AI, demand and the impact of productivity-enhancing technology on jobs: Evidence from Portugal

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Abstract

This study examines whether AI, as revealed in productivity improvements, may have the ability to threaten sectoral employment in Portugal. We first present a theoretical framework based on a supply and demand model for sectoral output. This model predicts that the impact of AI will depend on the response of labor demand to two opposing forces: as productivity improves less labor is required to produce the same output, while more output is demanded because of lower production costs brought about by higher productivity, which creates more jobs. Our estimates of the industry-level elasticities of employment with respect to productivity for a sample of 32 industries over 1995-2017 using a Bayesian multilevel approach are all negative and surprisingly similar across sectors.

Keywords: artificial intelligence, productivity, demand, employment, Portugal, Bayesian multilevel modelling

JEL Classification: E24, J20, O30

1. Introduction

New technologies have been at the heart of productivity enhancements in the past (see e.g. Battisti, Del Gatto, and Parmeter, 2018; Fiszbein et al., 2020; and Juhász, Squicciarini, and Voigtländer, 2020). More recently, artificial intelligence (AI) is regarded as the most important technological advancement and conjectures about its potential effects flourish. According to Naudé (2021), p. 17, more impressively since 2012 "(…)the world is seeing a AI-boom, reflected in a sharp increase in scientific publications, patents publications, and venture capital investment in AI-start-ups." Technological progress associated with AI has promoted the automation of many different types of tasks. Not surprisingly, the literature suggests that there is therefore "a substantial share of employment, across a wide range of occupations, at risk in the near future", Frey and Osborne (2017), p. 266. See also Bowles (2014); Autor (2015); Acemoglu and Restrepo (2020a); and Bowles (2014). Nevertheless, recent studies also show that employment has the potential to grow in industries and firms undergoing technological transformation (see e.g. Arntz, Gregory, and Zierahn, 2016; Autor and Salomons, 2017; Autor and Salomons, 2018; Bessen, 2018; Bessen, 2019; Bessen, 2020; Gries and Naudé, 2018; and Koch, Manuylov, and Smolka, 2021). In fact, developments in technology can be associated with different outcomes. As AI and associated automation progresses, labor requirements per unit of output produced decrease, which lowers production costs and possibly prices. Thus, as technology evolves within a certain industry, two scenarios may arise in terms of employment: 1) technology- induced reduction in labor requirements leads to a decrease in employment; 2) technology-induced reduction in labor requirements leads to a lower output price which, probably in association with quality improvements, generates higher demand and, consequently, the need for more workers. This increase in demand can be sufficient to offset the labor-saving technology effect on employment (see e.g. Autor and Salomons, 2017; Autor and Salomons, 2018; Bessen, 2019; and Gregory, Salomons, and Zierahn, 2018). Demand can thus play an important role in the context of the relationship between technology and employment.

In this study we examine the ability of AI, as reflected in productivity, to affect sectoral employment in Portugal, taking into account the role of demand. To this end, we first present a theoretical framework based on a supply and demand model for sectoral output that predicts that the impact of AI will depend on the response of labor demand to two opposing forces. First, as productivity improves (a latent result of AI and associated automation) less labor is required to produce the same output. Second, higher productivity lowers production costs and thus prices, which means more output is demanded and thus firms will need more workers. We next take this model of labor demand to the data, controlling for the set of variables suggested by standard theories of supply and demand behavior, considering a sample containing 32 industries in the Portuguese economy over the period 1995-2017. We adopt a Bayesian approach, through a multilevel model of the elasticity of employment with respect to productivity. We use an indirect approach to assess the impact of IA on sectoral employment. Following Autor and Salomons (2018), we are 'agnostic' regarding the measurement of technological adoption associated with IA and consider its impact on employment through (total factor) productivity. In this way we circumvent the challenge for reliable IA measurement posed by the heterogeneity of proxies available. Underlying this option is the assumption that "(…) all margins of technological progress ultimately induce a rise in TFP (…)", Autor and Salomons (2018), p.7.

Portugal is an interesting case study in this respect. The average growth rate of the Portuguese economy has been steadily decreasing during the twenty-first century, from 3.8% a year during the first 15 years after European integration (in 1986), to 0.2% on average over the period 2001-16, according to the data on real gross domestic product (GDP) provided by AMECO. This deceleration is essentially the consequence of the stagnation of aggregate productivity (see e.g. Pinheiro Alves, 2017; and National Productivity Board, 2019), which is a fundamental determinant of standards of living and social cohesion in the long run (Hall and Jones, 1999). Artificial intelligence (AI), with its many applications, has been seen as the solution to the productivity slowdown and the means to increase potential GDP, although delays in the diffusion of AI might be blocking the materialization of the associated productivity gains (Brynjolfsson, Rock, and Syverson, 2019). This potential role of AI has also been widely recognized at the political level and Portugal is no exception: in 2017 the Portuguese government established the "National Digital Competences Initiative e.2030, Portugal INCoDe.2030", a national strategy for the development of the Portuguese economy and society using AI in public and private activities. However, if AI adoption results in a decrease in employment, social cohesion in Portugal may come under stress. For the Portuguese economy this raises additional concerns due to the relatively low educational attainment levels of the population (in 2018 52% of the population aged 25-64 years old had not completed upper secondary education, while the OECD average stood at 22% — OECD data) and relatively high inequality levels (the Gini coefficient of income distribution was 33.5 in 2017 while the EU28 average was 30.5, and the income ratio of the top 20% relative to the bottom 20% was 5.7 while the EU average was 5.1 — Eurostat data). These characteristics may increase exposure to the risks posed to jobs by AI (see e.g. Acemoglu and Restrepo, 2020a; and Chiacchio, Petropoulos, and Pichler, 2018).

The paper is structured as follows. In the next section we review the related literature on the impact of automation on employment. We then present in section 3 the methodology and the data used in our empirical analysis. The results of the empirical analysis are reported in the fourth section. Section 5 discusses the main results and concludes.

2. Productivity-enhancing technology and employment

Productivity-enhancing technology, besides being a major source of economic growth, has the potential to influence employment levels (Autor and Salomons, 2017).[1] AI is considered as the most important technological advancement in the world today and conjectures about its potential effects abound (see e.g. Berg, Buffie, and Zanna, 2018; Caselli and Manning, 2019, Frey, 2019; Alonso et al., 2020); Faber, 2020; Korinek and Stiglitz, 2021b; Korinek and Stiglitz, 2021a; Naudé, 2021; and Trammell and Korinek, 2021). Computer technologies that can be deployed in the automation of tasks have recorded significant progress over the past decades, particularly from the 1990s onwards, accelerating automation of tasks previously performed by workers. This scenario has given rise to a phenomenon designated by Autor

[1] Moscoso Boedo (2019), for the case of the former communist economies, examines how the optimal choice of technologies, motivated by the structural break corresponding to the collapse of communism in the early 1990s, explains the costly transition of these countries. In this specific case, the initial relatively high availability of human capital seems to have led to increases in the stock of skilled workers and a decline in physical capital.

(2014) as automation anxiety corresponding to soaring concerns that new technologies will replace labor. Indeed, the literature suggests that a significant proportion of jobs may be negatively affected by automation. For example, Bowles (2014) estimates that this is the case for a range between 45 to more than 60% of jobs in European countries. Similarly, Frey and Osborne (2017) 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, and Zierahn (2016) followed a task-based approach, considering that only high-automatability jobs (i.e. at least 70% of the tasks associated with the job are automatable) are at risk, and found that, across OECD countries, 9% of jobs are automatable.

