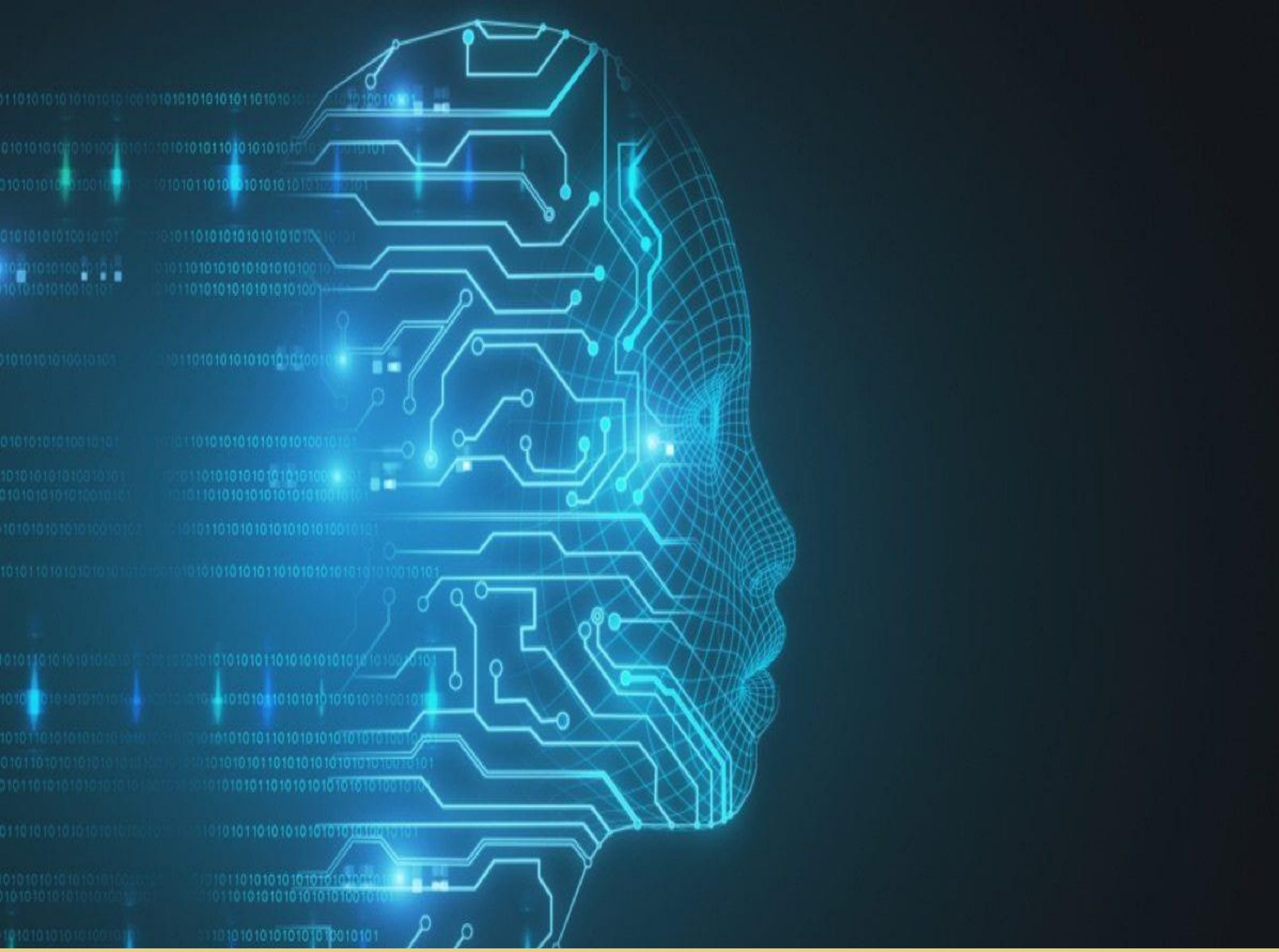

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AI, demand and employment: A sectoral analysis for the Portuguese economy

Master's Dissertation in Economics, advised by Professora Doutora Marta Simões and Professor Doutor Pedro Bação, and presented to the Faculty of Economics of the University of Coimbra

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AI, demand and employment: A sectoral analysis for the Portuguese economy

Work Project for the Master in Economics, specialization in Economic Growth and Structural Policies presented to the Faculty of Economics of the University of Coimbra in order to obtain the Master's Degree

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Abstract

Past technological developments raised concerns that automation could replace labour. Recent advances in automation induced by Artificial Intelligence (AI) have been reinforcing these concerns, giving rise to a widespread belief that AI will destroy a significant proportion of jobs. This work project investigates the impact of AI and automation on employment in the context of the Portuguese economy considering the mediating role of demand, focusing on 37 sectors of activity over the period 1995-2016 in order to provide an adequate framework to analyse how AI is likely to affect employment over the next years. For that, a model that accommodates productivity and demand effects deriving from the introduction of new technologies was considered. The results of the estimation of the impact of productivity on sectoral employment reveal that employment is not being impacted by automation in half of the sectors considered. In the remaining sectors, automation is contributing to employment reduction (especially in manufacturing sectors, where the effect is more intense). The only exception refers to the case of social work activities, in which technology has been contributing to an increase in employment. This project concludes that although there is potential for *technological unemployment* in certain sectors of the Portuguese economy, the introduction of AI technologies will not necessarily result in unemployment. Additionally, it is highlighted that a significant period of time might be needed to accommodate restructuring processes associated with the introduction of AI which can cause a delay between the recognition of AI's potential and its measurable effects on productivity and employment.

Keywords: Artificial intelligence, automation, productivity, demand, employment

JEL Classification: E23, E24, E27, J20, J24

Resumo

Avanços tecnológicos passados geraram preocupações relacionadas com o facto de a automação poder substituir os indivíduos nas suas tarefas. Recentemente, no seguimento de desenvolvimentos verificados no campo da Inteligência Artificial (IA), tem vindo a ressurgir uma preocupação generalizada de que a automação possa destruir um número significativo de postos de trabalho. Este projecto estuda o impacto da automação no emprego em 37 sectores da economia portuguesa, considerando o período 1995-2016, e destacando o papel da procura, tendo como objectivo construir um quadro de análise que permita compreender o modo como a IA poderá impactar o emprego nos próximos anos. Para tal, foi considerado um modelo que contempla efeitos de produtividade e procura resultantes da introdução de novas tecnologias. Os resultados da estimação do impacto da produtividade no emprego sectorial revelam que o emprego não é afectado significativamente pela automação em cerca de metade dos sectores analisados. Nos restantes sectores, a automação contribui para a redução do emprego (especialmente no caso dos sectores de manufatura, onde o efeito se faz sentir de forma mais intensa). A única excepção refere-se ao caso das actividades de apoio social, onde a tecnologia tem contribuído para o aumento do emprego. O projecto conclui que, apesar de existir margem para uma situação de *desemprego tecnológico* em determinados sectores da economia portuguesa, a introdução de tecnologias de IA não conduzirá necessariamente a uma diminuição do emprego. Para além disso, o projecto alerta para o facto de poder ser necessário um período de tempo significativo para acomodar processos de reestruturação associados à AI, o que poderá levar a que os efeitos reais da IA na produtividade e emprego se façam sentir numa fase posterior.

Palavras-chave: Inteligência artificial, automação, produtividade, procura, emprego

Classificação JEL: E23, E24, E27, J20, J24

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1. Introduction

In recent years, major advances in Artificial Intelligence (AI) have been observed. This continuous technological development has been able to increasingly promote the automation of tasks. In this context, the rise of AI has been associated with concerns related to job losses. Specifically, a recent survey reveals that over 70% of individuals show concerns regarding the implications of AI, namely in terms of replacement of jobs that are currently performed by humans (Smith and Anderson, 2017). Accordingly, nowadays there is a general belief that AI technologies will potentially contribute to significant unemployment in the future - a phenomenon designated by Autor (2014) as automation anxiety. The literature also suggests that there is "a substantial share of employment, across a wide range of occupations, at risk in the near future" (Frey and Osborn, 2013). However, recent studies show that employment has the potential to grow in industries undergoing technological transformation (Bessen, 2017; Bessen, 2018).

In fact, developments in technology can be associated with different outcomes. First, as automation progresses, the reduction of labour requirements per unit of output produced is observed. Second (as a consequence of the first outcome), it can contribute to the reduction of prices. Third, it can lead to improved product quality. Thus, as technology evolves within a certain industry, two different scenarios can occur in what refers to employment: 1) technology induced reduction in labour requirements leads to a decrease in the number of jobs; 2) technology induced reduction in labour requirements encourages a situation of price reduction that, together with product quality improvements, generates higher demand and, consequently, the need for more workers - the increase in the amount demanded can be sufficient to offset the technology effect on employment, i.e., the number of jobs created by demand is higher than the number of jobs destroyed by automation (Bessen, 2017).

Demand seems to play an important role in the context of the relationship between technology and employment. Specifically, it is important to consider the nature and responsiveness of demand (i.e. whether it is elastic or inelastic), which can change over time (Bessen, 2018). Bessen (2018) proposes a model about the relationship between technology and employment that considers income and price effects on demand, allowing both elasticities to vary over time. The work developed by Bessen suggests that if technology developments occur within a satiated industry (i.e. where consumers' needs are fulfilled), where the elasticities are low (i.e. less than 1), jobs will be lost within that industry because demand will not increase sufficiently. If, on the other hand, the technology advances occur within an industry associated with consumers' unmet needs (i.e. elasticity greater than 1), than the induced increase in productivity will originate a higher demand level that will offset the reduction in labour derived from technology advances. The same logic can be applied to new technologies, where AI is included.

