\boldsymbol{hum2}}$ and $H_{\boldsymbol{hum1}}$) is more difficult to distinguish by using *LC*.

In other words, the study introduces an alternative measure, the labour composition, to represent general labour quality. In much prior intangible literature (Mahoney 2012; Marrano et al. 2009 Borgo et al. 2012), the Becker-type assumption (1962) is applied, assuming that the investments by firms will not raise workers' wages since these skills are hard to use outside individual firms. However, our estimations indicate that it may involve double-counting issues when simultaneously including the labour composition and training in the production function. This wage-based measure can capture the effects of experience, which to some extent, can be gained from uncertified skills from informal training.

Panel **A** in Part II lists the overall marginal effects of AI, interpreted conditionally, on the interaction with LC. The marginal effects are evaluated at various points of the distribution of LC, namely 25%, median, 75%, 90%, 95% and a maximum of the log form of labour composition. According to the results, only a small number of industries (5%) in our sample experience positively significant gains from the growth in AI technology. More specifically, industries ranked in the 95^{th} percentile of up-skilling labour employed can significantly realise 0.041% growth in labour productivity with each 1% unit increase in the growth of AI capital. After that, the marginal effects of AI increase as labour quality increases and reach 0.51% at the maximum value. In comparison, AI is associated with 0.031% growth in labour productivity, corresponding to the 95^{th} percentile level in vocational training, and attain up to 0.15% at the maximum value. Hence, growth in labour quality or, more specifically, higher-skilled labours would enhance AI's productivity effects, conformed as a more effective moderator variable.

On the other side, the main effect of labour composition shows a negative relationship with productivity growth. It reflect that some industries are paying higher wages to employees employed when they are better qualified with higher education and/or are more experienced in doing the same work. However, the decision does not guarantee a positive return on productivity; it seems only worth it for industries that invest more in AI technology. As illustrated in Panel **B** of Part II, those industries that achieve more than 35% growth in AI capital or emerging technology would experience positive effects on labour productivity for an additional increase in employing higher-skilled labour. In sum, investments in AI and/or skills cannot be considered separately to enhance overall productivity growth. Using more skilled labour with relatively higher wages is more beneficial for industries that are accelerating their digital transformation process.

In addition, the last column indicates some underlying relation when we include the interaction between two human capital components as an additional control. In the last column, the results show that the coefficient of the interaction between LC and training is negatively significant. We suppose LC, the wage-based measure for the value of human capital, can pick up the seniority or skilled labours. In that case, the investments in training are expected to be significantly correlated with LC in a negative way. This is because the more senior the staff or, the higher education they already have, the less vocational training is used within firms. Moreover, Tables 3 and 4 reveal the importance of other intangible capital, such as R&D, the design of new products, and other organisational capital. Together, these intangibles contribute to the growth of labour productivity by appx 0.1 percentage point for an additional unit increase. The underlying role of intangibles is consistent with our findings in the first chapter, and hence some omitted variable bias can be reduced by including these elements as controls.

TABLE 3.6-2. IMPACTS OF AI AND HUMAN CAPITAL ON LABOUR PRODUCTIVITY (WITH LABOUR COMPOSITION)

PART I					
		(1)	(2)	(3)	(4)
COUNTRY-INDUSTRY FIXED EFFECT		FEa	FEb	FEc	FEd
AI	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$	0.006	0.008	0.009	0.009
		(0.017)	(0.017)	(0.017)	(0.017)
TANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{tan_{cjt}}}{L_{cjt}}\right)$	0.092**	0.096**	0.087**	0.091**
		(0.038)	(0.038)	(0.038)	(0.038)
HUM1: VOCATIONAL TRAINING	$\Delta\ln(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}})$	0.051*	0.055**	0.039	0.043*
		(0.026)	(0.026)	(0.024)	(0.023)
HUM2: LABOUR QUALITY (LABOUR COMPOSITION)	$\Delta\ln(LC_{cjt})$	-0.029	-0.086**	-0.024	-0.063*
		(0.045)	(0.041)	(0.043)	(0.038)
COMPLEMENTARITIES					
AI AND HUM1	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}}\right)$			0.247*	0.131
				(0.148)	(0.171)
AI AND HUM2	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln(LC_{cjt})$		0.356**		0.619**
			(0.18)		(0.262)
CONTROLS					
OTHER INTANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{\boldsymbol{intan}_{cjt}}}{L_{cjt}}\right)$	0.101**	0.104**	0.100**	0.102**
		(0.041)	(0.042)	(0.042)	(0.042)
HUM1 AND HUM2	$\Delta\ln(LC_{cjt}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}}\right)$				-0.514*
					(0.267)
YEAR DUMMIES		Yes	Yes	Yes	Yes
N		8248	8248	8248	8248
STANDARD ERROR IN PARENTHESES * P<0.1 ** P<0.05***P<0.01					

PART II

PANEL A. MARGINAL EFFECTS OF AI ON LABOUR PRODUCTIVITY AT LEVELS OF LABOUR COMPOSITION GROWTH				
		ME in (4)		
PERCENTILE	Growth of labour composition $\Delta\ln(LC_{cjt})$	dy/dx	Delta-method Std. Err.	P>z
25%	-0.012	0.002	0.018	0.907
50%	0.001	0.010	0.017	0.554
75%	0.013	0.017	0.017	0.318
90%	0.032	0.029	0.019	0.124
95%	0.051	0.041*	0.021	0.054
99%	0.121	0.084**	0.035	0.017
MAX	0.813	0.512**	0.107	0.015

PANEL B. MARGINAL EFFECTS OF LABOUR QUALITY ON LABOUR PRODUCTIVITY AT LEVELS OF AI GROWTH				
		ME in (4)		
PERCENTILE	Growth of AI capital $\Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$	dy/dx	Delta-method Std. Err.	P>z
25%	-0.019	-0.074	0.039	0.055
50%	0.050	-0.032	0.037	0.396
75%	0.115	0.009	0.043	0.844
90%	0.223	0.075	0.063	0.233
95%	0.322	0.137	0.086	0.110
99%	0.682	0.360**	0.175	0.040
MAX	2.738	1.633**	0.711	0.022

In Table 3.6-3, we examine if the labour productivity gains from the growth of AI capital would vary across emerging [22] (the low-middle income group) and developed economies (the high-income group). We include the dummy variable to classify the group and its interaction with the growth of AI capital. Again, the results confirm that the complementarities between human capital (skills) are significant and robust by changing measures. According to the estimated coefficient in columns 2 and 3, the group of developing or, in other words, low to middle income countries constantly gain 0.05 percentage points higher in terms of AI productivity growth than the developed countries. The following margin plots display how the marginal effect of AI capital growth changes with the growth of in-firm training across developing and developed countries, respectively. Given the average value of human capital investments, additional percentage growth in AI capital invested is associated with appx significant 0.042 percentage point growth in labour productivity for the low-middle income group of countries.

Columns a & b show the estimation results by using labour composition as changing in human capital accumulation. Based on column b, the following table of Part II illustrates the pattern of AI's marginal effects across changes in labour composition for both groups. It can be observed that the low-middle income economies gain more considerable benefits from an additional increase in AI capital investments, given each level of growth in human capital (LC_{cjt}). The estimated marginal impact on labour productivity is, on average, 0.4–0.5 percentage points higher than that in developed countries. The differences in marginal effect between the two groups do not remain in a fixed value under different skill levels, but they are still consistent with the estimated coefficient of the interaction term in columns 2 and 3. Hence, our results do not fully support the argument mentioned in the motivation that AI brings job displacement. It is featured by the declining importance of cross-country labour cost arbitrage and therefore widens the poverty gap between the high-income and low-income countries. Instead, more promising net productivity gains are found in the evidence. In emerging markets, AI may offer opportunities to lower costs and business entry barriers. New business models are delivered through new AI applications, and

[22] The term 'developing' in this study is used interchangeably with the term 'emerging'. Both terms refer to the countries that belong to low-middle income group in 1995, based on the World Bank classifications.

it may help some middle, but fast-growing economies to leapfrog existing developing challenges, catching up in a non-traditional pathway.

TABLE 3.6-3 IMPACTS OF AI AND HUMAN CAPITAL ON LABOUR PRODUCTIVITY BETWEEN DEVELOPED AND DEVELOPING ECONOMIES

OLS		1	2	3	a	b
AI	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$	0.005	-0.007	-0.005	0.014	0.009
		(0.018)	(0.023)	(0.043)	(0.016)	(0.018)
TANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{tan_{cjt}}}{L_{cjt}}\right)$	0.170***	0.164***	0.164***	0.108***	0.111***
		(0.043)	(0.045)	(0.045)	(0.035)	(0.037)
HUM1: VOCATIONAL TRAINING	$\Delta\ln(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}})$	0.109***	0.093***	0.093***	0.069***	0.071***
		(0.03)	(0.028)	(0.028)	(0.022)	(0.022)
EDU	Edu_{ct}	-0.004	-0.006	-0.005		
		(0.021)	(0.021)	(0.024)		
HUM2: LABOUR QUALITY	$\Delta\ln(LC_{cjt})$				-0.035	-0.096**
					(0.041)	(0.04)
EMERGING ECONOMIES	$Developing_i$	0.001	-0.003	-0.003	0.002	-0.001
		(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
COMPLEMENTARITIES						
AI AND EMERGING ECONOMIES	$Developing_i * \Delta\ln\left(\frac{AI_{cjt}}{L_{cjt}}\right)$		0.050*	0.050*		0.047
			(-0.03)	(-0.03)		(-0.031)
AI AND HUM1	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}_{cjt}}}{L_{cjt}}\right)$		0.238*	0.238*		
			(0.137)	(0.137)		
AI AND HUM2	$\Delta\ln(AI_{cjt}) * Edu_{ct}$			0.002		
				(-0.135)		
AI AND LC	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln(LC_{cjt})$					0.377**
						(0.17)
CONTROLS						
OTHER INTANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{\boldsymbol{intan}_{cjt}}}{L_{cjt}}\right)$	0.082**	0.076**	0.076**	0.089**	0.092**
		(0.036)	(0.037)	(0.037)	(0.04)	(0.04)
YEAR DUMMIES		Yes	Yes	Yes	Yes	Yes
INDUSTRY DUMMIES		Yes	Yes	Yes	Yes	Yes

N		7053	7053	7053	8248	8248

STANDARD ERROR IN PARENTHESES * P<0.1 ** P<0.05*P<0.01**

PART II

MARGINAL EFFECTS OF AI ON LABOUR PRODUCTIVITY AT LEVELS OF LABOUR COMPOSITION GROWTH

ME IN (B)

		Emerging economies			*Developed economies*		
PERCENTILE	Growth of labour composition $\Delta\ln(LC_{cjt})$	dy/dx	Delta-method Std. Err.	P>z	dy/dx	Delta-method Std. Err.	P>z
25%	-0.012	0.052**	0.025	0.036	0.005	0.018	0.790
50%	0.001	0.057**	0.025	0.023	0.010	0.018	0.584
75%	0.013	0.061**	0.025	0.015	0.014	0.018	0.429
90%	0.032	0.068***	0.026	0.009	0.021	0.018	0.251
95%	0.051	0.076***	0.027	0.005	0.028	0.019	0.144
99%	0.121	0.102***	0.034	0.003	0.055*	0.027	0.041
100%	0.408	0.210***	0.076	0.006	0.163*	0.071	0.022

Robustness

One way to review longitudinal data is as a series of repeated measurements nested in individual subjects. The impact of AI and human capital on economic growth may vary, and the magnitude is determined by the nature of industries and country characteristics. Under this assumption, random effect parameters can be applied in the analysis to allow the variation of estimated slope coefficients of AI capital, vocational training and labour composition across our observations. A unique id is used to identify each country-industry observation as the lowest (individual) level. The estimators in the multilevel analysis (random effect parameters) are the maximum likelihood estimators. Table B in the appendix displays the impact of AI and human capital growth on labour productivity by applying the random coefficients model. The results obtained are, overall, consistent and robust with what has been found using fixed-effects estimations (Table 3.6). Hence, we may conclude that the results are not especially sensitive to the alternative estimation method employed under a different assumption.