AI is a new form of automation. In 2016, the World Economic Forum called AI the Fourth Industrial Revolution. AI systems rely on large databases and use classes of algorithms to map tasks in an autonomous way, which contrasts with previous computer programs that required very precise coding activities. Therefore, the advent of AI enables automation to go one step further, extending from routine and easily codifiable tasks to more complex tasks, namely tasks requiring prediction capabilities, Agrawal, Gans, and Goldfarb (2017). In a recent study Trajtenberg (2019) classifies AI as the new General Purpose Technology (GPT), i.e., a major new technology that is pervasive, likely to improve over time and to contribute to the proliferation of complementary innovations, Bresnahan and Trajtenberg (1995), although Naudé (2021) argues that this GPT potential of AI is still hard to realize since AI is difficult and expensive to implement by businesses. Trajtenberg (2019), however, expects AI to have a substantial negative impact on employment. Similarly, Brynjolfsson and McAfee (2014) refer to the need to study policies to deal with the possibility that androids will take over a substantial share of jobs and reduce wages to below subsistence levels. Thus, a new wave of concern regarding employment is emerging in the context of AI developments. Previous waves of concern have, nevertheless, proved to be exaggerated, Naudé (2021). Advances in automation do not necessarily lead to job losses because of feedback mechanisms that may contribute to the stabilization of, or even to increases in, employment, Arntz, Gregory, and Zierahn (2016).

From the point of view of an individual firm, automation technology can have two distinct effects on jobs: 1) a substitution effect; and 2) a complementarity effect (see Autor, 2014; and Autor, 2015). The substitution effect occurs when workers are replaced by machines, leading to lower employment. It is generally related with routine tasks, i.e. tasks that follow well-defined protocols that can be easily codified; mostly those involving middle-skilled cognitive and manual activities. This effect arises in the context of "human-replacing innovations" — technical advances that replace human intervention, Trajtenberg (2019). The 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 problem-solving skills, interpersonal skills, intuition, and creativity. This effect arises in the context of "human- enhancing innovations" — technologies that help workers in their tasks, Trajtenberg (2019). Bessen (2019) provides an illustration of the complementarity effect, featuring teller machines (ATMs) as an example of technology complementing workers. ATMs took over cash handling tasks. However, the rise in ATMs was accompanied by an increase in the number of full-time 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).

The substitution and complementarity effects are primarily firm-level effects of automation. When the effect of automation is analyzed at other levels additional effects emerge. Gregory, Salomons, and Zierahn (2018) argue that, from a regional perspective, routine-replacing technological change (RRTC), i.e. the introduction of new automation technologies in the context of routine tasks, produces three forces that can impact employment in different ways. The first force is the substitution effect: declining costs of equipment incorporating new automation technologies incentivize firms to adopt those new automation technologies; consequently, labor is replaced by capital and employment decreases. The second refers to a product demand effect: new automation technologies reduce costs and prices, leading to higher demand and, consequently, employment. The third effect is product demand spillovers: automation increases output and income, and the additional income may be spent in other goods produced in the region, raising overall demand in that region and, therefore, employment. Based on a theoretical model that attempts to incorporate these premises, the authors estimate the economy-wide effect of RRTC on employment using data over the period 1999-2010 for 238 regions across 27 European countries (the parameters of the model are assumed to be the same for all regions, apart from a constant term). The findings point to a substantial decrease in employment resulting from the substitution of capital for labor. However, the product demand effect and the product demand spillovers effect act as countervailing forces that are sufficient to offset the job destruction associated with the substitution effect. In their simulation, Gregory, Salomons, and Zierahn (2018) found a net increase in aggregate employment as a result of increased automation.

Similarly, Autor and Salomons (2018) also analyze impacts of automation that go beyond the level of the firm. In their case, the focus is on industries instead of regions. They argue that there are three channels through which automation impacts employment. The first one refers to own-industry effects: introduction of new automation technologies in one sector may result in labor being replaced by capital, with employment decreasing — this is akin to a substitution effect at the industry level. The second is a final demand effect: the introduction of new automation technologies increases productivity, which in turn raises income and boosts final demand, leading to higher employment — this is similar to the product demand spillovers effect. The third refers to a cross-industry input-output linkage effect and is related to 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: an industry will benefit, through lower input prices, from automation upstream, and also, through increased demand, from automation downstream. To study the impact of these channels, Autor and Salomons (2018) use cross-country and cross-industry data (18 developed countries; 28 industries) for the period 1970-2007, imposing, similarly to Gregory, Salomons, and Zierahn (2018), equality of coefficients across industries and countries. They found that productivity growth, as a result of the introduction of new automation technologies in one particular industry, reduced employment through own- industry effects. However, this is offset by the final demand effect. Additionally, they 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 yields a positive “net effect” of productivity gains on aggregate employment.

The aforementioned studies focused on either regional- or industry-level effects, including effects that work through the demand channel. Other recent studies have considered the role of demand (besides the fundamental substitution effect) in either a more general, macroeconomic framework, as in Gries and Naudé (2018), or in the context of specific industries, as in Bessen (2019) and Bessen (2020).

Gries and Naudé (2018) develop a product-variety model of endogenous growth at the heart of which lies the issue of income distribution. Progress in AI has the usual substitution effect relative to labor. What the model also predicts is that wages will rise, but may not rise enough so as to avoid a decline in labor's share of national income.[2] The key parameter is the elasticity of substitution between labor and AI: if this elasticity is high, AI will lead to a decline in employment. Consequently, demand will be sluggish, since its source are the wage earners. Demand will only increase if the economic agents that are willing to purchase the national output have the resources to do so. If the additional income generated by the introduction of AI in the productive process accrues mainly to the capitalist class, the introduction of AI may depress rather than stimulate demand.

Bessen (2019) reports estimates of the effect of AI on employment in three specific industries: textile, steel and automotive. The empirical analysis is based on a model which attempts to encapsulate the basic ideas of the substitution and product demand effects. Therefore, in this model, adoption of AI increases productivity in the industry, leading to a lower price for the industry's output. As the price lowers, the quantity that the market demands increases. The impact of AI on the industry's employment will be positive if the demand for the industry's good is elastic with respect to the price, i.e., if the percent increase in demand is larger, in absolute value, than the percent decrease in the price. According to Bessen, this elasticity is likely to vary over time: in a mature industry, demand will probably be satiated and the price elasticity should be low. Jobs in mature industries (such as textile, steel and automotive) should therefore be at a greater risk of destruction by AI.

[Insert Table 1 here]

Table 1 summarizes the predicted employment effects of AI and related forms of automation in the studies reviewed in the previous paragraphs. Put together, they imply that AI's influence on employment is not clear-cut. Besides the well-known substitution effect, there are other, conflicting effects, some of them operating at different levels, namely industry or region. In the next section we present our approach to estimating the impact of AI on employment at the sector-level in Portugal.