This project examines the impact of AI on employment in the context of the Portuguese economy incorporating Bessen's argument on the mediating role of demand on the relationship between technology and employment to analyse employment at the sectoral level. For this purpose, we perform an econometric analysis using time series sectoral data for 37 sectors of the Portuguese economy, considering the statistical classification of economic activities in the European Community, to estimate the impact of technological improvements through AI and automation on sectoral employment. The period under analysis is 1995-2016 and the main data sources are Instituto Nacional de Estatística (Portuguese National Statistics Agency) and OECD.

The remainder of this work is organized as follows: after the Introduction, section 2 presents literature review. Section 3 describes the Portuguese economy in terms of technology, productivity and employment. In section 4 methodology and data are presented. Section 5 outlines and discusses our results, and Section 6 concludes.

2. Literature review

In the past decades significant progress has been observed within the field of computer technologies resulting in substantial increases in the automation of tasks. The accelerated automation of tasks previously performed by workers has been raising concerns that new technologies will replace labour - a phenomenon designated by Autor (2014) as *automation anxiety*. Indeed, the literature suggests that a significant proportion of jobs are susceptible to automation. For example, Bowles (2014) mentions a range between 45 to more than 60% of jobs for the case of European countries. Similarly, Frey and Osborn (2013) argue that 47% of US jobs are at high risk of being automated. However, both studies considered an occupation-based approach, assuming that whole occupations rather than isolated tasks are automated, which might lead to overestimation of jobs at risk of automation. In contrast, Arntz, Gregory, Lehmer, Matthes, and Zierahn (2016) followed a task-based approach, considering that only high automatability jobs (i.e. an automatability of at least 70%) are at risk and they found that, across OECD countries, only 9% of jobs are automatable.

Artificial Intelligence (AI) is currently viewed as a new improved form of automation. In 2016, the World Economic Forum called AI *the Fourth Industrial Revolution*. According to the American Merriam-Webster dictionary, AI is defined as "the capability of a machine to imitate intelligent human behaviour". AI systems rely on large databases and use classes of algorithms to map different kinds of tasks in an autonomous way, which contrasts with previous computer programs that required very precise coding activities performed by programmers. Therefore, the advent of AI brings the possibility to take automation one step further, considering not only routine and easily codifiable tasks, but also tasks involving higher levels of complexity. According to Agrawal, Gans, and Goldfarb (2017), AI systems show particular relevance in tasks involving prediction (e.g. prediction of a disease's cause, prediction of consumers' preferences), which works as an input for automation. Additionally, at present, AI comprises technologies such as Smart Factories, Cyber-Physical Systems, Big Data and Cloud Computing Systems.

A recent study conducted by Trajtenberg (2018) classifies AI as the new General Purpose Technology (GPT)[1], expecting it to have a substantial negative impact on employment. Similarly, Brynjolfsson and McAfee (2014) refer to "the danger of massive job destruction".

[1] GPT represents a major new technology that is pervasive, able to be improved over time and to contribute to the proliferation of complementary innovations (Bresnahan and Trajtenberg, 1996).

Additionally, a recent survey reveals that over 70% of individuals show concerns regarding the implications of AI, namely in terms of replacement of jobs that are currently performed by humans (Smith and Anderson, 2017). Accordingly, it is evident that a new wave of concern with regards to employment is emerging in the context of the development of AI as an improved form of automation.

Although there is a widespread concern about *technological unemployment*[2], the literature reveals that advances in technology automation do not necessarily lead to job losses because there are macroeconomic feedback mechanisms that may contribute to the stabilization or even to increases in employment (Arntz et al., 2016). In this context, it is important to highlight that automation technology can have two distinct effects on jobs: 1) a substitution effect; 2) a complementarity effect (Autor, 2015, 2014). First, a substitution effect occurs when workers are replaced by machines, leading to employment reduction. It is generally related with routine tasks, i.e. tasks that follow well-defined protocols that can be fully codified and easily automated; mostly those involving middle-skilled cognitive and manual activities. The substitution effect arises in the context of "human-replacing innovations" ("HRI"), that is, technical advances that replace human intervention (Trajtenberg, 2018). Second, a complementarity effect arises when, as a result of the introduction of new technologies, workers become more productive and creative in their tasks. This is mostly related with nonroutine tasks, i.e. tasks implying tacit knowledge that require problem-solving skills, interpersonal skills, intuition, and creativity. The complementarity effect arises in the context of "human-enhancing innovations" ("HEI") (Trajtenberg, 2018), that is, technologies that help workers in their tasks, making them more effective. Therefore, this scenario illustrates the fact that the introduction of new automation technologies may not necessarily result in employment reduction. On the contrary, it may contribute to enhance the potential of workers in terms of productivity.

It is evident that the introduction of new automation technologies can result in different scenarios with regards to employment. In fact, the work developed by Gregory, Salomons and Zierahn (2018) argue that routine-replacing technological change (RRTC), i.e. the introduction of new automation technologies in the context of routine tasks, result in several forces that can impact employment in different ways. Moreover, the intensity of these forces

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[2] *Technological unemployment*, a concept introduced by Keynes (1930), refers to the unemployment associated with the implementation of new technologies that reduce the use of labour. Considering the author's view, *technological unemployment* is "only a temporary phase of maladjustment" that in the long run leads to higher standards of living for the individuals.

will depend on two factors: 1) routine task intensity – sectors with higher share of routine tasks are more susceptible to the introduction of new technologies since these tasks are easier to automate; 2) nature of the sector – it is assumed that tradable sectors use labour and capital in the production processes, thus it is possible to replace labour by capital; it is assumed that non-tradable sectors only use labour in the production processes hence no replacement is possible in this case. Thus, the first force to consider is the *substitution effect* – declining capital costs incentivize firms to adopt new automation technologies; consequently, labour may be replaced by capital and employment decreases (this effect only occurs in tradable sectors). The second refers to *product demand effect* – new automation technologies reduce costs and prices; this can lead to an increase in product demand and, consequently, to higher employment (this effect only occurs in tradable sectors). The third effect is called *product demand spillovers* – the increase in product demand within a particular (tradable) sector, as a result of the introduction of a new automation technology in that sector, can raise income which in turn can be spent in other (tradable and non-tradable) sectors, raising demand and consequently employment in those other sectors. Based on these premises, the authors propose an empirical estimate of the economy-wide effect of RRTC on employment. For that, data over 1999-2010 for 238 regions across 27 European countries was used, considering 14 sectors (C-P; NACE revision 1.1). The authors observed a substantial decrease in employment resulting from the substitution of capital for labour. However, the *product demand* effect and *product demand spillovers effect* act as countervailing forces that are sufficient to offset the job destruction associated with the *substitution effect.* Overall, the authors found that, on net, employment increased in Europe in the period considered.

Similarly, Autor and Salomons (2018) argue that there are three channels through which automation impacts employment. The first one refers to *own-industry effects* (direct effect): introduction of new automation technologies in one particular sector may result in the substitution of labour by capital which results in employment decrease. The second is *final demand effect* (indirect effect): the introduction of new automation technologies increases productivity which in turn raises individuals' incomes and boosts final demand, resulting in higher employment. The third refers to *cross-industry input-output linkage effect* (indirect effect) and it is related with the fact that the introduction of new automation technologies can lower input costs in downstream customer industries, leading to output and employment growth in these downstream sectors. To study the impact of these channels, the authors used cross-country and cross-industry data (18 developed countries of the European Union, Australia, Japan, South Korea and United States; 28 industries) for the period between 1970 and 2007. It was found that productivity growth, as a result of the introduction of new automation technologies in one particular industry, reduced own-industry employment. On the other hand, final demand effects more than offset the direct effect. Additionally, it was found a large positive effect of rising productivity in upstream (supplier) industries on employment in customer industries, leading to output and employment growth in these downstream sectors. The sum of these components resulted in a positive "net effect" of productivity gains on aggregate employment. A similar pattern was found when considering heterogeneity across industries.

Thus, the two highlighted studies show that although some jobs might be destroyed due to the introduction of new technologies that enable higher levels of automation in the production processes, there are countervailing forces that can create additional jobs, resulting in a positive net effect in terms of employment.

In line with these views, recent studies considering an approach that highlights the role of demand show that employment has the potential to grow in industries undergoing technological transformation (Bessen, 2017; Bessen, 2018). In this context, Arntz., Gregory, and Lehmer. (2017) argue that "technology significantly affects firms' employment structure through product demand". Moreover, the authors sustain that automation's ability to complement labour will conduct to increased productivity which in turn may lower costs and prices. Consequently, higher product demand may arise, resulting in the need for more employees to keep up with the increased product demand (i.e. an increase in employment will be observed). An example given by Bessen (2016) illustrates this situation. The author considers automated teller machines (ATMs) as a representative example of technology complementing workers. ATMs took over cash handling tasks. However, the author shows that the rise in ATMs was accompanied by an increase in the number of full equivalent bank tellers because the increase in productivity associated with the introduction of ATMs allowed banks to operate branch offices at lower cost and this encouraged them to open more branches, requiring additional workers (i.e. an increase in employment was observed). Thus, there are circumstances under which, within the same industry, job destruction caused by the introduction of a new automation technology can be compensated by job creation, resulting in increased employment.

