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Abstract:
This paper investigates the impact of artificial intelligence on unemployment in the most high-tech and developed countries, using a theoretical model that is also supported empirically. The empirical methodology follows a nonlinear approach by using panel threshold and GMM-system estimations. The dataset covers the period 1998-2016, and includes 23 countries.
The main results show that artificial intelligence has a nonlinear impact on unemployment, with the acceleration of the use of artificial intelligence reducing unemployment, but only occurring at low levels of inflation. In this case, no “switch effect” between “displacement effect” and “replacement effect” is registered. Otherwise, the contribution of artificial intelligence to unemployment is rather neutral.

Key words: artificial intelligence; unemployment; implications; high-tech countries

JEL-codes: F22, O17, C23

1. Introduction

In recent decades, artificial intelligence has inspired significant interest in the social sciences, given this technology’s controversial effect on unemployment. Pentland et al. (2019, p.2) show that the “future strategic advantage depends on the ability to leverage artificial intelligence, such as machine learning, computer vision, and autonomous systems, and integrate it with the workforce to create symbiotic human-machine teams.”

Having modern roots in the period of the First World War, this concept was introduced for the first time in 1956 at a conference at Dartmouth College, during its artificial intelligence session. As Nilsson (1984, p.5) notes, the process generates a “different class of machines - machines that can perform tasks requiring reasoning, judgment, and perception that previously could be done only by humans.”

Currently, artificial intelligence is not only the continuation of automation processes; it also represents the culmination of these processes and has deep implications on the labour market. Stevenson (2019) claims that the use of artificial intelligence enhances economic growth by improving productivity, which raises the level of future income. He also shows that this positive effect is valid as long as the benefits generated by artificial intelligence are able to compensate the workers negatively impacted by their lost wages.

All processes which imply the use of artificial intelligence determine strong movements in labour demand in both the short- and long-term. In the short-term, Frank et al. (2019, p.6531) stress that “the rapid advances in artificial intelligence and automation technologies have the potential to significantly disrupt labour markets.” The main issue is the fall of demand for different jobs and the loss of professional status being more important that the lost of wages (Stevenson, 2019). Otherwise, in the long-term, technological change is expected to potentiate human skills via newly created jobs. In fact, artificial intelligence creates new ways to take advantage of human skills.

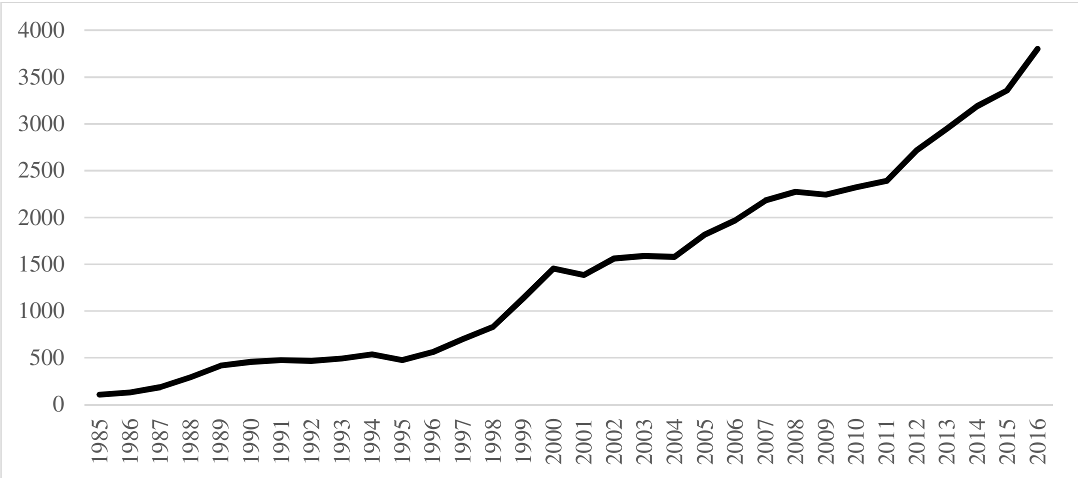
Therefore, because different opinions have arisen regarding the effects generated by artificial intelligence, the main worry is about the contribution of artificial intelligence as it relates to the unemployment level.

The theoretical **transmission channel** from artificial intelligence to unemployment is quite simple, and is explained as a pass-through to labour productivity.

The first type of effect is a *positive one*, implying that artificial intelligence reduces the level of unemployment. In this case, artificial intelligence is not very different with respect to other new technologies, generating higher productivity in a similar way. Therefore, the resulting economic expansion creates more jobs, thus reducing the rate of unemployment. Isolated episodes of structural unemployment can be registered, but they are transitory, as they are reduced as soon as the labour market returns to equilibrium.

The second type of effect is a *negative one*, with artificial intelligence helping to cause increased unemployment. In this case, Nilsson (1984, p.5) emphasises that "if it does create more work, this work can also be performed by artificial intelligence devices without necessarily implying more jobs for humans."

The number of artificial intelligence patent applications worldwide has continuously increased in the last decades, as shown in Figure 1.



Source: constructed based on the Organization for Economic Co-operation and Development (OECD) online database (2020).

Figure 1: Number of artificial intelligence patent applications worldwide (1985-2016)

A flat trend is registered until 1995-1997, while a more steeply increasing tendency is observed afterward. This upward dynamic is strongly related to the big changes in the types of technology (Fuji and Managi, 2018) that valorise the transformational potential of artificial intelligence on society that is widely recognized by nations in their strategic plans (Fatima et al., 2020).

In this light, this paper analyses the impact of artificial intelligence on unemployment based on a theoretical model. An empirical section, including 23 of the most high-tech and developed economies, supports the theoretical contribution. The estimations are performed based on nonlinear panel models covering the period from 1998 to 2016. The main results show that there is a nonlinear relationship between a country's level of artificial intelligence and its unemployment rate. More precisely, artificial intelligence improves employment at low inflation rates, while its effect is null otherwise.

The contribution of this paper to the literature is threefold. First, to the best of our knowledge, this investigation is one of the first contributions that analyses the influence of artificial intelligence on unemployment using a nonlinear approach. Unlike existing papers that claim linear connections, our study finds evidence of a positive effect of artificial intelligence on employment but only until a threshold, conditioned by the level of inflation, is reached. Further, this effect becomes neutral beyond this threshold, proving the nonlinear link. Second, also as a novelty, the study considers inflation as a main "ingredient" in the "artificial intelligence-unemployment" nexus. Herein, the real and expected levels of inflation define the effect of artificial intelligence on unemployment according to identified threshold. The artificial intelligence facilitates the reduction of unemployment, but only at low inflation rates, without a "switch effect" between the "displacement effect" and the "replacement effect". Third, compared to current studies, this paper offers an empirical analysis based on an extended dataset that includes the most high-tech and developed world economies. The empirical findings fully support the results of the theoretical model. Moreover, the outputs are reinforced including a number of variables in parallel with various econometric techniques in different scenarios. Unlike existing empirical studies, our approach uses both panel thresholds and Generalized Method of Moments (GMM)-system estimators.

