INTELLIGENT AUTOMATION UPTAKE AND LABOR PRODUCTIVITY IN UNITED KINGDOM

BY

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the research project.

(4) The word count for this research report is 14743 words.

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AI	Artificial Intelligence
AGI	Artificial General Intelligence
BP-LM	Breusch-Pagan Lagrange Multiplier
CAP	Capital Stock
CNC	Computer Numerical Control
CPI	Consumer Price Index
EE	Employee Earnings
EU	European Union
EDU	Tertiary Education
EIU	Economist Intelligence Unit
EU KLEMS	EU level analysis of K (capital), L (labor), E (energy), M (materials), S (service) inputs
EWH	Employee Working Hours
GCSE	General Certificate of Secondary Education
GDP	Gross Domestic Product
GTP	General Purpose Technologies
ICT	Information and Communication Technology
IFR	International Federation of Robotics
IPP	Intellectual Property Products
LP	Labor Productivity

MGI	McKinsey Global Institute
NAI	Non-Artificial Intelligence
NBER	National Bureau of Economic Research
OBR	Office for Budget Responsibility
OECD	Organization for Economic Cooperation and Development
ONS	Office of National Statistics (UK)
PWC	Price Waterhouse Cooper
RD	Research and Development
RE	Real Employee Earning
SIC	Standard Industrial Classification
SME	Small and Medium Enterprises
UK	United Kingdom
US	United States of America
4IR	Fourth Industrial Revolution

PREFACE

This study is submitted in partial fulfillment for the degree of Bachelor of Economics (HONS) Financial Economics in Universiti Tunku Abdul Rahman (UTAR). This research project is supervised by Dr. Eng Yoke Kee.

Due to the continuous advancement of technology, artificial intelligence is set to make waves to the technology industry. It is vital for us to understand the bright future of how artificial intelligence will change the structure of labor industry and how it affects labor productivity and the economy of United Kingdom. Automation is likely to transform the job composition of UK industries leading to job polarization.

This research will investigate the relationship between labor productivity, artificial intelligence automation (AI capital stock), non-AI related capital stock, research and development expenditure, fraction of workforce equipped with tertiary education, average actual working hours and average weekly earnings. This study provides an understanding on the impact of artificial intelligence automation on labor productivity in each industry of United Kingdom respectively and how minimum wage have played a role in igniting the need for automation.

ABSTRACT

Growth of labor productivity is at historic lows in the United Kingdom and the decline has accelerated since the Great Economic Recession in year 2008. Weak productivity growth in United Kingdom has raised concerns as a developed nation relies heavily on productivity growth in order to promote and sustain lasting growth as well as prosperity in a globalizing economy.

This study attempts to shed light on how minimum wage have sparked an early adoption of artificial intelligence (AI) automation, bringing about most important societal changes in labor productivity in each industry of UK as well as the job distribution in the landscape of UK industries. The determinants of labor productivity in each sector is examined from year 2008 to year 2015 in order to grasp the relationship between labor productivity and AI automation along with other control variables which consists of non-AI related capital stock, expenditure of research and development, fraction of workforce with tertiary education, average weekly earnings and average actual working hours.

The findings of this study aims to provide a clearer picture of the potential of AI automation in improving the current labor productivity shortfall for economists and policy makers with a glimpse of what AI automation can do to improve their daily tasks and the firms to know where to target their investments. However, continued research will be required to accurately capture the effects of AI automation on labor productivity as there are no explicit measurements for AI due to unavailability of standardized methods.

CHAPTER ONE: RESEARCH OVERVIEW

1.1 Research Background

Labor and capital are no longer the only factor that drives economic growth as what the world was accustomed to. A new factor of production is on the rise and it is poised to transform the basis of economic growth on the international platform. There has been a decline in the ability to increase the conventional factor of production i.e. labor and capital. Thus, they are unable to sustain and increase the wealth of economy like it once used to.

However, fortuitously with the recent convergence of a transformative technologies, the international economy is marching towards a new era of evolution whereby artificial intelligence possess the potential to overcome the limitations of the traditional drivers of production and bring forth a change of new source for economic growth. Due to the increasing integration of automation and AI being paved to transform the way humans live and work, it is believed that the artificial intelligence can contribute to the workforce and boost economic growth. (Purdy & Daugherty, 2016)

The evolution of the machine learning, robotics and artificial intelligence (AI) are ushering in to the new age of automation. Over the next decade, AI industry is expected to have a huge growth and its impact on the economy will start to emerge. There will be a new beginning of true autonomy as rapid recent advancement of AI will begin to firmly plant progress into the phase of artificial general intelligence (AGI) whereby the machine intelligence could fully accomplish and match the intellectual capability of a human being by the end of the decade. (Stiehler & Gantori, 2018)

Research findings have deduced that artificial intelligence can contribute to the economy in three ways. Firstly, intelligent automation which is the ability to automate complicated physical tasks that requires high levels of adaptability and agility. AI could increase growth and productivity by creating a new virtual workforce. For instance, retrieving goods in a crowded warehouse by using Fetch Robotics equipped with 3D depth-sensors and lasers to navigate safely without moving obstacles. (McKeefry, 2017)

Secondly, AI can contribute towards economic growth through capital and labor augmentation. A significant portion of increasing economic growth and labor productivity does not comes from AI substitution but by enabling the AI at work to be used more effectively to complement the workforce. For example, the Relay fleet which is a fleet of autonomous service industry robots developed by Savioke that enables hotel staffs to redirect their time towards increasing customer satisfaction by making routine room deliveries with more than eleven thousands guest deliveries made within one year in five large hotel chains where it is deployed. Thus, this shows that AI can help to improve labor productivity by allowing humans to focus on tasks that adds value to their job. (Hamacher, 2015)

Thirdly, artificial intelligence diffusion will drive labor productivity and economic growth through its ability to propel innovations. For instance, driverless vehicles that will free up human’s time by accomplishing tasks like banking or shopping which will opens up options for financial institutions and retailers. The AI innovation in one region of the industry will have a cascading effect on other sectors as well as innovation begets innovation. Autonomous vehicles will eventually extend well beyond the automotive industry as well as other AI automated robotics. For example, Ford is collaborating with Stanford University and Massachusetts Institute of Technology (MIT) while BMW is working with Chinese multinational technology company Baidu which specializes in internet related services and products. (Purdy & Daugherty, 2016)

As a new factor of production, AI will change the future of work in terms of how human and machine work together. Companies must actively prepare for the new era of work because automation will assist employees with their current role of jobs. In the future, people will help machines become more empathetic. AI not only has the potential to provide a deep understanding of a firm's consumers, but AI also provides a great ability to personalize and tailor the service, products, and experiences a company offers. As artificial intelligence makes its advancement on customer experience, it grows beyond just an intelligent interface. With each customer interaction becoming more personalized and natural, AI becomes symbol of recognition for firms and as the brand for their digital platform. Besides that, AI can also upgrade consumer's experience through intelligent automation with a virtual workforce. Instead of interacting with one customer at a time, an AI system can interact with an infinite number of customers at once sustaining consistency in service to consumers.

In comparison to other countries, UK are generally seen as behind US and China in terms of scale of AI investment and activity. In terms of global deal share, UK still lags far behind United States with 62 percent of investment going into startup firms in US in year 2016 while only 6.5 percent going into UK based startup firms. Based on table 1.1, there are only 5 percent of value of global venture capital fundraising for AI companies went to UK businesses from year 2010 to 2016. Moreover, three quarters of the total number of UK artificial intelligence firms are seeking for seed or angel investments which shows that the firms are in the earlier stages of development compared to only one half of US firms. In addition, only one tenth of UK artificial intelligence firms are looking for growth capital investments in comparison to one fifth in the US.

Table 1.1 – Value of venture capital fundraising among international competitors

Country	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**Total**
US	£112m	£171m	£228m	£399m	£843	£1,503m	£1578m	£4,833m
China	£6m		£1m	£15m	£55m	£124m	£199m	£401m
UK	£6m	£9m	£24m	£18m	£19m	£67m	£152m	£294m
Canada	£3m	£17m	£11m	£4m	£2m	£23m	£11m	£71m

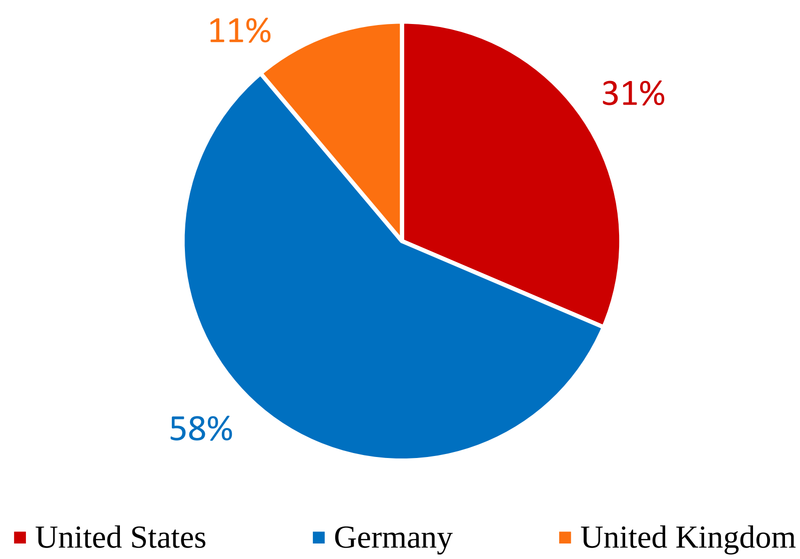
Source: Standford, Cox, Standfill, Hammond and Sam, Pitchbook Analyis (2017)

Based on the study by Economist Intelligence Unit (EIU) for Google in 2016, they have predicted that unless United Kingdom makes a drastic change in the support of AI and data sharing, UK will face a great setback and fall behind other developed nations. In the Economist Intelligence Unit Risk and Rewards report, they have caution that from labor productivity and GDP growth perspective, United Kingdom is expected to underperform compared to other leading economies in their analysis. Based on the report. United Kingdom will underperform in comparison to developing Asia, United States, Japan, Australia and Asia with a fall of 1.83 percent in gross domestic product and 1.79 percent in terms of productivity growth due to its poor public policy implemented. These alarming decline stems from various reasons such as the curtailment of highly productive financial sector and looming Brexit. The baseline data suggests that UK's productivity will be in negative value starting from now until 2030 if no radical change is made. (Saran, 2018)

The rationale behind the report is recent poor performance of UK in labor productivity. UK's struggle with poor productivity has long been a vital concern for economic policymakers and the report states that the best option for UK to improve on their current situation is through AI adoption whereby AI complements human productivity. However, the EIU also forecasts that if UK does not take a huge initiative to support AI development, the country's economy will be 420 billion USD smaller in year 2030 than it was in year 2016. In addition, without proper policy planning labor costs will affect AI investment. The report states that 9 percent of the jobs will be completely taken over by AI with 25 percent of automated tasks in the workforce in the next two decades based on the projections from the 2016 OECD report. (Clague, 2017)

The potential of AI automation could be revolutionary but the uptake is at a slow pace. United Kingdom's weak productivity record is unlikely to grow hugely from artificial intelligence helpers that augment human work and UK is falling behind its competitors in usage of automation. Recently, in a government review on industrial digitization, Barclays Intelligent Manufacturing report warned that failure in the adoption of fourth industrial revolution (4IR) technologies will blew a great opportunity for UK manufacturers. New research from Barclays Corporate Banking stated that roughly 83 percent which is around four in five manufacturers are confident about UK's potential to compete in the international platform in the coming next 5 years. These findings mirrored the findings of the Made Smarter report published in 2017. However, confidence is not translating into capital investment. For those already invested in the AI capital stock, 27 percent of manufacturers reported that they are already seeing returns on investment while 51 percent of manufacturer stated that adoption of 4IR technologies has significantly improved productivity. Despite these, there are still resistance in the latest innovation investments. (Rigby, 2017)

Figure 1.1 – The uptake of manufacturing automation per 10,000 workers



Source: Made Smarter Review by Professor Juergen Maier (2017)

As shown in figure 1.1, Professor Juergen Maier stated that with United Kingdom's pivotal role as the leader of industrial age according to history, it is unsettling to see that United Kingdom is falling behind its rivals of other nations under the list of digitalize and automated developed economies. The uptake of AI automation in the UK is very slow compared to other leading nations. The review by Professor Juergen Maier also states that while US has 93 robots (31 percent) and Germany has 170 robots per 10,000 employees (58 percent) respectively, UK only has 33 robots per 10,000 employees (11 percent). Moreover, this gap is widening as

Germany has invested 6.6 times greater than UK in AI automation development even though the manufacturing sector is only 2.7 times larger than UK. So far, UK has failed to grasp the significance of embracing the future of technology while many developed economies like China are seizing on robots as their key of future growth in the evolution of change for productivity.

Due to this, UK business face the risks of being left behind as only 28 percent of UK firm CEOs are considering the future impact and AI skills required for growth while 39 percent of firm CEOs are considering the impact with 38 percent currently exploring the benefits of AI and human working together. Furthermore, 58 percent of UK business leaders states that they believe emerging technologies involving AI poses threat to their firms in terms of trust levels within organization according to the 21st CEO Survey by PWC.