3. Modelling strategy and data

Our empirical analysis examines whether AI, as revealed in productivity improvements, has the ability to threaten sectoral employment in Portugal at the A38 sector-level,

[2] This concern with the downward trend in the labor share observed in many developed countries since the 1980s has resulted in an expanding literature trying to identify its causes, namely the substitution of capital for labor (see e.g. Growiec, 2012; and Elsby, Hobijn, and Sahin, 2013).

according to the statistical classification of economic activities of the European Community (NACE Rev. 2) — see Eurostat (2008). Of the 38 sectors in which economic activity is subdivided in this classification, we leave out of the analysis sectors "O — Public Administration and defence; compulsory social security", "T — Activities of households as employers of domestic personnel and undifferentiated goods and services production of households for own use" and "U — Activities of extraterritorial organizations and bodies". The reason for excluding these sectors is that they are not populated by firms making hiring and production decisions based on costs and market outlook. We also dropped the sectors "CD — Manufacture of coke, and refined petroleum products", "CL — Manufacture of transport equipment" and "MB — Scientific research and development" because of missing data. Table 2 contains the list of 32 sectors considered in our analysis.

[Insert Table 2 here]

To estimate the possible impact of AI on employment in those sectors we estimate a model relating employment in each sector to a set of variables. Among those variables is productivity, and the coefficient attached to this variable is the coefficient of interest to us, given that, as the literature review presented in the previous section made clear, the spread of the use of AI is expected to increase productivity (see e.g. Damioli, Van Roy, and Vertesy, 2021), with other effects following from that initial impact. As in Bessen (2018), our model accounts for substitution and product demand effects. The overarching premise of our model is that AI is a relatively recent technology with a huge potential to improve productivity and through this channel influence employment. Nevertheless, productivity may react to AI with a time delay and thus the full impact on employment may take some time to appear in the data. Brynjolfsson, Rock, and Syverson (2019) hypothesize that the productivity impact of AI may emerge gradually and only be visible over time given the initial investment necessary for firms to learn how to use and deploy the AI technologies, what they call implementation lags. Our quantitative interpretation of the impact of AI on employment should thus be seen as conservative, taking the possibility of this time lapse into account, and thus not fully reflecting the impact of AI on productivity and employment. For instance, Bughin et al. (2018) estimate that the contribution of AI to economic growth may be three or more times higher by 2030 than over the five years following the publication of their study. We also limit ourselves to hypothesizing what could happen to employment in a scenario where AI is responsible for productivity increases. We do not attempt or intend to quantify the contribution of AI to our productivity variable (measured as TFP retrieved from a Cobb-Douglas production function with physical capital and labor as inputs). Our empirical approach considers all increases in TFP irrespective of their source as in e.g. Autor and Salomons (2018) and Bessen (2019). In this way we take a wider view and do not have to make choices regarding the measurement of AI that involve some degree of arbitrariness (e.g. computer use, robots, routine intensity of occupations, AI patent applications or AI-related scientific publications). Also, we face limited data availability at the sectoral level with sufficient time coverage to produce robust evidence.

The choice of the variables to include in our empirical model is based on a standard model of supply and demand behavior that we can briefly describe as follows. The model assumes that production costs and the behavior of demand drive firms' decisions on how much to produce and, consequently, how much to acquire of the services of the factors of production (labor and capital). Production costs depend on productivity, wages and the cost of capital. The behavior of demand depends on the price of the good, as well as on the prices of other goods (namely of substitutes, but also of complements) and on how much buyers plan to spend overall —a popular, among economists, mathematical model of this sort of demand behavior is provided by Dixit and Stiglitz (1977). Since the sectors' output may be exported, we also include in the model variables related to foreign demand and foreign prices.

Below we present an example of a mathematical version of the model. The mathematical version of the model is based on the behavior of a representative firm in each sector. This mathematical model provides not only an alternative way of presenting the mechanisms that we wish to capture in our empirical analysis (carried out at the sector level), but also guidance as to the choice of control variables. Thus, the model leads to an equation relating employment to productivity and a set of control variables, which is formulated in very general terms and does not depend on specific functional forms, namely for the production function. The equation to be estimated will be obtained by taking a log-linear approximation to that general equation. However, the key variable in our analysis is productivity, which is unobserved. To obtain a measure of productivity in each sector, we will then employ the standard approach based on a Cobb-Douglas production function.

Assume that firms maximize profits defined in the standard way, equation (1):

$$\Pi = PY - RK - WL \qquad (1)$$

where PY is the firm's revenue, factorized into a price (P) and a volume Y component. As is usual in the literature we assume that the volume is a function of the production inputs (K: capital stock; L: labor input) and of total factor productivity (A) so that:

$$Y = f(A,K,L) \qquad (2)$$

Thus, the cost of production depends on capital and labor and on the prices of these two production inputs, which are the rental rate of capital (R) and the wage rate (W).

The first order conditions of the firm's problem lead to:

$$\frac{\partial \pi}{\partial K} = 0 <=> Pf_k(A,K,L) = R \qquad (3)$$

and

$$\frac{\partial \pi}{\partial L} = 0 <=> Pf_L(A,K,L) = W \qquad (4)$$

where $f_K(\cdot)$ and $f_L(\cdot)$ are the derivatives of $f(A,K,L)$ with respect to K and L, respectively. Under the conditions of the implicit function theorem, equations (3) and (4) imply that there exist functions $g^K(\cdot)$ and $g^L(\cdot)$ such that:

$$K = g^K(A,W,R,L) \qquad (5)$$

$$L = g^L(A,W,R,K) \qquad (6)$$

Substituting equation (6) for L in the production function, equation (2), we obtain

$$Y = f(A,K,g^L(A,W,R,K)) \qquad (7)$$

Again assuming that the conditions of the implicit function theorem hold, equation (7) may be written as a capital demand equation:

$$K = K^d(A,W,R,Y) \qquad (8)$$

From Eqs. 2 and 5, and proceeding in a similar way, we can also obtain a labor demand equation:

$$L = L^d(A,W,R,Y) \qquad (9)$$

In this setup, both the average and the marginal cost of production depend on total factor productivity, the factor prices and output. If the firm sets its price (P) as a function of either average or marginal cost, then the price will also be a function of those variables:

$$P = m(A,W,R,Y) \qquad (10)$$

This completes the description of the supply side of the model. As for demand, modern economic models employ a framework similar to the Dixit-Stiglitz model, in which demand depends on the price of the good, the aggregate price level (which will be denoted $\tilde{P}$) and aggregate demand ($\widetilde{D}$). Given that we wish to model an open economy, we add to these determinants of demand the level of aggregate foreign demand (D^*) and the foreign aggregate price level (P^*). Therefore, our demand equation may be written as:

$$Y = Y^D\left(\widetilde{D}, D^*, \tilde{P}, P^*, P\right)) \qquad (11)$$

Therefore, substituting for P and appealing again to the implicit function theorem, in equilibrium the following holds:

$$Y = Y^D\left(\widetilde{D}, D^*, \tilde{P}, P^*, m(A, W, R, Y)\right) \qquad (12)$$
$$= Y^e\left(A, W, R, \widetilde{D}, D^*, \tilde{P}, P^*\right) \qquad (13)$$

Using equation (13) to substitute for Y in the labor demand equation (equation 9) and using once more the implicit function theorem, in equilibrium labor demand may be written as a function—$L^e(\cdot)$—of the following arguments:

$$L = L^e\left(A, W, R, \widetilde{D}, D^*, \tilde{P}, P^*\right) \qquad (14)$$

Our empirical strategy is based on the estimation of a log-linear approximation to $L^e(\cdot)$:

$$l = \beta_1 + \beta_2 a + \beta_3 w + \beta_4 r + \beta_5 \tilde{d} + \beta_6 d^* + \beta_7 \tilde{p} + \beta_8 p^* + \varepsilon \qquad (15)$$

where the lower case letters denote logs and the parameter of interest is β_2, i.e. the elasticity of labor demand with respect to productivity. According to equation (15) the (log of the) number of employed workers in each sector, l, depends on the log of productivity, a, the log of the wage rate, w, the log of the rental price of capital, r, the log of aggregate domestic demand, $\tilde{d}$, the log of aggregate foreign demand, d^*, the log of the domestic aggregate price level, $\tilde{p}$, the log of the foreign aggregate price level, p^*, and ε is an error term.