The rest of the paper is it as follows: Section 2 reviews the literature. Section 3 presents the theoretical model, and Section 4 shows the empirical part, including the data description, methodology and results. Section 5 concludes.

2. Literature review

Artificial intelligence has deep implications for the socioeconomic environment, and covers many areas, from unemployment and inequality to productivity.

During the last few decades, the literature regarding the impact of artificial intelligence on unemployment has been significantly developed (Ernst et al., 2019, Martens and Tolan, 2018), although many contributions treat artificial intelligence as part of a more complex automation process (Wang and Siau, 2019). In the broad sense, two strands of literature can be identified. The first strand claims a "replacement effect" of jobs by artificial intelligence, while the second one promotes the "displacement effect" between them.

The first strand of literature supports the "replacement effect", which includes both theoretical and empirical papers. Herein, the use of artificial intelligence has a negative impact on the labour market, generating unemployment because of jobs loss as an effect of replacement.

One of the first *theoretical works* regarding the destructive effect of artificial intelligence on employment belongs to Leontief (1983). He underlines that in future decades, nearly all jobs would be replaced by artificial intelligence, increasing unemployment as a result. This effect can be absorbed when the government has the correct redistributive policies, using the benefits of new technologies. Zeira (1998) develops a model of economic growth by focusing on technological innovations. He considers that innovations require more capital but reduce the need for a larger labour force.

Although there is no clear specification regarding artificial intelligence, Zeira (1998, p. 1091) claims that new types of machines replace "workers in production, such as the steam engine, the train, the automobile, the computer, and many more, which reduced labour input," ...or... "nonskilled with skilled labour." In all cases, the new alternatives generate more productivity requiring less labour. More recently, Hirst (2014) refers to low-skilled workers by claiming that the rate of unemployment for that category rises as the level of innovation and technology increases. Therefore, the contribution of artificial intelligence seems to be destructive for the creation of new labour inputs. Roubini (2014) supports this idea in some way by considering that high-skilled workers (e.g., software developers, engineers, researchers) will generally benefit more than low-skilled ones during the automation process.

Stiglitz (2014) also argues that employment falls due to the pressure of artificial intelligence. Unlike the previous authors mentioned, he considers that the rate of unemployment increases because of replacement decisions made by capital owners and human-resource management.

For the first time, Bessen (2018, 2020) introduces into the discussion the elasticity of demand by theoretically supporting the idea that employment falls due to automation pressures only if demand is inelastic. Otherwise, he highlights, when demand is elastic, there are positive effects on job vacancies. Atkinson (2018, p. 9) proposes a "sector translation". The author claims that artificial intelligence has a destructive role on employment, explaining that "as automation reduced agricultural jobs, people moved to manufacturing jobs. After manufacturing jobs were automated, they moved to service-sector jobs. But as robots automate these jobs, too, there will be no new sectors to move people into next."

As a novel contribution, Acemoglu and Restrepo (2018a) develop an extended theoretical model by focusing on the race between man and machine. They take into account the implications of technology for growth, factor shares, and the level of employment. The authors state that when "capital is fixed and technology is exogenous, automation reduces employment and the labour share, and may even reduce wages, while the creation of new tasks has the opposite effects" (p. 1488). Furthermore, Acemoglu and Restrepo (2019) offer more "flavour" by stressing that the acceleration of artificial intelligence use reduces labour demand, lowers the national income, generates inequality, and lowers productivity growth.

Other groups of authors propose *empirical approaches* by quantifying the "artificial intelligence - unemployment" nexus. For example, Frey and Osborne (2017) estimate that the job losses under automation processes in U.S. would be at 47 percent of total jobs in the next ten to twenty years. Unlike Frey and Osborne (2017), Arntz et al. (2017) revise the estimations of job losses due to automation in the U.S for 21 OECD countries, advancing a rate of 9 percent. Analysing the U.S. as well, Atkinson and Wu (2017) reveal that since 2000, the decline in positions represents only 42 percent of the historical levels registered during the period from 1850 to 2000. Acemoglu and Restrepo (2017) combine their empirical study with a theoretical one. The authors explore the impact of industrial robot usage between 1990 and 2007 in U.S. local labour markets. The results show that robot usage is destructive for U.S. local labour markets, and also reduces the level of wages. Based on the authors' estimations, "one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent" (p. 1). Finally, Bowles (2017) focuses on the EU, finding that for the same 10-20 year horizon, the process will replace 54 percent of total jobs. The same EU area (i.e., six country members) is the target for Chiacchio et al. (2018). The authors defend the idea that any additional robot per 1,000 workers reduces employment by 0.16-0.20 percentage points.

The second strand of the literature proposes the "displacement effect". In this case, artificial intelligence positively influences the labour market, reducing unemployment because of the job-creation effect. Two groups of contributions suggest this strand: the first group strongly promotes strict positive effects, while the second one stands for a cautionary vision.

Albus (1983) produced one of the first papers devoted to the *strict positive impact* of artificial intelligence on employment. He finds no evidence that higher productivity, generated through technological progress, reduces the number of jobs. On the contrary, more efficient production generates growth and determines the appearance of new markets, with new products and services. Furthermore, those new extensions will require additional jobs, reducing the level of unemployment. Referring to the Nobel Prize winner in Economics Herb Simon, Boden (1987, p. 17) argues that the artificial intelligence revolution is a replicable one. According to him, “there will be all sorts of problems in the transition period, but finally there will be many more jobs created, different perhaps, but many more jobs than there were before, so we do not need to worry about the unemployment issue in the long term.” In the same note, Dauth et al. (2017) conclude that in Germany no net job losses were registered as an effect of the automation process. As a new contribution, Frey and Osborne (2017) introduce the idea of sectors with high and low risks to be automatized. In this light, they conclude that unemployment increases only in the sectors most exposed to the influence of automation.

Unlike these previous studies, Su (2018) explains the reduction of unemployment due to artificial intelligence, through job structure. More precisely, the jobs replaced by artificial intelligence require less demand in the labour market, causing unemployment. In this case, policymakers will compensate these lost jobs by stimulating the creation of the new ones in other sectors. Hence, the main target of these measures is to prevent the structural unemployment caused by artificial intelligence. In a different approach, Gries and Naudé (2018) incorporate artificial intelligence into an economic growth model, with constraints on aggregate demand. They show that artificial intelligence does not result in an immediate rise in unemployment.