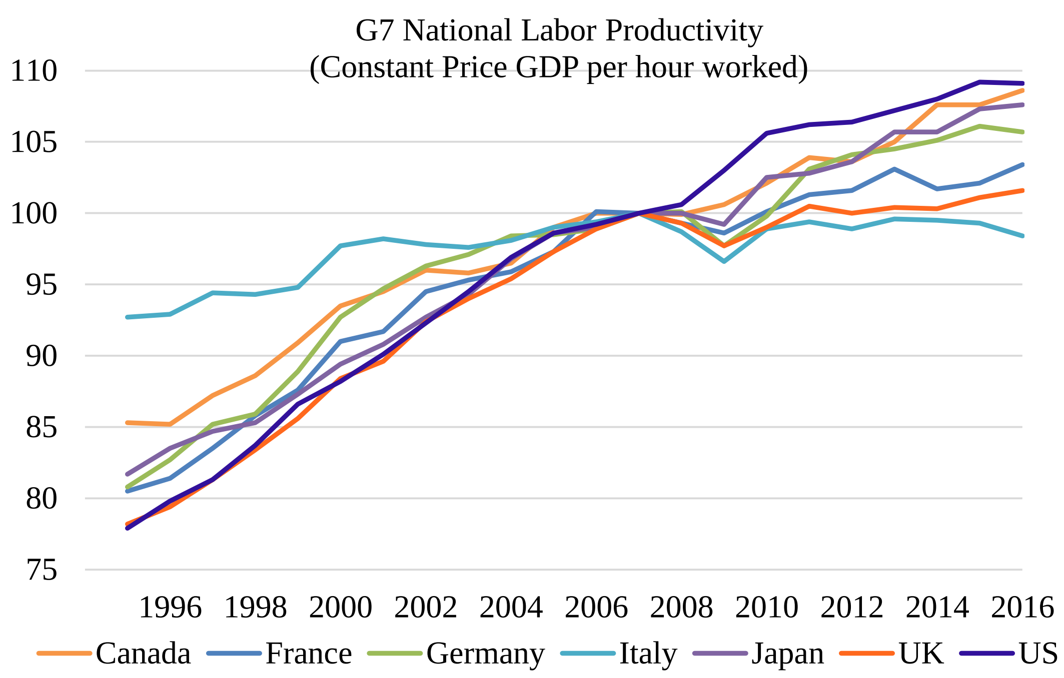
Kevin Ellis from PWC points out that Brexit is an opportunity for UK to accelerate to the forefront technology innovation to position UK as the place for technology investment and innovation in support of AI startups to scale rapidly. He also outlines that companies must actively prepare for the new generation of work and the risks of being left behind in comparison to other developed nations as UK has a long way to go before being on the same pace of Japan and US with sixty-two percent CEOs of Japanese firms and 47 percent of US firms respectively are actively considering the positive ways of which humans and machines can work together who are much ahead on the race of digitalization. (PWC, 2018)

The focus of our research would be on how AI will boost labor productivity and economic growth through capital and labor augmentation as we extends the exploration of the potential of AI whether it will simply replace workers to automation or augments the workforce by complementing the way of work of labor to increase productivity to enhance the low productivity crisis face by UK. Furthermore, we would like to know whether the investment in AI can lift UK’s weak productivity and how it is being deployed by firms that have adopted these technologies across various sectors along with the exploration of AI potential in transforming economic growth.

1.2 Problem Statement

Interminably weak growth in productivity since financial crisis in 2008 has forced the OBR (Office for Budget Responsibility) which is the independent UK government economic forecaster to reduce its forecasted expectation for productivity growth. The OBR outlook for productivity has weakened public finances and discussions by ministers over Brexit is likely to create a further shockwave on the UK economy. Chief executive and senior partner of Deloitte United Kingdom, David Sproul have mentioned that with the lowered expectations on UK productivity by OBR, the Chancellor of Exchequer is anticipating digitalization will be able to improve the persistently weak labor productivity. (Partington & Monaghan, 2017)

Figure 1.2 – Labor productivity of UK and other G7 nations (2007 = 100)



Source: Office for National Statistics (2016)

As observed from figure 1.2, in the late 1990s up until early 2000s, the UK productivity gap with other developed nations has gradually narrowed. However, that improvement immediately declined after the years preceding the financial crisis. Since the economy recession, labor productivity in the UK has continued to widen and ranked as the second lowest in 2016 compared to other G7 nations.

Figure 1.2 also shows that Italy has the lowest labor productivity. However, when we zoom into observing the growth of productivity for Italy, we can see that it shows a constant trend where productivity growth has stagnated from 2010 to 2016. The severity of the economic downturn in Italy has displayed a clear cyclical phenomenon since 1996 due to lack of initiative to reform which creates a broad competitiveness gap. (Manasse, 2013) Hence, in comparison to study the persistently low productivity of Italy, we are more intrigued to place our focus on UK as they once had the highest level of labor productivity in Europe in 1960s but notably UK has lost ground to other more efficient G7 economies with productivity growth plummeted from 2.3 percent to 0.4 percent annually in last 10 years. This phenomenon has piqued our interest to study the productivity problem that yawns across all industries of UK. (Giles, 2018)

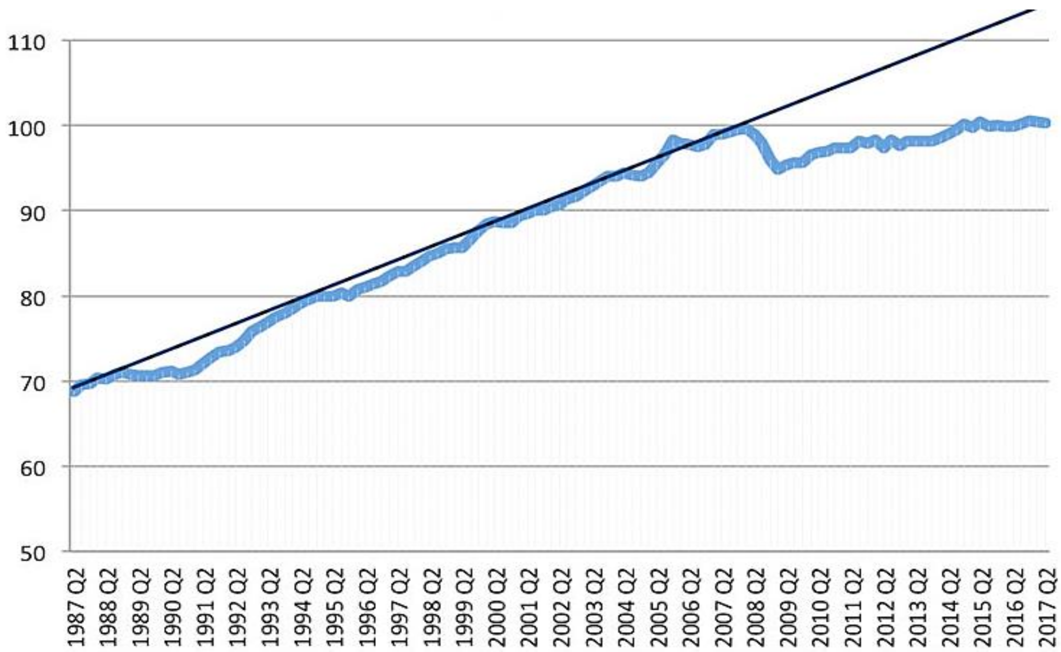
The government economic policy's central consideration is to increase the UK productivity growth which would directly result in the increase of living standards of UK citizens. Based on McKinsey Global Institute's (MGI) study on recent UK economic performance which they have compared productivity of UK companies with world economy top performers in six main industry markets which consists of food processing, software, hotels, food retailing, telecommunications and automotive. Their findings showed that despite the UK labor and capital market reforms of the past 20 years, output per capita in the market sector remains almost 40 percent behind in comparison to US, and 20 percent behind in comparison to West Germany. The root cause of this gap stems from low labor productivity. (McKinsey Global Institute, 2018)

In contrast to traditional wisdom, the main factor of weak labor productivity is the deficiency in exposure to world best practices and lack of competitive intensity.

Consequences to these causes are poor skills and performance of labor along with low capital investments. In addition, reasons frequently cited for weak performance in UK also includes land use regulations, trade barriers and price constraints. In some cases, these barriers constrain competition and so limit the pressure on management to adopt global best practices. (Diamond, 2004)

There have been several factors that contribute to the deterioration in the UK labor productivity such as availability of unskilled labor, capital misallocation and overworking effect. According to the statistical report by UK government in Office for National Statistics, since the start of the great recession in early 2008, UK labor productivity growth has remained very low which is well below the historical average. The Office for National Statistics estimates 20 percent below its pre-crisis trend. Reasons for this productivity deterioration includes more flexible labor markets, stagnant real wages, lack of investment, increase in part-time or temporary work, and research in technological development. (Office for National Statistics, 2007)

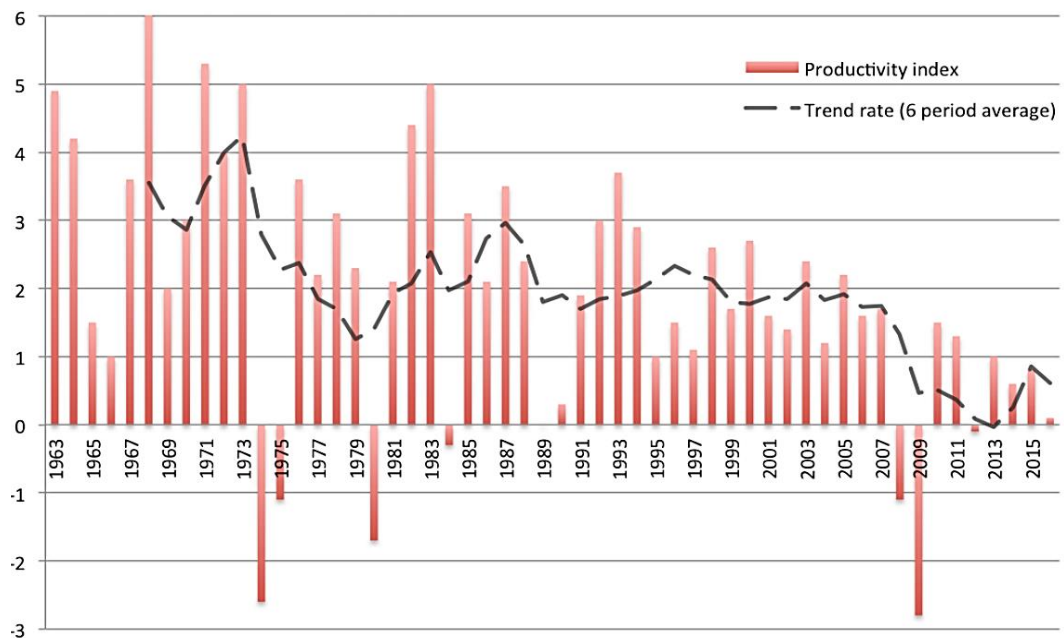
Figure 1.3 – UK labor productivity (Output Per Work, 2010 = 100)



Source: Office for National Statistics (2017)

Based on figure 1.3, since the 2007 crisis, UK labor productivity has stagnated and falling well below its pre-crisis trend. This has had a serious impact on real earnings growth, prospects for future economic growth and tax revenues. As observed from the past twelve years since year 2005, UK labor productivity has only marginally improved on the pre-crisis peak. Between the year 2010 and 2015, the productivity growth in UK increased at a very slow pace of 0.2 percent per year which is far below the UK productivity long term average growth rate of 2.4 percent from year 1970 to 2007. Hence, this poses an uncertain outlook for UK in their trade and investment industry as well as whether the country is able to withstand the looming Brexit idiosyncratic shocks.

Figure 1.4 – UK labor productivity growth
(Annual percentage change in output per worker)



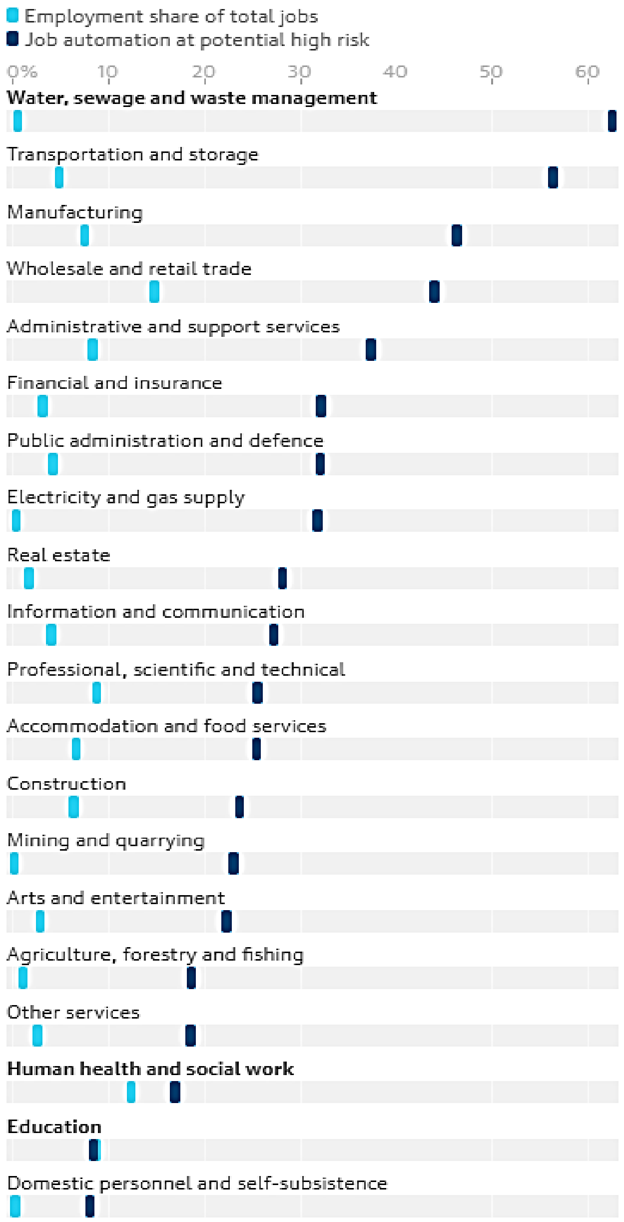
Source: Office for National Statistics (2016)

As shown on figure 1.4, in the post-war period, UK labor productivity growth was averaging at roughly 2 percent to 3 percent a year. However, since the start of the recession in 2008, labor productivity in United Kingdom has shown persistent decline and this level is similar to the level at the start of 2008 financial crisis.