3.7 Conclusion

This empirical exercise unlocks the underlying mechanism of AI's effects on labour productivity growth by introducing various elements of human capital investment. The industry-level analysis of multiple EU countries suggests robust complementary impacts of human capital investments to enhance AI's productivity growth across different estimation methods and measures of human capital. In terms of the size of the synergies, vocational training investments generate a more significant contribution than tertiary education, which measures general labour quality. According to our estimated marginal effects table, the positive effects of AI investment can be ensured only for some industries, which can provide enough relevant training in time to support the use of new technology. The estimated marginal effects of AI on productivity range from negative to appx 0.15 percentage points, given the range of growth in vocational training in our sample. Further, the study introduces an alternative measure, the labour composition, to represent general labour quality. In much prior intangible literature (Mahoney 2012; Marrano et al. 2009 Borgo et al. 2012), the Becker-type assumption (1962) is applied, assuming that the investments by firms will not raise workers' wages since these skills are hard to use outside individual firms. However, our estimations indicate that it may involve double-counting issues when simultaneously including the labour composition and training in the production function. This wage-based measure can capture the effects of experience, which to some extent can be gained from uncertified skills from informal training. In terms of the last hypothesis, we expect Eastern Europe to experience a different development trajectory, and classify them as the low-middle income group (developing economies), given the observational period. The net effects of AI on labour productivity growth for emerging economies remain positive. Although it is widely considered that AI technology poses a threat to kill the development of developing economies due to job displacement, our empirical evidence tends to support the positive side of utilising AI applications that are characterised by lower entries and requires diverse sets of soft skills. The low-middle income economies gain more considerable benefits from an additional increase in AI capital investments, given varying levels of growth in the accumulation of human capital. However, it is worth noting that our empirical results on emerging economies tend to rely on the choice of countries (four Eastern European countries in our case) and may introduce some bias.

Further research is expected to unpack the sights of other major developing economies, such as China, India and South Africa, potentially more representative. We may find a different pattern by extending the analysis. In addition, although our results in particular point to the importance of vocational training, the role of tertiary education cannot be neglected. It is highly likely that general education will bring substantial effects in terms of AI and innovations, which could be investigated in depth in future studies.

Appendix

TABLE B. IMPACTS OF AI AND HUMAN CAPITAL ON LABOUR PRODUCTIVITY

		(1)	(2)	(3)	(4)
RANDOM-EFFECTS PARAMETERS		a	b	c	d
AI	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}})$	0.015	0.018	0.02	0.02
		(0.013)	(0.013)	(0.013)	(0.013)
TANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{tan\,cjt}}{L_{cjt}}\right)$	0.166***	0.164***	0.159***	0.160***
		(0.051)	(0.051)	(0.051)	(0.051)
HUM1: VOCATIONAL TRAINING	$\Delta\ln(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}})$	0.093***	0.095***	0.083***	0.088***
		(0.02)	(0.02)	(0.019)	(0.02)
HUM2: LABOUR QUALITY (LABOUR COMPOSITION)	$\Delta\ln(LC_{cjt})$	-0.012	-0.060*	-0.009	-0.046
		(0.039)	(0.036)	(0.039)	(0.036)
COMPLEMENTARITIES					
AI AND HUM2	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln(LC_{cjt})$		0.521***		0.402**
			(0.149)		(0.202)
AI AND HUM1	$\Delta\ln(\frac{AI_{cjt}}{L_{cjt}}) * \Delta\ln\left(\frac{H_{\boldsymbol{hum1}\,cjt}}{L_{cjt}}\right)$			0.354**	0.220
				(0.161)	(0.192)
CONTROLS					
OTHER INTANGIBLE CAPITAL	$\Delta\ln\left(\frac{K_{\boldsymbol{intan}\,cjt}}{L_{cjt}}\right)$	0.093***	0.096***	0.093***	0.095***
		(0.034)	(0.034)	(0.033)	(0.034)
YEAR DUMMIES		Yes	Yes	Yes	Yes
N		8248	8248	8248	8248

STANDARD ERROR IN PARENTHESES * P<0.1 ** P<0.05*P<0.01**

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3.8 Supplementary Evidence – AI and innovation

Besides labour and capital, technology might influence innovation and growth through **competition pressure** in an ambiguous direction (Aghion, Jones and Jones 2017). On the one hand, AI, due to its capability of inducing reverse engineering, will facilitate the **imitation** of existing leading products and technologies. Easier imitation associated with the intensively competitive market competition motivates firms who are at the current technological frontier to become more innovative and capture benefits from imitation, in order to become more competitive. The positive effects on innovation and growth are likely to occur under the low initial level of market competition. On the counteracting side, as one sector gradually becomes congested over time, there is a quicker decreasing return of innovating in existing sectors or lines. Too intensive imitation threats might discourage innovation. Immediate imitation threats might push potential innovators to escape from current competition or devote their resources towards creating other new product lines to avoid excessive expropriation and rapidly decreasing returns (Bloom, Garicano, Sadun and Van Reenen 2014). The net effects of AI on innovation depend on the counteracting channels. Aghion et al. (2017) also point out that AI can also affect innovation and growth through its impact on the degree of product market competition. Adopting AI can bring greater learning opportunities and improve firms' innovation. However, broader access to knowledge by firms' existing and potential competitors can reduce expected returns and harm innovation and growth. In addition, the extent of productivity gains induced by AI or digital technologies can vary among sectors and industries. Firms that adopt AI are more likely with a higher capability of learning and greater accessibility to knowledge from external environments.

Capital skill complementarity

In theory, firms are profit-maximising and will choose to adopt or use a skill-biased technology only when it is profitable; their decision is based on relevant factor of cost and profitability (Goldin and Karz 1998; Acemoglu 2002). Because of the capital-skill complementarity, the installation of complex machines or technology would constantly increase the demand for supervisory or skilled labour to operate or maintain them. At the same time, skills premium occurs (wage difference between low and high-skilled workers), as the related occupational supply is much less inelastic to the demand. In addition, since the progress of technology may gradually reduce the price of capital, the firm will further deepen their investment in new equipment, resulting in a gradual rise in labour demand and the skills premium. Skilled labour is believed to be less elastic than unskilled labour. This could be applied to the case of AI, assuming capital-skill complementarities characterise it as previous waves of technology.

The increases in the spending on human capital, such as education or preparing for the right talent pool to match requirements, would reduce the wage premium of skilled labour. As a result, this reduces the cost for firms to recruit additional skilled labour and improve the profitability of their AI investments. As soon as the supply of skilled labour increased and the relative price of skilled versus non-skilled labour decreased accordingly, new technologies would become more profitable and further developed (Goldin and Katz 1998). In sum, a sufficient supply of high-skilled labour through human capital investment could increase the firm's incentive to shift towards investing in AI technology as well as developing related innovations. If firms' innovation activities are effectively protected, for instance, through patents, impacts from capital-skills complementarity can be ultimately reflected in productivity growth. New ideas would be protected against imitation, ensuring that firms would extract benefits from their investment in R&D.

H: AI, moderated by human capital investments, generate a positive effect on developing new innovations.

Table 3.8-1. Impact of human capital and AI on innovation activities

Part I						
		(1)	(2)	(3)	(4)	(5)
Country-industry fixed effect						
AI capital	$\Delta\ln(AI_{cjt})$	0.087**	0.087**	-0.120	-0.121	-0.126
		(0.043)	(0.043)	(0.092)	(0.094)	(0.094)
Hum1 Vocational training	$\Delta\ln\left(H_{\boldsymbol{hum1}_{cjt}}\right)$	0.080**	0.078**	0.080**	0.077**	0.245
		(0.040)	(0.039)	(0.040)	(0.039)	(0.199)
Hum2 Workforce with tertiary education (%)	Edu_{ct}	0.592***	0.592***	0.501**	0.501**	0.497**
		(0.217)	(0.217)	(0.217)	(0.217)	(0.217)
Complementarities						
AI and Hum1	$\Delta\ln(AI_{cjt}) * \Delta\ln\left(H_{\boldsymbol{hum1}_{cjt}}\right)$		0.075		0.128	0.120
			(0.393)		(0.375)	(0.375)
AI and Hum2	$\Delta\ln(AI_{cjt}) * Edu_{ct}$			0.811**	0.818**	0.832**
				(0.402)	(0.406)	(0.405)
Hum1 and Hum2	$\Delta\ln\left(H_{\boldsymbol{hum1}_{cjt}}\right) * Edu_{ct}$					-0.498
						(0.520)
Constant			Yes	Yes	Yes	Yes
Year dummies			Yes	Yes	Yes	Yes
N			7822	7822	7822	7822
Se in parentheses * p<0.1 ** p<0.05*p<0.01**						
***F*-statistics of joint hypotheses**						
All AI variables and interactions = 0			2.02 (0.134)	2.95 (0.053)	3.00 (0.051)	3.00 (0.050)
All Hum1 variables and interactions = 0			2.05 (0.130)		2.02 0.1338	0.83 0.4359
All Hum2 variables and interactions = 0				6.06 0.0025	6.06 0.0025	6.12 0.0024

Part II				
Marginal effects of AI at levels of tertiary education				
Workforce with tertiary education (%)	dy/dx	Delta-method Std. Err.	z	P>z
0.079	-0.056	0.0646	-0.86	0.39
0.129	-0.015	0.0496	-0.3	0.762
0.179	0.026	0.0395	0.65	0.517
0.229	0.066*	0.0382	1.73	0.084
0.279	0.107**	0.0466	2.29	0.022
0.329	0.147**	0.0608	2.42	0.015
0.379	0.188**	0.0776	2.42	0.015
0.429	0.228**	0.0957	2.39	0.017
0.479	0.269**	0.1144	2.35	0.019

The table examines the joint effects of two components of human capital and AI on innovation. In column 1, our results confirmed that both AI uptake and two types of human capital investments generate a significantly positive effect on R&D spending, crucially enhancing innovation activities. To further uncover the underlying mechanism, the linear regression model is augmented by including the interaction term of AI and two types of human capital accordingly in columns 2 and 3. In column 3, the significance of the interaction term with general labour quality is significant at 5% level. This indicates that the effects of AI-uptake on innovation happen in a non-linear way, which depends on the overall tertiary education of the working population rather than specific in-firm training. More specifically, according to the estimated coefficients of the interaction term in columns 3–5, the impact on innovation of additional percentage growth in AI uptake is greater, by the amount of approximately 8% percentage points, for each 0.1 unit increase in the level of workforce with tertiary education. By adding the interaction with labour quality (columns 3–5), although the main effect of AI-uptake (appx -0.12) is insignificant, the joint *F*-statistics of AI's main effect and its interaction term is 2.95, which has a *p*-value of 0.05, and hence overall AI's effect is still significant at 5% level. Therefore, both general education and specific vocational training are important to promote the innovation activities of companies, while highly educated employees are crucial to AI technology to develop new innovations.

To know the magnitude of AI uptake on the growth of R&D capital, the lower panel of the Table displays changes in marginal effects given different education levels.[23] In our sample, the fraction of the workforce with tertiary education across countries varies from the value of 0.079 to 0.45, taking the average value of 0.27. According to the table, AI investment contributes significantly to innovation as the country's tertiary education has reached approximately 22% or higher. Given the average level of labour quality, an additional percentage growth in AI capital invested is associated with 0.098 percentage point growth of innovation measured by R&D capital, by the estimation results in columns 3, 4 and 5. Due to the non-linearity, the marginal influence of AI's innovation effects differs markedly between those countries. For some countries, AI's marginal effects are insignificant and hence do not necessarily promote innovation, given that their tertiary education is far below the average.

[23] This table of marginal effects is computed based on the regression results in Table 4 column 3. These computed results are very similar in columns 4 and 5.

4 Chapter 4: The Adoption of Cloud Computing and Firms' Profitability

Abstract

This empirical paper brings new insights into the impact of cloud computing on firms' financial performance. We use newly available data – the UK E-Commerce Survey and the UK Annual Business Survey – to describe the overall pattern of the depth and breadth of cloud computing usage in UK enterprises in recent years. We examine the corresponding impact of emerging cloud computing technologies, as one typical application of digital technology adoption and diffusion, on firms' profitability indicators. In this panel data analysis, we test if cloud computing adopters and the intensity of adoption are associated with positive gains on firms' current profitability in terms of both net and operating profits. The paper also sheds light on the mechanisms or multiple channels through which cloud computing potentially operates to drive higher profitability. The discussion involves examining if cloud computing can successfully facilitate **product innovations** or new market shares, **reduce production costs** to expand existing market shares, and **increase profit margins**, etc.

4.1 Introduction

Traditionally, investment in ICT technology used to be associated with considerable upfront sunk costs in purchasing hardware infrastructure, software, training and maintenance of the IT service. Cloud computing is a relatively new technology that provides storage, processing capability, and software applications for firms through the 'cloud computing' service as an on-demand subscription. According to the OECD (2014, 2021), cloud computing technologies are generally referred to as a set of computing resources (e.g. networks, servers, storage, applications and services) that can be accessed in an on-demand and flexible way. The US National Institute of Standards and Technology (2011) describes some essential features of cloud computing to understand where it sits within the standard product classification. Three key characteristics can be summarised regarding cloud computing services: on-demand, rapid elasticity or scalability, and low management effort. The computing resources from the provider are pooled and serve multiple users (multi-tenant model) through a remote internet connection. Users or firms can access the computing resources, for instance, storage, processing, memory and network bandwidth, dynamically as needed in a self-service way. These resources can be elastically provisioned and released to users in any quantity and at any period of time. Hence, firms can scale rapidly outwards or inwards, fully commensurate with the demand or their business needs. Cloud computing services generally have broad network access. This means capabilities are easily accessed through a standard mechanism by heterogeneous end-point devices such as phones, laptops and workstations. Moreover, capability usage can be transparent for both the provider and users of the services, which can be monitored, controlled and reported.