Other important findings include those of Acemoglu and Restrepo (2018b), who investigate the link between artificial intelligence, automation, and work. They claim that artificial intelligence and automation improve the level of productivity, which is subsequently complemented by additional capital accumulation. With more capital, existing machinery will be technically improved using a larger labour force, which generates new jobs. Further, as result of automation, output per worker increases more than wages, lowering the share of labour in national income.

One of the first *cautionary visions* regarding the positive influence of artificial intelligence on unemployment belongs to Trehan (2003). He empirically shows that the reduction in unemployment due to technological pressure is valid, but only when the situation and conditions persist several years. Further, the effect can have a retrograde effect. On the contrary, Autor (2015) shows that automation affects the tasks performed rather than jobs *per se*. More precisely, he states that the automation process transforms the nature and content of jobs, and not the jobs themselves. In fact, new jobs replace the old ones. Berriman and Hawksworth (2017) also suggest this “job-to-job” replacement. The authors stress that the net impact of automation on jobs is neutral because the initial job reduction is compensated by newly created jobs (i.e., new products support the new jobs as a vector of new technological innovation).

Gordon (2018) finds that the automation process is an evolutionary, rather than a revolutionary, one. Analysing the case of the U.S., he finds that the process slowly replaces jobs, but only in a minority of sectors. Analysing the automation process via robots, Carbonero et al. (2018) point out that the use of robots has a small negative impact on the number of jobs in developed countries. In these developing countries, this negative impact is about 14 percent over the period from 2005 to 2014.

Finally, Ernst et al. (2019, p. 31) put forth a neutral opinion. They conclude that the implications of artificial intelligence-based innovation on employment “remain highly uncertain.”

In summary, the literature helps to identify three main research gaps. The first is related to the lack of papers focusing on nonlinear effects between artificial intelligence and unemployment. The second gap refers to the lack of papers that consider inflation as a main “ingredient” for the “artificial intelligence-unemployment” nexus, although inflation has strong implications on the labour market via nominal and real wages. The third gap underscores the existence of just a few contributions using large datasets in terms of both countries and years. As a consequence, using this general literature framework, this paper aims to fill all three of these gaps.

3. Theoretical model

When we consider artificial intelligence to be a crucial determinant of productivity, it becomes theoretically connected with unemployment via the output channel. There is an extended literature that claims a positive impact of artificial intelligence on productivity, especially through information technologies (Smith, 2008). For example, Brynjolfsson and Brown (2005) show that the benefit of artificial intelligence can be obtained only by changing business practices. Mahmood and Mann (2005) show that the benefit of artificial intelligence can only come about by following a multiyear research process. This is because information technology investments typically take time to produce measurable performance improvements.

The simple model we propose is inspired by the literature, but is an adjusted version. In fact, we follow the approaches of Dornbusch et al. (2017) and Folawewo and Adeboje (2017) as a mix of the Phillips curve (Phillips, 1958) and Okun's law (Okun, 1962). Unlike these studies, our approach controls the potential output with the contribution of artificial intelligence through productivity. Additionally, we investigate the effect of artificial intelligence on unemployment by considering both real and expected levels of inflation. Therefore, we show that a nonlinear link between artificial intelligence and unemployment is driven by the level of inflation.

The basis for the Phillips curve is described by the inverse interaction between the unemployment rate and inflation, with this form:

$$\Omega_w = -\alpha(u - u^*). \tag{1}$$

Here, Ω_w is wage inflation, α is the elasticity of unemployment to wage inflation, u is the unemployment rate, and u^* denotes the natural unemployment ratio. Wage inflation can be considered:

$$\Omega_w = \frac{w_t - w_{t-1}}{w_{t-1}}, \tag{2}$$

where w represents the wage, t is the current period of time, and t-1 is the previous time period.

Alternatively, equation (1) can be written as:

$$\frac{w_t - w_{t-1}}{w_{t-1}} = -\alpha(u - u^*), \text{ and } w_t = w_{t-1}[1 - \alpha(u - u^*)]. \tag{3}$$

By integrating the expected price inflation ψ^e, equation (1) becomes:

$$\Omega_w - \psi^e = -\alpha(u - u^*). \tag{4}$$

Assuming that the real wage is constant, when actual inflation ψ equals Ω_w, then:

$$\psi - \psi^e = -\alpha(u - u^*). \tag{5}$$

Further, ψ and ψ^e can be written as $\psi = \frac{P_t}{P_{t-1}}$ and $\psi^e = \frac{P_t^e}{P_{t-1}}$, respectively, where P denotes the price level. In this case:

$$\frac{P_t}{P_{t-1}} - \frac{P_t^e}{P_{t-1}} = -\alpha(u - u^*); \tag{6}$$

$$\frac{P_t - P_t^e}{P_{t-1}} = -\alpha(u - u^*); \tag{7}$$

$$P_t = P_t^e - \alpha P_{t-1}(u - u^*). \tag{8}$$

Okun's law has this general form:

$$\frac{Y - Y^*}{Y^*} = -\beta(u - u^*), \tag{9}$$

where Y is the actual output, Y^* is potential output, and β is the elasticity of unemployment to output. Equation (9) can also be written as:

$$-\frac{Y - Y^*}{\beta Y^*} = (u - u^*). \tag{10}$$

By replacing $(u - u^*)$ in equation (8), equation (10) becomes:

$$P_t = P_t^e + \frac{\alpha}{\beta} P_{t-1} \frac{Y - Y^*}{Y^*} \text{ or } P_t = P_t^e [1 + \frac{\alpha}{\beta} \frac{P_{t-1}}{P_t^e} \frac{Y - Y^*}{Y^*}]. \tag{11}$$

Supposing that $\varphi = \frac{\alpha P_{t-1}}{\beta P_t^e Y^*}$, then $\alpha = \frac{\varphi \beta P_t^e Y^*}{P_{t-1}}$. Further, by replacing $\alpha = \frac{\varphi \beta P_t^e Y^*}{P_{t-1}}$ in equation (7), we obtain:

$$(u - u^*) = -\frac{P_t - P_t^e}{P_t^e} \frac{1}{\varphi \beta Y^*}. \tag{12}$$

Equation (12) shows that unemployment is inversely related to inflation and output, supporting the mix of the Philips curve with Okun's law.