Unlike previous crisis that has affected United Kingdom, the labor productivity growth of the nation has not been able bounced back after the crisis has ended. It can be observed from figure 1.4 that the productivity growth has been struggling to remain positive. (Newman, 2015)

According to the UK Economic Outlook March 2017 by PWC, within these 15 years of automation in routine tasks, there are more than 10 million workers at high risk of replacement by automation in the gathering pace of upcoming new machine age of 2030. The study by PricewaterhouseCoopers also found that there are estimated 30 percent of UK jobs are under potential threat from the breakthroughs of AI. In some of the sectors which required intensive routine cognitive tasks, 50 percent of the jobs would be replaced by AI and machines. There are 2.25 million workers at high risk of replacement in the retail and wholesale sector which employs the most people in Britain while 950,000 jobs in transport and storage, 1.2 million jobs in manufacturing and the report also forecasted that AI automation will boost labor productivity and generate new job opportunities. (Berriman & Hawksworth, 2017)

Figure 1.5 – PWC estimation for employment in each industry at risk of automation



Source: NS Workforce Job Survey for Employment Shares (2016)

According to figure 1.5, the water, sewage and waste management industries have the highest proportion of jobs facing potential high risks of automation, while education and health are estimated to face the lowest risks. Education and health and social care were the two sectors that are least threatened by AI because of the higher proportion of tasks that is hard to automate. Based on the survey, women tend to work in sectors that require a higher level of education and social skills. The report by PricewaterhouseCoopers stated that they would be less in jeopardy of losing their jobs in comparison to men that are more likely to work in industrial sectors such as manufacturing and transportation. 35 percent of male jobs were identified as being at high risk in comparison to 26 percent of female jobs. (PWC, 2017)

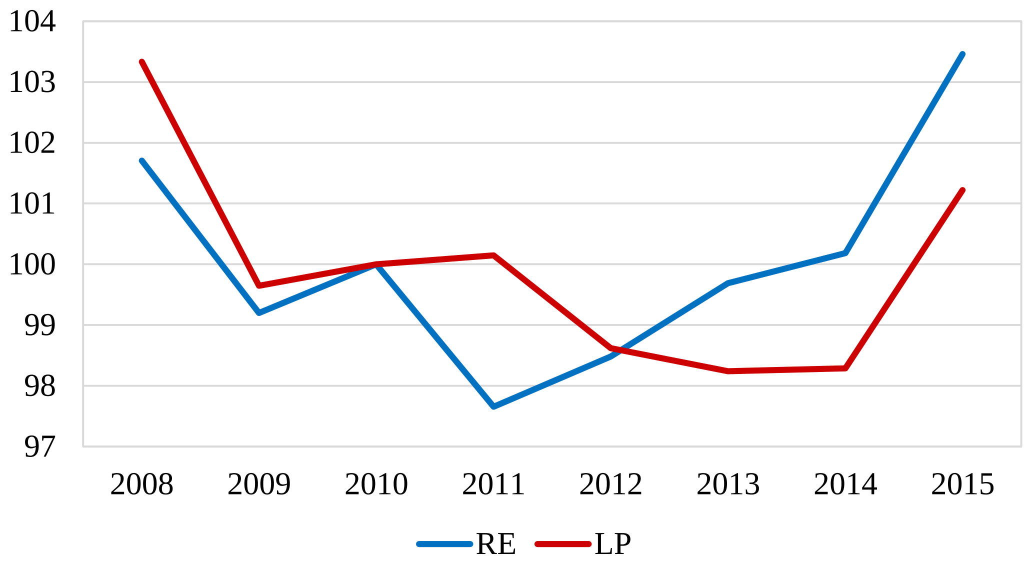
Based on the reports mentioned in our research background, many studies have stated that UK is clearly galling behind other countries in AI automation adoption and many firms in UK still have concerns with the usage of AI in businesses. This will worsen the low labor productivity of UK currently jeopardizing the nation's productivity in the future. According Dell Technologies research, UK is lagging behind the rest of Europe including France, German and Italy when it comes to getting on board with the latest technology breakthroughs such as virtual reality and artificial intelligence.

UK was found lagging behind in investments on key areas of technology such as internet of things with 34 percent UK investments in comparison to 46 percent Global Investments, high performance computer technologies with 29 percent UK investments in comparison to 36 percent Global Investments and virtual reality or augmented reality with 23 percent UK investments in comparison to 28 percent global Investments. However, despite the apparent lack of interest, several business in UK are keen to obtain input and collaboration on all levels of an organization in order to spur on change.

According to Claire Vyvyan, senior vice president of Dell EMC of UK and Ireland, stated that UK will need to accelerate on their planning on the adoption of emerging technologies in order to get ahead of the demand in the future as rate of technology advancement is causing a shift in how people view their roles and industries. The growth of the UK economy is critically dependent on performance of productivity.

After a recession recovery, it is normal to anticipate productivity growth as there will be workers that previously dropped out of labor force are being placed back into the employment system and firms raise their investment as the economy recovers. However, UK stands out as one of the worst among its European peers as a productivity performer during the pre-crisis period as their productivity in recent years has slowed down sharply. (Bughin, et al., 2018)

Figure 1.6 – Aggregate real employee earning (RE) and labor productivity (LP) of UK industries (2010 = 100)



Source: Office for National Statistics (2018)

Besides the slow uptake of technology, another economic challenge face by the UK government is that despite the effort of to increase wage rate, the productivity growth does not operate normally as it should have been which can be observed in figure 1.6. Both real employee earning and labor productivity exhibits a trend of decline in the early post-crisis period (2008 – 2011) with labor productivity being higher than of real wage rate. In the later period (2011 – 2015), it can be observed that both variables are slowly picking up pace of recovery. However, labor productivity is falling behind in comparison to the increase in real employee earning which contradicts its position in the early post-crisis period.

Even though interest rates are low and business profitability are impending to pre-crisis state, capital investments from companies remains subdued. One of the reason is that due to the decline in wages since economic recession in 2008 has made employing labor relatively cheap, thus, lowering incentives for companies to pump in more capital, leading to sluggish investment in the economy. (Jackson, Strauss, Bernard, & Pearson, 2018)

In October 2012, a higher adjustment of national minimum wage was introduced in the UK and this has shifted the low paying occupations to the higher income segment. However, a productivity puzzle was created as productivity is still weak below the growth trend line as compared to the real employee earning. It can be seen that although wage rate has increased but this rise in real employee earning does not seem to translate in boosting the labor productivity. (Giupponi & Machin, 2018)

When adoption of robots in UK industry is picking up at a slow pace in comparison to other nations that are entering a phase where digitization are vital to economic growth and the increase of real wage rate does not spur the growth of labor productivity, we seek to identify and study the linkage between these factors that impede the readiness of UK for the diffusion of AI at work.

1.3 Research Objectives

1.3.1 General Objective

This study aims to analyze the contribution of various factors towards labor productivity, assess the relative importance of these factors and focuses on examining the capital investment in AI uptake as well as exploring its potential to drive labor productivity in UK using sectoral data of each industry.

1.3.2 Specific Objective

This study specifically intent to examine the following:

I. To investigate the determinants of labor productivity.
II. To examine the impact of real employee earning on labor productivity.
III. To examine the impact of capital investment in AI uptake on labor productivity.

1.4 Research Questions

The research questions in this study are:

I. Does AI automation have a significant impact on labor productivity of UK?
II. Does real employee earning have an impact on UK industries?
III. Does capital investment in AI uptake have an impact on UK industries?

1.5 Significance of Study

The AI application is based on the foundation of digitization. The ability of companies building digital assets, expanding digital usage and creating a more digitized workforce to aid companies to accelerate shift in market share, revenue and minimize costs.

An undeniable question is raised as AI is determined and will transform the way we work and live in the near future. We would like to know how much technologies can impact firms, consumers and economies. The workforce would want to understand how much AI can affect their wage rate and job opportunities. Firms raises the inevitable question of how they can seize the opportunities presented by artificial intelligence and where should they target their investments at. Covering all these considerations is how economies should develop artificial intelligence in a more trustworthy and translucent way so that stakeholders can be protected.

Conventionally, past studies done by Autor, Levy and Murnane (2003) as well as by Frey and Osborne (2013) has focused on the effects on employment, as some jobs and tasks become automated and firms seek to make their business run more efficiently. More recently, some authors have focused on the benefits that could come from productivity gains associated with this automation. However, the possible benefits and opportunities of AI go much further. The ability to collect, store and analyze data at the scale, speed and in the ways facilitated by AI technologies will allow firms to improve the quality of products and tailor them to consumers, increasing their value. AI can also reduce the amount of time that consumers spend doing low-value tasks or reduce frictions in the consumption process, all leading to increased consumer demand.

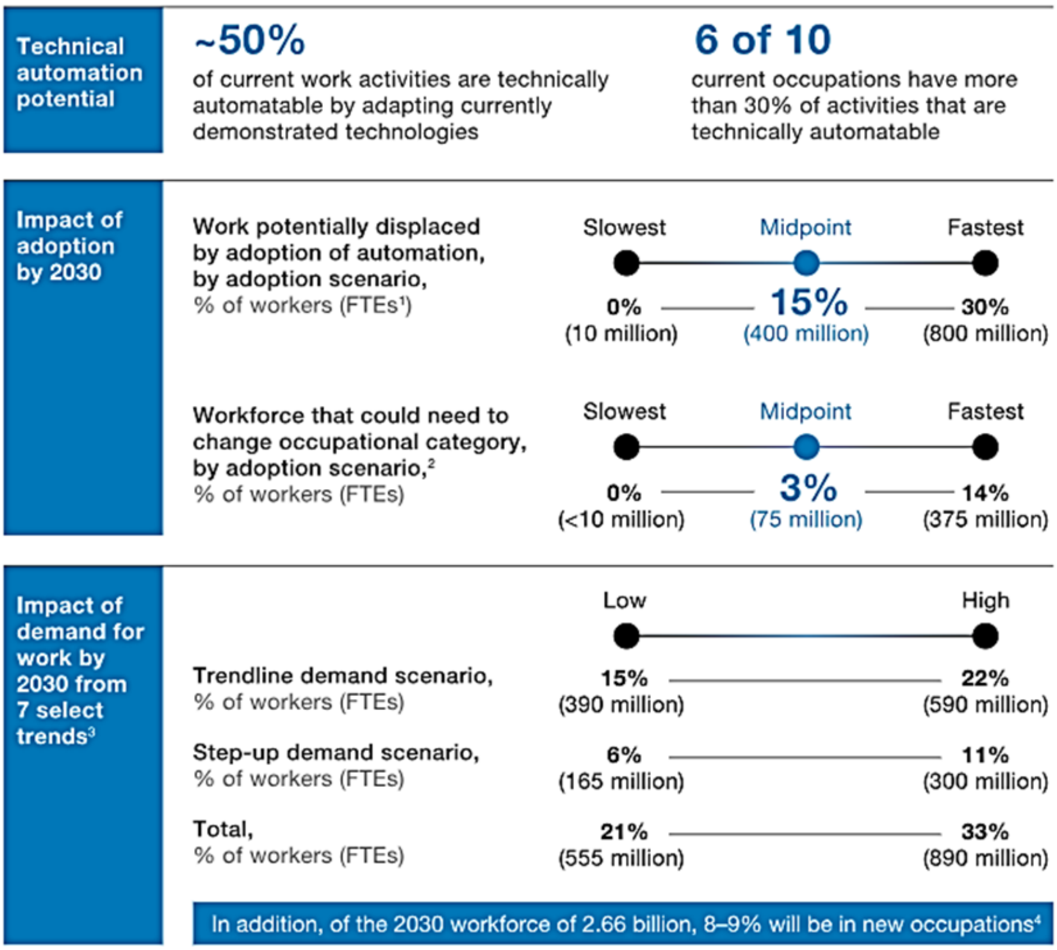
This study seeks to provide a clearer picture of how capital investment in AI automation in UK will help the falling labor productivity of UK and whether UK is ready for this new change of automation in its industry especially for its current workforce which consists of low, middle and high educated workers. It also aims to extend the exploration on the potential of artificial intelligence outside the limits of simple workers displacement effect to how artificial intelligence can augment the labor market and the nation’s productivity as these are the elements that has not been considered by other literatures covering the artificial intelligence topic in significant description.

Based on studies of changes spurred by communications and information technology as well as automation, job polarization of the workforce will happen. The study by Acemoglu and Autor (2010) have showed that middle educated workforce that will be displaced by automation will not move into high level non-routine cognitive work as it is occupied by high educated workers that possess higher demand, hence, these two classes compete for non-routine manual work which will affect the growth of wage rate for low educated individuals.

As for the study done by Goos and Manning (2004) have been focusing on how the job polarization occurs in UK and showed that clerical and skill manual jobs in manufacturing decreased while there is a rise in low paid service occupations and professional and managerial jobs. They have agreed that technology has an impact on the labor market and there is a partial truth on the hypothesis which suggests that skill-biased technical advancement but does not describe all the important difference technology has brought about in the labor market.

Fast forward to 2017, research done by McKinsey Global Institute have found that automation and AI can increase productivity and economic growth but dynamic change is set to happen in the labor market which causes workers to have the need of switching occupations or the need to upgrade skills. Their studies shows that the potential impact of automation on employment varies by occupation and sector. Physical activities in predictable environments such as preparation of fast food in restaurants and machine operation are most susceptible to AI diffusion. Other activities that can be carried out more efficiently and effectively by AI also comprise of analyzing, collecting and processing data in the workplace. This could displace large amounts of labor at work. For example, labor displacement could take place in mortgage origination, paralegal work, accounting, and back-office transaction processing.

Figure 1.7 – Impact of automation on global workforce



Source: McKinsey Global Institute Analysis (2017)

However, one important point to take note of is that when some tasks are automated, according to the findings of McKinsey Global Institute Analysis (2017) in figure 1.7, employment in those occupations may not decline but rather workers may perform new tasks. Automation will have a lesser effect on jobs that involve managing people, applying expertise, and social interactions, where machines are unable to match human performance for now. As for jobs in unpredictable environment for example, occupations such as gardeners, plumbers, or providers of childcare and eldercare will also generally see less automation by 2030, because they are technically difficult to automate and often command relatively lower wages, which makes automation a less attractive business proposition for firms. Nevertheless, low wage rate occupations of routine tasks will have a substantial change. For advanced economies such as UK, the share of workforce that will need to take up new skills and find new occupations will be higher. (Manyika, et al., 2017)

CHAPTER TWO: LITERATURE REVIEW

2.1 Artificial Intelligence (AI)

Nowadays, with most aspects of our lives being computerized or digitalized, mobile cellphones and the World Wide Web have significantly alter and reconstruct the way we work and live. A flood of technology is anticipated and the axis of it focuses on data. Artificial intelligence (AI) will utilize data will be able to carry out tasks that the mind of humans never conceived of before and can assist us with all the tasks that we are currently performing in our daily lives. Artificial Intelligence represents the data processing machine that is aware of their surroundings and is capable to determining, study and carry out an operation as a decision. The capacity of AI to behave differently depending on the environment allows AI to be distinctive from the normal machinery of routine tasks. Examples of how AI is being incorporated in our lives today is the use of machine learning innovations.