In this study, we will build on the small literature on the effects of cloud computing on firms, in particular, the gap in financial performance. There is a growing literature that discusses the trends in digital technologies and, in particular, the linkages to outcomes to enterprises, primarily focusing on productivity. The discussions focus on addressing two issues: first is the current slowdown issues in productivity growth in many developed economies from the mid-2000s (Lafond et al. 2021); second is the evidence of the growing productivity gaps between frontier firms and the remaining firms (Andrews et al. 2019). From a distinct viewpoint, this study will contribute to the debate on digital technology and firms' performance by investigating the contribution to financial performance rather than the productivity paradox, which has been heavily discussed in the previous two chapters. Apart from the question of whether emerging technologies can significantly impact the benefits of productivity (the TFP or labour productivity statistics), evidence indicates some linkages between the exploitation of digital technology and other financial performances. For instance, innovations in new goods and services provided could be a channel to enhance firms' profitability, but not necessarily their productivity growth. Hence, the potential benefits are not merely revealed on productivity improvement, but could be upon other financial performance indicators such as profitability, market share, return on investment, etc. The role of digital adoption and its link to productivity outcomes only captures an incomplete story of a firm's potential gains from adopting the emerging technology.

Given an entire review of empirical studies, very few quantitative studies investigate or estimate cloud computing and firms' financial performance, and existing analysis relies on the cross-sectional and/or event study approach (e.g. Chulkov et al. 2021; Khayer, Bao and Nguyen 2020; Hossain 2020). To the best of our knowledge, the study by DeStefano, Kneller and Timmis (2020) is the only empirical analysis that systematically examines the impact of cloud computing on firms' performance, the impact on the growth of sales and employment (an indicator of productivity growth), by applying the fixed effects estimation and instrumental variables. Therefore, this study will be the first systematic research on cloud computing and firms' profitability. It extends the discussion to unpack and identify the underlying channels through which cloud computing can lead to profitability.

Our working sample is 6,543 firms, of which 70% had adopted cloud computing by 2019 (compared with appx 40% of firms in 2013). However, the intensity of technology deployment inside those firms showing the acquisition of additional units is still relatively low, with less than 20% of the advanced or enhanced. Current studies on cloud computing fail to distinguish the intensity of technology deployment with inter-firm diffusion. Firms are heterogeneous in terms of their investment in modern cloud technologies, which may lead to different impacts on their improvement in profitability. Unlike other empirical studies, this exercise will examine the diffusion process from both the extensive and intensive dimensions.

Structure

The structure of the paper is as follows. Section 2 reviews relevant literature and develops the hypothesis. Part I of Section 2 focuses on the theoretical grounds for establishing the link between technological change and firms' profitability from different perspectives. The literature review starts from the Schumpeterian growth paradigm and brings into the theory of technology adoption and diffusion on firm performance and complementarities. We highlight multiple levels or mechanisms through which a general-purpose technology can enhance profitability. Section 3 presents our research settings. It includes the theoretical framework for measuring the impacts of new technology on profitability, the econometric strategies and the estimation model derived from testing our key hypothesis. Section 4 is focused on understanding the cloud and how we construct each measure in empirical specifications. This section highlights the benchmark choices of profitability indicators, cloud computing adoption and extent of use. Section 5 presents the overall pattern of cloud computing adoption over the observational years and the sample's descriptive statistics. Finally, Section 6 analyses the empirical outputs and checks the robustness.

4.2 Literature Review

4.2.1 Innovation (technological change) and profits

It is generally believed that most of the value of new products and prices is eventually passed on to consumers in the form of lower prices of goods and services. Under perfect competition, profit maximisation yields a standard result: the marginal revenue of inputs (price) equals their marginal cost. Firms will act to maximise the excess profits and employ additional factor inputs until all abnormal profits can be exhausted. Therefore, if perfect market competition holds, innovation activities from technological change will not be expected to generate any excess or abnormal profits.

However, there are some cases where cost reductions for some innovations in the industries are at least partially appropriable by producers. Hence, only partial benefits are passed on in price reduction. For these innovations, producers or investors can obtain a temporary increase in profits. Investors and innovators can still get a slice of returns to productivity growth. The excess profits arising when the firm can appropriate the return from innovative activities are defined as Schumpeterian profits, initially prosed by Schumper 1911. These are the profits above those that would represent the normal return on invested capital and risk-taking (Krugman and Wells 2009).

The US experienced a remarkable resurgence of growth and innovations in the late 1900s, followed by a sharp rise in the stock market. To better understand some inquiries on the role of innovational profits in the total profits and stock market return, Nordhaus (2004) derives the model from estimating the size of the slice that can go into the originator of the technological change, as well as the relative magnitude for the entire economy. The model shows that the equilibrium Schumpeterian profits margin, calculated as the percentage of the difference between market price and monopoly cost, depends on the appropriability ratio and dynamic factors, which are the rate of dissipation and technological progress (multi-factor productivity). According to the estimation, the appropriability ratio is 5%–8% for US non-farm business sectors, and the average value of the Schumpeterian margin is appx 0.55%–0.58%, conditional on different levels of depreciation rate. The share of Schumpeterian profits is estimated to be 2.2% of the total social surplus. This number results from a low rate of initial appropriability (appx 7%) and a high rate of depreciation (appx 20% per year) of Schumpeterian profits. Besides, the estimated Schumpeterian profits are 3.8% of corporate profits over the period 1948 to 2001. Hence only 20 basis points of the rate of return to capital are due to the Schumpeterian profits, given the estimated rate of profits on the replacement costs of capital is 0.19 % per year over 1948 to 2001. Overall, they suggest part of the puzzle about the profitability of US capitalism is resolved here, even though the rate of Schumpeterian profits is low under the enormous innovativeness.

Battisti and Stoneman (2019) use the definition of innovation as 'the successful exploitation of new ideas', and measure 'successfulness' by calculating the contribution of innovation activities to firms' operating profits. In their study, the definition of innovation employed stresses the outputs from innovation activities. In other words, innovation is considered to have little economic relevance unless those activities can generate success or value to corporates. The idea is consistent with the BEIS 2007's definition that innovation is a form of changing the way to exploit new ideas successfully. It covers a wide range of areas of innovation that are not limited to the scientific and technological but also organisational, managerial marketing and soft innovations (Battisti and Stoneman 2010). Moreover, profitability is viewed at a point in time or from an inter-temporal viewpoint, which will eventually be reflected in the firm's market value. In particular, their study points out that as the market is forward-looking, it may be difficult to distinguish whether the market value can reflect the current innovation, technological change or the future expectation of those activities. From this perspective, current profit measures are advantageous and closely linked to measures derived from the growth accounting literature. According to their derived model, the contribution of exploiting new ideas is calculated as a residual equal to the difference between the growth rate of nominal profits and effects from the growth of exogenously determined wage rates and demand shifts in the market. The mean value of the innovativeness measure, in other words, is appx 5.1% positively significantly over the whole panel with a more considerable variance and wide range.

In sum, the Schumpeterian growth paradigm confirms at least part of the fraction of the benefits from new technologies will be captured by innovators, compared with the fractions that are all passed on to a lower price. Innovation by the firm will create divergence from a perfectively competitive steady-state and temporarily increase the firm's abnormal profits above zero. It is worth noting that the discussion regarding profit maximisation typically refers to the net profits. It represents the profits after interest, tax, debt repayment, depreciation and amortisation, which is, in other words, the revenue left after subtracting all expenses (costs of goods sold, operating expenses, interest and taxes). However, if we cannot know the firm's capital structure given the various sources of financing and related income and expenses such as interest repayments, dividends and debts, net profits are more difficult to analyse. The choices of profitability measures will be discussed in detail in the later sections.

H1: We expect the adoption of general-purpose technology will positively impact firms' profits.

To further understand the firm's level of profitability in terms of new technological change and innovation, this section brings into the literature on the economics of technology diffusion and adoption. According to technology diffusion literature, four main effects are considered to provide reasons theoretically and empirically in order to explain the existence of lags of diffusion after the technology has been first introduced to the market, and more importantly, the underlying link with investment return on technological adoption. The four models were initially proposed by Karshenas and Stoneman (1993) and are epidemic, stock, order and rank effects.

The **epidemic model** (Mansfield 1981) refers to new technology that can only be learned and adopted by a new firm through communication with previous adopters (epidemic learning). The speed of technology diffusion across firms, in other words, inter-firm diffusion, depends on learning factors and availability of information spillover, including the current proportion of existing users, firms' previous experience and so on. A similar approach based on information spreading, e.g. advertising, can be found in the marketing literature (Bass 1969, Mahajan and Wind 1992). The above are part of a class of disequilibrium approaches extensively used but also criticised for their over-reliance on information dissemination (Battisti 2000). The **stock effect** suggests one firm's adoption will negatively impact the profitability of existing adopters. It is one of the equilibrium diffusion model components, built based on the assumption of competitive markets and firms' homogeneity (Götz 1999). It argues that both diminishing costs and decreasing returns on technology adoption occur as adopters increase. The competitive advantage of firms is quite obvious in the early stage when there are only a small number of adopters. Hence, one firm's adoption decision will downward the investment profitability acquired for further adoption by other firms as well as existing gains of current or early adopters (Fusaro 2007). **Order effects** refer to that firm's position determines the technological return in the order of adoption. This dimension is developed and extended based on stock effects, again associating with market-intermediated externality. As more firms use new technology, the industry average costs for technology adoption decrease and, therefore, negatively affect the price and profits of the non-adopters, according to Schumpeterian grounds. Early adopters can still find an effective way to retain their profit gains, although later adopters follow and copy their steps. There is a battle for the first few places as the market leader, who would secure scarce resources such as consumers, labour, brands and intangible assets (brand). Hence, the time of adoption is crucial in determining the allocation of profits (Fudenberg and Tirole 1985).

Pioneers can extract high profits even though the adoption cost is very high at the early stage. Following down the ladder of time line, an adoption order can determine returns on this investment. One firm's adoption will decrease returns for the other firm, which adopts the same technology at a later date (Battisti and Stoneman 2013). Another approach found in the literature is based on **rank effects**. As first argued by David (1969), a firm's decision to adopt new technology is a function of its characteristics, such as size, age, R&D intensity, and market power. Benefits from the technology are independent of the number of users in the market. The firm's heterogeneity is the primary driver leading to the difference in investment return and reservation price, resulting in different incentives and time to conduct innovations. Firms endogenously choose other adoption dates relying on their characteristics and consideration of the changing nature of cost and return as diffusion proceeds.

To obtain a complete picture of the return to technological change, Stoneman and Kwon (1996) follow the above theoretical concerns and first derive an encompassing model of the diffusion of new process technology, predicting the relationship between technology adoption and profitability. In their model, all the possible dimensions discussed above regarding technology diffusion are incorporated. The empirical exercises test the encompassing model by examining the adoption of four different technologies (CNC, Computer, Micro-processors and Carbide Tools) in the UK engineering industry. Their results pointed out that non-adopters experienced reduced gross profit gains compared with other firms that adopted the new technology. The **pre-tax gross profits gains** for technology adopters are significantly affected by industry and firm characteristics (rank effects), the number of other users of new technology (stock effects), and the cost of technology acquisition. The order effects and epidemic learning contribute only in some specific cases of technologies.

4.2.2 The intensity of technological use and performance

It is worth noticing that most diffusion papers concentrate on the technology use across firms (extensive margin), while much smaller literature focuses on the intensive margin or the intensity of technological use within firms (Battisti and Lona 2009, Battisti and Stoneman 2005). Inter-firm diffusion refers to firms' first adoption of technology and is defined as the degree of penetration of the technology across firms in an industry (Karshenas and Stoneman 1995). However, the way of exploiting the benefits after the first adoption and the depth of use of the technology by each firm is potentially more important in terms of post-adoption firm profitability and performance. The intensive use is generally measured by the proportion of the firm's capital stock embedded in the new technology or the percentage of output produced by the use of new technology according to intra-firm diffusion literature (Mansfield 1981; Battisti and Stoneman 2003).