Now, we introduce artificial intelligence by "controlling" Y^* as follows:

$$Y^* = p_a \theta^*, \tag{13}$$

where p_a is the employed population (i.e., total number of people of any age who currently work), while θ^* represents the potential productivity per person. Herein, p_a can be written as:

$$p_a = \eta p, \tag{14}$$

where η is the ratio of employed persons to the total population, with $0 < \eta < 1$, and p equal to the total population. Further, θ^* is:

$$\Theta^* = \omega\Theta_-^*, \quad (15)$$

where ω is the level of artificial intelligence used to stimulate productivity ($\omega \geq 1$), while Θ_-^* denotes the potential productivity per person without the influence of artificial intelligence. When $\omega = 1$ (i.e., ω is neutral), no contribution of artificial intelligence is registered and, as a consequence, $\Theta^* = \Theta_-^*$. As ω positively increases, artificial intelligence improves potential productivity, as $\Theta^* > \Theta_-^*$.

By corroborating equations (13), (14) and (15), Y^* becomes:

$$Y^* = \eta p\omega\Theta_-^*. \quad (16)$$

Equation (16) shows that potential output directly depends on total population and their propensity to work, potential output without the contribution of artificial intelligence, and the level of artificial intelligence used to stimulate productivity. Herein, when the level of artificial intelligence used increases, Y^* rises.

By replacing the last form of Y^* in equation (12), we obtain:

$$(u - u^*) = -\frac{P_t - P_t^e}{P_t^e}\frac{1}{\varphi\beta\eta}\frac{1}{p\omega\Theta_-^*} = \left(1 - \frac{P_t}{P_t^e}\right)\frac{1}{\varphi\beta\eta}\frac{1}{p\omega\Theta_-^*}. \quad (17)$$

The product $\varphi\beta\eta$ is a strict positive parameter given by the country's characteristics, while both p and Θ_-^* are also positives, being quasi-constants for a long time period. In this context, two situations arise:

$$\text{When } \{\omega \uparrow\} \Rightarrow \begin{cases} \{u \downarrow\}, \text{if } P_t < P_t^e; \\ \{u \uparrow\}, \text{if } P_t > P_t^e. \end{cases} \quad (18)$$

In other words, when the level of artificial intelligence ω increases, unemployment falls below its natural rate ($u < u^*$) if the inflation rate is lower than the expected rate ($P_t < P_t^e$). Otherwise, the unemployment rate increases above its natural rate ($u > u^*$), when inflation is above the expected rate ($P_t > P_t^e$). Conversely, when the level of artificial intelligence ω decreases, contrary effects are registered: unemployment rises above its natural rate ($u > u^*$) if inflation is lower than the expected ($P_t < P_t^e$), while unemployment falls under its natural rate ($u < u^*$) if inflation is higher than expected ($P_t > P_t^e$).

It is worth noting that the acceleration of the use of artificial intelligence counteracts the Phillips effect, attenuating the negative influence of inflation on labour demand.

The next step is to linearize equation (17), as follows:

$$ln(u - u^*) = ln\left(\frac{P_t^e - P_t}{P_t^e}\right) - \ln(p) - \ln(\omega) - \ln(\Theta_-^*) - \ln(\varphi\beta\eta). \quad (19)$$

This model suggests a nonlinear connection between artificial intelligence and unemployment, with artificial intelligence having both positive and negative effects on unemployment but conditioned by inflation. Artificial intelligence seems to be a good incentive for employment if the inflation rate is less than expected, while a destructive influence is observed otherwise.

4. Empirical approach

4.1. Methodology

This theoretical model is supported by an econometric analysis focused on the impact of artificial intelligence on unemployment in the most high-tech and developed countries, where the use of artificial intelligence is substantial. As both the theoretical model and previous literature claim opposite signs between artificial intelligence and unemployment, a nonlinear relationship between them is suspected; but this requires further empirical investigation. In other words, the pure linear link is questionable.

To this end, threshold panels with fixed effects proposed by Hansen (1999) are considered, assuming threshold effects in non-dynamic panels. This tool offers four main advantages compared to classical ones (Pan et al., 2016, p. 3): "first, it does not need to set the nonlinear equations; second, the number of the threshold is totally determined endogenously by the sample data; third, it will calculate the confidence interval of parameters according to the asymptotic distribution theorem; four, it will estimate the statistical significance using the bootstrap method."

The starting point of the empirical section is equation (19), supposing that all variables are treated as elasticities.[1] According to equation (18), inflation represents a crucial factor for the sign of the artificial intelligence-unemployment nexus. Therefore, inflation *(P)* becomes a threshold variable, while artificial intelligence *(ω)* is the regime-dependent variable, as follows:

$$u_{it} = a_0 + a_{11}\omega_{it-1}(P_{it} \leq \gamma) + a_{12}\omega_{it-1}(P_{it} \geq \gamma) + \sum_{k=1}^{n} b_k X'_{k,it} + cu_{it-1} + v_i + \varepsilon_{it} \quad (20)$$

where γ denotes the threshold parameter of variable P dividing the equation into two regimes related to ω, with coefficients $a_{11,12}$; a_0 is the constant; X' is the vector of control variables (i.e., the inflation rate, population, and labour productivity) k by n type with slope b; c is the coefficient of lagged dependent variables; v_i stands for individual effects related to country i; and ε_{it} captures the disturbance at time t.

The artificial intelligence variable ω appears as a lagged variable for two main reasons: first, the use of artificial intelligence theoretically precedes unemployment, and second, the approach allows one to deal with any endogeneity issue that especially arises from potential simultaneity between ω and u. Additionally, the lagged u is also used as an independent variable to correct for autocorrelation in residuals.

By adding one more threshold, equation (20) becomes:

$$u_{it} = a_0 + a_{11}\omega_{it-1}(P_{it} \leq \gamma_1) + a_{12}\omega_{it-1}(\gamma_1 < P_{it} \leq \gamma_2) + a_{13}\omega_{it-1}(P_{it} \geq \gamma_2) + \sum_{k=1}^{n} b_k X'_{k,it} + cu_{it-1} + v_i + \varepsilon_{it} \quad (21)$$

where, $\gamma_{1,2}$ denote the threshold parameters which divide the equation into three regimes with coefficients $a_{11,12,13}$.

According to Bai (1997), and Bai and Perron (1998), the threshold panel approach assumes a consistent sequential estimator, following a three-step procedure (Wang, 2015):

Step 1: Fitting the parameter γ_1 and residual sum of squares (RSS) as $S_1(\hat{\gamma}_1)$ in order to estimate the single-threshold model.

[1] For simplification, the notations used in the theoretical approach are maintained in the empirical approach.