The AI in this research refers to software, digital hardware and equipment, databases which in aggregate covers the various types of artificial intelligence discussed. In this study, the AI refers to automation, displacement of manual and cognitive tasks by digital equipment that have basic capabilities of automation. These machines are not artificially intelligent but these components of study is included as they are recognized to be a vital progress towards advance AI innovations in the future as there is no current standardized proxy to capture the effects of AI automation. It is through the study of the PWC report on the economic impact of artificial intelligence, this research has adopted the same aspect of proxy for AI automation as they have come up with the most comprehensive current method of measuring and interpreting the impact of AI automation.

2.2 AI and Labor Productivity

The waning of a burgeoning starting in the 1990s and the financial crisis aftereffects including weak demand and heightened uncertainty have created a dynamic decline of productivity growth while digitization is under way. Digitization with AI automation contains the promise of significant opportunity to boost productivity but the benefits have not yet materialized at scale. This is due to the AI adoption barriers, lag effects and transition costs of each sector of economy.

The finest collection of current research on the link between AI and the economy appears in The Economics of Artificial Intelligence (EAI), an NBER research by Acemoglu and Restrepo (2018). In their research, the investigation of robotics and modern artificial intelligence practices is the extension of what other automation technologies have presented in the past. For instance, when executing a wide range of tasks and processing industrial materials, robotics have generated greater efficiency in terms of productivity.

Economists are commonly intrigued and enthusiastic about what AI could offer on economic growth. Literature on the economic platform have studied on the relationship between economic growth and potential of innovation. (Romer, 1990) Many economists believe in the prospects of AI and other forms of advancement in automation such as laser sensors and robotics which is in the general purpose technology (GPT) category will be able to spur continuous modifications and refine innovation that will ultimately boost productivity growth of the economy. (Cockburn, Henderson, & Stern, 2017) However, despite rapid technological progress in AI automation, there are no corresponding proof to show significant increase of productivity even though the theory of the AI diffusion potential may be true.

Recently, the study by Brynjolfsson, Mitchell and Rock (2018) has explored this question and argue this is due to a notable lag between technological progress and the commercialization of new innovative ideas building on this progress which often rely on complementary investments. The authors argue that lags of this sort are particularly notable in the case of general purpose technologies (GPTs), citing historical examples of electrification and the integrated circuit. On the other hand, Gordon (2014) reminds us that even though Moore's Law has led to exponential improvement in computing performance, there has been no such analogous improvement in productivity. Moreover, according to Bloom, Jones, Reenen and Webb (2017) document the many domains in which ideas are getting harder to find which means that larger research inputs are needed to produce additional productivity outputs.

For the case of productivity growth contributed by artificial intelligence, we can look at some of the empirical research conducted based on the potential of robotics for support. According to Graetz and Michaels (2015), by utilizing robotics at work, annual gross domestic product (GDP) growth have increased an estimated 0.4 percentage points on average. Their data spanned from year 1993 to 2007 with consideration of 17 countries which is a total 238 observations. Thus, their findings can be accounted for about 10 percent GDP growth in the time period observed. The authors note that in comparison to the use of steam engines that has created an impact on UK productivity growth, their findings have displayed a similar fashion in terms of impact magnitude. For instance, in the survey conducted by European Commission Report on Robotics and Employment (2016) on 3000 manufacturing firms, they found evidence which supports the usage of industrial robotics has correlation to the significant increase of labor productivity. This study is the pioneer investigation conducted on the potential of robotics on growth of firm-level productivity and has found a revolutionary finding which proves the impact of automation on productivity. (Lordan, 2018)

Currently, artificial intelligence has been viewed as a small element of the economy to have a significant impact on labor productivity. In the last 10 years, job opportunities have grown beyond expectations of economists but the gross domestic product of nations has declined. This phenomenon would be a complete reversal if automation took place by substituting a great amount of labor force. However, there has been a rapid increase in the advancement of AI in the modern technological era. With AI diffusion set to take place, the question of change in work hour resulting from higher productivity in terms of increment in output per hour is asked. Discussion on the possible outcome of hours unchanged and output increases or fall in hours worked leading to output being unaffected is highlighted.

There are three different perspective to the matter. A theoretical perspective, an empirical perspective or historical perspective as well as efforts to construct granular forecasts regarding budding future technologies, is able to offer unique insights on the impact of AI towards labor market respectively. From the first approximation, one of the logical inference made from these perspectives is that AI will not threaten to displace workers but there will be significant disadvantages and other concerns to these downsides when AI diffusion takes place.

From a theoretical perspective, innovation will create 4 types of impact on the labor market. Firstly, automation will substitute workers in affected industry. Secondly, automation will bring about new job opportunities in the emerging industries. For instance, according to the study of Mandel in 2017, job losses created by brick and mortar industry is able to be compensated by the new job opportunities created by call centers and social care industry. Thirdly, higher wage will increase the demand for jobs in the economy which might not be directly linked to nascent technology. For instance, people in the US is able to afford to travel and frequent restaurants due to the rise in share of labor in hospitality and leisure. Lastly, substantial room for improvement with human workers can be reduced as AI can complement the needs of workforce rather than displace workers in all tasks.

Study by Bessen (2018) argued that new technologies can improve productivity in the market by having a positive impact on employment if the market has a significant amount of unmet demands of labor. Bessen also pointed out that new automation such as computer technology is often associated with the decline of job opportunities in the manufacturing sector where labor demand is usually met. However, this situation can be observed to be correlated to growth in job opportunities in a less saturated, non-manufacturing sector in the context of automation and robotics.

There is potential to expect similar positive spillover effects on job opportunities if AI diffusion impact will occur in a similar way as other types of automation in the economy when machinery was being introduced in various sectors. In the research of Dauth, Findeisen, Südekum, and Wößner (2017), they have combined the whole labor market data of Germany in relation to the data of International Federation of Robotics (IFR) robot shipment. From their study, they gather that although one unit of new technologies like industrial robots will lead to the loss of two jobs in the manufacturing sector, there are adequate new job opportunities created in the service sector to compensate for the negative effect on labor market. Besides that, other evidence from various studies have shown a more mixed findings. Graetz and Michaels (2015) found a noisy effect between adoption of artificial intelligence in an industrial sector and the work opportunities in that sector while Acemoglu and Restrepo (2017) has found that adoption of artificial intelligence will create a significant and negative impact in the United States automotive industry and the job opportunities in that industry.

Some literature has also taken the liberty to view the whole situation from the task perspective which comprise of task application by AI specifically. Autor, Levy and Murnane (2003) took the approach by studying how computer use can impact on demand for work skills. Furthermore, a report by Organization for Economic Co-operation and Development based on the study of Arntz, Gregory and Zierahn (2016) argued that within the same job there is possibility of task variation. For instance, different company managers may treat independent shop personnel with contrasting attitude and this is dependent on whether these personnel are viewed as inputs or partners in a production function. (Helper, Martins, & Seamans, 2018) Overall, prior research has displayed that various use of technology with different management methods have brought about different practices by firms and the way they treat labor. (Brynjolfsson & Hitt, 2000)

Artificial intelligence has the potential to dramatically change the economy. Given the weak productivity growth in UK, possible ways to increase productivity is being sought after desperately and AI induced worker disruptions may exacerbate the issue of declining participation rate of male labor in the UK workforce. Early studies have suggest that robotics and artificial intelligence can boost productivity while the impact of the labor market is mixed. Hence, there is a rising need for more empirical research in order to confirm the findings of existing studies in order to better understand the productivity advantages and conditions of artificial intelligence in complementing or substituting the workforce. Due to these reasons, a number of studies carried out by Seamans and Raj (2018) as well as Brynjolfsson and Mitchell (2018) have used a systematic method and circulation of formulation rank to overcome the demand for publicly accessible data on the distribution and adoption of artificial intelligence and robotics in the service and manufacturing organizations.

2.3 Real Employee Earning and Labor Productivity

The productivity of the industrialized world has been adversely affected by financial crisis but its impact on UK industries was particularly marked. The impact has been reflected on misallocation of capital to most productive business activities due to weak banking system, UK's dependence on financial services with a loose monetary policy and incessant under-investment by firms. However, there is labor market reform in the post-crisis period and the flip side of it is new job opportunities created for low-skilled workers. This places a downward pressure on output per head in the labor market. (Macpherson, 2018)

The unemployment rate of UK has fell to its historic lows of 4.2 percent in 2018 while the employment rate stood the highest for UK at 75.4 percent. This robust employment data has shown a contrast to a more subdued view for the economy. For British households which are the main drivers of UK economy have been hit with a slow growth in wage rate and a bump in inflation that stems from the decline in value of pound after Brexit vote in 2016. This situation have led UK to fall in a wage puzzle whereby real wage rate has failed to increase at a faster rate as unemployment rate falls. (Bloom, Jones, Reenen, & Webb, 2017)

Labor demand and supply factors have contributed to this employment puzzle where wage rate is low in a fertile environment of high employment rate and flexibility of labor market. This low wage rate have prompt companies to hire labor instead of investing in capital investments especially during the post-crisis period of uncertainty.

Although wage rates are increasing but it is still low in comparison to other countries like Germany, France, US and Italy. For instance, UK workers have worked five days to make a product while German workers takes four days to do it as UK employees are 27 percent less productive than Germans. (Chapman, 2017)

In comparison, when German worker makes 1.35 Euros, a UK worker only earns 1 Euro. (Inman, 2016) Slow pace growth in wage rate have reinforced hiring ahead of capital investment in technology which explains why confidence of manufacturers are not translating into investment as we have discussed in Chapter 1.1. After the crisis, growth in demands are met by firms through increased hiring. Hence, capital investment declines due to a combination of uncertainty, overcapacity and low demand environment. (Bughin, et al., 2018)

Due to decrease in low wage rate, the use of capital by companies have been affected adversely. The study of Blundell et al (2013) has stated that increase in effective cost of capital and capital misallocation to less efficient users results in a reduction in capital labor ratio and coincides with lower wage rate and labor costs, thus, decreasing productivity in the end. Real employee earning have declined as a result of increased wage flexibility even though rate of unemployment is low in UK.

This phenomenon occurs due to the decline in nominal and real wage rates have made labor an effectively cheaper factor of production in comparison to capital. Rather than investing in intangible and physical capital, companies will opt to use more labor intensive method of production. Due to chronic underinvestment in intangible and physical capital such as product innovation and process innovation, capital stock per worker, production efficiency and output per work will deteriorate. Hence, growth in low productivity industries is more significant than high productivity industries, leading to an overall decrease in the productivity of UK economy. (Blundell, Crawford, & Jin, 2014)

Other factors that have exacerbated the decline of UK productivity comprise of improper resource allocation and financial crisis. Barnett et al (2014) stated that financial crisis have made firms harder to obtain credit and reduce their ability to meet daily operation expense through working capital. They also speculated that inefficiency in resource allocation arises from firms being uncertain of investments in capital and labor as well as firms poor capital allocation decisions. These factors have created unforeseen delays on capital stock replacement, lower frequency of innovation and loss in human capital when firms decided to cut on training expenditures. (Barnett, Batten, Chiu, Franklin, & Barriel, 2014)

2.4 Theoretical Framework

In the study of economics, firm's production function is being expressed as the increment of output if economic factors of input which comprise of capital, labor and materials whereby these factor can be independently increased or the aggregate of factor productivity has increased. Commonly, this relationship between the productivity and the factors of production is represented in the Cobb-Douglas form. This function acknowledge the collective results between the distinctive factor inputs and their respective efficiency towards each factors of productivity and in our research we have pursued in accordance of the specification typically adopted in past literatures.

The Cobb-Douglas production function is used to indicate the relationship between economic productivity or output and the factor inputs mentioned is applied along the total factor productivity which undertakes the functional form of $Y = AK^{1-\alpha}L^{\alpha}$. In this functional form, the A indicates the total factor productivity, K represents the capital stock, L indicates labor, $\alpha \in [0,1]$ is the labor share of wages, and Y is being expressed as output of the economy. As we attempt to capture the effects of AI automation, the new factor of production is denoted as $\text{LP} = f(AI, L, K)$ whereby LP represents labor productivity, AI represents the AI uptake, and K represents capital investment.

The Cobb-Douglas form is constructed to grasp the emphasis of factor inputs, the share of wages, unobserved effects of total factor of production the interactive effects the determinants of productivity. Furthermore, the Cobb-Douglas form can be expanded to include other comprehensive factor inputs which comprise of land and transitional materials.

Our research will not be discussing of the past literatures regarding the production function in great detail as these relationship of the function has been acknowledged and well recognized in nature. However, this study highlights the key users of the conceptualization of firm productive technology and vital contributors such as the study by Ramsey (1928) and Solow (1956) as well as the original creator of the function by Cobb and Douglas (1928) Instead, we turn to past literatures that covers on econometric methodology to assess the relationship between emerging digitalization and labor productivity, since these are the nearest approach we can find to determine the potential impact of AI on labor productivity of United Kingdom.

One of the most cited and well recognized academic literatures is the paper researched by Choudhry (2009) where the study provides key contributors of productivity that we should consider in our empirical analysis as control variables to restrict these key determinants from being excluded from potentially discombobulate our result findings. The empirical analysis also represents the efficacy of adopting the Fixed Effects panel data method to observational estimation for relationship of these key determinants and productivity. The research also stated that capital stock in technology and ICT and other investments in areas such as research and development expenditure are the key factors that contributes to the growth of productivity in his sample of 45 different nations. Hence, this concludes the fact that supply of distinctive factor inputs and investment are key contributors to productivity growth and this finding has displayed consistency to the standard conceptualization by production function of industries.

Additionally, other contributions of academic literatures is proposed by Stiroh (2001). His study has helped us to determine the determinants of productivity to be included in our econometric model. In his study, Stiroh has mentioned about various empirical studies and important economic theories that indicates the long term determinants of growth in productivity which is significantly contradictory from past neoclassical studies of exogenous growth in relation to the endogenous growth academic studies. His review found that the variables that contributes as a vital factor towards productivity growth is capital stock investment, research and development as well as the quality of capital by form of labor. The study also provides support on the method of measuring intelligent automation uptake with the amount of emerging technology innovations which is types of capital stock in relation to artificial intelligence. It should be note that the review also found that the theoretical and empirical effects of progress in technology on productivity of the economy is consistent with the emphasis of capital expansion that drives these effects. Overall, the amount of capital deepening is vital to illustrate the impact of intelligent automation uptake on labor productivity.

