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Threshold effects of technology import on industrial employment: a panel smooth transition regression approach

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Abstract
The relationship between imported technology and employment is a controversial issue. This study aims to test the hypothesis that the relationship between imported technology and employment is non-linear and evolves with the level of technology imports. The study covers two groups of developed and developing countries over the period 2000–2019. The Panel Smooth Transition Regression (PSTR) model is used to estimate the technology import threshold and its impact on industrial employment. The study finds a positive relationship between imported technology and industrial employment for technology import rates above the 13.667% threshold, above which imported technology begins to improve industrial employment in developed countries. In contrast, for developing countries, the results showed a negative relationship between imported technology and industrial employment for technology import rates above the 3.44% threshold above which imported technology begins to reduce industrial employment. These results suggest that the threshold level of technology imports can be considered as an indicator for promoting innovation policies in both developed and developing countries to minimize the negative effect of process innovation resulting from imported technology.

Keywords: Technology Import; Industrial employment, Panel Smooth Transition Regression, Developing countries, Developed countries

JEL Classification: B22, C01, C12, C24, E24, F16, F62, L16, L60, N70, O11, O14, O33

1 Introduction

From the first industrial revolution to the fourth, the fear of mass technological unemployment has grown with each new innovation. Historically, technological progress has generated concerns, although it is widely regarded as an essential driver of economic progress. Warnings have been issued over the past two centuries that new technologies would replace labor with machines, creating technological unemployment and increasing inequality in the short term. In the early nineteenth century, mechanization had only a limited capacity to supplant human activity, and the fears of the working class were ultimately unfounded. Above all, technological progress enabled product innovation and the creation of entirely new industries.

However, the waves of innovation in the twentieth century have led to a resurgence and amplification of concerns about the disruptive effects of technology. These concerns have been rekindled by the current technological revolution, which according to Barbieri et al. (2019) is the most rapid. Scientific publications have also reinforced skepticism about major technological advances including Brynjolfsson & McAfee's (2014) prediction of job disruption due to new technologies, and Frey & Osborne's (2017) study painting a bleak picture of technology's impact on employment, predicting the disappearance of half of all jobs in the US. These studies have had a significant impact on the theoretical and empirical debate about technology's impact on employment. This concern has spawned a vast literature suggesting that technological progress affects employment and the demand for labor.

Regarding the theoretical literature, it should be noted that since its inception, economics has emphasized that while technological change may have direct negative effects on employment, these effects are offset in the long run by indirect mechanisms at the sectoral or economy-wide level. Karl Marx summarized these mechanisms in the first half of the nineteenth century under the name "compensation theory". In the course of the twentieth century, compensation theory has been enriched by various schools, such as Freeman et al. (1982), Vivarelli (1995) and, more recently, Vivarelli (2014) and Calvino & Virgillito (2017).

However, it is difficult to empirically establish the link between technology and employment, as the negative and positive effects of technology pass through different direct and indirect channels (Calvino & Virgillito 2017). In recent decades, a wealth of research has addressed the relationship between technology and employment. Technological advances, considered essential for sustained economic growth, can lead to job losses in the short and medium term, as the time required to adapt to these changes can be considerable (Aghion & Howitt 1996). This adaptation has been linked by numerous empirical studies to the qualification of the workforce, indicating that technological change can be facilitated by specific skills (Berman & Machin 2004; Machin & Van Reenen 1998). In addition, importance has been given to the type of technology adopted in determining the relationship between technology and employment. Indeed, while the adoption of product-oriented technologies is generally considered to have a positive impact on employment, the adoption of process-oriented technologies can lead to job losses (Harrison et al. 2014).

Despite the abundant empirical literature on this subject, studies reflect a controversial association with mixed and inconclusive results (Frey & Osborne 2017; Arntz et al. 2017; Ford 2015; Autor 2015), reflecting gaps in the literature's findings on the impact of technology on employment.

It is against this backdrop of controversial empirical debate that this article attempts to provide new elements of response, starting from the methodological shortcomings observed in previous empirical studies. Firstly, studies of developed economies neglect imported technology as an important source of technology (see Domini et al. 2021). In contrast, research on developing economies tends to focus on technology imports (see Sharma & Mishra 2023). However, even developed countries import technologies that they do not produce in their own countries. Secondly, to our knowledge, no empirical study has considered developed and underdeveloped countries jointly in its macroeconomic analysis. Furthermore, the literature has mainly focused on microeconomic analysis (Van Roy et al. 2018; Coad & Rao 2011) and rarely on macroeconomic analysis (Piva & Vivarelli 2018; Feldmann 2013; Simonetti et al. 2003; Vivarelli 1995). Third, the use of linear models has been the most common approach in the literature. To our knowledge, the only studies that have taken into account the non-linear relationship between technological progress and employment are the recent study by Yildirim et al. (2022) and study by Bouattour et al. (2023a). Finally, the existing literature does not adequately address the relationship between the impact of technology on employment and the level of economic development.