Overall, demand seems to play an important role in the context of the relationship between automation technology and employment. Bessen (2018) proposes a model of the effect of AI on employment, considering the nature of demand. The basic intuition is that the impact of AI on employment will depend on the nature of the targeted industry: a) a satiated industry, characterized by a price elasticity of demand lower than 1; b) a non-satiated industry, characterized by a price elasticity of demand greater than 1.

First, let us consider a general situation where AI is introduced in a certain industry. As a result of the introduction of a new technology, productivity will be enhanced and labour requirements per unit of output will decrease (i.e. AI is considered a productivity driver). Consequently, the price will decrease (which is equivalent to an income increase). On the other hand, the introduction of a new technology may also improve product quality. Taken together, these two factors – lower price and improved quality - may promote an increase in demand. The degree of increase in demand will depend on the industry's characteristics/nature. Let us consider the case of a satiated industry. If AI is introduced in a satiated industry, i.e. an industry where consumers' needs are met (price elasticity of demand is less than 1), price reduction will not trigger a significant increase in demand because consumers are satisfied with regards to the product offered by that industry. In this case, the increase in demand will not be sufficient to generate enough jobs to offset the labour-saving effect of the technology and a decrease in employment will be observed. On the other hand, if we consider a non-satiated industry, i.e. an industry where consumers' needs are unmet (price elasticity of demand is greater than 1), price reduction will allow consumers to satisfy their unmet needs within that industry. This can result in a significant increase in demand. In order to keep up with the increased demand, companies will need to hire additional employees. Consequently, the number of additional jobs created by demand can be sufficient to offset the number of jobs destroyed by the labour-saving effect of the technology, resulting in an increase in employment.

It is important to note that not only different industries can show different price elasticities, but also that price elasticities can change over time within the same industry. Thus, the impact of new technologies in one particular industry should not be considered static. Bessen's manufacturing sector example illustrates this logic (Bessen, 2017). The author analysed two centuries of data (from 19th century to 21st century) referring to the US aggregate manufacturing sector (i.e. aggregation of separate manufacturing industries such as textile, steel and automotive industry) and observed an inverted U pattern in the relative share of employment in the stated sector. This is explained by the interaction between productivity growth and demand. With the introduction of new technologies, the price of manufactured goods decreased. Because of that, in an initial phase (rising phase), consumers rose their demand for manufactured goods (elastic demand). Consequently, new jobs were created to respond to the rise in demand. Later, the consumers' needs in terms of manufactured products were met (inelastic demand) and they gradually started to buy other products further down on their preferences hierarchy. Since manufacturing demand turned to be insufficient, jobs were destroyed and the share of relative employment in the manufacturing sector started to decline (descending phase). This example highlights the existence of changing demand elasticities over time.

AI's role as productivity driver can be present in an extensive variety of professions and industries. Thus, the study of its relationship with employment is particularly relevant given its prominent potential impact in different sectors of the economy, namely in terms of new opportunities for value creation and cost reduction. This project studies the impact of AI on employment in the context of the Portuguese economy incorporating Bessen's argument on the mediating role of demand on the relationship between technology and employment to analyse employment in 37 sectors of the Portuguese economy. Accordingly, it is important to consider not only the general context of the Portuguese economy in terms of technology, productivity and employment, but also to highlight specificities associated with each particular sector. The next section offers a concise overview of the context of the Portuguese economy and its most relevant sectors.

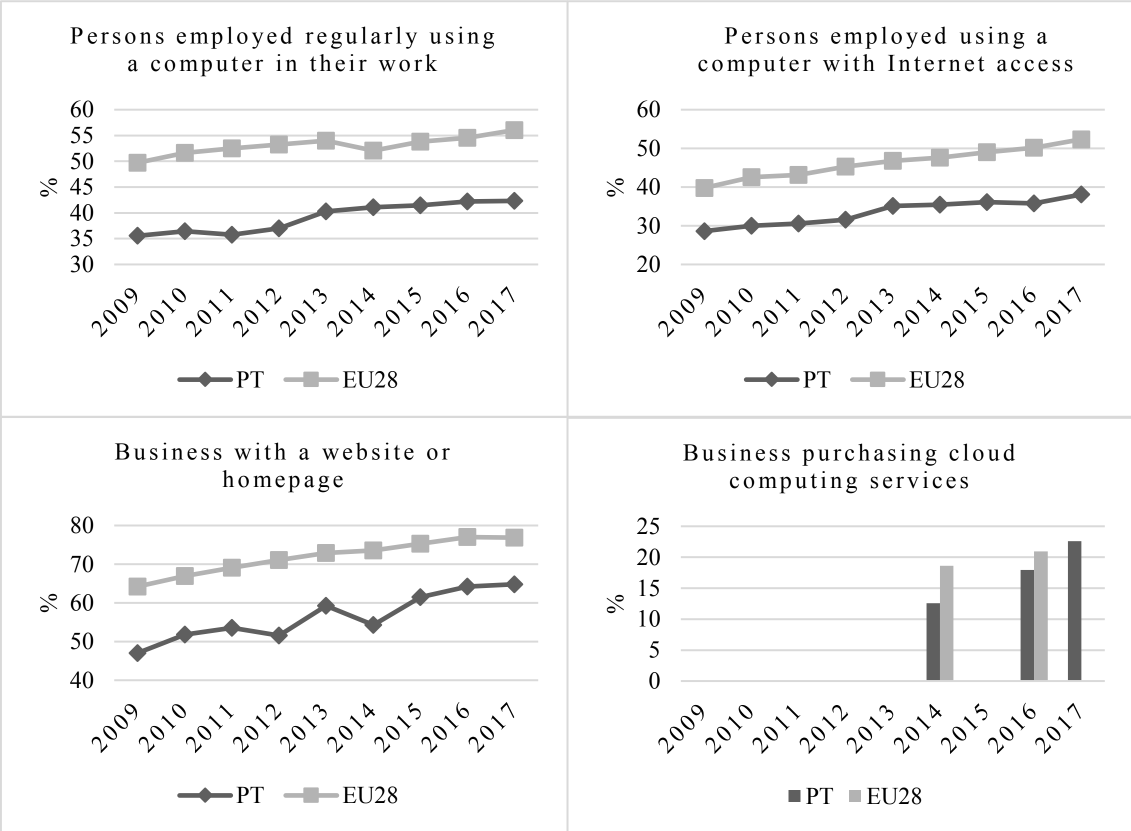
3. Contextualizing the Portuguese economy: technology, productivity and employment

This section is intended to contextualize the Portuguese economy in terms of technology, productivity and employment, in order to create a background for the analysis of the relationship between AI and employment in Portugal at the sectoral level, considering the impact of demand as suggested by Bessen (2017; 2018). Technology improvements (namely in the domain of AI) within a specific sector often result in higher levels of automation in the respective production processes, which can lead not only to productivity gains (i.e. reduction of labour requirements per unit of output), but also to improved quality of the products. As a result, employment within that particular sector can change and, in some cases, result in unemployment of workers qualified to perform the tasks that have been automated. Consequently, it is important to analyse the behavioural patterns of technology, productivity and employment in the context of the Portuguese economy to get an initial understanding of the potential for *technological unemployment*.

Regarding technology in the Portuguese economy (PT), a positive trend is visible in all the variables considered[3] (Figure 1). Thus, it is reasonable to admit that PT has been adopting new technologies over the last decade, namely AI technologies. However, the numbers revealed for PT are lower than those shown for the EU28, which indicates lower levels of technology within Portuguese businesses.

[3] The variables considered were selected based on the approach followed by Bessen (2017). The author considers computer technology (i.e. a measure of computer use in the workplace) to analyse the impact of technology on sectoral employment.

Figure 1. Technology adoption by businesses – Portugal 2009-2017



Source: OECD

Specifically, for the variable *persons employed regularly using a computer in their workplace (%)*, a pattern of convergence is observed between PT and the EU28 for the period between 2009 and 2014. In 2014, 41.09% of persons employed regularly in PT were using a computer in their workplace, while in the EU28, this number was 52.04%. After 2014, the convergence pattern started to fade away and in 2017, computer was used by 42.32% persons employed in PT, which contrasts with 56.06% in the EU28. With regards to *persons employed using a computer with Internet access (%)*, it is visible that between 2009 and 2013, PT and the EU28 adopted this kind of technology at a similar pace, although PT started with a lower value (28.64%) than the EU28 (38.78%) in 2009. After 2013, a slight divergence pattern starts to emerge and in 2017, the gap between both regions was bigger than in 2009 – 38.07% for PT and 52.34% for the EU28. In terms of *businesses with a website or homepage (%)*, once again PT reveals lower values than the EU28. Additionally, some fluctuations are observed over the time for PT – specifically, in 2013 a peak was observed, corresponding to 59.23% of business having a website or homepage. Finally, although the data about *businesses purchasing cloud computing services* is scarce, it is evident that PT has made progress between 2014 and 2016, getting closer to the EU28 values – in 2014, 12.56% of Portuguese businesses were using cloud computing services, while this value increased to 17.95%, respectively in 2016 (18.60% and 20.94% for the case of the EU28, respectively).