In addition, the UK Office of National Statistics (ONS) have also published a report in 2007 to further elaborate the determinants of productivity growth and provides support of theory on these drivers in the Office of National Statistics Productivity Handbook. The report have illustrated five main drivers for productivity growth. These drivers of the government's productivity framework can be identify as competition of firms, investments of various sectors, skills and competence of workers, technology innovation and enterprise. Our empirical model provides consistency with these productivity drivers as controls for investment, skills of labor and modeling of technology innovation have been explicitly included with industry specification within the defined sample period.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

In previous chapter, our study impart an intuitive discussion of AI automation in general, is anticipated to affect demand for labor and labor productivity. This chapter outlines an elementary model which underlines those conclusions by investigating the relationship between AI automation and labor productivity long with several control variables. First, an overview of the approach is provided then the detailed elements on different phase of our empirical analysis such as the data derived, specific methodology of analysis and intermediary results will be described.

Introduction of new techniques is bound to disrupt production and labor markets. Some skills will be rendered obsolete, while new skills may be required to implement the improved technology. At the same time, the increase in total productivity brought about by the technological change will increase total output, which may be associated with new entrepreneurial opportunities and jobs.

However, the historical tendency for employment and wages to increase as technological progress occurs is an empirical and historical phenomenon as it is not a law of nature or of economics. To assess the impact of technical progress on productivity of workforce in UK, some measure of the substitutability of labor and the new technology is required, along with a way of calculating the overall increase in output that accompanies the technological change.

3.2 Data Description

Our study have adopted econometric analysis of historical data on labor productivity to gauge the explicit impact of artificial intelligence automation on productivity of workforce in United Kingdom. Comparable data across various sector of industries in UK is used to assess the labor productivity to the utilization of AI technologies for each specific industry respectively.

Since the technology of incorporating artificial intelligence is a modern phenomenon, this results in paucity of data that could directly measure the AI automation in specific industries. Hence, a challenge in our study was to seek for a variable that could constitute as a proxy for AI automation and attempt to gauge the size of impact for artificial intelligence automation on labor productivity. In the European Level Analysis of (K) Capital, (L) Labor, (E) Energy, (M) Materials and (S) Service inputs database, we manage to retrieve data that consists of aggregated data with groupings of capital stock that encompasses AI technology which could potentially capture the effects of automation on labor productivity with assumption that the impact of artificial intelligence is similar to emerging technologies in those industry groupings.

The data in this study is an annual time series with a condensed list of standard industrial classification (SIC) division for economic activities in each industry respectively retrieved from EU KLEMS. We retrieved data on stock of capital on computer software and databases, computing equipment and machinery which in aggregate covers the types of artificial intelligence defined in our study. These capital formation is used to develop a variable to represent for the adoption and stock of AI technologies in each industry. In addition, if the association between all breakthrough in technology innovations and labor productivity continues to be analogous within each group of industry, the variable that we adopt should provide a consistent and unbiased estimation for the impact of artificial intelligence on labor productivity.

On the other hand, the endogenous variable in our research is output per hour worked by industry which proxied for labor productivity in United Kingdom. The data to measure productivity is sourced from Office for National Statistics (ONS). In addition, the control variables are non-AI related capital, research and development expenditure, total hours worked by employees, employee earnings, fraction of workforce with tertiary education and consumer price index (CPI). These variables are retrieved from the databases of EU KLEMS while the consumer price index data are sourced from World Bank Data. The data spanned from year 2008 to year 2015 with total of 16 industries segregated in accordance to the SIC division.

Table 3.1 – Classification of SIC division and specification of industry groupings

SIC Division	**Specification of Industry in UK**
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D-E	Electricity, Gas and Water Supply
F	Construction
G	Wholesale and Retail Trade; Repair of Motor vehicles and Motorcycles
H	Transportation and Storage
I	Accomodation and Food Services Activities
J	Information and Communication
K	Financial and Insurance Activities
L	Real Estate Activities
M-N	Professional, Scientific, Technical, Administrative and Support Service Activities
O	Public Administration and Defence; Compulsory Social Security
P	Education
Q	Health and Social Work
R-S-T-U	Arts, Entertainment, Recreation and Other Service Activities

Source: Office for National Statistics – UK standard Industrial Classification of Economic Activities 2007 (SIC 2007)

The table below shows a summary of variables adopted, sources for each data, description of data selected for our study and unit measurement in order to show a clear clarification.

Table 3.2 – Summary of data description for endogenous variable and exogenous variables

Endogenous Variable	**Source**	**Data Description**
Labor Productivity	Office for National Statistics	The proxy for this variable is output per hour worked and the measurement is chained volume measure adjusted to 2010 = 100.
Exogenous Variables	**Source**	**Data Description**
AI Automation	EU KLEMS	The proxy for this variable is real capital stock with potential to captures the effects of AI technologies on labor productivity which comprise of stock of capital on computer software and databases, computing equipment and machinery. The measurement for this variable is capital stock prices in pounds.
Non-AI Capital Stock	EU KLEMS	This variable captures the non-AI technologies effects on labor productivity with real capital stock of communications equipment, transport equipment, total non-residential investment, residential structures, cultivated assets, research and development and other intellectual property products (IPP) assets. The measurement for this variable is capital stock prices in pounds.
Research and Development	EU KLEMS	This variable represents the expenditure of research and development and its economic impact on labor productivity. The measurement for this variable is capital stock prices in pounds.
Fraction of Workforce with Tertiary Education	EU KLEMS	This variable refers to the fraction of workforce that has university level education that we have retrieved as a percentage of the total workforce in each industry sector. It is measured in shares of employment type in total industry employment.

Total Hours Worked by Employees	EU KLEMS	This variable refers to the total hours worked by employees in each sector of industry and its effects on labor productivity. The measurement for this variable is thousands of hours.
Real Employee Earnings (Compensation)	EU KLEMS	This variable represents to the total compensation to employees in each sector of industry and its effects on labor productivity. Employee compensation comprise of two components which is salaries and wages payable. It is measured in millions of Pounds divided by Consumer Price Index (CPI) to show real employee earnings.

3.3 Model Specification

Panel data analysis is applied to investigate the impact of each factors towards the labor productivity in UK industries. The main factors that we focus on is AI automation and its effects on modern labor productivity. Other variables contribute as controls for our analysis. The model specification of our study is constructed as follows:

3.3.1 Econometric Model

Initially, the conventional Cobb-Douglas function only examined on the impact of labor and capital on growth of economy with:

$$\mathrm{Y} = f(L, K)$$
$$Y_{it} = \beta_0 {L_{it}}^{\beta_1} {K_{it}}^{\beta_2} e^{\mu_{it}}$$

Whereby Y represents growth of economy with gross domestic product (GDP) as proxy and L represent labor while K represents Capital. However, in our study, we attempt to capture the effects of AI automation on labor productivity in each sector of UK industry. Hence, the function is modified to include respective variables concerned.

Let, $RE = \frac{EE}{CPI}$

$$\text{LP} = f(CAP, RD, EDU, EWH, \frac{EE}{CPI})$$

$$LP = \beta_0 CAP^{\beta_1} RD^{\beta_2} \beta_3 EDU\ EWH^{\beta_4} RE^{\beta_5} e^{\mu_{it}} \tag{1}$$

Where in Equation (1), LP represents labor productivity in each sector of industry in UK, CAP illustrates capital stocks, RD illustrates research and development expenditure, EDU is fraction of workforce with tertiary education, EWH indicate employee working hours which is the total hours worked by the workforce, RE representing real employee earnings whereby the earnings are divided by consumer price index (CPI) to indicate an inflation deflated variable and μ is error term which captures industry-specific time-trend and fixed effect. β_0 is the intercept and $\beta_1, \beta_2, \beta_3, \beta_4,$ and β_5 are the parameters and intercept to be estimated. *i* captures the dynamics of cross-sectional (industries) effects and *t* indicates the time series dimension.

Since the data are incorporated with different measurements, hence our study transformed some of the variables into the logarithmic form to minimize the skewness of data and increase the normality of data distribution, to perform an interpretable result.

$$ln(LP_{it}) = \beta_0 + \beta_1 \ln(CAP_{it}) + \beta_2 \ln(RD_{it}) + \beta_3 EDU_{it} + \beta_4 \ln(EWH_{it}) + \beta_5 \ln(RE) + \mu_{it} \tag{2}$$

Where in Equation (2), lnLP represents the natural logarithms of labor productivity and lnCAP, lnRD, lnEDU, lnEWH and lnRE refers to natural log of capital stock, fraction of workforce with tertiary education, total employees working hours and employee real earnings respectively. The error term, μ_{it} is assumed to be independent, normally distributed and has a constant variance. The parameters β_1, β_2, β_3, β_4, and β_5 are coefficients and parameters to be estimated which represents the long-run elasticity of the labor productivity and capital stock, fraction of workforce with tertiary education, total employees working hours and total sector specific real employee earnings where *i* represents each industry sector and *t* indicate the time series.

Table 3.3 – Expected sign and explanation for each variable

No.	Indicators	Expected sign	Explanation
1	AI Automation	Positive (+)	The higher the capital stock investment on AI, the higher the labor productivity. (Purdy & Daugherty, 2016)
2	Non-AI Capital Stock	Positive (+)	The higher the investment on other capital stock, the higher the labor productivity. (Owyang, 2018)
3	Research and Development	Positive (+)	The higher the investment on research and development, the higher the labor productivity. (Erdil, Cilasun, & Eruygur, 2013)
4	Fraction of Workforce with Tertiary Education	Positive (+)	The more educated workers earn higher wages, and higher wages leads to higher productivity. (Jones, 1999)
5	Total Hours Worked by Employees	Positive (+)	The more hours worked by employees, the higher the labor productivity. (Collewet & Sauermann, 2017)
6	Real Employee Earnings	Positive (+)	The higher the employee's earning, the higher the labor productivity. (Meager & Speckesser, 2011)

Table 3.3 presents the expected signs for the endogenous variable coefficients adopted in our research. The drivers of productivity such as AI Automation, Non-AI Capital Stock, Research and Development, Fraction of Workforce with Tertiary Education, Total Hours Worked by Employees and Real Employee Earnings have a positive relationship with labor productivity based on the findings of past academic literatures.

3.4 Model Estimation

3.4.1 Pooled Ordinary Least Square (POLS)

$$Y_{it} = \beta_0 + \sum \beta_i X_{it} + \mu_{it}$$

In the Equation, Y_{it} represents the endogenous variable and β_0 represents the intercept for the model. *i* in the model captures the cross sectional dimension of each industries data while *t* captures the time dimension for the sample derived. X_{it} represents the exogenous variable, β_i (i=1….n) depicts the parameters for the exogenous variables, and μ_{it} depicts the residual.

Pooled data arise in our study as there is a time series of cross section with different industries considered. In addition, this approach is recognized as the common constant model whereby the cross sectional data is assumed to possess a sharing identical intercept intrinsically. When the components of the groups are to be pooled display an identical or relatively similar attribute, this approach is preferred. This can be adhered when the pooled data is required prior to homogeneity. Pooled Ordinary Least Square approach has become one of the most confining models as pooled regression have the tendency to result in heterogeneity bias. However, Pooled Ordinary Least Square approach is the best model if the assumptions of consistency, linear and unbiased can be achieved. The model is said to be free from multicollinearity, serial correlation and heteroscedasticity issues once these assumptions are fulfilled. (Hassler & Thadewald, 2003)

Most of the time, the unobserved cross-sectional effects in the Pooled Ordinary Least Square approach are assumed to be zero. Thus, the Pooled

Ordinary Least Square estimator presumes that the panel data regression avert unobserved impacts. For daily practices, these assumptions can be hard to accomplish due to the reason of most panel data analysis possess the omitted variable bias issue. In some cases, the panel data regression may omit significant variables and incorporate unobserved impacts which consequently result in heterogeneity bias. Hence, the ordinary least square estimator that was applied will lead to inconsistent results. Furthermore, the presence of these unobserved impacts will result in high standard error value while the regression displays low t-statistic values. In order to rectify this result, it is vital to come up with an appropriate remedy. Fixed Effects Model and Random Effects Model is further developed to improvise the drawbacks of Pooled Ordinary Least Square regression model in order to acknowledge the finest estimator remain. (Hiestand, 2005)

3.4.2 Fixed Effects Model (FEM)

$$Y_{it} = \sum \beta_i X_{it} + \alpha_i + \mu_{it}$$

From the equation, α_i (i=1, 2, 3… n) represents the unexplained or unknown intercept for each industries of our study. Y_{it} represents the endogenous variable and *i* in the model captures the cross sectional dimension of each industries data while *t* captures the time dimension for the sample derived. X_{it} represents the exogenous variable and β_i represents the intercept for the exogenous variables, and μ_{it} represents the error term or residual.

The Fixed Effects Model represents one of the panel data model which has constant slopes with distinct intercepts depending on time dimension or cross-sectional dimension. Fixed Effects Model's underlying assumption is that if omitted variables correspond with the explanatory variables in a model $E(\boldsymbol{X_{it}}|\boldsymbol{\mu_i} \neq \mathbf{0})$, then the estimators will not be valid, leading to irrational inferences. A model will suffer from heterogeneity bias if it is found that the exogenous variable is correlated to the omitted variable and becomes the reasoning of estimator bias problem. Therefore, first differences fixed effects and within-groups fixed effects are adopted as a remedy to solve the issues mentioned when they arise. (Bell, Fairbrother, & Jones, 2018)

3.4.3 Random Effects Model (REM)

$$Y_{it} = \sum \beta_i X_{it} + \alpha + \mu_{it} + \varepsilon_{it}$$

From the equation, X_{it} represents the exogenous variable or the predicted variable, where *i* in the model captures the cross sectional dimension of each industries data while *t* captures the time dimension for the sample derived. Y_{it} is the endogenous variable which indicates labor productivity. β_i represents the intercept and the coefficient for the exogenous variables, where (i=1….n). ε_{it} represents the within-industries error and μ_{it} represents the between-industries error.