In this framework, the price is a function of the variables that affect production costs and of the other variables that determine demand behavior. This means that prices can be replaced with a function of those variables. Consequently, decisions concerning production — in particular, decisions concerning the level of employment — will depend on that same set of variables. The replacement of the good's price with that function of the other variables, including productivity, A, ensures that the coefficient of productivity in our model captures both the direct substitution effect and the product demand effect that links productivity, production costs, the goods' price, demand for the good and employment in the sector. To be clear, in this framework employment in a certain sector will depend on the following variables: productivity, wages, cost of capital, an indicator of the overall level of domestic demand, the prices of other domestically produced goods, an indicator of the overall level of foreign demand, the prices of foreign goods. Table 3 lists all the variables included in the model, the series used in our estimations, and the sources of the data.

[Insert Table 3 here]

All else equal, a positive (negative) estimated coefficient for productivity can be interpreted as automation having a positive (negative) impact on sectoral employment. To recapitulate, in our framework, the introduction of a new automation technology induces two distinct effects at the sectoral level, a substitution effect and a demand effect. The substitution effect reflects the decreasing labor requirements per unit of output, which results in job destruction. The demand effect is associated with the existence of decreasing costs (deriving from the introduction of new, more cost effective, automation technologies) that lower the price of the good and thus stimulate demand for it (both for intermediate and for final consumption), resulting in job creation. Three scenarios may arise: 1) substitution and demand effects offset each other and employment is not impacted (the estimated coefficient of productivity is not significantly different from zero); 2) the substitution effect exceeds the demand effect and employment is negatively impacted because the creation of jobs is not sufficient to compensate for the destruction of jobs (the coefficient is negative); 3) the substitution effect is smaller than the demand effect and employment is positively impacted (the coefficient is positive). Scenarios 2 and 3 are illustrated in Figures 1 and 2, respectively.

[Insert Figure 1 here]

[Insert Figure 2 here]

Our model describes the relation between labor demand (L) and total factor productivity (A). As in the related literature, to obtain an estimate of total factor productivity we assume a Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{1-\alpha} \tag{16}$$

The procedure then requires data on output, labor and the capital stock. We have national accounts sectoral data on output and labor, but not on the capital stock. To estimate the capital stock at the sector level we did as follows. We collected the aggregate capital stock from AMECO. We divided aggregate gross operating surplus income (i.e. RK) by that measure of the capital stock. This ratio is an estimate of the rental rate of capital (R). Given that investors may move their investments from one sector to another, we assume that the aggregate rental rate of capital is a good approximation to the sectoral rental rate of capital. Therefore, by dividing the sector gross operating surplus income by the aggregate rental rate of capital one obtains an estimate of the sector capital stock. The procedure also requires a value for the parameter α. Estimating the capital share (α) is beyond the scope of our study. We follow in this respect accounting approaches that use plausible values for the former production function parameter to compute TFP (see e.g. Hall and Jones, 1999; Caselli, 2005; and Hsieh and Klenow, 2010). We thus do not attempt or intend to explain what determines the capital and labor shares, which would be necessary if the former were derived from a regression model that would additionally require strong assumptions for identification such as that TFP is orthogonal to physical capital. Following this literature, we set $\alpha = 1/3$ (see e.g. Hall and Jones, 1999; Caselli, 2005; Arezki and Cherif, 2010; Hsieh and Klenow (2010); and Boppart and Li, 2021).

We estimate the model represented by equation 15 jointly for the 32 sectors listed in Table 2 using annual data for those sectors in Portugal over the period 1995-2017. Notice that our dataset contains longitudinal data (32 sectors observed over 23 years), but nevertheless we allow for some of the parameters to differ across sectors, differently from, e.g., Autor and Salomons (2017), Autor and Salomons (2018) and Gregory, Salomons, and Zierahn (2018). In particular, our approach allows for heterogeneous responses to AI (via productivity), depending on the characteristics of each sector. It is that heterogeneity that is of interest to us. The remaining variables are included as control variables, i.e., to lessen the possibility of contamination of our results by an omitted-variable bias.

We allow for heterogeneity in the (Bayesian) context of a multilevel model, Gelman and Hill (2006). The starting point is the following version of equation (15):

$$l_{s,t} = \beta_{1,s} + \beta_{2,s} a_{s,t} + \beta_3 w_{s,t} + \beta_{4,s} r_{s,t} + \beta_5 \tilde{d}_{s,t} + \beta_6 {d^*}_{s,t} + \beta_7 \tilde{p}_{s,t} + \beta_8 {p^*}_{s,t} + \varepsilon_{s,t} \qquad (17)$$

In equation (17), s identifies the sector and t is the period. As indicated above, the parameter of interest is $\beta_{2,s}$, which is the elasticity of employment with respect to productivity. For simplicity, the multilevel component of our model concerns only this parameter. In the first level, the model assumes that the estimated value of $\beta_{2,s}$ is a noisy measurement of the true coefficient (μ_s). This is achieved by modelling the estimate of $\beta_{2,s}$ as a random draw from a normal distribution centered at the true effect (with variance σ_s^2):

$$\beta_{2,s} \sim N(\mu_s, \sigma_s^2), \quad s = 1, \dots, 32 \tag{18}$$

In the second level, we assume that the true effects for the sectors are drawn from a normal probability distribution:

$$\mu_s \sim N(\mu, \sigma^2), \quad s = 1, \dots, 32 \tag{19}$$

We experimented allowing for two modes: a mode corresponding to a possibly negative effect of productivity on employment, and a mode corresponding to a possibly positive effect. We modelled this by means of a mixture of two normal distributions. However, the posterior distribution exhibited only one mode, suggesting that a simple normal distribution might be adequate, as the results reported below will show.

Following Stan Development Team (2018b), the priors for σ_s^2, μ and σ^2 are weakly informative:

$$\sigma_s^2 \sim lognormal(0,2), \quad s = 1,\dots,32 \tag{20}$$

$$\mu \sim N(0,2) \tag{21}$$

$$\sigma^2 \sim lognormal(0,2) \tag{22}$$

We opted for weakly informative priors for μ and σ^2 , the mean and variance of the coefficient of interest, $\beta_{2,s}$, due to the lack of benchmark values for these parameters in existing research or official statistics. For this same reason we did not try to consider informative priors as a robustness check. The increase in research devoted to this topic will conceivably make benchmark values available that can then be used as informative priors. We leave this to future research.