This depth of technology adoption is expected to be especially important in the adoption of multipurpose technologies such as ICT, AI and cloud computing with high potential for the scalability of operations. To this end, Battisti and Stoneman (2009) have developed an integrated diffusion model that innovatively captures the extent of usage of new technologies within the organisation to affect the marginal gains from adoption. They conducted a joint analysis in greater depth based on the third UK community innovation survey and modelled the usage of e-commerce across and between corporates in the year 2000. The diffusion models estimate both the inter-firm adoption decisions and intra-firm intensity of usage, and are estimated using standard bivariate logit and multinomial specifications. In their study, the intensity of e-commerce usage is classified into three categories: no use, basic use and enhanced use, according to the increases in sophistication in the range of tasks that firms perform using e-commerce, consistent with other technology adoption literature (Forman et al. 2003; Crespi et al. 2004; Bridgewater and Arnott 2004). Their study brings many interesting underlying insights, allowing for an integrated comparison between two states of diffusion, as well as policy implications. The model derived follows the idea, in line with the rank, stock, order effects, that the firm will adopt new technology when the marginal expected gross profits from the first use, or further use, are equal to the expected marginal costs. According to the evidence, by 2000, the inter-firm diffusion process for e-commerce was widespread, with well over 80% of the companies having adopted a website, while its depth of use, namely the intra-firm diffusion, was still quite limited with most companies using it at a very basic level. As technological diffusion is an endogenous choice, it is not necessarily the case that all basic users can make gains from enhanced usage. However, results show the introduction of process innovation impact positively, and significantly affects the probability of enhanced use of new technology. In contrast, it influences the group of non-users in the opposite direction, and has positive but no significant effects on being a basic user. More importantly, introducing innovative management, organisational practice and R&D are positively and significantly associated with the probability of being an enhanced user of new technology but negatively linked with the probability of being non-users. From this perspective, the evidence also supports the idea of complementarities that firms tend to innovate at one dimension; for example, technological or organisational tend to aggressively innovate in another, in this case, the intensity of e-commerce usage (see also Battisti and Stoneman, 2010; 2020).

Furthermore, some literature indicates the synergies under the co-existence of different innovation modes that have a different mix of products, process and other non-technological innovations. Economic performance is usually associated with the more systematic type of strategies (Brynjolfsson and Hitt 2000; Bresnahan et al. 2002). For instance, Evantelista and Vezzani (2010) compare the growth performance (turnover) of four distinctive innovation modes, namely 'pure' production innovation mode; 'pure' process-oriented mode; organisational mode associated with organisational change and process change; and complex mode where both process and product innovation are introduced accompanied by changes in the organisational structure and marketing strategies. Results show among different possible strategies; the complex mode suggests the most substantial effects on the growth of turnover, whereas pure product or process innovations appear to be the least effective, indicating synergies. They also point out the critical role played by organisational change, which is considered to be a complement or prerequisite for the enhanced performance and quality content of products and services.

Regarding the theory of competitive strategy, Hitt and Brynjolfsson (1996), pointed out that the only way that information technology can lead to sustainable abnormal profits is when the industry has barriers to entry. According to Bain (1956), barriers to entry are broadly defined as anything that enables firms to earn abnormal profits, such as patents, search costs, product differentiation or professional access to scarce resources. A firm's innovative use of technology under an intact barrier to entry enables them to make extra profits. Further, the use of IT may raise or reduce existing barriers or create new barriers, changing the profitability of a specific industry or individual firm. Following this perspective, it can be argued that the depth and breadth of use of new technologies is more likely to be involved in systematic or complex modes of innovation strategies, including both product or process innovations and changes in organisational, management practices or marketing. Therefore, we may expect more competitiveness obtained through improved quality of content, such as increased product differentiation and far greater rewards on profitability. As Battisti and Lona (2009) mentioned, organisational and management practice changes under the co-invention by individual firms are more difficult to imitate due to the context-specific nature of the successful implementation of the particular firm. If the profound use of new technologies accompanying organisational changes is difficult to replicate, we may expect more substantial divergence from normal profits in the short run.

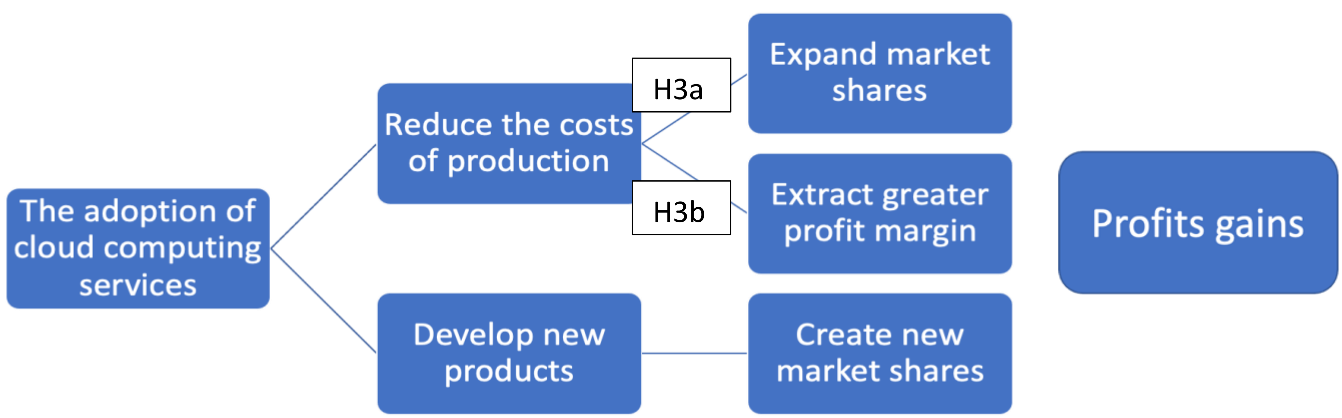
H2: The intensive use of a general-purpose technology (intra-firm diffusion) may bring the most substantial profitability gains.

4.2.3 The underlying mechanism of cloud computing on profits

There are several possible levels at which technology can potentially enhance profitability. First, the adoption of cloud computing may bring new innovations. For instance, subscribing platform as a service enables the IT teams to focus on more core business, where developers can directly build upon the framework to design new cloud-based applications. Firms can also leverage the business intelligence tools and/or purchased software through clouds if they are constrained by technical expertise or internal IT capabilities. The process of launching new products becomes faster as the preparation for necessary computing infrastructure can be ready in minutes or hours, as well as enhanced computing power. All these lead to a new product being developed and, as a result, expand the new market share by increased turnover. Alternatively, the adoption of general-purpose technology suggests a large potential to reduce the cost of production. For instance, both purchasing infrastructures as a service and platform as a service through clouds will bypass large hardware costs, the complexity of buying and managing physical infrastructure, etc. This will result in greater profit margins and/or expanding existing market share. Given the benefits of cost reduction, there are different strategies that firms can adopt to enhance profitability. If the market is highly competitive, in this scenario, the adopting firms are more likely to reduce the selling price of outputs and hence displace their competitors as a result of their increased turnover. From another perspective, if a company is in a monopolistic position, it is not necessarily required to reduce the price, but adoption enables it to extract more significant profit margins for current product offerings.

Based on the analysis in this section, the underlying channels through which cloud computing can enhance profitability may involve:

General Purpose Technologies and Profitability (Mechanisms)



4.3 Methodology

4.3.1 The Theoretical Framework – The determinants of firms' operating profits

To test our hypothesis, we develop the theoretical model according to Battisti and Stoneman's (2019) framework measuring innovation performance. Innovation or new technology will affect firms' production and profit gains through both embodied and disembodied forms. In addition, we also combine the framework of Stoneman and Kwon (1996) and include other factors, such as industry characteristics, particularly the **stock effects** through the intermediate market, in empirical modelling.

$$Y_{it} = A_{it}(K_{it})^{a_i}L_{it}^{\gamma_i} \tag{15.}$$

In the Cobb-Douglas production function, Y_{it} is the total output of firm i at time t; L_{it} is labour employed in firm i at time t. K_{it} captures the contribution from capital stock on total output in firms' production, which is the weighted sum of the technological process (capability) of the entire company's capital stock. The acquisition of new capital goods, such as new capital equipment, production lines or new software, is involved in the routine of commercialising new ideas into the production process, primarily representing process innovation (Battisti and Stoneman 2019). Additionally, firms' production can be affected without purchasing new equipment, for instance, by developing new product designs, changing organisational structure and management practices. These innovations are considered in the disembodied form and commonly employed in growth accounting where the overall technological progress happens, modelled by the term A_{it}. From this perspective, greater products and services will be produced given the same level of capital and labour inputs due to the technological change in the surrounding environment. Notably, we expect more profitability gains than productivity enhancement to be observed through the second innovation routine.

To explore the impact of digital technology on firms' performance, we allow the route for both embodied and disembodied innovations to occur, where the impact of cloud computing technologies is incorporated into the firm's production process. Similar to modelling embodied innovations, the technology adoption first involves acquiring new capital goods both in tangible and intangible forms. For instance, firms can invest in or purchase different forms of cloud computing services to store data from intelligent devices, expand computing capacity, access new software applications, etc., thus changing the production process. Using new technologies is likely to increase the capacity of the firm's existing capital stock. In the framework, we can separate the effects of cloud computing-related capital from the other fixed assets.

$$Y_{it} = A_{it} CL_{it}^{\lambda} {K_{it}}^{a_i} L_{it}^{\gamma_i} \tag{16.}$$

As we want to investigate the impact of digital technology on profitability, the value equation is introduced, following the production function.

$$V_{it} = P_{it} Y_{it} \tag{17.}$$

Where P_{it} is the price of the output of firm i in time t, Y_{it}it is the level of output in time t, $P_{it}Y_{it}$ is the **total revenues** of the firm obtained or the gross **value added** in the production (netting out the expense of the intermediate inputs).

Firms' total profits or total value-added are split into the firm's operating profits and total costs of labour employed.

$$V_{it} = S_{it} + W_{it} L_{it} \tag{18.}$$

Nominal value-added V_{it} consists of firms' operating profits S_{it} and costs of employees, which is the number of employees L_{it} multiplied by the nominal wage W_{it}. The share of labour and non-labour in value-added is defined $\frac{W_{it}L_{it}}{V_{it}} =$ by $1 - \beta(i)$ and $\frac{S_{it}}{V_{it}} = \beta(i)$ respectively, where $\beta(i)$ is constant over time as suggested by most of studies of applying the growth accounting framework.

Through the supply side, the investments in cloud computing technologies, capital and labour inputs affect the output level and, thus firms' operating profits. On the demand side, profits can also be indirectly affected by changes in the price level. Assuming an imperfectly competitive market, firms offer various goods and services, and experience a downward-sloping demand curve, as shown in the following equation (a).

$$P_{it} = C_{it}Y_{it}^{\frac{1}{\eta(i)}} \tag{19.}$$

In the above equation, price is partially endogenously determined by the number of output that firms could produce through demand elasticity. $\eta(i)$ represents negative demand elasticity for firm i if they increase the number of outputs. C_{it} represents how the general price level of products changes with the external demand shifts such as market, industry-specific factors or other exogenous forces. Both Y_{it} and P_{it} are endogenous.

By substituting (2) and (5) into (3), we have equation (6)

$$V_{it} = C_{it}Y_{it}{}^{1/\eta(i)}Y_{it} = C_{it}(A_{it}CL_{it}^{\lambda_i}K_{it}{}^{a_i}L_{it}^{\gamma_i})^{(\frac{1}{\eta(i)}+1)} \tag{20.}$$

Given the share of labour and non-labour in value-added (equation 4),

$$\beta(i) = \frac{S_{it}}{V_{it}}$$

We have the following baseline equation to model the return of digital technology on profitability,

$$S_{it} = \beta(i)C_{it}(A_{it}CL_{it}^{\lambda_i}K_{it}{}^{a_i}L_{it}^{\gamma_i})^{\left(\frac{1}{\eta(i)}+1\right)} \tag{21.}$$

The expression can be manipulated by taking the log to obtain a linear relationship

$$lnS_{it} = ln\beta(i) + lnC_{it} + \left(\frac{1}{\eta(i)}+1\right)ln(A_{it}) + \left(\frac{1}{\eta(i)}+1\right)\lambda_i ln(CL_{it}) + (\frac{1}{\eta(i)}+1)a_i ln(K_{it}) + (\frac{1}{\eta(i)}+1)\gamma_i ln(L_{it}) \tag{22.}$$

Overall, based on the approach of Battisti and Stoneman (2019), CL_{it} , K_{it} and L_{it} as inputs will directly affect the level of output and thus firms' profits, there is a substantial part of CL's effects due to the disembodied innovations is captured by A_{it}. Apart from that, profits are determined indirectly by changes in the price P_{it}. Price is partially endogenously determined by the number of outputs firms could produce through demand elasticity $\eta(i)$ and C_{it}, which represents exogenous forces, shifting the market demand or changing the product's general price level.

In addition, Stoneman and Kwon (1996) integrate several theoretical approaches to technology diffusion literature and construct an encompassing model to predict the relationship between technology adoption and profitability. According to their study, the pre-tax gross profits of firm i in time can be negatively affected by the number of other users of each technology in industry k at the time τ (stock effects).[24] For the technology adopters' firm i at time τ, the extra profits will be earned, related to the cost of acquisition of the technology. It is assumed in the theoretical model that when a firm adopts the technology, all the capacity is converted without any further intra-firm diffusion process. The cost of acquisition in their model is calculated as the total output of the firm times the cost per unit of acquiring technologies in time t. The extra gain is also affected by the change between t and τ in terms of the number of other adopters via the stock effect, the expected change in the number of adopters of technology j in industry k at the date of adoption t (order effect), firm, industry characteristics (rank effects) and any change in such characteristics between t and τ. Their theoretical framework also allows for the profits related to the number of years since firms initially adopted the technology due to learning-by-doing effects and the impact of epidemic learning due to information asymmetries (t - T). The relevant industry characteristics attributed to the base level profits and profit gains to adoption include industry size (for instance, real total sales), concentration ratio and wage rate. Two firm characteristics are included: the firm size and firm R&D (the number of R&D employees recruited). The empirical version of the model is based on the adoption of four different technologies in the UK engineering industry from 1965 to 1986. It is worth noting that, given the relatively long observational period, all the nominal variables, including the profits, wage rate and costs of acquisition of new technologies in their estimation, are real values, deflated by the retail price index (RPI) or PPI. These variables mentioned in Stoneman and Kwon's (1996) framework indicate some potential controlled factors when conducting the empirical estimation in the next section.