Unlike the Random Effects Model, Fixed Effects Model made an assumption that unobserved effects, μ_i have correlation with one or more exogenous variables. In contrast, the Random Effects Model suggests that μ_i can be acknowledged as part of the residual as μ_i in the model have no relation and no correlation to the exogenous variables but alter across the industries.

Random Effects Model represents a regression that comprise of a constant term that is arbitrary or random. This model’s main function is to remove omitted variable bias via measuring variation in a group which also refers to the unobserved impacts. Then the model categorizes various potential of the omitted variables all at once and evolve into an exogenous variable. Furthermore, the Random Effects Model is in contrast to other models as the method have an assumption that all respective individual impacts are not correlated with the explanatory variable. This assumption have permit the individual impact to act as the endogenous variable.

In the Random Effects Model, unobserved impacts is assumed to not be equivalent to zero ($\boldsymbol{\mu i} \neq \mathbf{0}$). Thus, it represents that unobserved impacts still prevail in the model. However, these impacts are being referred to as randomized and will be the conclusion for population based on the sample randomly chosen in Random Effects Model. (Clarke, Crawford, Steele, & Vignoles, 2010)

3.5 Model Selection

3.5.1 Poolability F-test

The Poolability F-test is adopted in the study to help decide whether the Pooled Ordinary Least Square approach or the Fixed Effects Model approach is the finest model to be used. In this test, there is a high chance for individual outcomes to be present in a panel data regression. However, the underlying assumptions of the Pooled Ordinary Least Square approach will be contravene and breached if this were to be the case. Thus, the situation would consequently led the regression model to be bias, inconsistent and inefficient.

Hence, to investigate whether the regression model suffers from individual impacts, the Poolability F-test will be the benchmark.

H_0: $\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=0$ (POLS is being preferred)

H_1: At least one of the $\beta_i \neq 0$, where i =1, 2, 3, 4, 5, and 6. (FEM is being preferred)

The null hypothesis (H_0) have stated that each of the independent effects are equivalent to zero in the above hypothesis testing. This signifies that the null hypothesis represents that the regression model is free from individual impacts and Pooled Ordinary Least Square model is recommended to be used as the underlying assumption of the ordinary least square estimators can be fulfilled. In comparison, the alternative hypothesis (H_1) decides if the independent effects occurs within the model and signifies that the Fixed Effects Model will be excelling when compared to the Pooled Ordinary Least Square model.

3.5.2 Breusch-Pagan Lagrange Multiplier Test (BP-LM)

H_0: $\sigma_\mu{}^2 = 0$ (REM is being preferred)
H_1: $\sigma_\mu{}^2 \neq 0$ (POLS is being preferred)

The BP-LM test is being carried out to assist us in the selection between the Random Effects Model and Pooled Ordinary Least Square Model. The null hypothesis (H_0) in the Breusch-Pagan Lagrange Multiplier represents that variances in residuals are equal to zero. It signifies that there is no panel effect as there is no meaningful distinction between the units of data which means that the hypothesis testing is carried out to test whether the error term variances ($\sigma_\mu{}^2$) is equivalent to the error term over time [cor (μ_{it}, μ_{iu})] where the error term is significantly distinctive from zero.

If the BP-LM test shows a significant result, the Random Effects Model will be chosen in comparison to the Pooled Ordinary Least Square Model. In addition, Hausman test will be continued to be carried out in order to decide whether the Fixed Effects Model or the Random Effects Model will be selected.

3.5.3 Hausman Test

H_0: Cov (μ_i, X_{it}) =0 (REM is being preferred)
H_1: Cov (μ_i, X_{it}) ≠0 (FEM is being preferred)

In the Hausman test, if the results shows that the Random Effects Model is being preferred than we shall select the result of Random Effects Model for inference to be made because the Hausman test has demonstrated that the REM is more efficient than the FEM. However, if the results shows that the Fixed Effects Model is being preferred than we shall select the result of Fixed Effects Model for inference to be made and will be the choice of our model selection.

Generally, Hausman test is being carried out to analyze the significant difference between the Random Effects Model and Fixed Effects Model. Time-varying regressors can only be derived by the Hausmen test statistics and below shows the test statistic for the Hausmen test.

$$H = \left(\hat{\beta}_{RE} - \hat{\beta}_{FE}\right)' \left[Var\left(\hat{\beta}_{RE}\right) - Var\left(\hat{\beta}_{FE}\right)\right]^{-1} \left(\hat{\beta}_{RE} - \hat{\beta}_{FE}\right) \quad \sim x^2(k)$$

$\hat{\beta}_{RE}$ in the test statistics represents the Random Effects beta value while $\hat{\beta}_{FE}$ is expressed the Fixed Effects beta value. Moreover, $Var\left(\hat{\beta}_{RE}\right)$ indicates the Random Effects Model beta variance and $Var\left(\hat{\beta}_{FE}\right)$ represents the Fixed Effects Model beta variance. As the Hausmen test is being carried out the, although the null hypothesis states that Random Effects Model is being preferred but it does not actually signify that the Random Effects Model is better than Fixed Effects Model. It is when the probability value is lower than the significant level, the null hypothesis will be required to be rejected. Otherwise, we do not reject the null hypothesis.

CHAPTER FOUR: DATA ANALYSIS

4.1 Descriptive Statistics

Table 4.1 – Descriptive statistic with natural logarithm

Variables	Mean	Median	Maximum	Minimum	Std. Dev.
LLP	4.5986	4.6052	4.8809	3.9933	0.1150
LAI	24.0974	24.0203	25.8271	22.5522	0.8935
LNAI	25.1032	25.2255	26.8922	23.5742	0.7139
LRD	20.3988	20.3002	24.0059	16.9166	2.1609
EDU	29.4843	28.9911	62.2280	8.4329	15.5741
LEWH	21.2828	21.4899	22.7108	18.5076	1.0583
LRE	**24.2911**	**24.6370**	25.4100	22.1378	1.0045
LRE^2	591.0562	606.9820	645.6660	490.0800	47.9061

*Notes: LLP – Log Labor Productivity, LAI – Log AI Automation, LNAI – Log Non-AI Capital Stock, LRD – Log Research and Development, EDU – Fraction of Workforce with Tertiary Education, LEWH – Log Total Hours Worked by Employees, LRE – Log Real Employee Earnings and LRE^2 – Log Real Employee Earnings Squared.

Table 4.1 shows the descriptive statistics based on the data of 16 different industries according to SIC division in United Kingdom. The data spanned from year 2008 to year 2015 which is a total of 128 observations, where **LLP** represents the Log Labor Productivity, **LAI** indicates the Log AI Automation, **LNAI** is expressed as Log Non-AI Capital Stock, **LRD** represents the Log Research and Development, **EDU** indicates the Fraction of Workforce with Tertiary Education, **LEWH** is expressed as Log Total Hours Worked by Employees, **LRE** represents the Log Real Employee Earnings and **LRE^2** indicates the Log Real Employee Earnings Squared. By comparing the minimum and maximum, it shows the spread of our data and the outliers. On the other hand, these outliers affect the median less than they affect the mean. Based on our data, it shows that the data of **LLP**, **EDU** and **LRE** are more symmetrical compared to other variables due to their mean and median have closer gap.

4.2 Model Specification

Table 4.2 – Empirical results for equation (2) and (3)

	Equation (2)			Equation (3)		
Variables	**POLS**	**FEM**	**REM**	**POLS**	**FEM**	**REM**
C	4.428***	24.537***	5.438***	4.548***	21.208***	5.489***
	(0.458)	(4.086)	(0.779)	(0.465)	(4.128)	(0.799)
LAI	-	-	-	0.010	0.205**	-0.006
	-	-	-	(0.013)	(0.092)	(0.023)
LNAI	-	-	-	-0.018	-0.047*	-0.032
	-	-	-	(0.021)	(0.032)	(0.026)
LCAP	0.005	-0.039	-0.016	-	-	-
	(0.013)	(0.033)	(0.019)	-	-	-
LRD	0.003	0.153***	0.022*	-0.005	0.128***	0.019
	(0.008)	(0.047)	(0.014)	(0.010)	(0.047)	(0.016)
EDU	-0.000	0.001	-0.002*	-0.000	-0.001	-0.003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
LEWH	0.134***	-0.701***	0.063	0.120***	-0.786***	0.052
	(0.034)	(0.154)	(0.054)	(0.035)	(0.152)	(0.055)
LRE	-0.122***	-0.256	-0.073	-0.090*	-0.256*	-0.056
	(0.045)	(0.180)	(0.070)	(0.051)	(0.174)	(0.073)
Poolability F-test		9.840***			10.763***	
BPLM Test	20.893***			19.331***		
Hausman Test			61.967***			72.876***

Note 1: LLP is Log Labor productivity, LAI is Log AI Automation, LNAI is Log Non AI Capital, LCAP is Log Capital Stock, LRD is Log Research & Development, EDU is Education, LEWH is Log Employee Working Hours, and LRE is Log Real Earning, where Employee Earnings is divided by Consumer Price Index. Robust standard errors in parenthesis. *,** and *** denotes as a significance at 10%, 5% and 1% level, respectively. *,** and *** suggests that the variable is highly significant, significant and moderately significant.

Based on the result shown in Table 4.2, in Equation (2), the traditional determinant of labour productivity which is the real employee earnings and capital stock shows a negative and insignificant to labour productivity. Therefore, we need to further decompose the variable capital stock due to fact that the variable is not in line with our expected sign of conventional findings. In Equation 3, we can clearly see that the AI Automation has a significant and positive relationship with labour productivity. However, the traditional capital stock investment has a negative relationship with labour productivity. Furthermore, the real employee earnings portrays a negative relationship with labour productivity which is not in line with the expected sign of conventional findings. Thus, we proceed to square the real employee earnings as shown in Table 4.3 in order to conclude a significant inference.

$$ln(LP_{it}) = \beta_0 + \beta_1 \ln(AI_{it}) + \beta_2 \ln(NAI_{it}) + \beta_3 \ln(RD_{it}) \\ + \beta_4 EDU_{it} + \beta_5 \ln(EWH_{it}) + \beta_6 \ln(RE) + \mu_{it} \quad (3)$$

Where in Equation (3), lnCAP is decompose into lnAI and lnNAI. Here, lnLP represents the natural logarithms of labor productivity and lnAI, lnNAI, lnRD, lnEDU, lnEWH and lnRE refers to natural log of AI automation, Non-AI capital stock, fraction of workforce with tertiary education, total employees working hours and real employee earnings respectively. The error term, μ_{it} is assumed to be independent, normally distributed and has a constant variance. The parameters β_1, β_2, β_3, β_4, β_5 and β_6 are coefficients and parameters to be estimated which represents the long-run elasticity of the labor productivity and AI automation, Non-AI capital stock, fraction of workforce with tertiary education, total employees working hours, total sector specific real employee earnings where *i* represents each industry sector and *t* indicate the time series. The reason why we propose to decompose lnCAP into lnAI and lnNAI is because the results from table 4.2 shows a negative relationship between LP and lnCAP, while on top of that lnCAP is insignificant to labor productivity. After decomposing lnCAP into lnAI and lnNAI, the result shows that the lnAI possess a positive relationship with labor productivity while lnNAI has a negative relationship with labor productivity, this shows that AI automation has role in boosting up the labor productivity in UK while the conventional Non-AI capital stock does not contribute in driving up labor productivity. However, as we have found in the literature review, another economic challenge for labor productivity in UK is that the real employee earning is negatively related to labor productivity.

$$ln(LP_{it}) = \beta_0 + \beta_1 \ln(AI_{it}) + \beta_2 \ln(NAI_{it}) + \beta_3 \ln(RD_{it}) + \beta_4 EDU_{it} + \beta_5 \ln(EWH_{it}) + \beta_6 \ln(RE) + \beta_7 \ln(RE^2) + \mu_{it} \quad (4)$$

Due to this economic challenge, we introduced $\ln RE^2$ to Equation (3) and the new equation is being represented by Equation (4) to capture the dynamic effects of real employee earning on labor productivity. In equation (4), the lnLP indicates natural logarithms of labor productivity and lnAI, lnNAI, lnRD, lnEDU, lnEWH, lnRE and $\ln RE^2$ refers to natural log of AI automation, Non-AI capital stock, fraction of workforce with tertiary education, total employees working hours, real employee earnings and real employee earnings squared respectively. The error term, μ_{it} is assumed to be independent, normally distributed and has a constant variance. The parameters β_1, β_2, β_3, β_4, β_5, β_6 and β_7 are coefficients and parameters to be estimated which represents the long-run elasticity of the labor productivity and AI automation, Non-AI capital stock, fraction of workforce with tertiary education, total employees working hours, real employee earnings where *i* represents each industry sector and *t* indicate the time series. The reason why $\ln RE^2$ is introduced into Equation (3) is because the result shows a negative relationship between LP and lnRE which is meaningless to our objective. After adding $\ln RE^2$ into the equation, the result shows a positive relationship between labor productivity and employee real earning which give rise to the comprehensive results in table 4.3 as shown below.