The other parameters of equation (17) are given simple flat (improper) priors in accordance with the theoretical framework described above:

$$\beta_{1,s}, \beta_{4,s} \sim uniform(-\infty,\infty), \quad s = 1,\dots,32 \tag{23}$$

$$\beta_3 \sim uniform(-\infty,0) \tag{24}$$

$$\beta_5, \beta_6, \beta_7, \beta_8 \sim uniform(0,\infty) \tag{25}$$

Note that our theoretical framework predicts that a rise in wages will lower employment, i.e. $\beta_3 < 0$, because capital will substitute labor in production and because production costs will increase, thus raising prices and reducing demand for the firm's output. According to the Dixit-Stiglitz model, an increase in the general level of aggregate demand, either domestic or foreign, should raise demand for the firm's output. Therefore, β_5 and β_6 should be positive. Likewise, in the Dixit-Stiglitz model, an increase in the prices of other goods (domestic or foreign) will divert demand towards the firm's output, i.e. β_7 and β_8 should also be positive. As for the rental rate of capital, its impact on employment is ambiguous, much like that of productivity. When the cost of renting capital increases, production costs increase and demand for the firm's output goes down, and hence employment should decrease. However, the firm fill attempt to substitute labor for capital and this may compensate the previous effect. Therefore we do not restrict the sign of $\beta_{4,s}$. The intercept is also unrestricted, as it must account for the differences in scale across industries.

The model is estimated by maximum likelihood using the Stan language for R, Stan Development Team (2018a).

4. Results and discussion

Since the parameter of interest is the coefficient associated with productivity, we focus only on the estimates related to this parameter. As described in the previous section, our empirical (multilevel) model distinguishes between estimates of the effect of productivity on employment ($\beta_{2,s}$) and the true effect of productivity on employment (μ_s).

[Insert Figure 3 here]

Figure 3 provides information about the distribution of the estimated effects ($\beta_{2,s}$), namely the 2.5% and 97.5% quantiles, the median and the mean of the distribution of $\beta_{2,s}$ over 5000 post-"warm-up" simulations. While classical regression analysis provides one estimate for each parameter in the model, Bayesian analysis provides, for each parameter, a sample of estimates from the simulated posterior distribution of the parameters. Thus, Figure 3 (and also Figures 4, 7 and 8) contains, for each sector A to S, an horizontal line/segment corresponding to the credible intervals (analogue to confidence intervals) for the parameter values, i.e. they have a 95% probability of containing the true value of the parameter, obtained by considering the 2.5% and 97.5% quantiles of the distribution of posterior draws; a vertical line/segment corresponding to the median of all the estimated coefficients; and a dot that gives the mean of all the estimated coefficients. In this as well as in the case of the other parameters, we take as the parameter "estimate" the mean of the distribution (the dot in Figures 3, 4, 7 and 8). As will be seen, the median is always very close to the mean.

The following examples illustrate the interpretation of the the results presented in Figure 3: for sector "A - Agriculture, forestry and fishing" the estimated β2 has a mean value of 0.1, a median value of 0.1 (the vertical segment, the median, coincides with the dot, the mean) and is located with a 95% probability in the interval between -0.22 and +0.41; for sector "F – Construction" the estimated β2 has a mean value of -1.35, a median value of -1.35 (the vertical segment, the median, coincides with the dot, the mean) and is located with a 95% probability in the interval between -1.72 and -0.97; for sector "QB - Social work activities" the estimated β2 has a mean value of 0.13, a median value of 0.13 (the vertical segment, the median, coincides with the dot, the mean) and is located with a 95% probability in the interval between -0.04 and +0.3. The same reasoning applies to the remaining sectors. Most of the estimated effects for the different sectors are negative, suggesting that the net sectoral employment impact of substitution and demand effects arising from the introduction of AI in production is negative, resulting in sectoral job destruction. Making use of the nomenclature in Bessen (2019), it seems that most sectors have matured and the demand for the goods they produce is essentially satiated. In other words, the price elasticity of demand in most sectors is not high enough to enable the price decrease associated with the reduction in costs (brought about by the introduction of new technologies that increase productivity) to generate an increase in demand (and thus output) that compensates for the adverse employment impact of those labor-saving technologies. The more intense negative impact seems to be in sector "F – Construction" followed by sectors "CG - Manufacture of rubber and plastics products, and other non-metallic mineral products", "D - Electricity, gas, steam and air-conditioning supply", "CC - Manufacture of wood and paper products, and printing" and "B - Mining and quarrying". It is not surprising to see that the estimated effect is negative in the traditional sectors of the economy, mostly associated with the "old economy". Production in these sectors involves manual routine tasks that can be easily automated; hence workers can be replaced by machines, resulting in job destruction, as discussed in Autor (2015) and Frey and Osborne (2017). Nevertheless, there are a few exceptions, i.e. sectors where the demand effect is slightly able to compensate for the substitution effect: "A- Agriculture, forestry and fishing" (0.10), "CB- Manufacture of textiles, wearing apparel and leather products" (0.32), "CJ - Manufacture of electrical equipment" (0.04), "JC- Computer programming, consultancy and related activities; information service activities" (0.15), "K- Financial and insurance activities" (0.04), "QB- Social work activities" (0.13). However, it is clear that these positive effects are nevertheless very close to zero, raising doubts about the signal of the true effect.

[Insert Figure 4 here]

The corresponding information concerning the estimates of the true effects is presented in Figure 4. The striking feature of this figure is the concentration of the estimates in the interval [−0.5,0.0]. This is true even for those sectors for which the estimated effect was positive (with the exception of sector QB). According to our estimates, these true effects come from a distribution with mean $\mu = -0.24$ and standard deviation $\sigma = 0.05$ - see Table 4. The posterior distributions for these parameters (μ and σ) are also very concentrated, in sharp contrast to the very flat, weakly informative priors that have been assigned to them. This can be confirmed in Figures 5 and 6.

According to the estimates of the true effects presented in Figure 4, the net impact of the substitution and demand effects of the introduction of new technologies on employment is negative in all sectors except possibly for "QB - Social work activities", with a 10% increase in productivity resulting in a decrease in employment between 3 and 2% in almost all sectors, and so leading to a very similar impact in terms of the respective intensity across the sectors. This result is expected in the case of traditional sectors (such as agriculture, construction, textiles, etc.), where demand is probably satiated and that employ a less skilled labor force, which is likely to be carrying out routine tasks. But the adverse employment effect also applies, and with a similar magnitude, to modern sectors that employ a skilled labor force (likely performing a higher share of non-routine tasks), such as the sectors "JC - Computer programming, consultancy and related activities, and information service activities", "K - Financial and insurance activities", "P – Education" and "QA - Human health services". These sectors have been the subject of much speculation concerning the impact of AI. Software that can maintain a conversation with humans (on the verge of passing Turing's test?) or rewrite itself in response to new information is increasingly less science fiction. "Fintech" is leading to a reinvention of financial services as a consequence of the introduction of new technologies, lowering costs, but the low financial literacy of the Portuguese population may be preventing the financial sector from reaching a wider audience than before and so the demand effect is not sufficient to compensate for the substitution effect. Additionally, there have been news about software that can diagnose medical conditions more reliably than humans (e.g. Google´s AI and Healthcare project). The negative impact for QA indicates that the price elasticity of health demand in Portugal is relatively low. This may be a structural feature (people are willing to pay for the healthcare they need) or it may be a consequence of the existence of health insurance systems (public and private) that top up the (low) price paid directly by the patient. The same kind of effect may be at work in education (P), where massive open online courses and other distance-learning methods may pose a threat to the traditional brick-and-mortar system.