[24] Suppose that the profit gains to the firm in time τ from the adoption of technology at time t are equal to the profit gain at time t and changes in the profits between the interval from the date of adoption time t to τ.

Regarding the empirical results, their empirical estimation only confirms that the profitability (pre-tax earnings) are determined by the rank, stock effects and costs of acquisition across several technologies, while the order effects and epidemic effects do not bring significance. Expected changes in the price of acquisition and the number of users of each technology do not carry a robust negative coefficient as hypothesised in the model. Among those firm and industry characteristics, the most effective measure is firm size, while the joint effects from the industrial real wage rate and concentration ratio are not significantly different from zero. Therefore, by reviewing Stoneman and Kwon's studies, firm and industry characteristics, particularly the **stock effects** through the intermediate market, must be considered in the empirical analysis.

4.3.2 The Estimation Model

Empirically, model 8 is operationalised so that:

$$lnS_{it} = \beta_0 + \beta_1 (Adopter)_{i,t} + \beta_2 (Intensity)_{i,t} + \beta_3 \ln(L)_{i,t-1} + \beta_4 \ln(I_{tan})_{i,t-1}$$
$$+\beta_5 \ln(I_{tan})_{i,t-2} + \beta_6 \left(D_{traning}\right)_{i,t-1} + \beta_7 N_{j,t} + Industry\ charactersitics + \mu_t + \mu_i + e_{i,t} \quad (23.)$$

The above equation 9 describes an empirical estimation model and key explanatory variables to examine the impact of digital technology on profitability. To test our hypothesis, we modify equation 8 by taking into account intra- and inter-firm diffusion of the new technology. $\boldsymbol{Adopter}$ stands for the firms' adoption decision of digital technologies. $\boldsymbol{Intensity}$ indicates the level of sophistication or intra-firm diffusion. $\boldsymbol{N}$ denotes the stock effects in the intermediate markets. Hence, we expect a positive relationship between firm size and profitability. $\boldsymbol{L}$ represents the labour input in the theoretical framework. $\boldsymbol{L}$ corresponds to the effects of firm size.[2] As firms expand their market sales and business lines, they will gain an advantage from economies of scale or scope (Goddard et al. 2005). Furthermore, size potentially picks up some other firm characteristics, such as efficiency and management practices (Baumol 1959), potentially correlated with the cost of acquiring the new technology and economies of scales.

Intangibles are taken into account in the model. We separate its effects from the disembodied innovation A_{it} (the total factor productivity) in the theoretical framework. Strategic management literature stresses the role of internal resources specific to the firms to explain the variation in profitability. Internal resources refer to both tangible such as physical, and financial capital, and intangible such as technology, human capital and reputation, reflecting the organisation's core capability (Lazear 2003; Jordan et al. 2013; Carmeli and Tishler 2004). Also, there is a strand of literature that focuses on the additional channel through which intangible investments (e.g., organisational capital, the R&D and design of new products) can affect better exploitation of ICT technologies and labour productivity accordingly (Brynjolfsson et al. 2018, 2021; Corrado, Haskel and Lasinio 2021). Hence, investment in human capital is considered one of the key intangibles of a firm's internal capability and economic competences, and is available for us to include in the model. $\boldsymbol{D_{traning}}$, denoting human capital, picks up some effects of unmeasured intangibles to overcome the omitted variable bias.

I_{tan} picks up the effects of tangible capital. In the theoretical framework, what should drive performance according to the theoretical framework is the stock of fixed capital. Due to the availability of data, the flow of fixed (tangible) capital investments is employed in the empirical estimation. These are considered highly correlated with the stock of accumulated capital investments (Chappell and Jaffe 2018). Our empirical model incorporates up to two-year lags of tangible capital investment. The lag effects of tangible investment are significantly larger than the immediate effects, according to the literature. For instance, Plant (2001) performed the Granger causality test with both one and two year lagged impacts of IT investments and observed mixed effects on firms' performance: negative effects on the growth of sales while positive effects on return on assets (ROA) and return on equity (ROE). Their study identifies lag effects of tangible IT investments and no immediate effects of these capital investments. Lee and Kim (2006) also suggest that a lagged effect of IT capital investments is significantly larger than an immediate effect, regardless of the information intensity of the industry.

Our basic setup is a fixed-effects panel estimation with some dynamic characteristics. To avoid endogeneity on explanatory variables, factors linked with endogenous choices (such as the firm size, capital investments and cost variables) are included in the lagged values, while all other variables treated as exogenous ones are instrumented with themselves. Introducing lagged value into the equation is based on the concern of reverse causality of investments and performance. For instance, profitability may affect capital investments when firms are constrained in their ability to generate the cash required for such investments. Firms that become more profitable are more likely to engage in a higher level of capital investment as necessary funds become viable (Hall and Lerner 2009). Our model excludes the lagged dependent variable.[25] Similar to the argument in Stoneman and Kwon (1996), the structure of our model is one where the adoption of cloud computing affects current or future profits instead of the persistency of profitability. The lagged profitability will reflect the information on adoption decisions that the model has already captured. In terms of the estimation methods, we include firm $\boldsymbol{\mu_i}$ fixed effects such that our estimate reflects the change in the level of profits driven by the adoption of cloud computing technologies, and removes the impacts from any time-invariant firm-industry confounders. Time trend $\boldsymbol{\mu_t}$ is also included in the model to represent the overall state of the economy or the macro factors (such as annual inflation rate and annual growth rate of GDP) and nets out the requirement for industry price. Regarding cost variables, the expenditure on digital technology acquisition is unavailable to include as additional explanatory variables as Stoneman and Kwon (1996) suggested. The total employment cost and cost of production have already been deducted when computing the dependent variable and thus are orthogonal to the net or operating profits. Following Roper and Bourke's study (2018), we also construct the sector dummies listed in the next section to control for industry characteristics emphasised in the theoretical perspectives.

Equation 9 will be used to test H1 and H2. Specifically, we will test **H1**(GPT adoption) via the significance of β_1, **H2** (the depth of use) via the significance of β_2.

Further, the following two equations are employed to test the assumptions on mechanisms. Given the limited information by ABS, only parts of the mechanisms are unlocked through testing regarding the cost of production and the profit margin. A similar approach is adopted where the

[25] Empirical exercises in finance literatures can include one or two lagged values of the dependent variables. These indicate the speed where competitive forces bring above or below the average value of profitability temporarily and may dissipate ultimately.

dependent variables are adjusted into the indicators of the cost of production (except employment cost) (C1) and gross profit margin (R1), respectively. The additional channel through innovation performances is not feasible to test as additional information is required from UKIS. Merging UKIS, E-Commerce survey and ABS will significantly reduce the sample size of the panel.

We use the following equation 10 to test for the impact on gross profit margin (**H3b**). Gross profit margin is represented by R1, which is defined as the ratio of operating profits S and revenue R.

$$lnR1_{it} = \beta_0 + \beta_1\left(D_{Adopter}\right)_{i,t} + \beta_2(Intensity)_{i,t} + \beta_3 \ln(L)_{i,t-1} + \beta_4 \ln(I_{tan})_{i,t-1}$$
$$+\beta_5 \ln(I_{tan})_{i,t-2} + \beta_6\left(D_{training}\right)_{i,t} + \beta_7 N_{j,t} + Industry\ characteristics + \mu_t + \mu_i + e_{i,t} \quad (24.)$$

In order to test **H3a**, a cost function specification should be introduced,

$$lnC1_{it} = \beta_0 + \beta_1\left(D_{Adopter}\right)_{i,t} + \beta_2(Intensity)_{i,t} + \beta_6\left(D_{training}\right)_{i,t} + \beta_7 N_{j,t}$$
$$+ firm\ characteristics\ (company\ size\ (L)) +\ Industry\ characteristics + \mu_t + \mu_i + e_{i,t} \quad (25.)$$

In both modes, we test the impact of general-purpose technology adoption upon costs (**H3b**), and gross profit margin (**H3a**) via the significance of β_1 and β_2 respectively.

4.3.3 The Context and Measures

This paper aims to unravel the relationship between the adoption of general-purpose technologies and firm performance beyond productivity. In section II, we are trying to infer the relationship between adopting emerging or general-purpose technology and profitability (H1 and H2), and the nature of gains (H3a and H3b) from a theoretical perspective. In this section, we will use the adoption of cloud computing technologies (the context) to illustrate our analysis. The basic setup is a fixed-effects model (equations 9, 10, 11), and it concerns the firm-level data availability on measuring various components in the model.

4.3.3.1 Part I. Understanding cloud computing services

In this section, we analyse the characteristics of the cloud. This session discusses in detail what type of services cloud computing can provide, and infers the key potential benefits of those offerings. Combined with economic theories, we will then gain a clearer picture of the mechanisms or the possible channels through which a general-purpose technology, in our application, cloud computing technologies, may enhance firms' profitability. Overall, there are three main types of cloud computing services, which are **IaaS**, **PaaS** and **SaaS**. In the following part, we will analyse the benefits of each case and then move to the empirical measures.

IaaS is an instant computing infrastructure offered by cloud vendors, which can be managed over the internet. IaaSs provides users with the capability of computing, storage and networking resources on a pay-as-you-go basis over the internet (Microsoft 2021). It is made up of a collection of physical and virtualised resources that offer users the basic building blocks required to run applications and workloads in the cloud. The provider will manage large data centres containing physical machines to power multiple layers of abstraction on top, making them accessible for users over the internet. In other words, users will receive a service instantly from the provider without seeing any physical infrastructure. In the typical example of IaaS service, users are able to obtain computing capability through the virtual machines (servers) to rent with the desired amounts of computing and memory/storage. Providers will offer GPUs and HPCs, which are in conjunction with traditional processors, for specific types of workloads such as **machine learning** or **AI**. For example, visual recognition pictures (AI workloads) are stored in the object storage cloud and can be used to train the AI model running on high-speed GPU servers. Networking is also made available programmatically in the cloud as a form of software, typically through APIs, rather than the traditional hardware, such as switches and routers. Each resource is provided as a separate service component; users will only purchase and pay for the particular resources (networking, storage, computing) as long as they are required.

***Analysis of benefits*.** Therefore, if organisations migrate their infrastructure to the IaaS solutions through a cloud computing service, they can bypass the hardware cost and complexity of buying and managing physical servers and data centres. It reduces the labour cost for maintaining onpremises physical infrastructure, enabling the IT teams to focus on core business. The process of launching new products becomes faster, as the preparation for necessary computing infrastructure can be ready in minutes or hours. As mentioned in the essential features, firms are able to conveniently scale infrastructure up or down and deploy web apps on IaaS when facing unpredictable demand.

PaaS. IaaS provides the essential underlying infrastructure (servers, networks, storage), while Platform as a Service (PaaS) is a complete development environment in the cloud, with all resources (infrastructure, operating system software, development tools, databases) in their hosts for developing, running and management applications (IBM 2021).

Analysis of benefits. Developers can directly build upon to **design** cloud-based applications on the framework, with the development tools built in to help reduce coding time for developers. Moreover, PaaS usually provides their users with Business Intelligence tools that allow organisations to analyse or mine the data and identify insights and patterns to enhance predictions and forecasting, new product design or other decisions. As with IaaS, PaaS can also reduce the sunk cost of capital investments (software licensing and hardware purchasing) associated with building and scaling the application development platform. Resources will not sit idle during low-traffic periods. When facing unanticipated traffic spikes, firms can quickly increase additional computing, storage and networking capacity to accommodate changes in time. Plus, the new model granted with firm greater flexibility for organisations to directly experiment on new products and new operating systems without substantial costs.

SaaS is the simplest form of cloud computing service to access the resources on demand, and requires the least responsibility and need for technical expertise from users. SaaS is a third-party application software accessed via an internet browser (cloud). Google Docs and Microsoft Office 365 are typical examples of SaaS. The cloud service provider will maintain and manage the applications for users with no overhead IT costs, as SaaS does not require software downloads or installation. It is compatible with any operating system and only needs an internet connection to function.

Analysis of benefits. Using SaaS-based cloud applications is associated with even lower upfront costs (initial investment) than PaaS and IaaS. This makes it particularly beneficial for the smallest business to develop and disrupt the existing market. Overall, SaaS prices are cheaper and more accessible to businesses of every size. Although with very little control over operating systems, infrastructure and application development, it offers firms applications or functions that only large enterprises could initially afford. Firms obtain the opportunity to reach a broader market without investing in additional general IT investments such as compatible software and hardware, servers and network switches. Firms can use the application in a scalable way that adjusts the billing plan depending on the number of users to the service. Similarly, as SaaS is run through a centralised platform, users can access the captured data reports and business intelligence tools for insights into their business operations.