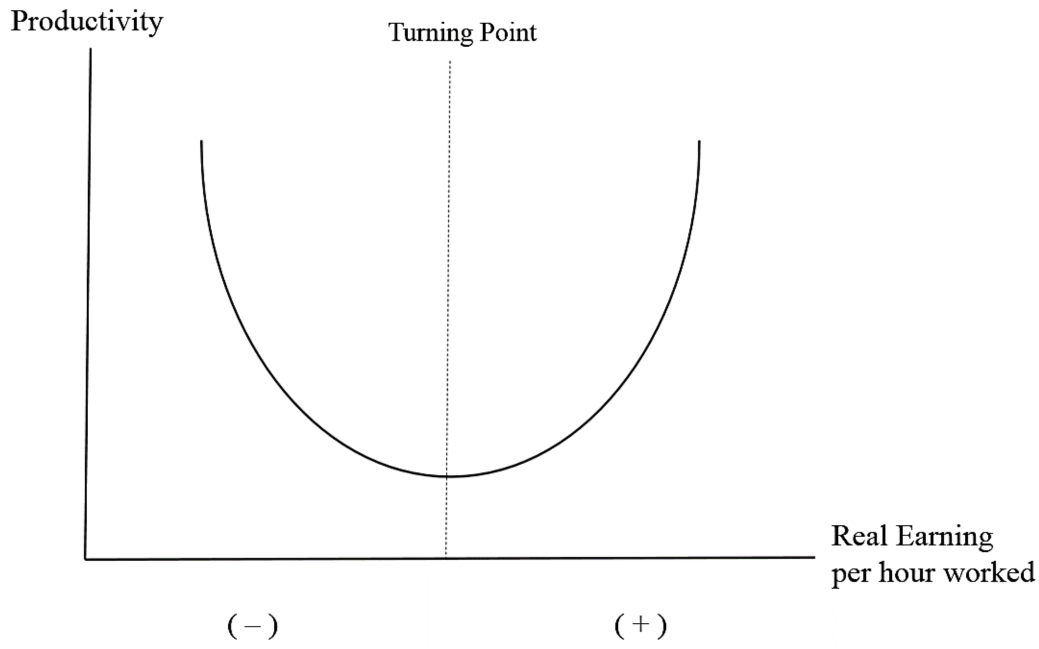
Table 4.3 – Empirical results for equation (4)

Variables	POLS	FEM	REM
C	21.8049**	**328.3045*** **	59.8041***
	(9.3731)	**(29.2269)**	(14.1605)
LAI	0.0218	**0.1559** **	0.0113
	(0.0146)	**(0.0646)**	(0.0227)
LNAI	-0.0117	**-0.0559*** **	-0.0264
	(0.0214)	**(0.0225)**	(0.0196)
LRD	-0.0214**	**0.0828*** **	0.0028
	(0.0130)	**(0.0329)**	(0.0169)
EDU	0.0010	**0.0038** **	-0.0014
	(0.0011)	**(0.0016)**	(0.0012)
LEWH	0.1179***	**-0.6057*** **	-0.0045
	(0.0350)	**(0.1081)**	(0.0490)
LRE	-1.5692**	**-26.0310*** **	-4.6014***
	(0.8039)	**(2.4441)**	(1.1987)
LRE^2	0.0314*	**0.5369*** **	0.0965***
	(0.0171)	**(0.0508)**	(0.0254)
Poolability F-test		**28.4118*** **	
BPLM Test	16.1699***		
Hausman Test			235.5595***

Note 1: LLP is Log Labor productivity, LAI is Log AI Automation, LNAI is Log Non AI Capital, LRD is Log Research & Development, EDU is Education, LEWH is Log Employee Working Hours, LRE is Log Real Earning, where Employee Earnings divided by Consumer Price Index and LRE^2 is Log Real Earning squared. Robust standard errors in parenthesis. *,** and *** denotes as a significance at 10%, 5% and 1% level, respectively. *,** and *** suggests that the variable is highly significant, significant and moderately significant.

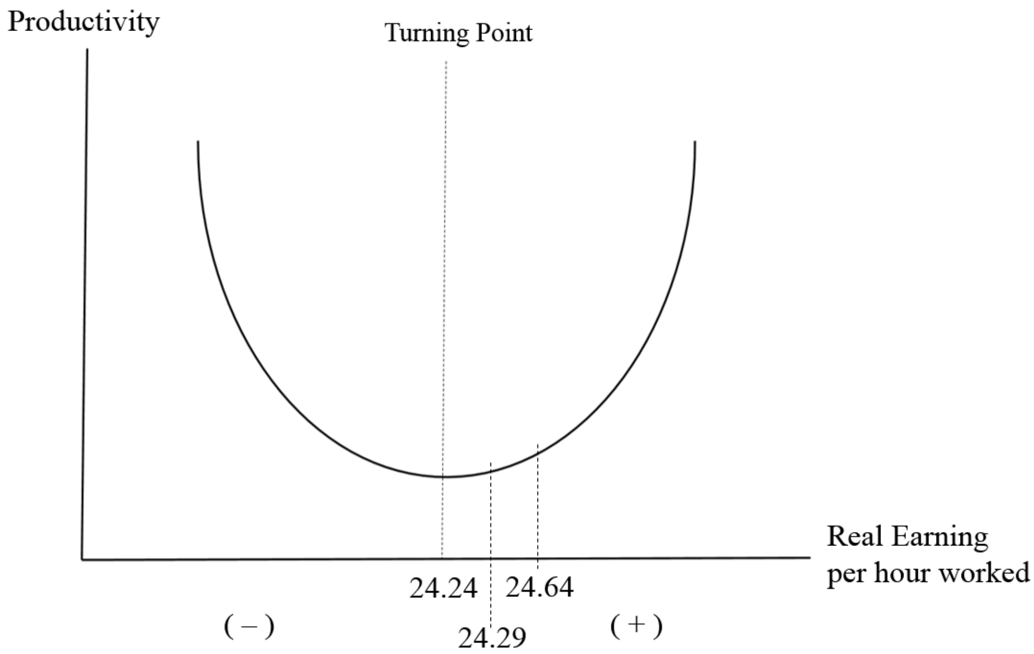
According to the result of Poolability F-test, it is suggested that Fixed Effects Model (FEM) is preferred. However, according to the BP-LM Test, Random Effects Model (REM) is being preferred. Thus, Hausman Test is used to solve the dilemma of selection between FEM and REM. Lastly, the final result shows that the FEM is most suitable for our model. Based on the result in Table 4.3, when we squared our real employee earnings, it shows a positive significant relationship towards labour productivity. Based on this, we detect a non-linear relationship between labour productivity and real employee earnings. Then we proposed a new finding of a quadratic U-shaped curve which will then be discussed in Figure 4.1. Moreover, according to the result, the AI Automation (+0.1559) has a greater impact than the Non-AI capital stock (-0.0559). This basically means that the investment in AI Automation will be able to boost up labour productivity compared to the traditional capital stock investment which proves the objective of our study.

Figure 4.1 – Proposed U-shaped curve for earnings and productivity



A quadratic U-shaped curve was proposed to show the relationship between real employee earnings and labour productivity. The turning point of the curve shows expected average employee real earning. After we have conducted our model estimation as shown in table 4.3, the empirical results shows that before the turning point in the figure 4.1, when real employee earning increases, labor productivity decreases. Hence, productivity of individuals has an inverse relationship with real earnings per hour worked which is in contrary of the conventional findings of these two variables as found by Katovich and Maia (2018). Besides that, according to our empirical findings, we found that AI could change the job market landscape. If UK workers fall under the low wage rate worker segment of the labor force which is before the turning point, there could be risk of substitution towards workers after automation takes place in the future. However, if UK workers fall under the high wage rate segment of the labor force after the turning point, it would be a relief for the workers as many of them is not threaten by the diffusion of AI which will take place in the future.

Figure 4.2 – Proposed U-shaped curve for earnings and productivity with empirical analysis



$$f(x) = ax^2 + bx + c$$

$$x = \frac{-b}{2a}$$

$$= \frac{-(-26.031)}{0.5369}$$

$$=24.2419$$

(Formula 1)

To further understand the relationship between real employee earnings and labour productivity, we use a quadratic formula (Formula 1) to calculate the minimum point of the U-shaped curve. The result shows the minimum point of 24.2419 and with this result, we are able to compare with the descriptive statistic shown in table 4.1. From table 4.1, we can observe a mean of 24.2911 and median 24.6370. This indicate that the average of employee real earning in UK is above the expected average of employee real earning. Hence, we can conclude that with AI diffusion set to take place in UK industry, the majority of the UK workers which falls under the high wage rate segment of the labor force will be able to incorporate technology into their working life instead of being replaced. This is a relief for UK workers since they can incorporate technology into their working life. From previous studies, the traditional determinant imply only linear relationship, but in our study we have found an interesting finding which is a non-linear relationship between real employee earnings and labour productivity.

Furthermore, it is compelling that our findings shows that UK workers can hop onto the age of digitalization by working alongside with robotic technology as automation will increase their way of work. With AI diffusion, jobs in UK will be led to a reduction in repetitive tasks. Hence, UK workers will improve themselves in becoming a modern society whereby they will require to receive high skill trainings and conduct professional tasks. Employees will now seek to utilize tools to allow them to be more proficient at their job as technology becomes an integral part of their business activities. (Daniel, 2019)

CHAPTER FIVE: CONCLUSION

5.1 Summary

Today, UK industry has one of the lowest levels of robotics adoption in the world especially in the manufacturing sector. UK is in the process of digitizing, but there are still significant gaps in adoption of automation, thus, benefits of the AI uptake are not yet materializing at scale. Digitization is happening unevenly in the UK as the country has been particularly good at digitizing some parts of the value chain, but there is gaps of digitization in core business processes such as supply chain management and customer relationship management as well as the investment for future technologies are subdued. UK has been lagging behind robotics adoption while AI uptake may be the key to boost labor productivity among other factors. (McKinsey Global Institute, 2018)

Based on our study, we have found that UK government are trying to increase real employee earnings in hopes that it will translate into higher labor productivity. However, although real employee earning has and labor productivity has exhibit increase trend showing recovery from recession but labor productivity growth remains sluggish. In addition, despite that real employee earning is increasing, when UK is placed on the international platform for comparison with it peers, it can be observed that UK workers are still underpaid. Hence, the low wage rate of workers have given employers an opportunity to focus on labor intensive production and deviate from capital investment in technology. Consequently, this phenomenon of dismal trade, chronic lack of investment and growth of low level service jobs with low level wage rate has drove UK's productivity to a steady decline. With a planned Brexit in 2019, UK export sector and trade is expected to be pushed down as a proportion of GDP. After examining the factors that impede the growth of labor productivity in UK, it is obvious that UK needs to embrace the automation transformation in order to capitalize on digital opportunity to pave the way for recovery of labor productivity. (Inman, 2016)

5.2 Policy Implication

Since the great depression in 2008, the economy of United Kingdom has been recovering slowly from the lowest point of the downturn. Even though there is evidence which suggests that the education and workforce competence are expanding, the productivity performance of the country remains faint. Besides that, although the past standards expected growth is not significantly imposing, but this can be mirrored in the modern advanced economies. It has been awhile that the forecasts derived from the Office for Budget Responsibility (OBR) of UK, Bank of England and other institutions have predicted a recovery for the real wages and productivity growth. In order for this to materialize, business investment needs to rebound strongly. Based on our analysis above of the causes of the productivity growth slowdown, the United Kingdom has an opportunity to boost productivity growth by focusing on education and skills so that there will be high workforce participation, further accelerating the adoption of digital technologies to capture the full potential of automation opportunities and supporting investments and exports to help the economy to be resilient towards boom or bust cycles and uncertainties.

We found that investment in AI can boost labor productivity unlike the traditional determinants of labor productivity such as real employee earning and investment in capital stock. Thus, this finding could be a new direction for UK to focus on as a centre of expertise, at least for the present. Based on our finding, it has shown that perhaps if UK government invest more in AI, the productivity puzzle for UK can be solved. While the employment puzzle described has had the positive effect of high levels of workforce participation, it also means that the United Kingdom has become increasingly dependent on labor to drive output growth. Like other nations, it will also need to respond to the digital transformations taking place in global markets and the rapidly changing competition that comes with them. This makes getting the most out of UK's human capital and equipping it with the skills of tomorrow an even more important task.

AI diffusion will chart a new path for United Kingdom's productivity in order to remain competitive in future years. According to our graphical analysis in figure 4.2, we found that UK workers fall under the high wage rate segment. Since real employee earning has a significant relationship to labor productivity, this shows that traditional determinants remain as being an important key factor of labor productivity. It is a relief for UK workers as they face a lower risk of substitution by AI. This finding is beguiling for us as other studies were not able to determine whether UK is facing the risk of substation by AI or not. Improving the skills of low wage rate labors will be vital as UK workers is expected to shift towards the high wage rate segment after AI uptake according to figure 4.2 because low skilled and repetitive tasks will be significantly reduced.

Nevertheless, it is reassuring that majority falls under the high skilled labor segment of the labor force as this will allow AI diffusion to take place at a faster rate as it would be easier for high skilled labor to transition in working cohesively with robotics. UK policy makers could further work with business to identify future skills demand and consider funding and financing for workers or employers to retrain and reskill continually. Recent MGI research identified that the key skill shifts will be affecting the UK economy by 2030. For example, as a result of the country's predominantly knowledge-based economy, social and emotional skills such as directing, supervising, managing, and coordinating will eventually overtake physical and manual skills as the largest skill group, rising from 21 percent of working hours in 2016 to 26 percent by 2030s when AI diffusion kicks in.

Higher cognitive skills and technological skills will also continue to grow in importance. To meet these skill shifts, the United Kingdom could adopt lessons from other nations that are already responding to changing skill requirements. For example, the Singapore government launched the SkillsFuture as a national initiative in 2014 to enable lifelong learning and to contribute to creating a highly skilled and competitive workforce that is prepared for the future of work.

SkillsFuture works with industry associations and government bodies to identify future skill requirements and provides career guidance and high quality training to support workers in continually developing and mastering new skills throughout their careers. Between 2015 and 2020, SkillsFuture expects to invest around $750 million a year in the framework, which will include a $375 credit to all of Singapore's 3.4 million citizens over the age of 25. (World Economic Forum, 2017)

5.3 Limitations and Recommendations

Although our study has reached the objective of investigating the impact of various determinants on labor productivity and how AI diffusion could transform the way UK industries operates, there were some unavoidable limitations. Firstly, our research explores the potential impact of each factor on the labor productivity. However, there is no exact measurement that shows the magnitude of the impact on each industry that we have studied. Different factors might have different effects that contributes towards the decline of labor productivity in each sector of industry.

Secondly, due to the paucity of data available for the AI Automation, we have assumed that capital stock on computer software and databases, computing equipment and machinery is able to capture the potential effect of AI technologies. A strong assumption is made whereby we assume that for nations that have invested heavily in AI investment would meant that they are readier for AI diffusion at work.

For the future research on this area of study, as there are other proxies such as Gross Domestic Product, Gross Value Added (GVA) or Real GDP per worker could be explored to capture the impact of AI on the industries of UK. For other variables, we also recommend that they can be explored with other proxies as some of the data we use is restricted to the specific needs cater to our research.