Step 2: The identification of the second threshold and its confidence interval, based on $\hat{\gamma}_1$:

$$\hat{\gamma}_2^r = \underset{\gamma_2}{\arg min}\{S_2^r(\gamma_2)\}, \tag{22}$$

$$S_2^r = S\{min(\hat{\gamma}_1, \gamma_1) max(\hat{\gamma}_1, \gamma_2)\}, \tag{23}$$

$$LR_2^r(\gamma_2) = \frac{\{S_2^r(\gamma_2) - S_2^r(\hat{\gamma}_2^r)\}}{\hat{\sigma}_{22}^2}, \tag{24}$$

where LR represents the likelihood ratio statistic and σ^2 the variance.

Step 3: Considering that $\hat{\gamma}_2^r$ is efficient while $\hat{\gamma}_1^r$ is not, the re-estimation of the first threshold is:

$$\hat{\gamma}_1^r = \underset{\gamma_1}{\arg min}\{S_1^r(\gamma_1)\}, \tag{25}$$

$$S_1^r = S\{min(\gamma_1, \hat{\gamma}_2) max(\gamma_1, \hat{\gamma}_2)\}, \tag{26}$$

$$LR_1^r(\gamma_1) = \frac{\{S_1^r(\gamma_1) - S_1^r(\hat{\gamma}_1^r)\}}{\hat{\sigma}_{21}^2}. \tag{27}$$

Further, the threshold effect is tested by investigating whether the coefficients in each regime are the same or not. Therefore, in the first instance, we compare the linear with single-threshold models, while in the second one, we discriminate between single and double-threshold models.

The null hypothesis of no-threshold effect (i.e., linear model) versus threshold effect (i.e., nonlinear model) is as follows:

$$H_0 = \alpha_{11} = \alpha_{12} \text{ or } H_a = \alpha_{11} \neq \alpha_{12}, \tag{28}$$

with an F-statistic $F_1 = \frac{(S_0 - S_1)}{\hat{\sigma}^2}$.

Based on a new F-statistic, the double-threshold model is tested if the null hypothesis of the simple-threshold model is rejected. It is as follows:

$$F_2 = \frac{\{S_1(\hat{\gamma}_1) - S_2^r(\hat{\gamma}_2^r)\}}{\hat{\sigma}_{22}^2}. \tag{29}$$

Nguyen and To (2016, p. 36) emphasize that "the double-threshold model corresponds to the null hypothesis of the existence of one threshold and the alternative of the existence of two thresholds." In other words, the double-threshold model is selected if the null hypothesis is rejected. Further, for models with more than two thresholds, the selection process is similar.

Additional determinants as controls and an alternative methodology are also considered in order to check for robustness (Subsection 4.4).

4.2. Dataset

The pillar of this empirical study is a panel with 23 cross-sections and 19 years (i.e., 1998-2016), including both high-tech and developed countries. Out of them, 20 are OECD members (i.e., Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, India, Ireland, Israel, Italy, Japan, Korea, the Netherlands, Norway, Sweden, Switzerland, the United Kingdom, and the United States), while 3 are non-OECD countries (i.e., China, Russia, and Singapore). This selection follows two important criteria: first, the countries are developed ones, having complex economies; and second, all of them occupied the first part of the Global Innovation 2019 rankings, exhibiting outstanding performances in innovation. The time period starts exactly with the years where the number of artificial intelligence patent applications “blew up” in the world.

The **dependent variable** represents the unemployment rate according to the theoretical model, denoting the labour force that is without work but available for and seeking employment as a percentage of total labour force.

The **interest variable** captures the level of artificial intelligence used to stimulate productivity. Although the literature is scarce in terms of the measurement of artificial intelligence, two variables are alternatively considered as proxies: Scenario 1 - *artificial intelligence patents by applicant residence*, and Scenario 2 - *artificial intelligence patents by inventor residence*. They denote the number of artificial intelligence patents by applicant or inventor residence, respectively. By extension, the variables suggest not only the number of applications potentially using artificial intelligence, but also the interest in the field from a research and development perspective. Two arguments strongly motivate their selection. First, quasi-all technology advancements are protected by patents, and second, applications for artificial intelligence patents facilitate the elimination of inefficiencies in using them (OEB, 2020). Last but not least, the patents fix any eligibility challenges and legal litigations. Therefore, the number of artificial intelligence patents successfully cover the idea of artificial intelligence use.

According to the theoretical model and related literature, both positive and negative signs of artificial intelligence are expected with respect to unemployment.

A set of **control variables** is considered to isolate the effects of interest variable. They are inspired by both the theoretical model and the literature: the inflation rate, the total population, and labour productivity.

The inflation rate reflects the consumer price index as the annual percentage of price changes in the economy as a whole. We expect an inverse relationship between inflation and unemployment according to the Phillips curve (Phillips, 1958), but we cannot exclude the same sign link. For example, Vermeulen (2017) claims that a low level of inflation represents a good condition for job creation, which further stimulates economic growth.

Total population (population ages 15-64) shows total residents from a legal status or citizenship point of view, with the values representing midyear estimates. Population growth is expected to increase unemployment. Meier (1995) states that population growth seriously imposes restrictions in the savings process, which reduces the investments and, as consequence, the creation of new jobs.

Labour productivity is the output per worker, having as its main components the Gross Domestic Product (GDP) and total employed population. The sign of the labour productivity coefficient in respect to unemployment is not very clear. For example, Basu et al. (2006) underscore the negative impact of productivity on unemployment as a result of technological shocks, while Gallegati et al. (2014) claim a positive one, but only in the long term, using a pure wavelet approach.

The variables are elasticities, appearing in percentages, with the exception of artificial intelligence patents by applicant/inventory residence, total population and labour productivity, which are expressed in their natural logarithm form. Table A1, in the Appendix, describes the variables and their expected signs according to both theoretical model and literature.

LM, CD and LMadj tests are employed to check for cross-sectional dependence, while Pesaran's (2007) second-generation unit root test is followed accordingly.

4.3. Results

As the cross-sectional dependence tests in Table A2 (Appendix) validate the existence of cross-sectional dependence in both scenarios, the second-generation of panel unit-root tests are employed in Table A3 (Appendix). The panel unit-root results show that all variables are I(1), with exception of *inflation*, which is I(0) and *total population*, which is I(2). Therefore, the variables are treated in their first difference in all estimations. *Inflation* is used in levels, while *total population* is its second difference. The matrix of correlations in Table A4 (Appendix) considers the variables to be stationary. The findings clearly show that all the coefficients are significantly below the critical level of 0.9 recommended by Hall and Asteriou (2011, p.101). Therefore, no multicollinearity bias is found.

All estimations have as an interest variable *artificial intelligence*, as follows: Scenario 1, with *artificial intelligence patents by applicant residence*, and Scenario 2, with *artificial intelligence patents by inventor residence*. Supposing a threshold level of *inflation* (see Subsection 4.1), Table A5 (Appendix) presents the results of tests for threshold effects for each scenario. Testing for three potential thresholds, the results clearly indicate that only one threshold is more appropriate for all cases, at a 1% critical value.