[Insert Table 4 here]

[Insert Figure 5 here]

[Insert Figure 6 here]

The fact that the estimated effect of productivity on employment is essentially the same across sectors is also somewhat surprising given that we are imposing homogeneity on other parameters. By constraining some parameters, one might expect the heterogeneity to show up more strongly in the unconstrained parameters. However, in this case heterogeneity does not manifest itself in the productivity parameter but appears to exist in the intercept (Figure 7) and in the coefficient on the rental rate of capital (Figure 8). We plan to investigate this issue further in future research. As a test of robustness, we carried out the analysis assuming α =1/2 instead of α = 1/3. Our conclusions are unaffected by this change in the parameterization, although the distribution of the true effects becomes concentrated closer to zero, with mean equal to -0.13 and variance equal to 0.001. In another robustness test we split the sectors between those that have high educational intensity and those that have low educational intensity, using the taxonomy presented by (Peneder 2007). As expected, the impact of productivity appears to be more negative on low educational intensity sectors; however, the difference to high educational intensity sectors is very small (the average of the true effect changes from -0.26 to -0.21). These results reinforce our confidence that the similarity found regarding the effect of productivity across sectors is a robust result. A final piece of evidence is provided by a standard fixed-effects estimation of the model, which yields a statistically significant (at the 1% significance level) estimate of the coefficient on productivity, β_2, equal to -0.46. According to our previous results, this appears to overestimate the magnitude of the average true effect of productivity on employment.

[Insert Figure 7 here]

[Insert Figure 8 here]

5. Conclusion

There are long-established concerns about technological improvements resulting in jobs being lost to automation/machines. Recent advances in AI have brought to attention the discussion about technological progress and job destruction once more because AI introduces the possibility of automation in a broader range of occupations, professions and sectors hence its impact can be diversified and transversal in the economy, Autor and Salomons (2017). Given its relevance, this topic was recently addressed by the Confederation of Portuguese Business in a study conducted by McKinsey Global Institute and Nova School of Business and Economics (Nova SBE). To the best of our knowledge this study is not publicly available, but press reports indicate that the study estimates 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.

Our estimate of the average impact of productivity-enhancing technologies such as AI on sectoral employment is an elasticity of −0.24, i.e. if AI increases productivity by 10%, 2.4% of jobs will be lost. To obtain this estimate of the impact of AI, we defined a model relating sectoral employment to productivity and a set of control variables. This model attempts to incorporate both the (negative) substitution and the (positive) demand effects of automation on employment based on the predictions of a standard model of supply and demand for the output produced in each sector. Our estimates, obtained in the context of a Bayesian multilevel approach, indicate that the expected employment impact of automation is negative, and, moreover, similar, across the sectors analyzed, i.e., in both traditional and modern sectors with variegated price elasticities of demand and different potential for automation of the tasks performed by workers - a somewhat surprising and worrisome result.

The purpose of this paper has been to reflect on the possible impact of AI, as a productivity-enhancing technology, on employment using sectoral level data for Portugal over the period 1995-2017. The empirical analysis carried out in this study is a tentative one, limited by data availability since we do not use direct information on the incorporation of AI technologies in production. The underlying contention of our work is that AI is a relatively new technology with a huge potential to improve productivity (see e.g. Trajtenberg, 2019; Brynjolfsson, Rock, and Syverson, 2019; and Damioli, Van Roy, and

Vertesy, 2021). Through this productivity channel AI may influence employment, either in a positive or negative (or zero) way, depending on the relative strength of opposite sign effects (substitution vs. demand). Our approach implies that the quantitative estimates of the impact of productivity on employment that we arrive at should be interpreted as an upper-bound corresponding to a situation when AI is responsible for an important part of the observed productivity improvements, which for now is still difficult to assess but is a probable future scenario. Furthermore, the diffusion of AI technologies through the economy may involve complex processes of restructuring (e.g. complementary investments) that may take considerable time. Therefore, a lapse of time may exist between the introduction of AI technologies and its effects on productivity and employment and these effects may still not be reflected in the data analyzed in this study (see e.g. Brynjolfsson, Rock, and Syverson, 2019; and Naudé, 2021). We must also not forget that AI does not have to be associated with job destruction via automation- 'technological determinism' in the words of Naudé (2021); it can also lead to job creation (complementarity), as argued by Acemoglu and Restrepo (2020b).

A natural extension of this study involves its replication for other countries as all economies will likely have to face the challenges of the incorporation of IA technologies, with associated benefits but also involving costs, namely in terms of employment losses. Wider international comparisons applying panel data methodologies could also allow for important generalizations on the relationship under analysis. As other proxies for the use of AI in production activities become available (see Frank et al., 2019) a more in depth analysis of its relationship with employment behavior will be possible. The consideration of the short- and long-run dimensions in the relationship under analysis is also an interesting extension of this work. This will likely demand the use of estimation methodologies that distinguish between short and long run effects of productivity on employment such as ARDL or error correction models, which is beyond the scope of the present study since to arrive at robust results these methodologies demand data with a longer time span than currently available.

Declaration of interest

The authors declare that they have no conflict of interests.

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Table 1: Summary of the employment effects of AI at different levels of analysis

Firms (Autor (2014), Autor (2015))	**Sectors** (Autor and Salomons (2018))	**Regions** (Gregory, Salomons, and Zierahn (2018))	**Individual sectors** (Bessen (2019); Bessen (2020))
→ Substitution effect (-). → Complementarity effect (+).	→ Intra-industry effect (-). → Final demand effect (+). → Inter-industry effect through input-output linkages (+).	→ Substitution effect (-). → Sectoral demand effects (+). → Demand spillovers effect (+).	→ Substitution effect (-). → Sectoral demand effect (+).

Notes: The first row identifies the level of analysis and the study. The signs in parenthesis indicate whether the corresponding employment effect of AI and related automation is expected to be positive (+) or negative (-).

Table 2: List of sectors

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
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.
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, audiovisual 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
MC	Advertising and market research; other professional, scientific and technical activities; veterinary activities
N	Administrative and support service activities
P	Education
QA	Human health services
QB	Social work activities
R	Arts, entertainment and recreation
S	Other services activities

Table 3: Data

Variable	Data	Unit	Source
Employment	Full-time equivalent employees (by sector)	Full-time equivalents	Statistics Portugal (INE)
Productivity	Total factor productivity (by sector)		Own computations based on data from AMECO and Statistics Portugal
Wages	Compensation of employees per hour worked by employees(by sector)	EUR per hour	Statistics Portugal
Rental rate of capital	Gross operating surplus per unit of capital	EUR	Own computations based on data from AMECO
Domestic aggregate demand	Real GDP, Portugal (market prices; chain linked volume data)	EUR, Millions, 2016	Statistics Portugal
Foreign aggregate demand	Real GDP, OECD (VIXOB, Volume index)	Index, Hundredths, 2015	OECD Stats
Domestic price level	GDP deflator, Portugal	Index, 2016	Own computations based on data from Statistics Portugal
Foreign price level	GDP deflator, OECD (DOBSA)	Index, Hundredths, 2015	OECD Stats

Table 4: Statistics from the posterior distributions

	mean	s.d.	2.5%	25%	50%	75%	97.5%
μ	-0.24	0.05	-0.33	-0.27	-0.24	-0.21	-0.15
σ	0.23	0.04	0.15	0.20	0.22	0.25	0.32