4.3.3.2 Empirical Measures

The data

The datasets used to construct the measure of variables are the UK Annual Business Survey and the E-commerce survey. The dataset used to build the profitability indicators is the UK Annual Business Survey (2012–2020). The Annual Business Survey (ABS) samples UK businesses according to other employment size and industry sectors and represents two-thirds of the UK economy in terms of gross value added (GVA). The questionnaire is divided into nine sections, including information on the return period, the total value of sales, expenditure, the value of stocks held, capital investments, R&D, and international trade in goods and services from 2003 to 2020. Based on the information, we are able to derive our benchmark profitability measure manually, given the information from the Income (Section B) and Expenditure (Section C) in ABS. The information on cloud computing technologies is collected from the UK E-commerce survey. It is an annual survey that is designed to measure the extent of the use of ICTs and electronic trading by businesses in the United Kingdom. However, the survey has been subject to a number of revisions each year and is still at an experimental stage. There are subtle changes in the survey questions, and the information on cloud computing technologies can be obtained only for 2013, 2015, 2017 and 2019.

The benchmark measures of profitability

This section discusses how we decide the benchmark to measure 'abnormal profits' in this paper. As discussed previously, the Schumpeterian growth paradigm suggests innovation by the firm will create divergence from a perfectly competitive steady-state and temporarily increase the firm's abnormal profits above zero. This discussion regarding profits maximisation typically refers to the **current profitability**. For instance, Stoneman and Kwon (1996) follow the above theoretical concerns and first derive an encompassing model of the diffusion of new process technology, predicting the relationship between technology adoption and profitability measured by **pre-tax gross profits gains**. In this paper, we will use **operating profits** that capture the 'abnormal profits above zero' as the benchmark results for our analysis. According to the standard accounting textbook, operating profitability stands for sales revenue (earnings) after subtracting the cost of goods sold, selling, general and administrative expenses (SG&A) and other operating expenses (Wahlen et al. 2014). Compared with the net income, operating profit measures gauge how well the firm is managed and how efficiently it can generate profits from its core business operations. It will, therefore, capture both the efficiency in controlling the operating costs and overall demand for the firm's products and services due to higher pricing, better marketing and consumers' appetites.

In accounting studies, many terms describe or measure the operating profits, including EBIT (earnings before interest and taxes) or EBITDA (earnings before interest, taxes, depreciation and amortisation), EBITA (earnings before interest, taxes and amortisation), operating income, etc. Practitioners and academics use alternative measures for a firm's operating profitability, where the most common definitions are EBIT and EBITDA. Both of these two measures refer to the profitability of a company's core operational performance before the deduction of capital assets, interest and taxes; in other words, without concerns about financing decisions, accounting decisions and tax environments. EBIT is often used interchangeably with the operating income calculated by subtracting operating expenses such as selling, general and administrative expense from gross revenue (Buckle 2014). In particular, Nissim (2019), points out that EBITDA implies some superiority and performs better than EBIT and EBITA in explaining market valuations and predicting US stock returns throughout the sample period from 1989 to 2019. As EBITDA does not capture depreciation, comparing the financial performance when two firms are substantially different in the amount of fixed assets is more informative. From another perspective, the ABS survey in the Expenditure section does not explicitly include the book value of depreciation and amortisation as standard corporate income statements. Therefore, in this study, EBITDA is a preferred measure of operating profits.

Our analysis will be consistent with using ROA as a performance indicator. It is worth noting that ROA is also a common choice to examine firms' financial performance in most financial literature (Goddard et al. 2005). It represents how well the company manages all its available resources, including debts and equity, to generate higher profits. There is some inconsistency in choosing the numerator of ROA in empirical finance studies. In most situations, using pre-tax operating profits such as EBIT or EBITDA is a standard way of accounting to calculate return on assets[26] (Goddard et al. 2005; Pervan et al. 2014). Like operating profits, ROA does not concern the proportion of debts versus equity financing that firms employ to finance total assets (Goddard et al. 2005).

Apart from the pre-tax return, we employ **net profits** as an alternative measure for current profitability. It refers to the income after subtracting all costs (costs of goods sold, operating expenses, interest and taxes) (Wahlen et al. 2014). This measure is informative on the business's profitability in general payable to shareholders and the resulting potential for firms' future growth in value. Net profits incorporate a firm's operating, investing and financing decisions, as well as tax payments. In accounting, the net profit is the denominator for adjusting and computing the return on shareholder equity ratios (ROCE/ROE).[27]

Measuring the adoption of the cloud and intensity

According to the literature review, the diffusion pattern of new technology can be decomposed into two components (Battisti and Stoneman 2003): inter and intra-firm diffusion. Inter-firm diffusion is defined as the degree of penetration of the technology across the firms in an industry. It refers to firms' first adoption of a technology or innovation (Hall 2004). The intra-firm diffusion,

[26] A small number of studies use the earning before interest after tax to calculate the return on assets (e.g. Fitzsimmons et al. 2005; Pattitoni et al. 2014).
[27] ROCE is useful for assessing the efficiency of firms where the debt financing is a substantial part of capital structure (Selvan 2022).

which refers to the intensity of use after their adoption decision, is believed to be potentially crucial to firms' future performance according to our hypothesis. The intra-firm diffusion (intensive margin) is often measured by the percentage of the firm's capital that incorporates new technology or the percentage of output produced utilising the latest technology (Battisti 2009). However, as our data source does not provide exact information on such measures, we introduce two new categorical variables that reflect both extent (adoption decision) and intensity of usage, then evaluate their impact on profitability gains. As CL technologies spread, we may expect the range of tasks performed employing the new technologies to expand. In other words, employees' tasks relying on those technologies gradually increase in sophistication or intensity under the technology diffusion process (Forman et al. 2003).

The UK E-commerce survey is collected through a question that asks firms to indicate the significance of the following categories related to cloud computing purchases in the survey year. The responses cover in total seven different categories of cloud computing technologies, covering emails, office software (e.g. Microsoft Office), hosting the database, storage of files, finance or accounting software applications, CRM software and computing capacity. In this analysis, we select the following five listed types of cloud computing services closely associated with deploying emerging technologies and then define the metric for the intra-firm diffusion given the concept of sophistication. The basic use of Microsoft Office and emails are not included in our analysis. Each type of cloud computing-related technology in the above categories is coded as a binary variable 0, being no use, and 1 being used. Subsequently, the five types of uses can be added together so that each firm gets 0 when no cloud computing-related technologies are adopted, while the firm gets the maximum value of 5 when all the types are adopted. It is assumed that firms with a relatively higher number of types of usage are more advanced in respect of adoption depth or intensity than firms that are not. This is because we expect advanced users to engage in more sophisticated activities to exploit the benefits of adopting new technologies. The descriptive tables in the next section illustrate the pattern of inter and intra-firm usage across groups.

Hosting the business's databases

Storage of files
Finance or accounting software applications
Customer Relations Management (CRM software)
Computing capacity to run the business's own software

To highlight, $S_{i,t}$ represents the current profitability of firm i at time t, measured using operating profits defined as earnings before interest, tax, depreciation and amortisation. Alternatively, net profits can be employed, measured using earnings after subtracting costs of goods sold, operating expenses, interest and taxes. $D_{Adopter}$ is a binary variable measuring the firms' adoption of any of the five cloud computing technologies in the E-commerce survey. $Intensity_{cl}$ indicates the level of sophistication, which is the number of types of cloud computing technologies adopted. L_{cjt-1} denotes the labour input as one of the inputs according to the theoretical framework, measured by the total number of employments. This measure also corresponds to the effects of firm size.[28] As firms expand their market sales and business lines, they will gain an advantage from economies of scale or scope (Goddard et al. 2005). $D_{training}$ picks up the effects from unmeasured intangibles. It is measured by whether a company provides any in-firm training for ICT or IT specialists. $\boldsymbol{I}_{(\boldsymbol{tan})}$ represents fixed capital investments. It is the total acquisition of tangible investments netting out the intangible capital counted into the national accounts. The calculations for all variables (including the intermediate variables) are displayed in the following table of variables construction (Table 4.3-1). The industry classifications are constructed following Roper and Bourke's approach (2018) listed in Table 4.3-2, to control for unobserved industry characteristics.

Table 4.3-1. Table of Variable Construction

[28] Firm size (*Size)* can be measured using different indicators such as the total assets (in logarithm), total sales (in logarithm) and some empirical studies use total number of employees in the company.

Variable Name	Label	Description	Code
Dependent variable			
Operating profits (Derived)	$S1$	EBIDA	WQ500-WQ450-WQ499
Net profits (Derived)	$S2$	Revenue left after subtracting all costs (costs of goods sold, operating expenses, interest and taxes.	WQ500+WQ317+WQ325-WQ450-WQ499+WQ414-WQ400
C1: Cost of production (except employment cost) (Derived)	$C1$	The cost of goods sold excluding operating expenses, interest and taxes. Includes direct labour, materials, overheads, commissions associated with a sale. Not including selling, general and administrative expenses, and costs of the sales and marketing department.	WQ499-(WQ404_WQ411+ WQ421+ WQ430)
Gross profit margin (Derived)	*R1*	Gross profit margin = (revenue – total costs) / revenue.	(wq550-wq499-wq450)/wq550
Independent variable			
Adoption of cloud computing (Dummy)	$D1_{Adopter}$	Yes or no 1. Hosting the business's database(s), as a cloud computing service. 2. Storage of files as a cloud computing service. 3. Finance or accounting software applications as a cloud computing service. 4. Customer Relations Management (CRM) software as a cloud computing service. 5. Computing capacity to run the business's own software as a cloud computing service. Firms adopt at least one category of cloud computing related technologies is defined as a cloud computing adopter.	
Intensity of CL services	$Intensity_{cl}$	The number of types of cloud computing related services purchased (*Intensity 1- Intensity5*) Contain both basic use of cloud computing and advanced user.	
Training on ICT specialist skills (Dummy)	$D2_{training,i}$	Did this business provide any type of training to develop the ICT/IT related skills of its employees?	Q165
Total value of acquisitions (Tangible)	I_{tan}	Total value of Tangible Capital Assets (Value of Acquisitions) Includes: land, existing building and structures, construction work including newly built, refurbishments or improvements to existing buildings, machinery and equipment. Excludes: computer software programs and databases, natural resources, other non-produced assets such as goodwill, intellectual property assets.	WQ1656= WQ763 + WQ764 + WQ1641 + WQ1644 (2018, 2017, 2016, 2015 only)
Firm size	L	Number of employees	EMP

Stock effect	N_{jt}	The fraction of cloud computing adopters (any of the five types) within the industry over time.	calculated from the E-commerce survey
Industry classifications	Dj		**A-S**
Other variables used for calculation			
C2: Expenditure on service for business use	$Costs2$	Amount payable for subcontractors, maintenance on computers and machinery, employment agency staff, advertising and market services, other services (leasing, hiring machinery, insurance premium, etc.).	(WQ404_WQ411+ WQ421+ WQ430)
Total cost	$Costs$	Expenditure – total purchase of goods, raw materials, energy and services; total employment cost	WQ450+WQ499
Total turnover	$Turnover$	Total amount receivable in respect of invoices raised for the sales of goods and services	WQ550

<table>
<tr><th colspan="4">Table 4.3-2. Industry Classification</th></tr>
<tr><td>1</td><td>A</td><td>AGRICULTURE, FORESTRY AND FISHING</td><td rowspan="14">Broad Sector Classification
1. ABDE – Primary
2. C – MANUFACTURING
3. F –CONSTRUCTION
4. G – WHOLESALE AND RETAIL TRADE
5. HI – TRANSPORTATION ACCOMMODATION AND FOOD
6. JKL – INFORMATION, FINANCIAL, REAL ESTATE
7. M – PROFESSIONAL, SCIENTIFIC
8. N – ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES
9. RS – OTHER SERVICE</td></tr>
<tr><td>2</td><td>B</td><td>MINING AND QUARRYING</td></tr>
<tr><td>3</td><td>C</td><td>MANUFACTURING</td></tr>
<tr><td>4</td><td>D</td><td>ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY</td></tr>
<tr><td>5</td><td>E</td><td>WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REMEDIATION ACTIVITIES</td></tr>
<tr><td>6</td><td>F</td><td>CONSTRUCTION</td></tr>
<tr><td>7</td><td>G</td><td>WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES</td></tr>
<tr><td>8</td><td>H</td><td>TRANSPORTATION AND STORAGE</td></tr>
<tr><td>9</td><td>I</td><td>ACCOMMODATION AND FOOD SERVICE ACTIVITIES</td></tr>
<tr><td>10</td><td>J</td><td>INFORMATION AND COMMUNICATION</td></tr>
<tr><td>11</td><td>K</td><td>FINANCIAL AND INSURANCE ACTIVITIES</td></tr>
<tr><td>12</td><td>L</td><td>REAL ESTATE ACTIVITIES</td></tr>
<tr><td>13</td><td>M</td><td>PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES</td></tr>
<tr><td>14</td><td>N</td><td>ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES</td></tr>
</table>

15	R	ARTS, ENTERTAINMENT AND RECREATION		
16	S	OTHER SERVICE ACTIVITIES		

4.4 The Descriptives

Figures 4.4.1 and 4.4.2 below illustrate the pattern of cloud adoption over the four observational years. It shows the evolution of the diffusion process of the emerging cloud, both in its inter- and intra-firm dimension. Overall, we can observe an increasing trend in terms of the adoption rate of cloud computing. The following figures show both the percentage and the absolute number of users that have adopted the technology, the evidence of the heterogeneity of the intra-firm diffusion process, which is the number of cloud computing services adopted. Fewer than 50% of firms are using some form of cloud starting in 2013, while more than 70% of firms have adopted this emerging technology by the end of 2019. Most of those adopting firms typically employ 1 or 2 types of cloud computing services, not all types of the cloud. Only a very small number of firms (appx 10% in our sample) adopt more than three types of cloud computing but under an increasing trend. It reflects the importance of distinguishing between the inter- and intra- dimension. Whereas most of the firms had purchased the cloud for business use by 2019, the process of intra-firm diffusion was much slower and longer lasting.