Taking into account one threshold effect in *inflation*, Tables A6 and A7 (Appendix) present the results of panel threshold estimations with fixed effects in both scenarios. Besides *inflation* and two regime coefficients for *artificial intelligence*, *total population*, *labour productivity* and *lagged unemployment* are gradually used as control determinants. As the F-tests for fixed-effect stands for Ordinary Least Square (OLS) panel regressions, additional OLS models are employed.

Table A6 reveals the outputs for Scenario 1. In all estimations (Models 1-3), the first regime coefficient of *artificial intelligence* is significant and has a negative sign, while the second one is not significant. With the exception of *total population*, all control determinants are significant, being negatively correlated with *unemployment*. The results of Scenario 2 are shown in Table A7 (Models 6-8). Herein, unlike the second regime coefficient of *artificial intelligence*, which is not conclusive, the first one maintains its significance and negative sign. In this case, only *labour productivity* is significant, having a negative sign.

In both scenarios, the positive and significant sign of *lagged unemployment* suggests that unemployment is a process with "memory". This indicates some persistent rigidity in the process of unemployment adjustment, with current unemployment being positively related to past unemployment. The results regarding *inflation* partially are in accordance with Phillips (1958), while *labour productivity* findings fully fit Basu et al. (2006).

All models underline the crucial role of *labour productivity* and partially confirm the Phillips effect between *inflation* and *unemployment*. The main results highlight a nonlinear connection between *artificial intelligence* and *unemployment*, strongly supporting the theoretical model. More precisely, when *inflation* is lower than the expected rate (i.e., under the threshold level), the intensive use of *artificial intelligence* reduces *unemployment*, improving the number of jobs available. This fact fully validates the "displacement effect". On the contrary, under the same regime of low *inflation*, the reduction in *artificial intelligence* use will not reduce *unemployment*; it is decreasing at a decreasing rate. Herein, it is noteworthy that the "replacement effect" is not possible under the presence of *artificial intelligence* at low levels of *inflation*. Interestingly, the findings do not offer evidence of any "switch effect" between the "displacement effect" and the "replacement effect" at low *inflation*. Otherwise, with *inflation* higher than the expected rate (i.e., over the threshold level), the results are not conclusive, suggesting a "null effect" instead. This neutral effect is strongly supported by all employed models.

4.4. Robustness check

This robustness check follows two sequences: the first considers additional control determinants, while the second uses an alternative set of estimations using the GMM-system types.

The first robustness check sequence extends the controls in the initial panel threshold estimations with fixed effects by adding two important determinants, strongly recommended in the literature: the size of the economy and Foreign Direct Investment.

Government size measures government spending as cash payments for operating activities in providing goods and services, expressed as a share of GDP. According to Feldmann (2006), a positive link between government size and unemployment is expected.

Foreign Direct Investment (FDI) captures the volume of investment as net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. Generally, the literature reveals that FDI has a negative impact on unemployment (e.g., Craigwell, 2006; Karlsson et al., 2009) as FDI inflows generate new jobs. Therefore, we expect FDI and unemployment to have an opposite sign.

For both scenarios, the results are presented in initial Table A6 (Models 4 and 5) and Table 7 (Models 9 and 10), respectively. With and without fixed effects, *government size* and *FDI* are significant and negatively correlated with unemployment in all cases, with the effects of *artificial intelligence* and the rest of the determinants remaining very robust. This fully confirms the results of Feldmann (2006), Craigwell (2006), and Karlsson et al. (2009). More precisely, the expansion of the public sector absorbs the unoccupied labour force in the countries under consideration, while net FDI inflows support this process.

The second robustness check sequence uses GMM-system estimations (Table A8, Appendix), where the nonlinear effect of *artificial intelligence* is tested by using interacted variables. The main advantage of GMM-system estimators is that they make it possible to deal with any endogeneity issue by fixing the bias related to autocorrelation in residuals.

Concretely, for each scenario, two interacted variables are constructed based on artificial intelligence patents and a *dummy threshold* variable driven by *inflation*. The inflation rate of 0.3127 is considered as a threshold for both scenarios, as it is a result from naïve Models 1 and 6.

Two regime dummy variables are obtained, as follows:

$$Dummy_{threshold} \Rightarrow \begin{cases} Dummy_{under\ threshold} = 1 \text{ if } P<0.3127 \text{ and 0 otherwise;} \\ Dummy_{over\ threshold} = 0 \text{ if } P>0.3127 \text{ and 1 otherwise.} \end{cases} \quad (30)$$

In Scenario 1, the two *interacted variables* are the product between artificial intelligence patents by applicant residence and dummy under threshold, and artificial intelligence patents by applicant residence and dummy over threshold. Similarly, in Scenario 2, the two calculated interacted variables are the product of artificial intelligence patents by inventor residence and the dummy under the threshold, and artificial intelligence patents by inventor residence and the dummy over threshold.

All GMM-system estimations in Table A8 (Appendix) consider as instruments the lags of unemployment and the interacted variables. The results of Scenario 1 (Models 11 and 12) clearly show that the *interacted variable "under threshold"* is significant, being negatively related to *unemployment*. Like the panel threshold outputs, the *interacted variable "over threshold"* is not significant, being inconclusive in respect to *unemployment.* Similar findings illustrate Scenario 2 (Models 13 and 14), the *interacted variable "under threshold"* being significant with a negative sign and inconclusive otherwise. With the exception of *FDI*, the rest of the controls are also significant, maintaining their signs from the panel threshold estimations. The Hansen test and Arellano-Bond p-vales test for AR(2) indicate that the instruments are well identified, while no autocorrelation in the residuals is evidenced. As a consequence, *artificial intelligence* is also robust under different methods of estimation, mainly GMM-system.

Overall, the effect of *artificial intelligence* on *unemployment* seems to be robust under different control determinants and alternative tools, reinforcing the findings suggested by the theoretical model and empirical panel threshold estimations.

The analysis has several research limits. First, the investigation does not consider emerging and developing countries due to the lack of data availability regarding the number of artificial intelligence patents. Second, the study does not take into account all determinants of unemployment (e.g., trade openness, the structure of population, migration, etc.) in order to avoid any multicollinearity issues. Finally, the study does not capture activities in the underground economy, as the measurement of informal economy is still controversial (Breusch, 2005).

5. Conclusions

This paper analyses the influence of artificial intelligence on unemployment in the most high-tech and developed countries in the world, based on a theoretical model supported by an empirical model that applies panel threshold estimations. A set of robustness checks are also considered. The dataset covers the period from 1998 to 2016 and includes 23 countries.