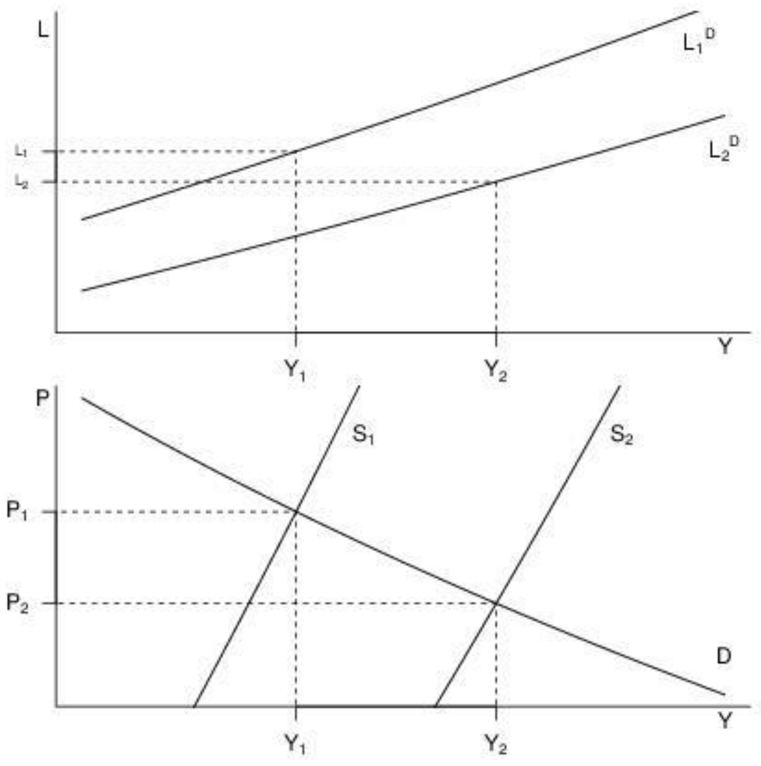

Figure 1. Productivity and demand effects with a negative total effect on jobs.

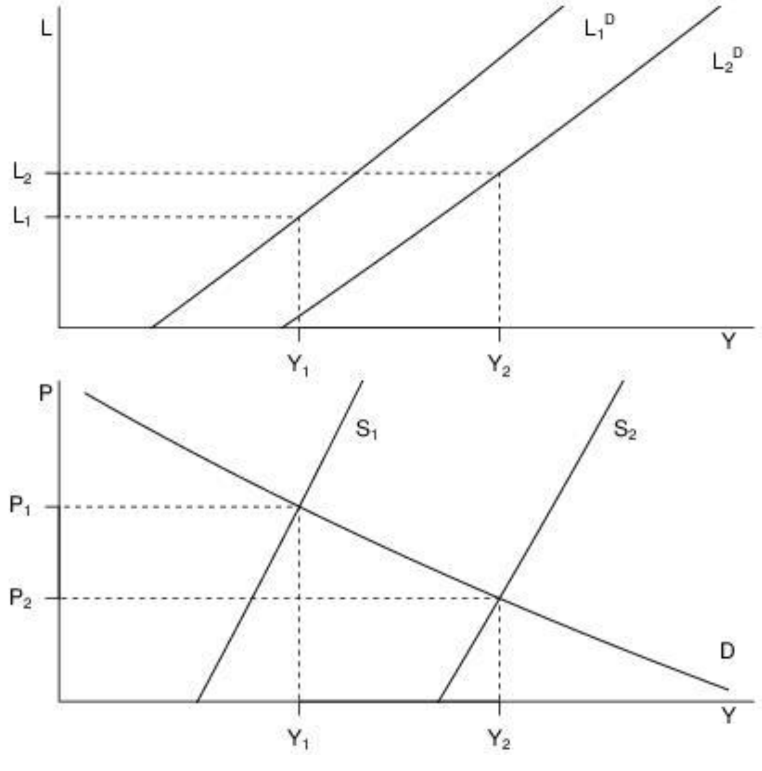

Figure 2. Productivity and demand effects with a positive total effect on jobs.

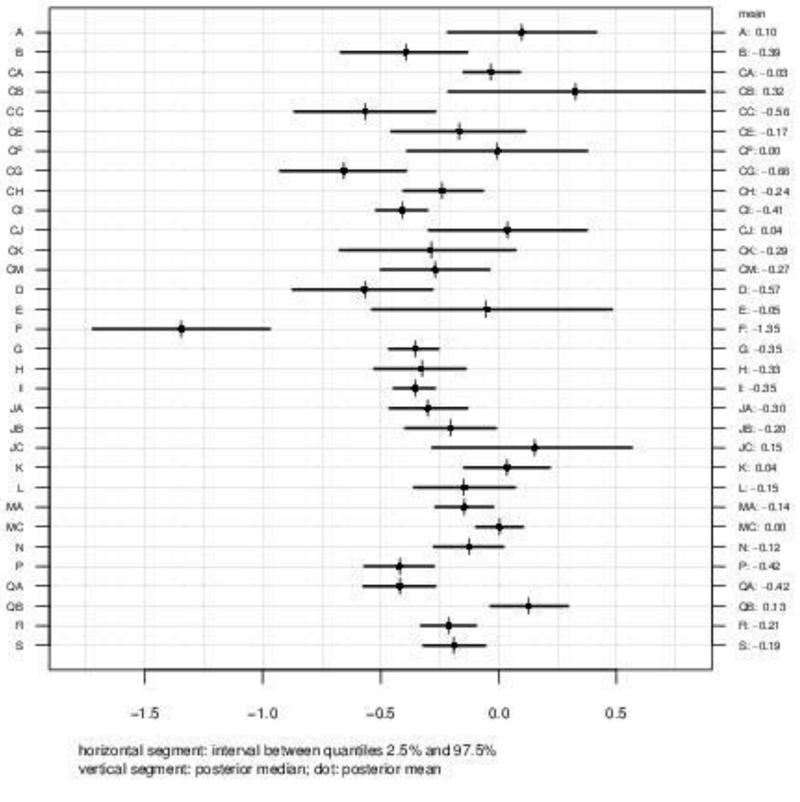

Figure 3. Estimated effects of productivity on employment.

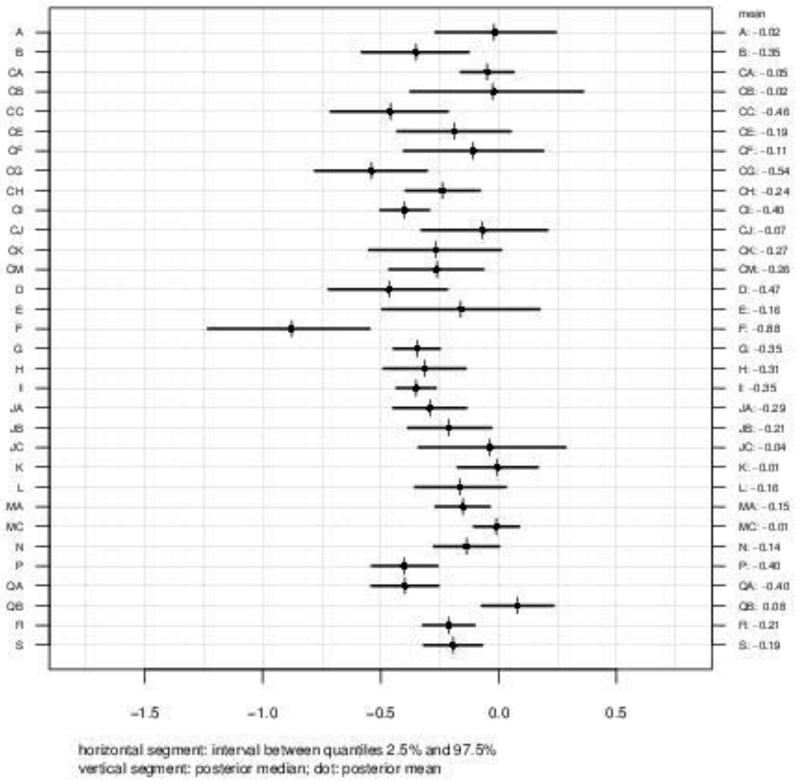

Figure 4. Estimated true effects of productivity on employment.