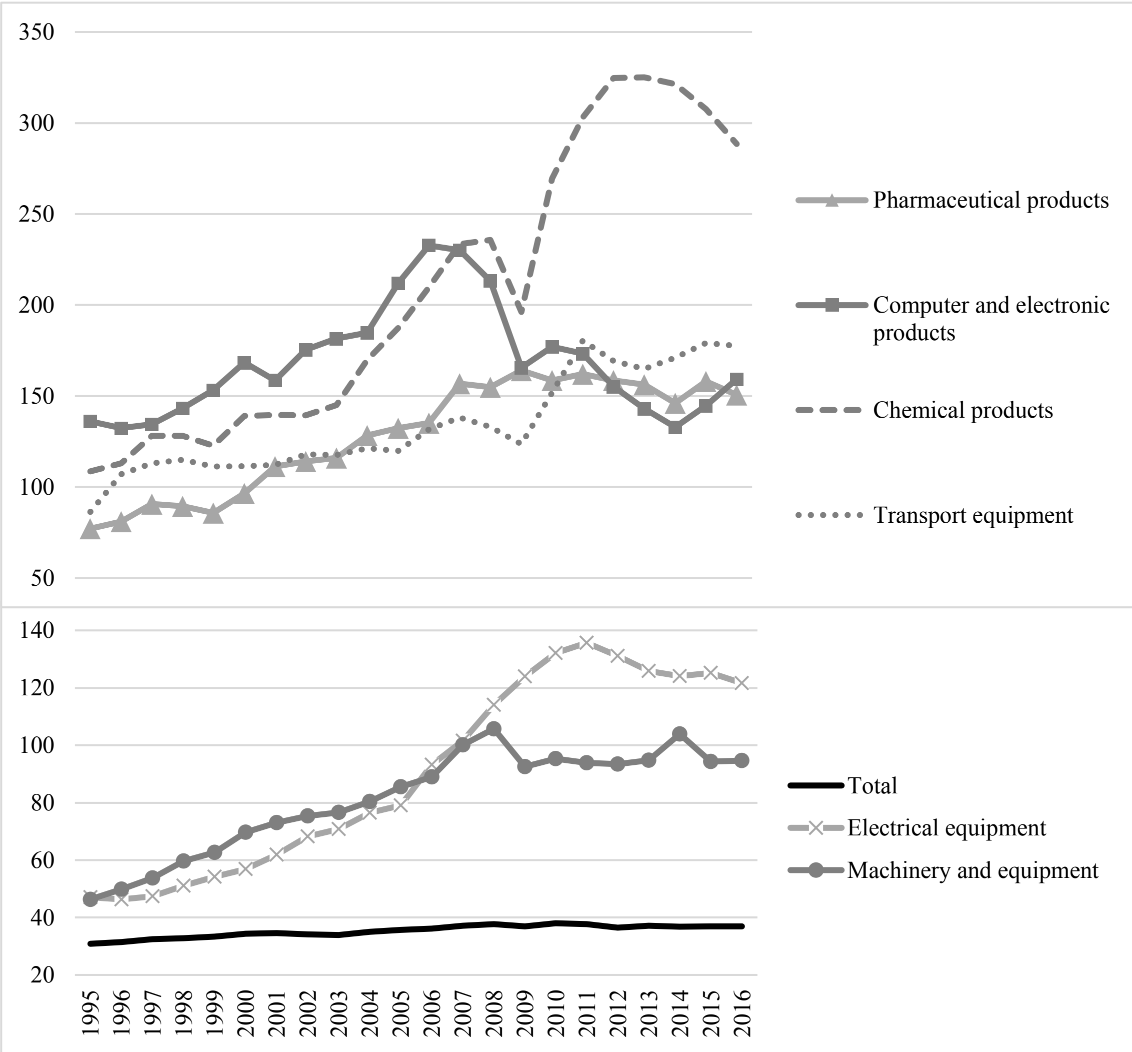
In sum, although the Portuguese economy is not at the same level as the EU28 in terms of technology adoption in the workplace, significant positive progress has been made since 2009 and a pattern of convergence is observed in the period considered for some of the variables under analysis.

The adoption of new technologies often leads to substantial increases in automation of tasks which in turn result in productivity gains (i.e. reduction of labour requirements per unit of output). Thus, it is important to analyse the Portuguese economy in terms of productivity, considering not only a global view, but also some of the most relevant sectors in terms of technological intensity. For that, *high-technology* and *medium-high-technology*[4] manufacturing industries were considered in the analysis.

Considering *GDP per hour worked* (Figure 2), a positive trend is observed for the Portuguese economy which is indicative of a trajectory of increased productivity over time. However, after 2007-2008 the rising tendency slowed down and a negative growth rate of -2.33% was observed between 2008 and 2009.

[4] According to the *high-tech classification of manufacturing industries* used by the Eurostat (NACE Rev. 2, 2-digit level), *high-technology* sectors are: a) manufacture of basic pharmaceutical products and pharmaceutical preparations, b) manufacture of computer, electronic and optical products; *medium-high-technology sectors* are: a) manufacture of chemicals and chemical products; b) manufacture of electrical equipment; c) manufacture of machinery and equipment; d) manufacture of motor vehicles, trailers and semi-trailers, e) manufacture of other transport equipment. In this project, the last two sectors were aggregated into one single sector: f) manufacture of transport equipment.

Figure 2. GDP per hour worked (EUR, constant prices, 2012) by sector – Portugal 1995-2016



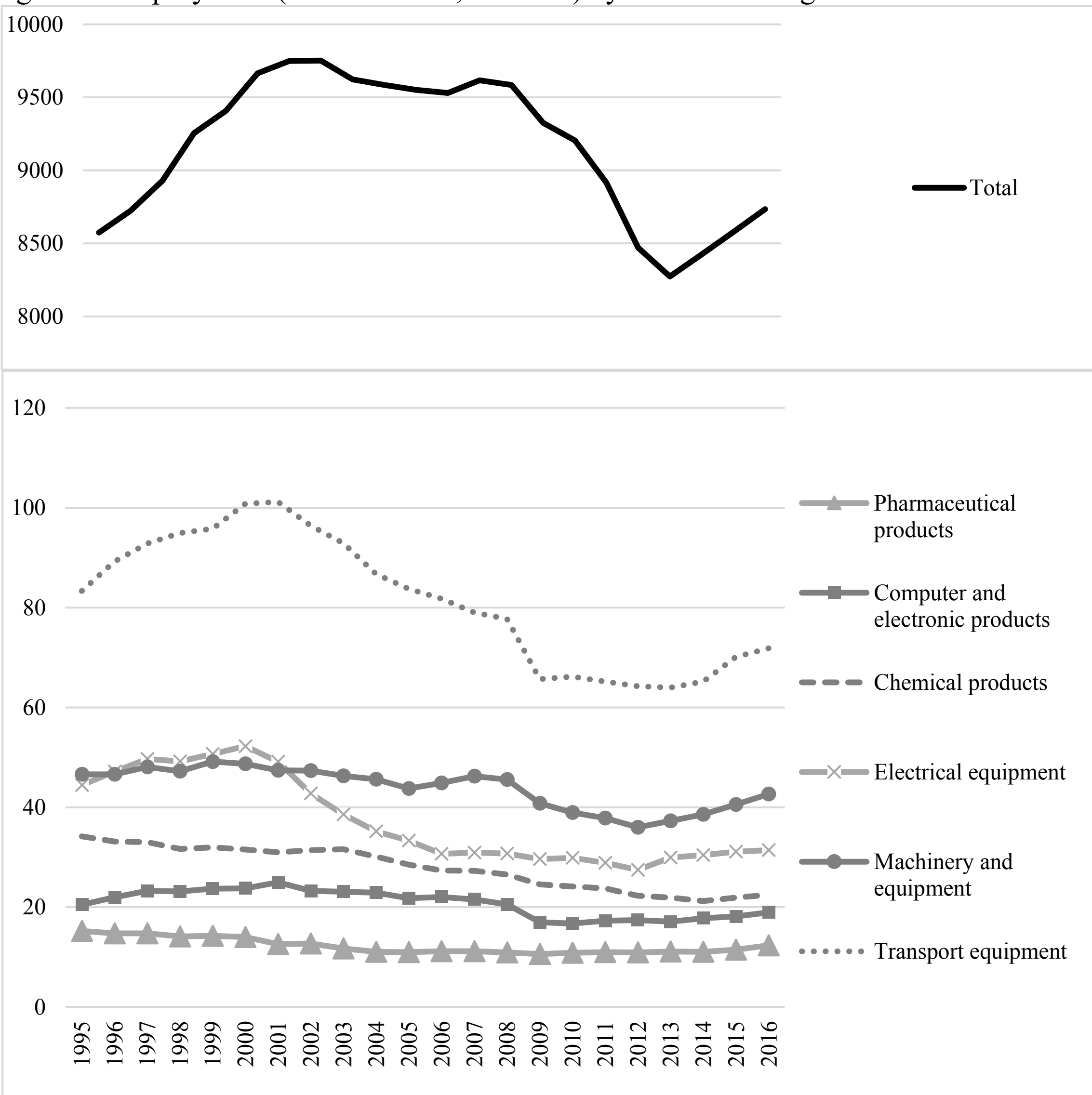
Source: Instituto Nacional de Estatística (Portuguese National Statistics Agency)

Considering the different sectors under analysis, more specific productivity patterns can be observed. First, *chemical products* and *transport equipment* reveal a similar behaviour: a positive trend until 2007-2008 followed by an abrupt decrease (growth rates for the period 2008-2009 were -16.78% and -7.15%, respectively). After 2010, a period of fast recovery is observed followed by decrease/ stagnation. *Machinery and equipment* followed a similar pattern, except that recovery was not so pronounced as in the previously mentioned sectors. On the other hand, the productivity associated with *computer and electronic products* sector shows a positive trend until 2006 (in 2006, GDP per hour worked was 232.70), followed by a marked downward trend (growth rate for the period 2008-2009 was -22.29%). Finally, *pharmaceutical products* and *electrical equipment* sectors have been showing a tendency of rising productivity and since 2010-2011 a pattern of stagnation/ decreasing productivity, respectively.