The main results suggest a nonlinear relationship between artificial intelligence and unemployment, conditioned by the level of inflation. Under low levels of inflation, the use of artificial intelligence improves employment, while its effect seems to be null otherwise.

Artificial intelligence improves unemployment when inflation is under its expected rate. In this case, when inflation is low, the intense use of artificial intelligence reduces unemployment as long as the tendency to increase wages is compensated by growth and the creation of new jobs. The "displacement effect" is validated. This positive effect gradually is reduced, as inflation tends to rise. One very interesting result seems to be that artificial intelligence use counteracts the "Philips" effect at low inflation levels. Moreover, when artificial intelligence use is attenuated, unemployment does not rise; it is reduced, but at a decreasing rate. Herein, the "replacement effect" is not proved. Therefore, no "switch effect" between the "displacement effect" and the "replacement effect" is found at low *inflation* rates.

Furthermore, when the inflation rate is higher than the expected rate, the "Phillips effect," which is counteracted, disappears, with the use of artificial intelligence having no influence on unemployment. This suggests that the intense use of artificial intelligence under high rates of inflation does not affect wages, with unemployment automatically being reduced because of the "Phillips effect." In other words, the effect works well under high inflation, with the contribution of artificial intelligence being limited (i.e., artificial intelligence cannot counteract the "Phillips effect" under high inflation rates). Rigidity in the labour market can explain this fact, with unemployment being a "memory" process in high-tech and developed countries.

Additionally, there are significant implications regarding government size and FDI net inflows, with both strongly supporting the aforementioned mechanisms.

Overall, it is worth noting that the use of artificial intelligence has a positive effect on unemployment under low inflation rates, while its implications are neutral at high rates. More precisely, despite the acceleration of the use of artificial intelligence, the "Phillips effect" replaces its benefits at high inflation, automatically reducing unemployment.

Regarding policy implications, it is required for policymakers in high-tech and developed countries to strongly support the use of artificial intelligence in economic processes in order to reduce unemployment as long as inflation is low. This will help control wages via the economic growth and new jobs created via this new technology. Otherwise, interventions to stimulate the use of artificial intelligence are in vain under high inflation rates, as the economy has a self-regulating mechanism regarding the level of unemployment.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1: Description of variables and their expected signs

Variables	Explanation	u. m.	Source	Expected sign
Unemployment ratio - dependent variable	Percentage of unemployed persons of total labour force.	%	World Development Indicators (2018).	
Artificial intelligence patents by applicant residence	Volume of artificial intelligence patents by applicant residence	Number	OECD online database - Patents statistics, (2020)	+/-
Artificial intelligence patents by inventory residence	Volume of artificial intelligence patents by inventory residence	Number	OECD online database - Patents statistics, (2020)	+/-
Controls:				
Inflation ratio	Annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly.	%	World Development Indicators (2020).	+/-
Population	Total residents ages 15-64, from legal status or citizenship point of view.	Persons	World Development Indicators (2020).	-
Labour productivity	Output per workers having as main components GDP and total employed population.	GDP constant 2011 international $ in PPP	International Labor Organization (ILOSTAT) 2020.	+/-
Government size	Expense is cash payments for operating activities of the government in providing goods and services, as share of GDP.	%	World Development Indicators (2020).	+
FDI	Foreign direct investment as net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor.	%	World Development Indicators (2020).	-

Table A2: Cross-sectional dependence test results

Scenario	Test statistics	p-value
(a) Artificial intelligence patents by applicant residence		
LM test	435.8***	0.0000
CD test	13.6***	0.0000
LM_{adj} test	12.97***	0.0000
(b) Artificial intelligence patents by inventory residence		
LM test	427.3***	0.0000
CD test	12.91***	0.0000
LM_{adj} test	13.01***	0.0000

Note:
(1) *, ** and *** are the significance for at 0.1, 0.05 and 0.01 levels;
(2) LM test, CD test and LM_{adj} test represent the cross-sectional dependence tests of Breusch and Pagan (1980), Pesaran (2004), and Pesaran et al. (2008), respectively.

Table A3: Panel root tests of variables

Variable	Level		First difference	
	Constant	Constant and trend	Constant	Constant and trend
Unemployment ratio	-2.003	-2.360	-2.069*	-2.041
Artificial intelligence patents by applicant residence	-2.420***	-2.346	-3.263***	-3.348***
Artificial intelligence patents by inventor residence	-2.450***	-2.426	-3.565***	-3.726***
Inflation rate	-3.745***	-4.174***	-4.197***	-3.957***
Total population	-1.976	-2.196	-1.854	-1.976
Labour productivity	-1.465	-1.696	-2.098**	-2.301
Government size	-1.812	-2.149	-2.500***	-2.557***
FDI	-1.978	-2.503	-4.064***	-4.367***

Note:
(1) *, **, *** denote significance at 10%, 5% and 1% level, respectively;
(2) “Total population’ variable is I(2).

Table A4: Matrix of correlations

Variable	Unemployment	Artificial intelligence patents by applicant residence	Artificial intelligence patents by inventor residence	Inflation	Population	Productivity	Government size	FDI
Unemployment	1							
Artificial intelligence patents by applicant residence	-0.012	1						
Artificial intelligence patents by inventor residence	-0.087	0.761	1					
Inflation	-0.011	-0.012	-0.037	1				
Population	0.081	0.012	0.001	0.017	1			
Productivity	-0.203	0.119	0.158	-0.064	-0.047	1		
Government size	0.377	-0.131	-0.248	-0.120	0.068	-0.308	1	
FDI	-0.071	-0.044	-0.038	0.009	-0.044	0.196	-0.118	1

Table A5: Tests for threshold effects

Models	Scenario 1: Artificial intelligence patents by applicant residence	Scenario 2: Artificial intelligence patents by inventor residence
Test for single threshold		
F_1	18.85***	24.49***
P-value	0.0033	0.0000
(10%, 5%, 1% critical value)	(9.6297; 11.7137; 16.4656)	(7.4740 ; 9.5493; 12.2197)
Test for two thresholds		
F_2	1.06	3.23
P-value	0.9200	0.6367
(10%, 5%, 1% critical value)	(8.2071; 11.1947; 15.4006)	(9.8939; 13.2196; 19.0448)
Test for triple thresholds		
F_3	1.69	2.89
P-value	0.8000	0.8100
(10%, 5%, 1% critical value)	(9.6675; 13.0643; 16.4928)	(8 12.6668; 15.7307; 21.5987)

Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively.