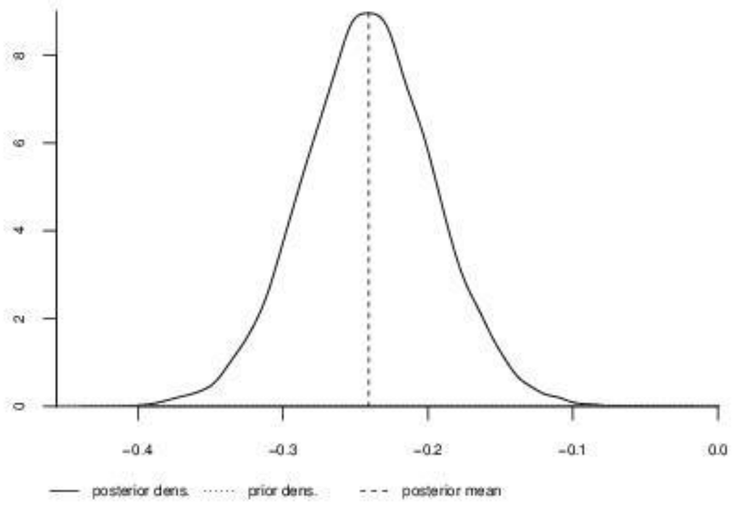

Figure 5. Posterior density of the mean true effect of productivity on employment.

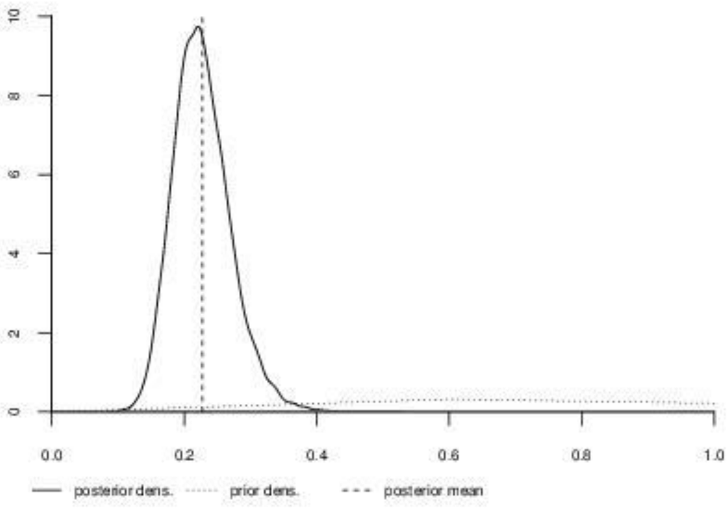

Figure 6. Posterior density of the variance of the true effect of productivity on employment.

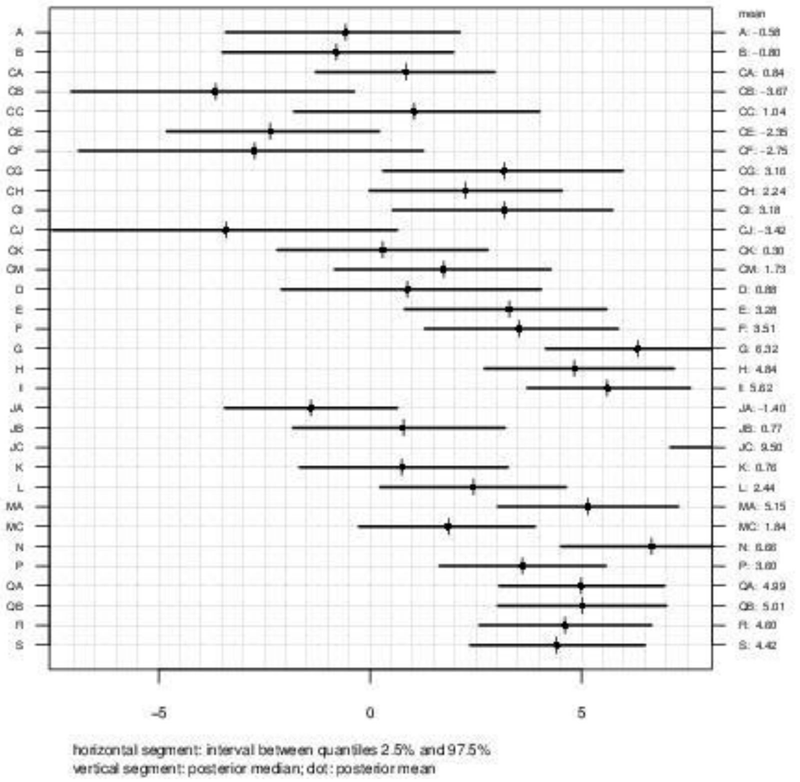

Figure 7. Estimated intercepts.

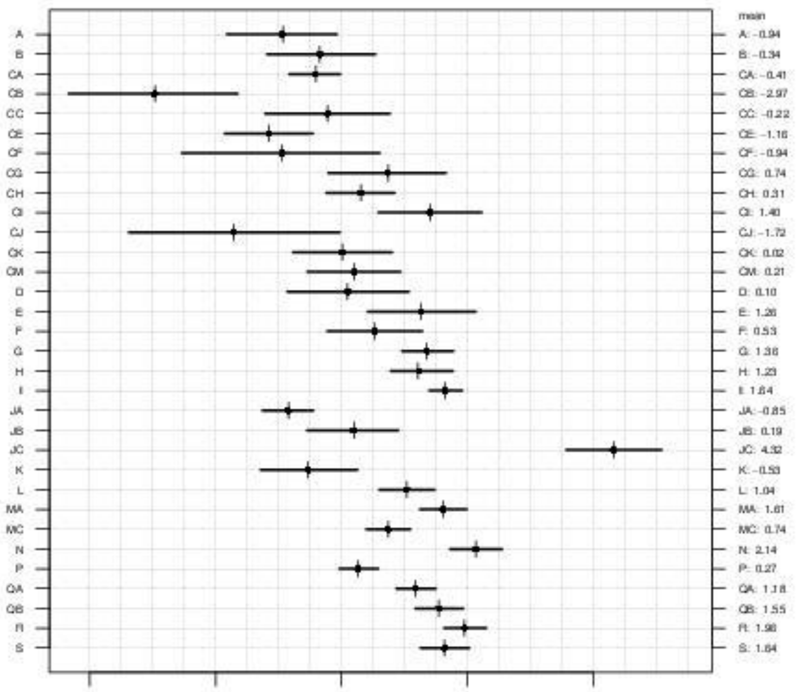

Figure 8. Estimated coefficient on the rental rate of capital.