In sum, it is evident that the majority of the sectors under analysis showed a positive trend in terms of productivity until 2009-2010. After that, different scenarios emerged, as described above. Since productivity reflects labour requirements per unit of output, it is important to investigate how the referred changes in productivity may be related with changes in employment. Thus, employment is next analysed, considering the same six sectors.

Figure 3 shows that, considering the Portuguese economy as a whole, employment rose between 1995 and 2002. After that period, a decreasing trend starts to emerge, and a more pronounced negative trajectory arises in the context of the 2007-2008 financial crisis. After 2013, a new period of prosperity in terms of employment emerges with annual growth rates of 1.8% each year until 2016. In general, the majority of the sectors under analysis follow a similar pattern, although less pronounced. The sectors of *chemical products* and *pharmaceutical products* should be highlighted since they show a negative/ stagnation trend during the period considered. The year of 2015 represents a turning point for these sectors – growth rate of 3.14% for *chemical products* and 4.36% for *pharmaceutical products*.

Figure 3. Employment (hours worked, millions) by sector – Portugal 1995-2016



Source: Instituto Nacional de Estatística (Portuguese National Statistics Agency)

Overall, the Portuguese economy has been adopting new technologies over the years since 1995, in the context of workplace. This finding reflects two possible outcomes. First, automation of tasks in the workplace has been increasing in the last decades. Second, the Portuguese economy has the potential to adopt new technologies such as AI technologies and, consequently, take the automation of tasks in the workplace to a higher level. The automation of tasks often results in increased productivity, since workers can perform their tasks more effectively. As expected, the analysis performed show that, considering the Portuguese economy as a whole, for the period between 1995 and 2008, a pattern of increasing productivity is observed. Additionally, in the referred timeframe, employment showed both a subperiod of increase and decrease. Thus, it is reasonable to assume that the adoption of new technologies increased productivity (i.e. decrease in labour requirements per unit of output) which in turn contributed to an increase of employment in a first phase (1995-2000) and then, in a second phase (2000-2008), to a decrease of employment. Therefore, one can assume that some of the economy's characteristics might have changed over time – it would explain why an increase in productivity is associated first to increasing employment and then to decreasing employment. Considering the literature on this topic (Bessen, 2017; 2018), it is reasonable to assume that the first phase corresponds to a period in which individuals' needs were unmet in a considerable number of sectors. Thus, the introduction of new technologies raised productivity, i.e., decreased labour requirements per unit of output (jobs destroyed). Consequently, prices decreased and, because individuals' needs were not met, demand rose significantly. The referred increase in demand lead to job creation sufficient to offset jobs destroyed by productivity gains, resulting in an increase in employment. On the other hand, the second phase is likely to illustrate a subsequent period in which individuals' needs were already met, corresponding to a progressive decrease in demand and consequent decrease in employment. This situation corresponds to the scenario of changing elasticities pointed by Bessen (2017).

After 2009, overall productivity shows a pattern of stabilisation, making it difficult to establish a logic relationship with employment which in turn showed periods of steep decrease and increase. Specifically, the patterns of productivity and employment observed for the sectors under analysis are also varied. Therefore, it is important to establish a model of causal relationship, not only to understand the relationship between technology adoption in the workplace (and consequent automation of tasks), productivity and employment in the context of the whole Portuguese economy, but also to understand the different patterns for these relationships that may arise in the context of sectors with different characteristics. Additionally, in order to have a more comprehensive understanding on the relationship between technology, productivity and employment it is important to reflect about variations of *intensity* of demand, considering the fact that the nature of demand for each particular sector can change over time.

4. Methodology and data

This project focuses on the impact of technological improvements through automation on employment in 37 sectors of the Portuguese economy, considering the role of demand. The goal is to present a model that helps to predict the rise and fall of employment in 37 sectors of the Portuguese economy in order to deliver a convenient framework to analyse how AI is likely to affect employment. This section explores the data and model considered.

This project uses time series sectoral data for 37 sectors of the Portuguese economy, considering the statistical classification of economic activities of the European Community (cf. Appendix A, Table A.1). The period under analysis is 1995-2016 (yearly data) and the main data sources are *Instituto Nacional de Estatística* (Portuguese National Statistics Agency) and OECD stats (https://stats.oecd.org/).

The model suggested in the context of this project is intended to analyse the impact of technology on employment in each of the 37 sectors considered and it builds on the suggestion of Bessen (2017; 2018) regarding the role of demand. For that, it is assumed that the behaviour of one particular sector may be represented by that of a representative firm operating in a competitive market.

The profit of the representative firm is then given by:

$$\pi = P.f(A,K,L) - R.K - W.L \quad (1)$$

where,

P is the market price of the sector's output;

$f(A,K,L)$ = Y is the level of aggregate output in the sector (i.e. output supply) and it is influenced by the amounts of inputs that are being used – in this case, capital (K) and labour (L) – as well as by the productivity of such inputs (A);

R is the rental price of capital;

K is the level of capital;

W is the price of labour (nominal wage);

L is the level of labour.

The representative firm of the sector will choose the levels of capital (K) and labour (L) in order to maximize profits. Thus, the first order conditions required to maximize profit are given by equations (2) and (3).

$$\frac{\partial \pi}{\partial K} = 0 \iff P f_K(A,K,L) = R \quad (2)$$

Equation (2) describes the demand for K. The firm will choose the level of K for which the marginal productivity of capital (nominal, i.e. the extra revenue the firm can make from selling the output produced by an additional unit of capital, *ceteris paribus*) is equal to the rental price of capital (R).

$$\frac{\partial \pi}{\partial L} = 0 \iff Pf_L(A,K,L) = W \tag{3}$$

Equation (3) describes the demand for L. The firm will choose the level of L for which the marginal productivity of labour (nominal, i.e. the extra revenue the firm can make from selling the output produced by an extra unit of labour, *ceteris paribus*) is equal to the nominal wage (W) prevailing in the labour market.

Accordingly, relative input usages are optimal when the marginal rate of technical substitution equals input price ratio:

$$\frac{f_K(A,K,L)}{f_L(A,K,L)} = \frac{R}{W} \tag{4}$$

From the assumptions and optimizing conditions above, equations (5) and (6) show that the levels of K and L to be chosen by the sector will depend on A, W, R and L or K, respectively.

$$K = g^K\,(A,W,R,L) \tag{5}$$

$$L = g^L\,(A,W,R,K) \tag{6}$$

Therefore, considering the level of output supplied in the sector (Y), the levels of K and L chosen are given by equations (8) and (10), respectively:

$$Y = f(A,K,L) = f\big(A,K,g^L(A,W,R,K)\big) = f^k(A,W,R,K) \tag{7}$$

$$K = K^d(A,W,R,Y), \text{ demand for capital} \tag{8}$$

$$Y = f(A,K,L) = f(A,g^k(A,W,R,L),L) = f^L(A,W,R,L) \tag{9}$$

$$L = L^d(A,W,R,Y), \text{ demand for labour} \tag{10}$$

Total costs are then given by:

$$TC = W.L + R.K \tag{11}$$

And thus the marginal cost function is:

$$MC = W.L_Y^d(A,W,R,Y) + R.K_Y^d(A,W,R,Y) = m(A,W,R,Y) \tag{12}$$

Finally, under the assumption of perfect competition, profit maximization implies:

$$P = MC = m(A, W, R, Y) \tag{13}$$

which corresponds the supply curve for the output of the representative firm.

On the demand side, considering the work of Dixit and Stiglitz (1977) with the addition of foreign variables (G^*, P^*), demand for the sector's output is given by:

$$Y = Y^D(G, G^*, \bar{P}, P^*, P) \tag{14}$$

where,

Y^D is output demand;

G represents aggregate (overall sectors) domestic demand;

G^* represents aggregate foreign demand;

$\bar{P}$ represents the domestic price level;

P^* represents the foreign price level;

P is the market price of the sector's output.

Accordingly, demand for the sector's output will increase if both domestic (G) and foreign (G*) aggregate demand increase. Similarly, increases in the domestic price level ($\bar{P}$) and decreases in the market price of the sector's output (P) will stimulate demand for the sector's output. Additionally, a relative increase in the foreign price level (P*) will increase demand for the sector's output since foreign goods become relatively more expensive when compared to domestic goods.

Thus, in equilibrium, demand equals supply so that

$$Y = Y^D(G, G^*, \bar{P}, P^*, P) = Y^D\big(G, G^*, \bar{P}, P^*, m(A, W, R, Y)\big) \Leftrightarrow \tag{15}$$

$$Y = Y^e(A, W, R, G, G^*, \bar{P}, P^*) \tag{16}$$

where Y^e corresponds to equilibrium output.