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Appendices

Appendix 1: Empirical Results for POLS, REM and FEM

Results for Equation 2

Pooled Ordinary Least Square (POLS)

Dependent Variable: LLP
Method: Panel Least Squares
Date: 03/25/19 Time: 15:09
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.428126	0.458068	9.666969	0.0000
LCAP	0.004582	0.012614	0.363265	0.7170
LRD	0.002745	0.007648	0.358897	0.7203
EDU	-7.16E-05	0.000890	-0.080415	0.9360
LEWH	0.134176	0.033835	3.965597	0.0001
LRE	-0.122040	0.044536	-2.740256	0.0071

R-squared	0.192676	Mean dependent var	4.598619
Adjusted R-squared	0.159589	S.D. dependent var	0.114962
S.E. of regression	0.105390	Akaike info criterion	-1.616553
Sum squared resid	1.355067	Schwarz criterion	-1.482864
Log likelihood	109.4594	Hannan-Quinn criter.	-1.562234
F-statistic	5.823322	Durbin-Watson stat	0.368847
Prob(F-statistic)	0.000074		

Breusch-Pagan Lagrange Multiplier Test

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	20.89266	0.523586	21.41625
	(0.0000)	(0.4693)	(0.0000)
Honda	4.570849	-0.723592	2.720421
	(0.0000)	(0.7653)	(0.0033)
King-Wu	4.570849	-0.723592	1.980820
	(0.0000)	(0.7653)	(0.0238)
Standardized Honda	6.610661	-0.537654	-0.029160
	(0.0000)	(0.7046)	(0.5116)
Standardized King-Wu	6.610661	-0.537654	-0.774776
	(0.0000)	(0.7046)	(0.7808)
Gourieroux, et al.*	--	--	20.89266
			(0.0000)

Fixed Effects Model (FEM)

Dependent Variable: LLP
Method: Panel Least Squares
Date: 03/25/19 Time: 15:11
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	24.53699	4.085580	6.005755	0.0000
LCAP	-0.039403	0.033067	-1.191615	0.2360
LRD	0.152686	0.047325	3.226331	0.0017
EDU	0.000512	0.002151	0.238200	0.8122
LEWH	-0.700678	0.154435	-4.537046	0.0000
LRE	-0.255942	0.179655	-1.424627	0.1572

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.660705	Mean dependent var	4.598619
Adjusted R-squared	0.597285	S.D. dependent var	0.114962
S.E. of regression	0.072955	Akaike info criterion	-2.249032
Sum squared resid	0.569496	Schwarz criterion	-1.781121
Log likelihood	164.9380	Hannan-Quinn criter.	-2.058917
F-statistic	10.41798	Durbin-Watson stat	0.606587
Prob(F-statistic)	0.000000		

Poolabilty F-test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	9.839820	(15,107)	0.0000
Cross-section Chi-square	110.957341	15	0.0000

Random Effects Model (REM)

Dependent Variable: LLP
Method: Panel EGLS (Cross-section random effects)
Date: 03/25/19 Time: 15:11
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.437583	0.779224	6.978201	0.0000
LCAP	-0.016086	0.018827	-0.854442	0.3945
LRD	0.022166	0.013698	1.618240	0.1082
EDU	-0.002314	0.001271	-1.819711	0.0713
LEWH	0.063096	0.053832	1.172099	0.2434
LRE	-0.073044	0.069574	-1.049872	0.2959

Effects Specification

	S.D.	Rho
Cross-section random	0.067307	0.4598
Idiosyncratic random	0.072955	0.5402

Weighted Statistics

R-squared	0.041590	Mean dependent var	1.645579
Adjusted R-squared	0.002311	S.D. dependent var	0.088463
S.E. of regression	0.088361	Sum squared resid	0.952533
F-statistic	1.058842	Durbin-Watson stat	0.488062
Prob(F-statistic)	0.386631		

Unweighted Statistics

R-squared	0.093675	Mean dependent var	4.598619
Sum squared resid	1.521238	Durbin-Watson stat	0.305603

Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	61.967018	5	0.0000

Results for Equation 3

Pooled Ordinary Least Square (POLS)

Dependent Variable: LLP
Method: Panel Least Squares
Date: 03/25/19 Time: 15:06
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.547533	0.465445	9.770282	0.0000
LAI	0.010224	0.013275	0.770125	0.4427
LNAI	-0.018211	0.021298	-0.855047	0.3942
LRD	-0.004753	0.009492	-0.500717	0.6175
EDU	-0.000223	0.000895	-0.248750	0.8040
LEWH	0.120071	0.035368	3.394892	0.0009
LRE	-0.090158	0.050491	-1.785644	0.0767

R-squared	0.204239	Mean dependent var	4.598619
Adjusted R-squared	0.164780	S.D. dependent var	0.114962
S.E. of regression	0.105064	Akaike info criterion	-1.615354
Sum squared resid	1.335659	Schwarz criterion	-1.459383
Log likelihood	110.3826	Hannan-Quinn criter.	-1.551982
F-statistic	5.175962	Durbin-Watson stat	0.358023
Prob(F-statistic)	0.000090		

Breusch-Pagan Lagrange Multiplier Test

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided
(all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	19.33117 (0.0000)	0.616411 (0.4324)	19.94759 (0.0000)
Honda	4.396723 (0.0000)	-0.785119 (0.7838)	2.553790 (0.0053)
King-Wu	4.396723 (0.0000)	-0.785119 (0.7838)	1.831796 (0.0335)
Standardized Honda	6.845223 (0.0000)	-0.585629 (0.7209)	-0.081791 (0.5326)
Standardized King-Wu	6.845223 (0.0000)	-0.585629 (0.7209)	-0.834368 (0.7980)
Gourieroux, et al.*	--	--	19.33117 (0.0000)

Fixed Effects Model (FEM)

Dependent Variable: LLP
Method: Panel Least Squares
Date: 03/25/19 Time: 15:07
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	21.20818	4.128247	5.137333	0.0000
LAI	0.205069	0.092020	2.228534	0.0280
LNAI	-0.046798	0.032137	-1.456183	0.1483
LRD	0.128282	0.046645	2.750206	0.0070
EDU	-0.001410	0.002192	-0.643529	0.5213
LEWH	-0.786185	0.152610	-5.151591	0.0000
LRE	-0.256039	0.174028	-1.471248	0.1442

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.684602	Mean dependent var	4.598619
Adjusted R-squared	0.622117	S.D. dependent var	0.114962
S.E. of regression	0.070670	Akaike info criterion	-2.306441
Sum squared resid	0.529386	Schwarz criterion	-1.816249
Log likelihood	169.6123	Hannan-Quinn criter.	-2.107274
F-statistic	10.95634	Durbin-Watson stat	0.615002
Prob(F-statistic)	0.000000		

Poolabilty F-test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	10.762786	(15,106)	0.0000
Cross-section Chi-square	118.459243	15	0.0000

Random Effects Model (REM)

Dependent Variable: LLP
Method: Panel EGLS (Cross-section random effects)
Date: 03/25/19 Time: 15:07
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.489105	0.798498	6.874288	0.0000
LAI	-0.006010	0.023414	-0.256686	0.7979
LNAI	-0.031686	0.025527	-1.241283	0.2169
LRD	0.019436	0.015454	1.257717	0.2109
EDU	-0.002510	0.001274	-1.971275	0.0510
LEWH	0.051480	0.054952	0.936806	0.3507
LRE	-0.056331	0.072564	-0.776291	0.4391

Effects Specification

	S.D.	Rho
Cross-section random	0.070333	0.4976
Idiosyncratic random	0.070670	0.5024

Weighted Statistics

R-squared	0.043839	Mean dependent var	1.539397
Adjusted R-squared	-0.003573	S.D. dependent var	0.087903
S.E. of regression	0.088060	Sum squared resid	0.938292
F-statistic	0.924631	Durbin-Watson stat	0.486412
Prob(F-statistic)	0.479863		

Unweighted Statistics

R-squared	0.081338	Mean dependent var	4.598619
Sum squared resid	1.541945	Durbin-Watson stat	0.295987

Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	72.876179	6	0.0000

Results for Equation 4

Pooled Ordinary Least Square (POLS)

Dependent Variable: LLP
Method: Panel Least Squares
Date: 03/25/19 Time: 14:59
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	21.80489	9.373083	2.326331	0.0217
LAI	0.021780	0.014564	1.495454	0.1374
LNAI	-0.011681	0.021386	-0.546193	0.5859
LRD	-0.021436	0.013048	-1.642802	0.1030
EDU	0.000954	0.001092	0.873873	0.3839
LEWH	0.117860	0.035043	3.363262	0.0010
LRE	-1.569193	0.803901	-1.951974	0.0533
LRE*LRE	0.031436	0.017053	1.843391	0.0677

R-squared	0.226153	Mean dependent var	4.598619
Adjusted R-squared	0.181012	S.D. dependent var	0.114962
S.E. of regression	0.104038	Akaike info criterion	-1.627653
Sum squared resid	1.298878	Schwarz criterion	-1.449401
Log likelihood	112.1698	Hannan-Quinn criter.	-1.555228
F-statistic	5.009908	Durbin-Watson stat	0.364336
Prob(F-statistic)	0.000053		

Breusch-Pagan Lagrange Multiplier Test

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided
(all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	16.16987	0.393376	16.56325
	(0.0001)	(0.5305)	(0.0000)
Honda	4.021178	-0.627197	2.399907
	(0.0000)	(0.7347)	(0.0082)
King-Wu	4.021178	-0.627197	1.750359
	(0.0000)	(0.7347)	(0.0400)
Standardized Honda	6.901163	-0.425548	-0.128598
	(0.0000)	(0.6648)	(0.5512)
Standardized King-Wu	6.901163	-0.425548	-0.828716
	(0.0000)	(0.6648)	(0.7964)
Gourieroux, et al.*	--	--	16.16987
			(0.0001)

Fixed Effects Model (FEM)

Dependent Variable: LLP
Method: Panel Least Squares
Date: 03/25/19 Time: 15:03
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	328.3045	29.22691	11.23295	0.0000
LAI	0.155931	0.064557	2.415399	0.0174
LNAI	-0.055897	0.022504	-2.483876	0.0146
LRD	0.082822	0.032921	2.515746	0.0134
EDU	0.003808	0.001611	2.363754	0.0199
LEWH	-0.605651	0.108146	-5.600301	0.0000
LRE	-26.03100	2.444074	-10.65066	0.0000
LRE*LRE	0.536917	0.050849	10.55901	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.847030	Mean dependent var	4.598619
Adjusted R-squared	0.814980	S.D. dependent var	0.114962
S.E. of regression	0.049450	Akaike info criterion	-3.014413
Sum squared resid	0.256754	Schwarz criterion	-2.501939
Log likelihood	215.9225	Hannan-Quinn criter.	-2.806192
F-statistic	26.42778	Durbin-Watson stat	1.501135
Prob(F-statistic)	0.000000		

Poolabilty F-test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	28.411829	(15,105)	0.0000
Cross-section Chi-square	207.505379	15	0.0000

Random Effects Model (REM)

Dependent Variable: LLP
Method: Panel EGLS (Cross-section random effects)
Date: 03/25/19 Time: 15:03
Sample: 2008 2015
Periods included: 8
Cross-sections included: 16
Total panel (balanced) observations: 128
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	59.80405	14.16052	4.223294	0.0000
LAI	0.011292	0.022688	0.497720	0.6196
LNAI	-0.026389	0.019601	-1.346326	0.1807
LRD	0.002811	0.016930	0.166014	0.8684
EDU	-0.001421	0.001155	-1.230286	0.2210
LEWH	-0.004517	0.048973	-0.092225	0.9267
LRE	-4.601418	1.198678	-3.838744	0.0002
LRE*LRE	0.096503	0.025422	3.796025	0.0002

Effects Specification

	S.D.	Rho
Cross-section random	0.073711	0.6896
Idiosyncratic random	0.049450	0.3104

Weighted Statistics

R-squared	0.088565	Mean dependent var	1.061284
Adjusted R-squared	0.035398	S.D. dependent var	0.085810
S.E. of regression	0.084278	Sum squared resid	0.852326
F-statistic	1.665796	Durbin-Watson stat	0.487383
Prob(F-statistic)	0.123792		

Unweighted Statistics

R-squared	-0.475336	Mean dependent var	4.598619
Sum squared resid	2.476305	Durbin-Watson stat	0.167753

Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	235.559490	7	0.0000

Appendix 2: Descriptive Statistic

Descriptive Statistic with Natural Logarithms

	LLP	LCAP	LRD	EDU	LEWH	LRE	LRESQ
Mean	4.598619	49.20053	20.39881	29.48430	21.28275	24.29105	591.0562
Median	4.605170	49.29501	20.30029	28.99114	21.48994	24.63699	606.9820
Maximum	4.880920	51.62158	24.00589	62.22795	22.71076	25.40996	645.6660
Minimum	3.993340	46.49482	16.91660	8.432906	18.50757	22.13775	490.0800
Std. Dev.	0.114962	1.125542	2.160864	15.57413	1.058348	1.004471	47.90612
Skewness	-2.898690	-0.283113	0.021449	0.432199	-0.937270	-0.896576	-0.849453
Kurtosis	15.85476	2.665910	1.650200	2.024853	3.256259	2.552453	2.471004
Jarque-Bera	1060.557	2.305213	9.726934	9.056506	19.09103	18.21704	16.88598
Probability	0.000000	0.315812	0.007724	0.010800	0.000072	0.000111	0.000215
Sum	588.6233	6297.668	2611.047	3773.991	2724.192	3109.254	75655.19
Sum Sq. Dev.	1.678468	160.8893	593.0052	30804.31	142.2528	128.1381	291464.6
Observations	128	128	128	128	128	128	128

Appendix 3: Covariance Analysis

	LLP	LCAP	LRD	EDU	LEWH	LRE	LRESQ
LLP	1.000000	0.018475	0.034262	-0.147163	0.284537	0.152692	0.155108
LCAP	0.018475	1.000000	0.297667	-0.239546	0.403367	0.508596	0.505216
LRD	0.034262	0.297667	1.000000	0.468927	0.635379	0.760547	0.766873
EDU	-0.147163	-0.239546	0.468927	1.000000	0.085604	0.240693	0.238113
LEWH	0.284537	0.403367	0.635379	0.085604	1.000000	0.938511	0.938935
LRE	0.152692	0.508596	0.760547	0.240693	0.938511	1.000000	0.999835
LRESQ	0.155108	0.505216	0.766873	0.238113	0.938935	0.999835	1.000000