Table A6: Scenario 1 - Artificial intelligence patents by applicant residence (single threshold)

Dependent variable: unemployment					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Estimated threshold	0.3127	0.0375	0.0375	0.0375	0.0375
$\omega^{+/-}$ - first regime coefficient (α_{11})	-0.012*** (0.003)	-0.012*** (0.003)	-0.012*** (0.005)	-0.013*** (0.003)	-0.013** (0.005)
$\omega^{+/-}$ - second regime coefficient (α_{12})	0.0005 (0.0006)	0.0003 (0.0006)	0.0003 (0.0004)	-0.00005 (0.0006)	-0.00005 (0.0003)
Inflation rate $^{+/-}$	-0.0004** (0.0002)	-0.0004* (0.0002)	-0.0004* (0.0002)	-0.0005*** (0.0002)	-0.0005*** (0.0001)
Total population $^{-}$		-0.174 (0.106)	-0.174 (0.104)	-0.126 (0.102)	-0.126 (0.091)
Labour productivity$^{+/-}$		-0.111*** (0.017)	-0.111*** (0.017)	-0.047** (0.019)	-0.047*** (0.016)
Unemployment ratio$_{t-1}$ $^{+/-}$	0.328*** (0.047)	0.355*** (0.046)	0.355*** (0.063)	0.266*** (0.047)	0.266*** (0.057)
Constant	0.0008*** (0.0006)	0.002*** (0.0007)	0.002*** (0.0006)	0.002*** (0.0007)	0.002*** (0.0005)
Government size $^{+/-}$				0.124*** (0.019)	0.124*** (0.032)
FDI $^{-}$				-0.015*** (0.005)	-0.015*** (0.005)
Fixed effect	yes	yes	no	yes	no
R-squared	0.183	0.201	0.201	0.313	0.313
F-test for fixed-effects	0.35 Prob.= 0.99	1.31 Prob.= 0.15		1.05 Prob.= 0.41	
Number of observations	391	391	391	391	391
Number of groups	23	23	23	23	23

Note:
(a) *, **, *** show significance at 10%, 5% and 1% level, respectively;
(b) (…) denotes the standard error!
(c) +/- represent the expected signs of variable.

Table A7: Scenario 2 - Artificial intelligence patents by inventor residence (single threshold)

Dependent variable: unemployment					
Variable	Model 6	Model 7	Model 8	Model 9	Model 10
Estimated threshold	0.3127	0.3127	0.0375	0.3464	0.3464
$\omega^{+/-}$ - first regime coefficient (α_{11})	-0.011*** (0.002)	-0.012*** (0.002)	-0.012*** (0.003)	-0.013*** (0.003)	-0.012*** (0.004)
$\omega^{+/-}$ - second regime coefficient (α_{12})	0.0004 (0.0008)	0.0003 (0.0007)	0.0003 (0.0005)	-0.0001 (0.0007)	-0.0001 (0.0004)
Inflation rate $^{+/-}$	-0.0004* (0.0002)	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0005** (0.0002)	-0.0005*** (0.0001)
Total population $^{-}$		-0.148 (0.105)	-0.148 (0.104)	-0.103 (0.101)	-0.103 (0.095)
Labour productivity$^{+/-}$		-0.117*** (0.017)	-0.117*** (0.013)	-0.056*** (0.019)	-0.056*** (0.017)
Unemployment ratio$_{t-1}$ $^{+/-}$	0.324*** (0.047)	0.355*** (0.046)	0.355*** (0.057)	0.264*** (0.046)	0.264*** (0.053)
Constant	0.0006 (0.0007)	0.002*** (0.0007)	0.002*** (0.0005)	0.002*** (0.0007)	0.002*** (0.0005)
Government size $^{+/-}$				0.117*** (0.018)	0.117*** (0.038)
FDI $^{-}$				-0.017*** (0.005)	-0.017*** (0.005)
Fixed effect	yes	yes	no	yes	no
R-squared	0.191	0.216	0.216	0.321	0.321
F-test for fixed-effects	0.34 Prob.= 0.99	1.37 Prob.= 0.12		1.17 Prob.= 0.27	
Number of observations	391	391	391	391	391
Number of groups	23	23	23	23	23

Note:
(a) *, **, *** show significance at 10%, 5% and 1% level, respectively;
(b) (…) denotes the standard error!
(c) +/- represent the expected signs of variable.

Table A8: Robustness check: GMM-system estimations

Dependent variable: unemployment				
Variables	Model 11	Model 12	Model 13	Model 14
Scenario 1: Artificial intelligence patents by applicant residence				
$\omega^{+/-}$ (Artificial intelligence patents by applicant residence x Dummy $_{\text{under threshold}}$)	-0.0004* (0.0002)			
$\omega^{+/-}$ (Artificial intelligence patents by applicant residence x Dummy $_{\text{over threshold}}$)		0.0002 (0.0002)		
Scenario 2: Artificial intelligence patents by inventor residence				
$\omega^{+/-}$ (Artificial intelligence patents by inventor residence x Dummy $_{\text{under threshold}}$)			-0.0006** (0.0002)	
$\omega^{+/-}$ (Artificial intelligence patents by inventor residence x Dummy $_{\text{over threshold}}$)				0.0002 (0.0007)
Inflation rate $^{+/-}$	-0.0004** (0.0001)	-0.0004** (0.0001)	-0.0006** (0.0002)	-0.0004** (0.0001)
Total population $^{-}$	-0.244** (0.116)	-0.245** (0.117)	-0.244** (0.116)	-0.242** (0.116)
Labour productivity $^{+/-}$	-0.046*** (0.015)	-0.048*** (0.015)	-0.046*** (0.015)	-0.049*** (0.016)
Unemployment ratio$_{t-1}$ $^{+/-}$	0.298*** (0.055)	0.294*** (0.057)	0.301*** (0.055)	0.296*** (0.057)
Constant	0.001*** (0.0006)	0.001*** (0.0006)	0.001*** (0.0006)	0.001*** (0.0006)
Government size $^{+/-}$	0.137** (0.065)	0.135** (0.065)	0.138** (0.065)	0.135*** (0.065)
FDI $^{-}$	-0.008 (0.005)	-0.008 (0.005)	-0.008 (0.005)	-0.008 (0.005)
Type of estimation	GMM-system	GMM-system	GMM-system	GMM-system
Hansen test	[0.039]	[0.074]	[0.051]	[0.105]

Arellano-Bond p-vales test for AR(2)	[0.268]	[0.239]	[0.291]	[0.236]
Number of observations	374	374	374	374
Number of groups	22	22	22	22

Note:
(a) *, **, *** show significance at 10%, 5% and 1% level, respectively;
(b) (…) denotes the standard error, while [...] is the p-value;
(c) +/- represent the expected signs of variables.