Consequently, considering Y^e and its determinants, demand for labour will be given by:

$$L = L^d(A, W, R, Y) = L^d\big(A, W, R, Y^e(A, W, R, G, G^*, \bar{P}, P^*)\big) \Leftrightarrow \tag{17}$$

$$L = L^e(A, W, R, G, G^*, \bar{P}, P^*) \tag{18}$$

Based on the theoretical approach described above, and considering a log-linear approximation to L^e we propose the following econometric model, where the lower-case letters represent logarithms of corresponding lower-case letters[5]:

$$emp_t = \beta_{1_t} + \beta_2 a_t + \beta_3 w_t + \beta_4 r_t + \beta_5 g_t + \beta_6 {g^*}_t + \beta_7 \bar{p}_t + \beta_8 {p^*}_t + u_t \quad (19)$$

This model assumes that the dependent variable – employment (*emp)* – depends on productivity (a), the price of labour (w), the rental price of capital (r), aggregate domestic demand (g), aggregate foreign demand ($g*$), the domestic price level ($\bar{p}$) and the foreign price level ($p*$), according to the theoretical model described above. Since the main goal of this project is to understand the specific impact of productivity (a) – representing technological improvements - on sectoral employment (*emp*), the parameter of interest is β_2. Accordingly, the remaining variables are included as control variables. This way, it will be possible to consider the mediating role of demand on the relationship between productivity deriving from the introduction of new technologies and sectoral employment.

It is assumed that improvements in productivity result from the introduction of new AI technologies. Therefore, all else equal, a positive (negative) estimated coefficient for labour productivity (β_2) can be interpreted as automation having a positive (negative) role on sectoral employment (*emp*). Specifically, it is assumed that the introduction of a new automation technology induces two distinct effects: 1) a *productivity effect*; and 2) a *demand effect*. The *productivity effect* reflects the existence of decreasing labour requirements per unit of output which results in the destruction of jobs. The *demand effect* is associated with the existence of decreasing costs (deriving from the introduction of new, more cost effective, automation technologies) that lower prices and stimulate demand, resulting in the creation of jobs. In this context, three scenarios may arise: 1) productivity and demand effects show similar dimensions and employment is not impacted because jobs created *exactly* compensate jobs destroyed (β_2 is not significant); 2) the intensity of the productivity effect exceeds the intensity of the demand effect and employment is negatively impacted because jobs created are not sufficient to compensate jobs destroyed (β_2 is negative); 3) the intensity of the productivity effect is smaller than the intensity of the demand effect and employment is positively impacted because jobs created more than compensate jobs destroyed (β_2 is positive).

[5] See Appendix B for computation of *r*

It is also important to stress, once more, that the impact of some of the explanatory variables on sectoral employment may be different, depending on the characteristics of the sector under analysis, i.e., whether the demand for the sector's output is inelastic or not. On the other hand, other explanatory variables may have a similar impact on employment (in terms of the sign of the impact), regardless of the characteristics of the sector under analysis.

Let us first consider the explanatory variables whose impact on employment (*emp*) may vary according to the characteristics of the sector considered. First, if demand for the sector's output is sufficiently inelastic, the coefficient associated with labour productivity (β_2) is expected to exhibit a negative sign. The introduction of automation technologies will result in a reduction of labour per unit of output and, consequently, in the reduction of costs and prices. Because consumers are already satiated (demand is inelastic), the price reduction will not lead to increased demand for the goods. As a result, the reduction of labour per unit of output will contribute to an employment decrease – i.e. the productivity effect is larger than the demand effect. On the contrary, if the sector under analysis refers to a non-satiated market (elastic demand), the coefficient associated with labour productivity (β_2) should show a positive sign. If labour productivity (a) increases, as a result of the introduction of new automation technologies, costs and prices will be lower, and consumers will wish to buy more of those goods. In order to satisfy the increase in demand, companies will hire more employees, resulting in higher employment.

Finally, let us consider the variables which are expected to have an impact on employment with a sign that does not depend on whether the market is satiated or not. The coefficient associated with the price of labour (β_3) is expected to display a negative sign. If price of labour (w) increases, industries will tend to use less labour (and, consequently, more capital) because it becomes relatively more expensive when compared to capital. Therefore, employment will decrease. Regarding the coefficient associated with the rental price of capital (β_4), it is expected to show a positive sign. If the rental price of capital (r) increases, industries will tend to use more labour because it becomes relatively cheaper when compared to capital. Therefore, employment will increase. Regarding the coefficient associated with aggregate domestic demand (β_5), it is expected to have a positive impact on employment. An increase in aggregate domestic demand (g) is expected to stimulate demand in all sectors. The coefficient associated with aggregate foreign demand g^* (β_6) is, likewise, expected to show a positive sign – if foreign demand (g^*) increases, companies will need to hire more employees in order to keep up with the higher external demand. Thus, employment will increase. The coefficient associated with domestic price level (β_7) is expected to show a negative sign because increases in prices lead to a reduction in demand and, consequently, less labour is required in the production processes – employment decreases. Finally, the coefficient associated with the foreign price level (β_8) should exhibit a positive sign. If foreign prices increase, foreign goods become relatively expensive. Thus, this may lead foreign consumers to prefer the domestic goods and demand for domestic products will increase. Consequently, domestic companies will hire additional employees and employment increases.

Table 1 below lists all the variables considered in the model, as well as the correspondent proxies used in our estimations and their respective description, unit and source.

Table 1. Variables and data

Variable	Proxy	Description	Unit	Source
emp	Employment (log)	Full-time equivalent employees (by sector)	Full-time equivalents	Portuguese National Statistics Agency
a	Labour productivity (log)	Real gross value added per hour worked by employees (by sector)	EUR per hour	Portuguese National Statistics Agency
w	Wages (log)	Compensation of employees per hour worked by employees (by sector)	EUR per hour	Portuguese National Statistics Agency
r	Cost of capital	The opportunity cost of making a specific investment (nominal; see appendix B)	EUR	Own computations based on data from AMECO
g	Domestic GDP (log)	Real gross domestic product (market prices; chain linked volume data)	EUR, Millions, 2011	Portuguese National Statistics Agency
g*	Foreign GDP (log)	Real OECD GDP (VIXOB, Volume index)	Index, Hundredths, 2010	OECD Stats
$\overline{p}$	GDP deflator (log)	Portugal GDP deflator	Index	Portuguese National Statistics Agency
p*	Foreign GDP deflator (log)	OECD GDP deflator (DOBSA)	Index, Hundredths, 2010	OECD Stats

Employment was measured using the number of full-time equivalent employees in each of the sectors considered because it gives a tangible measure for the number of people employed in each sector. Input productivity was measured using labour productivity because our goal is to analyse the impact of changes in labour productivity (assumed to reflect changes in technologies) in employment. For that, real gross value added (GVA) per hour worked by employees (by sector) was considered as a measure of labour productivity. Real gross value added was computed using GVA by sector at current prices and GVA by sector at previous year's prices. Additionally, real GVA was divided by hours worked by employees in order to obtain a measure of labour productivity (by sector). The price of labour was measured using compensation of employees (current prices) per hour worked by sector (i.e. wages). The rental price of capital (r) was measured as the cost of capital because it reflects the opportunity cost of making a specific investment (e.g. in new AI technologies) – see Appendix B for details on the calculation of this proxy. Aggregate domestic demand (g) was measured as Portugal's real GDP and for foreign aggregate demand (g*), real OECD GDP was used as proxy because it combines the GDPs from more than 30 advanced economies. The domestic price level was measured using Portugal GDP deflator which refers to a price index that was computed dividing Portugal nominal GDP by Portugal real GDP. Finally, the foreign price level was measured using the OECD GDP deflator, to match the choice for the measure of foreign demand.

Considering the model and data described, our econometric analysis uses ordinary least squares (OLS) to estimate the employment equation for each of the 37 sectors of the Portuguese economy. The analysis was performed using Gretl. The next section contains the results of the 37 OLS regressions performed, corresponding to the 37 sectors under analysis.

5. Results and discussion

The first step of our econometric analysis involved the examination of the impact of the explanatory variables in the dependent variable – *emp*, employment - using OLS to estimate equation (19) for each of the 37 sectors considered. Since the parameter of interest is β_2 - because it represents the coefficient associated with labour productivity (α) which in turn reflects the role of automation technologies -, we focus on the results for this variable.

Table 2 contains the estimates of the impact of productivity on sectoral employment. Overall it shows that productivity significantly impacts employment (i.e. β_2 is significant) in about half of the sectors considered, more precisely in 18 out of the 37 sectors under analysis. Thus, this indicates that new automation technologies, namely AI, affect employment in some of the sectors under analysis. On the other hand, some other sectors seem not to be affected by changes in productivity which means that the introduction of new automation technologies does not affect employment in those sectors (i.e. β_2 is not significant)[6].

Considering a broad level of analysis, it seems that the sectors for which employment was found to be significantly impacted by changes in productivity, deriving from the introduction of new automation technologies, refer to sectors that are likely to be satiated sectors (inelastic demand), e.g. agriculture, forestry and fishing (A); construction (F); transportation and storage (H). On the other hand, the sectors in which productivity does not impact employment are mostly related with non-satiated markets (elastic demand), e.g. publishing, audio-visual and broadcasting activities (JA); scientific research and development (MB); arts, entertainment and recreation (R).

Let us first consider the sectors in which productivity does not impact employment (i.e. β_2 is not statistically significant). We classified these sectors into four categories: 1) services; 2) creative activities; 3) manufacture of inputs; 4) other activities.

[6] We are taking the p-values at face value. Obviously, it is possible that there are type I and type II errors.