Figure 4.4.1

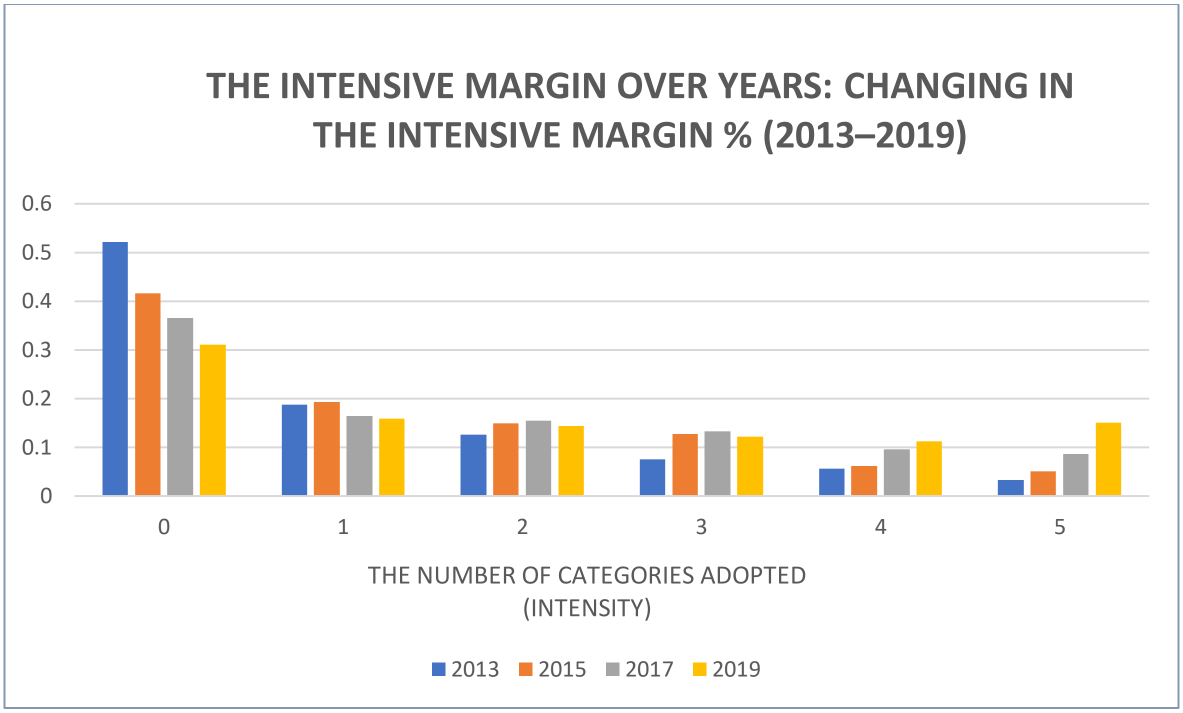
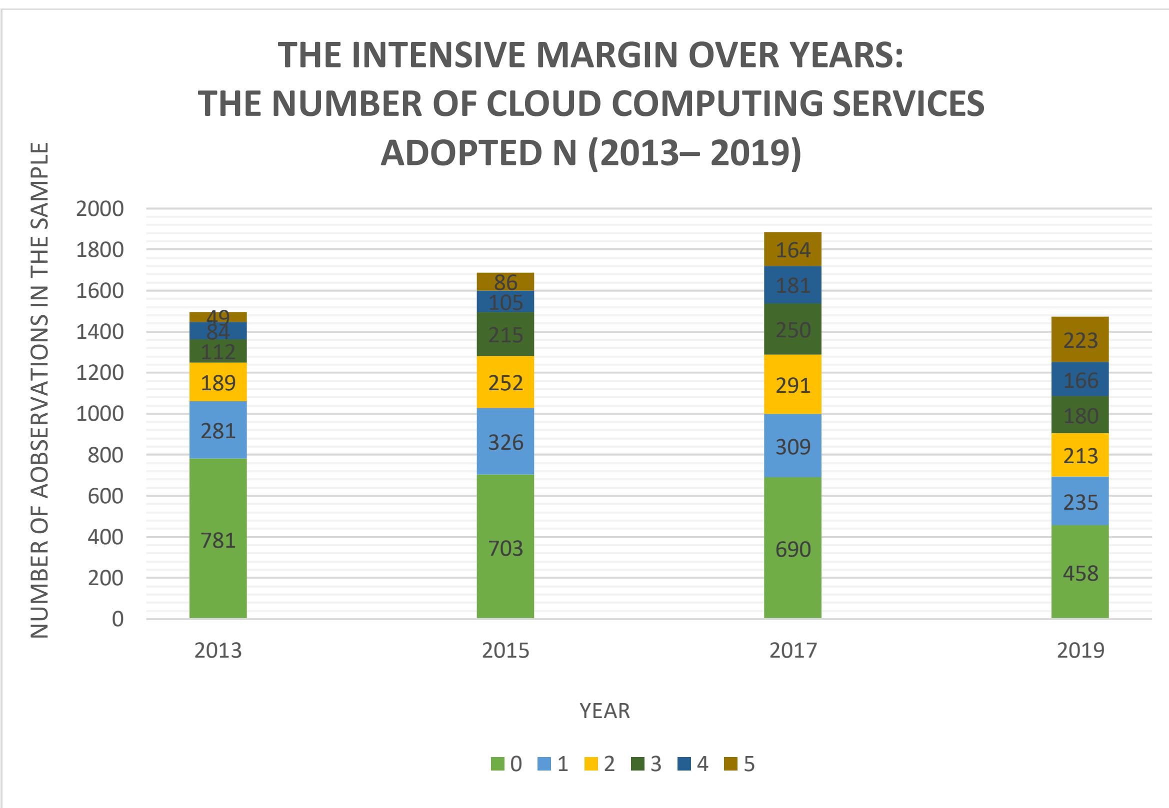


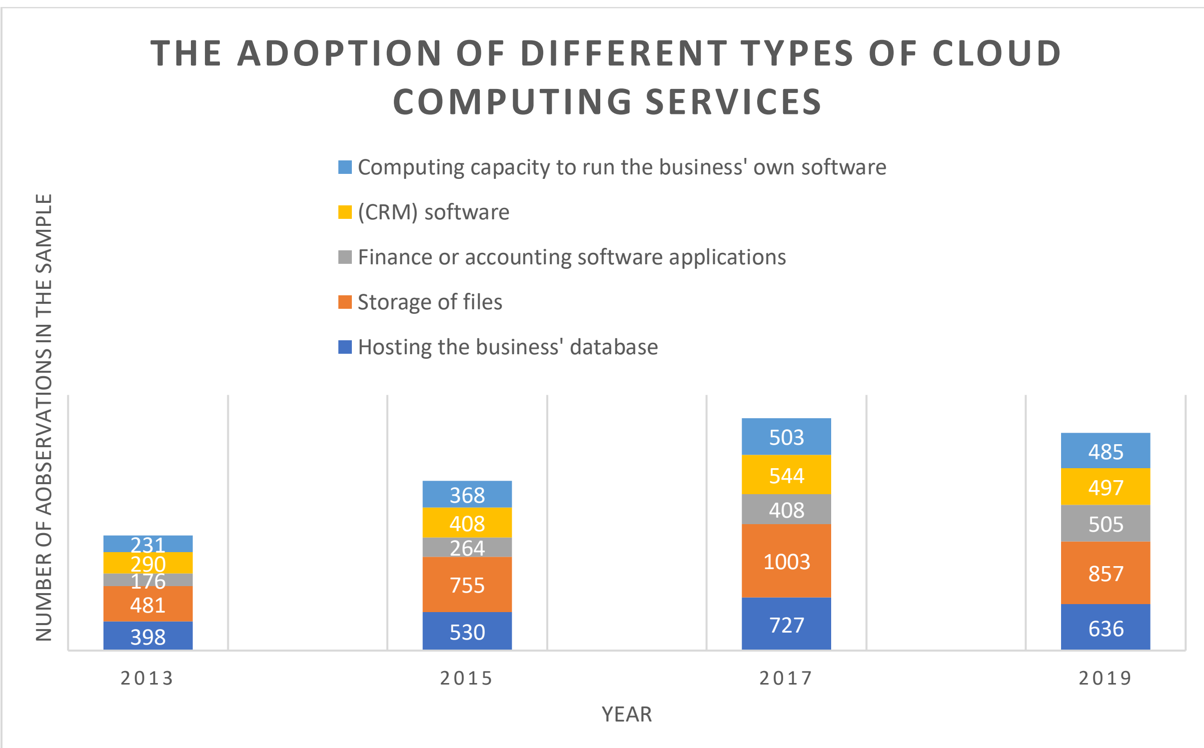
Figure 4.4.2



Source: Merged sample (E-Commerce Survey), own calculations

Figure 4.4.3 indicates the number of purchases on the five types of cloud services provides separately. From the distribution pattern, we can observe the switch over to cloud services has been more substantial for the types of the cloud where the service provision tends to be homogeneous, such as business databases, file storage and some types of software, than the types of the cloud where the service requirements are more likely to be firm-specific. In particular, the computing capacity through the cloud to run the business software is the least frequently purchased service across four years. Most of the enterprises purchased services predominately for hosting business datasets and storage of files.

Figure 4.4.3



Source: Merged sample (E-Commerce Survey), own calculations

Table 4.4-1 Summary Statistics

Variable	Obs	Mean	Std. Dev.
Net profits (log)	13,657	9.690993	1.813035
Operating profits (log)	13,565	9.733062	1.818072
Total value of acquisitions (Tangible assets)(log)	9,615	7.39757	2.671503
Cost of production (log)	15,392	10.3074	2.467132
Firm size (log)	3,360	6.910119	1.232173
The percentage of other CL adopters (%)	6,543	41.23405	10.53613
Gross profit margin (%)	15,505	14.32747	19.35446
Adopters	6,543	0.597738	0.490392
Number of cloud computing technologies adopted	6,543	1.538438	1.653401
(Intangible) Training on ICT specialist skills	6,543	0.705334	0.455927
Hosting the business's database(s)	6,543	0.350145	0.477052
Storage of files	6,543	0.473177	0.499318
Finance or accounting software applications	6,543	0.206786	0.405032
Customer Relations Management (CRM) software	6,543	0.26578	0.441782
Computing capacity to run the business's own software	6,543	0.242549	0.428658

4.5 Results

In the first table, we include the dummy variable $D_{Adopter}$ to indicate if a company has adopted any of the five cloud computing services in the definition. The measure of intensity represents the total number of cloud computing services they have adopted. The results reject the H1, which indicates that being a cloud computing adopter does not necessarily bring higher gains in terms of current profitability. The measure of intensity shows a more important role than the adoption decision, overall suggesting a positively significant contribution to operating profits. Column 3 shows as firms increase the number of categories of cloud computing services, positive gains gradually manifest via an increased profit margin.

However, it is worth noting that, in Table 4.5-1, we are not able to distinguish the effects of different types of cloud computing services. It can be a situation where adopting some specific types of cloud computing services is more important than others. Some types of cloud computing technologies may bring positive effects, while some bring negative effects, and hence make the overall effects of $D_{Adopter}$ on profit gains insignificant. For instance, based on the discussion in the previous section, adopting cloud computing used to enhance firms' computing capacity is potentially more beneficial to firms in terms of creating new innovations or increasing the competitiveness of existing products or services offering than that to expand the storage of files or host the business database. Therefore, to distinguish the individual effects of different types of cloud computing services, we explicitly include each category of cloud computing services in the regression analysis in the next table.