Table 2. Summary of the estimation results (OLS) – estimated impact of productivity on sectoral employment

Sector	β_2	Standard error	R^2	Durbin-Watson	F
A	−0.612 ***	0.143	0.962	1.537	50.019 ***
B	−0.068	0.225	0.988	2.159	167.501 ***
CA	−0.698 ***	0.132	0.983	2.164	117.734 ***
CB	−0.837	0.593	0.982	1.108	107.823 ***
CC	0.027	0.207	0.995	1.680	419.165 ***
CD	0.042	0.050	0.947	1.727	35.933 ***
CE	0.017	0.202	0.982	1.586	109.228 ***
CF	−0.391 **	0.153	0.969	2.075	63.294 ***
CG	−0.574 *	0.277	0.993	1.713	304.312 ***
CH	−0.062	0.146	0.958	1.912	46.169 ***
CI	−0.269 ***	0.083	0.975	2.068	76.534 ***
CJ	−0.411	0.446	0.953	1.520	40.398 ***
CK	−0.930 ***	0.265	0.923	1.265	24.076 ***
CL	0.014	0.063	0.961	1.306	49.398 ***
CM	−0.083	0.436	0.946	1.302	34.848 ***
D	−0.194	0.261	0.992	2.167	247.385 ***
E	0.155	0.205	0.928	1.838	25.672 ***
F	−0.970 ***	0.312	0.990	2.277	195.687 ***
G	−0.383 ***	0.094	0.987	1.839	152.247 ***
H	−0.227 **	0.082	0.990	1.287	201.172 ***
I	−0.409 ***	0.105	0.992	1.958	250.998 ***
JA	0.333	0.322	0.954	1.308	41.691 ***
JB	−0.443 ***	0.075	0.918	2.326	22.501 ***
JC	−0.551 **	0.194	0.998	1.852	881.259 ***
K	0.083	0.129	0.893	2.037	16.609 ***
L	−0.754 ***	0.177	0.920	2.622	22.953 ***
MA	−0.204	0.209	0.991	1.764	211.381 ***
MB	−0.305	0.176	0.779	1.534	7.0587 ***
MC	−0.379	0.261	0.943	1.431	33.043 ***
N	0.111	0.233	0.994	1.851	315.035 ***
O	−0.477 **	0.200	0.976	1.756	81.508 ***
P	−0.491 ***	0.137	0.965	1.657	55.800 ***
QA	−0.428 **	0.189	0.989	1.697	173.675 ***
QB	0.330 *	0.170	0.988	1.957	165.939 ***
R	−0.065	0.206	0.985	2.130	130.614 ***
S	−0.203 *	0.115	0.996	2.219	501.308 ***
T	0.019	0.599	0.809	1.934	8.469 ***

Notes: β_2 - coefficient for labour productivity (α); *** significance level, 1%; ** significance level, 5%; * significance level, 10%. See Table A.1 in the Appendix for the identification of the sectors A to T.

Source: own computations using GRETL

The services category (1) includes financial and insurance activities (K); legal and accounting activities; activities of head offices; management consultancy activities;

architecture and engineering activities; technical testing and analysis (MA); and administrative and support service activities (N). The creative activities category (2) includes publishing, audio-visual and broadcasting activities (JA); scientific research and development (MB); advertising and market research; other professional, scientific and technical activities; veterinary activities (MC); and arts, entertainment and recreation (R). The tasks associated with the sectors belonging to these two categories are labour intensive and require creativity, intuition and problem-solving skills that are difficult to automate (Autor, 2015; Frey and Osborn, 2013). Thus, it is unlikely that new automation technologies will have the ability to directly replace workers – automation's role is more likely to be that of complementing their tasks, making them more productive.

The manufacture of inputs category (3) refers to a group of sectors that mainly produce goods that are used as inputs in other industries (as opposed to the manufacture of goods that are mostly directed towards the final consumer, i.e. manufacture of outputs); it comprises: manufacture of textiles, wearing apparel and leather products (CB); manufacture of wood and paper products, and printing (CC); manufacture of coke, and refined petroleum products (CD); manufacture of chemicals and chemical products (CE); manufacture of basic metals and fabricated metal products, except machinery and equipment (CH); manufacture of electrical equipment (CJ); manufacture of transport equipment (CL); and manufacture of furniture; other manufacturing; repair and installation of machinery and equipment (CM). These sectors are associated with routine activities, involving repetitive physical operations, that can be easily codified and automated (Autor, 2015; Frey and Osborn, 2013). Accordingly, the introduction of new automation technologies has the potential to replace workers, increasing productivity and reducing costs.

The fourth category considered (other activities) includes mining and quarrying (B); electricity, gas, steam and air-conditioning supply (D); water, sewerage, waste management and remediation activities (E); and activities of households as employers of domestic personnel and undifferentiated goods and services production of households for own use (T). These represent sectors associated with activities that reveal high probability of automation (Frey and Osborn, 2013). Therefore, the potential for new automation technologies to replace workers is present in this category.

Although a significant proportion of jobs can be destroyed in the four categories considered due to the introduction of new automation technologies, it seems that these sectors are also creating sufficient jobs that allow overall employment not to be impacted – this is an indication that the productivity and demand effects reveal similar dimensions. On the other hand, although the number of jobs is not affected, it should be noted that the composition of employment may change, i.e. the skills of the individuals employed in one particular sector may change with the introduction of new automation technologies.

Regarding the sectors for which productivity significantly impacts employment, two scenarios were observed: a) sectors in which the impact is negative; b) one sector in which the impact is positive.

Sectors in which productivity negatively impacted employment represent those for which the productivity effect was bigger than demand effect, i.e. the number of jobs created was not sufficient to compensate the number of jobs destroyed. These sectors were classified into three categories: i) manufacture of outputs; ii) services involving human interaction; iii) others.

The manufacture of outputs category (i) refers to sectors that generally produce goods for the final consumer (as opposed to the manufacture of goods that are generally used as inputs by other industries) and to sectors producing machines and computers that are essential to the production of the referred goods. This category includes: manufacture of food products, beverages and tobacco products (CA); manufacture of basic pharmaceutical products and pharmaceutical preparations (CF); manufacture of rubber and plastics products, and other non-metallic mineral products (CG); manufacture of computer, electronic and optical products (CI); manufacture of machinery and equipment n.e.c. (CK); agriculture, forestry and fishing (A); and construction (F). These sectors involve manual routine tasks that can be easily codified and automated, hence workers can be replaced by machines, resulting in job destruction (Autor, 2015; Frey and Osborn, 2013). As a matter of fact, this category includes some of the sectors with higher absolute β_2 coefficients, which shows that these are the sectors in which the negative consequences of technology are felt with higher intensity. Thus, for example, for construction sector (F), for which the impact is quantitatively the highest, all else equal, if productivity increases by 10%, a 9.7% decrease in employment is expected in the referred sector. On the other hand, manufacture of computer, electronic and optical products (CI) is the sector in which the absolute value of β_2 (-0.269) is smaller within this category (i.e. impact of productivity on employment is less intense) – in this case, all else equal, if productivity increases by 10%, a 2.69% decrease in employment is expected.

The services involving human interaction category (ii) comprises wholesale and retail trade, repair of motor vehicles and motorcycles (G); transportation and storage (H); accommodation and food service activities (I); public administration and defence; compulsory social security (O); education (P); human health services (QA);

telecommunications (JB); computer programming, consultancy and related activities; information service activities (JC); and real estate activities (L). This category represents sectors in which human interaction is relevant (e.g. skills such as empathy and adaptability) hence they are less susceptible to automation and, consequently, the negative effects of technology should not be so intense (Autor, 2015; Frey and Osborn, 2013). In fact, the absolute values of β_2 coefficient are lower when compared with the previous category. For example, for real estate activities sector (L), all else equal, if productivity increases by 10%, a 7.54% decrease in employment is expected in the referred sector. On the other hand, transportation and storage (H) is the sector in which the absolute value of β_2 (-0.227) is smaller within this category (i.e. impact of productivity on employment is less intense) – in this case, all else equal, if productivity increases by 10%, a 2.27% decrease in employment is expected.

As mentioned in the beginning of this section, the sectors in which the β_2 coefficient was found to be significant tend to represent satiated markets. In other words, the goods and services produced by these sectors correspond to individuals' fulfilled needs (inelastic demand). In this case, the decrease in prices resulting from the introduction of new technologies, namely AI, will not raise demand because consumers' needs are already met hence the dimension of the demand effect will be small. On the other hand, enhanced productivity will destroy jobs. Overall, these sectors are not creating sufficient jobs that allow employment not to be impacted – the productivity effect is larger than demand effect.

Finally, it is important to mention that social work activities (QB) reveal a significant positive sign for β_2 (0.329). Specifically, all else equal, if productivity increases by 10%, an increase of 3.29% in employment is expected in the referred sector. This sector includes social assistance services such as day-care activities for children and the elderly. In this case, it is likely that the introduction of new automation technologies contributed to complement social workers' activities, leading to prices reduction. Because prices decreased, individuals started to be able to access these services, increasing demand. Consequently, in order to keep up with higher demand, more employees were admitted in this sector. Overall, the demand effect turned out to be larger than the productivity effect.

To sum up, our results show that the introduction of new technologies in the Portuguese economy, namely AI technologies, has contributed to the emergence of a variety of employment scenarios that depend on the characteristics of the sectors under analysis.