Table 4.5-1 **Cloud computing on profits, costs and gross profit margin (1)**

		Operating profits (log)	**Cost of production**	**Gross profit margin (%)**
		$\ln(S1)_{i,t}$	$\ln(C1)_{i,t}$	$\frac{Turnover - cost}{turnover}$
Total value of acquisitions (Tangible assets)(log)	$\ln(Invest_{tan})_{i,t-1}$	-0.019		-0.143
		(0.025)		(0.348)
	$\ln(Invest_{tan})_{i,t-2}$	0.060**		0.863*
		(0.028)		(0.481)
Adopters	$D_{adopter\ i,t}$	-0.155	-0.018	-2.714**
		(0.107)	-0.061	(1.264)
Number of cloud computing technologies adopted	$Intensity_{CL\ i,t}$	0.051*	-0.016	0.589**
		(0.029)	(0.011)	(0.302)
Firm size	$\ln(L)_{i,t}$	0.442	0.471***	2.383
		(0.289)	(0.18)	(2.068)

(Intangible) Training on ICT specialist skills	$D_{training\ i,t}$	0.346***	-0.124**	1.134
		(0.133)	(0.062)	(0.993)
The percentage of other CL adopters	$N_{j,t}$	0.039**	-0.027	0.913**
		(0.018)	(0.034)	(0.383)
Firm fixed effects	μ_i	Yes	Yes	Yes
Sector controls	Dj	-0.189***	-0.012	-3.606
		(0.041)	(0.278)	(2.225)
Time effect control	μ_t	-0.144**	0.143	-3.493**
		(0.069)	(0.139)	(1.53)
N		1957	2247	2266

*Se in parentheses * p<0.1 ** p<0.05***p<0.01*

Table 4.5-2 directly displays the importance of different types of cloud computing services. According to the results of the F test, the coefficients of cloud computing technologies (D1–D5) are jointly different from 0. In this table, we can observe that the adoption of cloud computing capacity contributes the most to profitability gains compared with the other four types of cloud computing services, including hosting the database, file storage, finance, accounting, and CRM software applications. Firms adopting cloud computing technology to increase the computing capacity of their software can significantly enhance current operating profits via the effects of reducing the cost of production. Therefore, as firms increase the efficiency of product or service offerings in a competitive market, they can reduce the selling prices of outputs and therefore displace their competitors by increased turnover. From this side, these results could be compatible with the positive effects from the intensity in the first table that firms with the most intensive use of cloud computing will experience significant positive gains in profits, in fact, largely attributed to adopting D5.

Table 4.5-2. **Cloud computing on profits, costs and gross profit margin (2)**

		Operating profits	Cost of production	Gross profit margin
		$\ln{(S1)}_{i,t}$	$\ln{(C1)}_{i,t}$	$\frac{Turnover - cost}{turnover}$
Total value of acquisitions (Tangible assets)(log)	$\ln{(Invest_{tan})}_{i,t-1}$	-0.019	0.004	
		(0.025)	(0.019)	
	$\ln{(Invest_{tan})}_{i,t-2}$	0.058**		0.819*
		(0.029)		(0.48)
Training on ICT specialist skills (Intangible)	$D_{training\ i,t}$	0.335**	-0.131**	1.267
		(0.131)	(0.061)	(-0.998)
Hosting the business's database(s)	$D1_{i,t}$	-0.118	0.033	-0.197
		(0.086)	(0.056)	(0.941)
Storage of files	$D2_{i,t}$	-0.007	0.033	-0.48
		(0.096)	(0.051)	(1.046)
Finance or accounting software applications	$D3_{i,t}$	0.005	-0.026	0.303
		(0.078)	(0.056)	(0.97)
Customer Relations Management (CRM) software	$D4_{i,t}$	0.031	-0.059	1.065
		(0.098)	(0.067)	(0.98)
Computing capacity to run the business's own software	$D5_{i,t}$	**0.213****	**-0.097****	-0.214
		(0.088)	(0.045)	(0.787)
Firm size	$\ln{(L)}_{i,t}$	0.423	**0.470*****	2.378
		(0.292)	(0.179)	(2.127)
The percentage of other CL adopters	$N_{j,t}$	**0.036****	**-0.026**	**0.899****
		(0.017)	(0.034)	(0.387)
Firm fixed effects	μ_i	Yes	Yes	Yes
Sectors	Dj	-0.181***	-3.538	-0.014

		(0.041)	(2.266)	(0.278)
Time	μ_t	-0.139**	-3.552**	0.139
		(0.068)	(1.547)	(0.137)
N		1957	2247	2266

*Se in parentheses * p<0.1 ** p<0.05***p<0.01*

Table 4.5-3 further illustrates the contribution of adopting cloud computing to increase firms' computing capacity and intensity of adoption and the robustness of findings in the previous two tables. In this table, both D5 and the total number of types that firms adopted are included in the three regressions. We observe the positive contribution of D5 on cost reduction and therefore operating profits. However, overall, according to our results, the intensity/ greater variation of cloud computing service purchase enables firms to extract greater profit margins but not necessarily increase the profit gains. In our sample, firms who purchase cloud computing to enhance their computing capacity are more likely to be intensive users.

Table 4.5-3 **Cloud computing on profits, costs and gross profit margin (3)**

		Operating profits (log)	**Cost of production**	**Gross profit margin (%)**
		$\ln{(S1)_{i,t}}$	$\ln{(C1)_{i,t}}$	$\frac{Turnover - cost}{turnover}$
Total value of acquisitions (Tangible assets)(log)	$\ln{(Invest_{tan})_{i,t-1}}$	-0.019	0.004	-0.127
		(0.025)	(0.019)	(0.346)
	$\ln{(Invest_{tan})_{i,t-2}}$	0.061**	-0.014	0.868*
		(0.029)	(0.015)	(0.482)
Adopters	$D_{adopter\ i,t}$	-0.114	-0.039	-2.912**
		(0.108)	(0.063)	(1.317)
Computing capacity to run the business's own software	$D5_{\ i,t}$	0.207*	-0.099*	-0.925
		(0.106)	(0.056)	(1.011)

Number of cloud computing technologies adopted	$Intensity_{AI\ i,t}$	0.002	0.008	0.813**
		(0.036)	(0.025)	(0.414)
Firm size	$\ln\ (L)_{i,t}$	0.413	0.481***	2.473
		(0.288)	(0.180)	(2.053)
(Intangible) Training on ICT specialist skills	$D_{training\ i,t}$	0.327**	-0.120*	1.179
		(0.13)	(0.061)	(0.992)
The percentage of other CL adopters	$N_{\ j,t}$	0.037**	-0.026	0.921**
		(0.018)	(0.035)	(0.389)
Firm fixed effects	μ_i	Yes	Yes	Yes
Sector controls	Dj	-0.181***	-0.018	-3.724*
		(0.042)	(0.278)	(2.213)
Time controls	μ_t	-0.140**	0.138	-3.526**
		(0.069)	(0.142)	(1.558)
N		1957	2247	2266

*Se in parentheses * p<0.1 ** p<0.05***p<0.01*

As the robustness check, we employ net **profits** as the alternative measure for current profitability. Net profits refer to the revenue left after subtracting all costs (costs of goods sold, operating expenses, interest and taxes) and measuring the business's profitability in general. Adopting cloud computing to enhance a firm's computing capability is associated with a 0.19 percentage points increase in net profits. Results are consistent with Table 4.5-1, Table 4.5-2, and Table 4.5-3, the intensity indicator suggests a positive sign on net profit gains and however, the contribution is again largely attributed to the adoption of cloud for improved capacity.

Limitation to conclude

To conclude, the results presented in this chapter are still preliminary and therefore contain sample selection problems. Following the framework we use, descriptive analysis in the sample suggests that there are some firms that choose to adopt cloud computing technologies, and then some are intensive users measured by the number of types. It is better to follow the Heckman-Selection model to estimate and explicitly identify the counterfactual groups. In the first stage, we can run the regression to determine who the adopters and non-adopters are, and in the second stage, estimate the impact of the intensity of cloud computing adoption on profitability gain separately. Reducing the cost of production can increase the productivity of a company. Paper 1 and Paper 2 focus more on labor productivity and output growth. In this paper, we are not focusing on labor productivity. Instead, the discussion involves several types of costs, such as total costs, fixed costs in constructing different profitability measures, and profit margins. Profitability gains can be generated through higher margins or new innovations, not merely by reducing the cost of production via productivity. Hence, I need to explain more about the motivation and how the mechanisms operate.

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5 Concluding Remarks

In the first paper, we start with the theoretical suggestions by Brynjolfsson et al.'s (2018) and extend the scope of 'complementary changes' to tackle the AI productivity paradox. This 'study develops its own framework, synthesises and measures intangibles by taking categories identified in the literature to unpack the mechanism of AI within the production function, and estimate corresponding effects on productivity growth. Our evidence confirms that those intangibles, whose contributions are not fully measured in traditional estimations, are crucial in production and productivity growth. The more substantial growth of intangibles accumulated drives greater productivity growth of AI and related emerging technologies. Investments in a broad range of intangibles help adapt and better absorb AI technology and in total, generate a more significant impact on labour productivity growth than other fixed capital. In particular, the innovative intangible assets suggest greater importance in complementing AI productivity growth. The innovative capital is associated with developing the long-term capability/innovative capacity to commercialise AI and emerging technologies through new business practices and offerings. Beside complementarity, we also find positive evidence of AI on innovation inputs – R&D growth.

Within the production channels, we observe that the uptake of AI and related emerging technologies can effectively substitute ordinary tangible capital. This is a process innovation with digitally embedded equipment or smart technology with AI capabilities, which maintains the output of goods and services but reduces fixed capital investments. For instance, deploying AI solutions can increase the life span of assets and thus reduces purchasing new equipment in the future. In terms of impacts on labour inputs, though, according to current literature, AI can automate human activities or, in other words, replace labour in production. It does not ultimately lead to the reduction of labour inputs required. Empirical evidence does not confirm the net effects of labour substitution but instead the increased use of labour. The labour creation can be attributed to improved competitiveness of products and services and/or new product innovations provided in the market by AI.The mechanisms behind labour productivity dynamics tend to support some labour augmentation effects after considering different intangibles. New jobs or labour might be needed to build AI infrastructure and monitor its operations during the technology adoption. At the same time, AI may advance some types of labour over others. Adopting AI and related emerging technologies may reorganise existing jobs towards non-routine tasks requiring digital skills, accompanied by rising productivity gains. For instance, higher-skilled workers are needed to extract patterns or transfer insights from AI technologies or work consistently with the capabilities of AI. Overall, our empirical evidence suggests AI improves the efficiency of labour employed by augmenting human capabilities, thus enabling current labour to become more productive.

Further, we complete the overall picture of emerging technology by investigating the relevant impacts on profits. We examine the corresponding impacts of emerging cloud computing technologies, as one typical application of digital technology, on firms' profitability indicators. In this panel data analysis, we test if cloud computing adopters and the intensity of adoption are associated with positive gains on firms' current profitability in terms of both net and operating profits. It is confirmed that firms adopting cloud computing technology to increase the computing capacity of their software can significantly enhance current operating and net profits by reducing the cost of production. As firms increase the efficiency of product or service offerings in a competitive market, they can reduce the selling prices of outputs and therefore displace their competitors by increased turnover. In our sample, firms who purchase cloud computing to enhance their computing capacity are more likely to be intensive users. The intensity/ greater variation of cloud computing service purchases enables firms to extract greater profit margins. This highlights the important role of machine learning which is concerned with a typical way to enhance computing capacity on firms' profitability.

The industry-level analysis of multiple EU countries suggests robust complementary impacts of human capital investments to enhance AI's productivity growth, contributing to slowing down EU productivity. In terms of the size of the synergies, vocational training investments generate a more significant contribution than tertiary education. The positive effects of AI investment can be ensured only for some industries, which can provide enough relevant training in time to support the use of new technology. The estimated marginal effects of AI on productivity range from negative to appx 0.15 percentage points, given the range of growth in vocational training in our sample. Further, the study introduces an alternative measure, the labour composition, to represent general labour quality. In much prior intangible literature (Mahoney 2012; Marrano et al.

2009, Borgo et al. 2012), the Becker-type assumption (1962) is applied, assuming that the investments by firms will not raise workers' wages since these skills are hard to use outside individual firms. However, our estimations indicate that it may involve double-counting issues when simultaneously including the labour composition and training in the production function. This wage-based measure can capture the effects of experience, which to some extent, can be gained from uncertified skills from informal training. Further, we expect Eastern Europe to experience a different development trajectory and classify them as the low-middle income group (developing economies), given the observational period. The net effects of AI on labour productivity growth for emerging economies remain positive. Although it is widely considered that AI technology poses a threat to bring negative sides to the development of developing economies due to job displacement, our empirical evidence tends to support the positive side of utilising AI applications that are characterised by lower entries and requires diverse sets of soft skills. The low-middle income economies gain considerable benefits from an additional increase in AI capital investments, given varying levels of growth in the accumulation of human capital. However, it is worth noting that our empirical results on emerging economies tend to rely on the choice of countries (four Eastern European countries in our case) and may introduce some bias.