Additionally, it is also important to highlight the role of the other variables considered in our model. Regarding price of labour (w), it was found that 28 of 37 the sectors under analysis revealed a negative sign for the correspondent coefficient (β_3) which corroborates our hypothesis. Price of labour (w) was significant in predicting employment in 24 of total number of the sectors under analysis. Rental price of capital (r) revealed a negative sign for the correspondent coefficient (β_4) in 22 of the 37 sectors – this result goes against our initial hypothesis (i.e. positive sign). Rental price of capital (r) was significant in predicting employment in 24 of total number of the sectors under analysis. Aggregate domestic demand g (β_5) showed a positive sign in 32 of the 37 sectors under analysis as we first suggested; and it was a significant variable in 25 of the total number of sectors. For the coefficient associated with aggregate foreign demand g^* (β_6), about half of the sectors considered showed negative sign, which goes against our initial hypothesis. Additionally, it proved to be significant in only 12 of the 37 sectors considered. With regards to the coefficient associated with domestic price level $\bar{p}$ (β_7), it showed a negative sign in 29 sectors (as it was expected) and it was significant in 16 of the sectors considered. Finally, coefficient associated with foreign price level p^* (β_8) was positive in 24 sectors, as it was expected. This variable was significant in 21 of the 37 analysed sectors.

Also, the value for R^2 for the different regressions covering the sectors under analysis range between 0.77 and 0.99 which is indicative of a good model fit in the vast majority of the sectors: the model explains 77%-99% of the variability in employment. Additionally, all the regressions performed reveal a significant F-statistic which indicates that the variables considered are jointly significant, i.e. the model has significant predictive capability. Finally, Durbin-Watson statistic was also considered in order to test for autocorrelation in the residuals. It is important to highlight that values between 0 and 2 indicate positive autocorrelation and values from more than 2 to 4 indicate negative autocorrelation. Thus, values in the range of 1.5 to 2.5 should be considered relatively normal (i.e. no autocorrelation in the residuals). The Durbin-Watson value for majority of the regressions performed fall within the referred normal range hence no concerns are raised in terms of autocorrelation of the residuals. The exceptions refer to the regressions associated with the following sectors: manufacture of textiles, wearing apparel and leather products (CB); manufacture of machinery and equipment n.e.c. (CK); manufacture of transport equipment (CL); manufacture of furniture; other manufacturing; repair and installation of machinery and equipment (CM); transportation and storage (H); publishing, audio-visual and broadcasting activities (JA); advertising and market research; other professional, scientific and technical activities; veterinary activities (MC) – these correspond to regressions in which autocorrelation of residuals was found to be positive (i.e. less than 1.5) (Table 2).

6. Conclusion

There are long-established concerns about technological improvements resulting in jobs being lost to automation. Recent advances in the fields of robotics and AI have brought to attention the discussion about technological development and job destruction once more because AI introduces the possibility of automation in a broader range of occupations that are not restricted to routine tasks. Moreover, AI technologies can be introduced in a variety of professions and sectors hence its impact can be very diversified and transversal in the economy. As such, it is extremely relevant to anticipate its potential effects on employment. Given its relevance, this topic was recently addressed by the Confederation of Portuguese Business (CIP) in a study conducted by McKinsey Global Institute and Nova School of Business and Economics[7]. This study reveals that 1.1 million jobs can be destroyed in Portugal until 2030 due to advances in robotics, mainly those associated with routine tasks (e.g. manufacturing sectors). However, between 600 thousand and 1.1 million jobs are expected to be created also due to automation in health, social work and science sectors.

In this project we present a model that predicts the rise and fall of employment in 37 sectors of the Portuguese economy based on changes in productivity that result from the introduction of new automation technologies in the referred sectors, considering the role of demand that can have different effects, given the nature of the sectors under analysis. The goal was to create an initial framework that allows us to anticipate how AI is likely to impact employment in the future in order to understand the potential for *technological unemployment* in the Portuguese economy.

First, we found that for half of the sectors under analysis, productivity is not a significant predictor of employment (e.g. scientific research and development; arts, entertainment and recreation). These sectors represented 30% of total employment in 2016 (i.e. full-time equivalent employee). Thus, it seems that changes in productivity are not affecting certain sectors with regards to employment which may translate one possible scenario where jobs destroyed by automation are compensated by jobs created as a result of higher demand induced by price reduction. Nevertheless, although the number of jobs might be stable, it is important to note that the referred compensation process might introduce changes in the

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[7] https://www.jornaldenegocios.pt/economia/emprego/mercado-de-trabalho/detalhe/maquinas-e-robos-podem-levar-18-milhoes-de-portugueses-a-mudar-de-emprego (accessed in January 30, 2019)

composition of jobs, i.e. the skill content of jobs may evolve over time as a result of technical change (McCrory, Westerman, Alhammadi, and Brynjolfsson, 2014).

Second, we found that employment in the remaining sectors is negatively impacted by productivity (e.g. construction; transportation and storage). These sectors represented 66% of total employment in 2016. In other words, the introduction of new automation technologies seems to contribute to employment decrease. This means that the jobs destroyed by productivity gains are not compensated by jobs resulting from demand effect. This happens because it is likely that these sectors represent markets for which individuals' needs are met. Thus, significant increases in demand are not expected even if a price decrease is observed as a result of the introduction of new technologies. Only one exception was found for social work activities. In this sector, productivity shows a positive significant impact on employment, i.e. technology contributes to employment increase. This sector represented 4% of total employment in 2016.

Considering these findings, it is possible to conclude that the introduction of new automation technologies does not necessarily result in employment reduction. Certainly, there are sectors that are more susceptible to automation and in which employment can decrease, as pointed in this project and in the study conducted by the McKinsey Global Institute and Nova School of Business and Economics. However, both studies also identify the potential of new technologies, such as AI, to create new jobs. Specifically, our study admits the possibility of job creation through demand effects in ways that can compensate and even exceed the number of jobs destroyed by the introduction of new automation technologies in a particular sector. In fact, in the present study, some of the sectors that were found to be not significantly impacted by productivity show positive signs (e.g. financial and insurance activities) which means that there is the possibility in the future for these sectors to generate additional jobs in the context of the introduction of new technologies, namely AI technologies. Therefore, there are certain sectors in the Portuguese economy where AI might have a positive impact on employment – these sectors represent 19% of total employment.

Additionally, it is important to highlight that AI is classified as a new General Purpose Technology (Trajtenberg, 2018) which means that it has the ability to be improved over time and to contribute to the proliferation of complementary innovations. Therefore, the generalisation of AI technologies in the economy might involve complex processes of restructuration (e.g. complementary investments, changes in business processes) that may take considerable time. As such, a gap between the introduction of AI technologies and its effects on productivity and employment may exist (Brynjolfsson, Rock and Syverson, 2017). Thus, these effects might still not be reflected in the data considered in this project.

Overall, our results show that the Portuguese economy has some potential for *technological unemployment* in the next years, considering a broader introduction of AI technologies. However, according to Keynes (1930), this refers to “only a temporary phase of maladjustment” that in the long run can lead to higher standards of living for the individuals. In fact, as AI is considered a GPT, time will be fundamental to adjust to the changes introduced. In this context, it might be a good option to start promoting the introduction of AI technologies in the sectors that showed a positive sign in terms of the relationship between productivity and employment.

Future studies on this topic should include one variable reflecting exclusively the adoption of AI technologies in each sector in order to understand its direct effects on employment. Besides that, it would be important to quantify the productivity effect and the demand effect described above, in order to understand the real effect of the introduction of AI technologies. Additionally, it would be useful to consider forecasting technics to predict the impact of AI in terms of total number of jobs destroyed or created in each sector.

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Appendix A

Table A.1. Sectors considered in the analysis (Statistical classification of economic activities in the European Community, Rev. 2)

A38	Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
CA	Manufacture of food products, beverages and tobacco products
CB	Manufacture of textiles, wearing apparel and leather products
CC	Manufacture of wood and paper products, and printing
CD	Manufacture of coke, and refined petroleum products
CE	Manufacture of chemicals and chemical products
CF	Manufacture of basic pharmaceutical products and pharmaceutical preparations
CG	Manufacture of rubber and plastics products, and other non-metallic mineral products
CH	Manufacture of basic metals and fabricated metal products, except machinery and equipment
CI	Manufacture of computer, electronic and optical products
CJ	Manufacture of electrical equipment
CK	Manufacture of machinery and equipment n.e.c.
CL	Manufacture of transport equipment
CM	Manufacture of furniture; other manufacturing; repair and installation of machinery and equipment
D	Electricity, gas, steam and air-conditioning supply
E	Water, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade, repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
JA	Publishing, audio-visual and broadcasting activities
JB	Telecommunications
JC	Computer programming, consultancy and related activities; information service activities
K	Financial and insurance activities
L	Real estate activities
MA	Legal and accounting activities; activities of head offices; management consultancy activities; architecture and engineering activities; technical testing and analysis
MB	Scientific research and development
MC	Advertising and market research; other professional, scientific and technical activities; veterinary activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
QA	Human health services
QB	Social work activities
R	Arts, entertainment and recreation
S	Other services activities
T	Activities of households as employers of domestic personnel and undifferentiated goods and services production of households for own use

Appendix B

Formula for the computation of *r*

$$r = \delta \times P\,Inv + \frac{ir}{100} \times P\,Inv_{(-1)} - \left(P\,Inv - P\,Inv_{(-1)}\right)$$

where,

$$\delta = \frac{FCC \times 100}{P\,Inv \times K_{(-1)}}$$

FCC is Consumption of Fixed Capital;

K is the capital stock;

P Inv is the Gross Fixed Capital Formation deflator;

ir is the interest rate.

Table B.1. Variables for the computation of *r*

Variable		Description	Source
FCC	Consumption of fixed capital	Current prices	AMECO
K	Capital stock	Net capital stock, total economy, constant prices	AMECO
P Inv	Gross fixed capital formation deflator	Index	AMECO
ir	Nominal short-term interest rate	3-month interbank rates	AMECO