Based on these shortcomings, this article takes advantage of neglected areas by empirical research to propose a macroeconomic analysis of the non-linear relationship between technology and employment. To this end, it examines the impact of technology imports on industrial employment to draw out some possible implications. The aim is to examine whether these imports are a transition variable whose level influences both the direction and the intensity of the impact of technology imports on employment. In other words, this article proposes to study the possible existence of a non-linear relationship between imported technology and industrial employment, taking into account possible threshold effects.

This relationship is being examined for industrial employment in developed and developing countries over the period 2000–2019. Our empirical strategy involves using the Panel Smooth Transition Regression (PSTR) model, developed by González et al. (2005) and González et al. (2017). The PSTR model is chosen because it offers advantages over classical linear models, which were frequently used in previous studies. These linear models were limited to exploring only the direction (positive or negative) of the relationship and did not account for changes in the trend. These linear models assumed that the impact of innovation on employment is constant, which is restrictive and can lead to biased results, as the effects of innovation on employment may vary depending on several variables, including the intensity of technology imports and the evolution of industry dynamics. The PSTR model has the advantage of detecting nonlinear dynamics between variables and demonstrating the existence of threshold effects caused by the transition function, leading to regime-switching behavior.

Our results suggest the existence of a critical threshold for each group of countries that influences the impact of imported technology on industrial employment. For developed countries, a positive impact on industrial employment is observed above a given threshold of imported technology. Conversely, for developing countries, above a given import threshold, imported technology has a negative impact on industrial employment. Thus, the threshold and intensity of the impact vary with the level of development of the economy.

The remainder of this study is organized as follows. In the second section, the theoretical background is presented and the empirical literature on the relationship between imported technology and employment is reviewed. The empirical model and data are then introduced in the third section. The fourth section examines the model used, along with a descriptive analysis of the variables and an overview of the PSTR test. The fifth section discusses the main estimation results of the PSTR test. Finally, the sixth section presents the conclusions and policy implications.

2 Review of the literature

Technological progress has always given rise to growing concerns about the possibility of mass technological unemployment. This concern has given rise to an extensive literature exploring the consequences of technological innovations on employment and labor demand. However, it is difficult to empirically determine the link between these two factors, as the positive and negative effects of technology manifest themselves through various direct and indirect channels (Sharma & Mishra 2023).

2.1 The theoretical framework

In the analysis of the effects of technological change on employment, it is necessary to examine the direct effects of different types of technological change on the level of employment. Product and process innovations have different direct effects on employment, according to Schumpeter (1934). In general, process innovation tends to lead to labor savings, while product innovation is more likely to lead to an increase in employment. However, these two direct effects are only the beginning of a feedback process that is related to the compensating mechanisms that influence the final impact of technological change on the level of employment.

These mechanisms refer to the "compensation theory" introduced by Karl Marx in the first half of the nineteenth century (Marx 1867). This theory emphasizes that, although technological change may have direct adverse effects on employment, these effects are offset in the long term by indirect mechanisms operating at sectoral or economy-wide level. This theory of compensation has been enriched by various schools of thought (Freeman et al. 1982; Vivarelli 1995, 2014; Calvino & Virgillito 2017). The mechanisms that promote employment as a result of technological progress are: the introduction of new machinery in the production sector, lower prices thanks to technological progress which increases productivity and demand, lower wages stimulating demand for labor, new investments by innovative entrepreneurs, higher incomes for workers leading to increased demand for labor, and the emergence of new products and economic branches.

The first four mechanisms can be attributed to the classical and neoclassical schools, while the last two are more likely to be attributed to Keynesian-Schumpeterian thinking (Calvino & Virgillito 2017). Moreover, the first five mechanisms, highlighted by previous studies (Dosi 1988; Nelson & Winter 1982) and proven by empirical analyses (Parisi et al. 2006; Conte & Vivarelli 2007), concern the compensation of the initial labor-saving effect of process innovation (Vivarelli 2014). The initial labor-saving effect of process innovation is offset by investing in new machinery, known as "embodied technological change". Conversely, the sixth mechanism, known as the "Schumpeterian mechanism", involves product innovation and disembodied technological change.

Thus, the ultimate impact of technological progress on employment depends on the effectiveness of these compensation mechanisms, which in turn depends on several factors that may hinder them (Dosi et al. 2021; Vivarelli 2014). Indeed, several elements interact, such as institutional factors, macroeconomic and cyclical conditions, and labor market dynamics, making it difficult to comprehensively predict their effectiveness ex ante (Calvino & Virgillito 2017; Vivarelli 2014). For example, price and income compensation mechanisms can be affected by market competition, demand elasticity, agents' expectations, and other factors, delaying the translation of additional gains into effective demand. On the other hand, measures such as shorter working hours, social safety nets, and appropriate union strategies can mitigate the labor-saving effects of innovation (Vivarelli 2014; Pasinetti 1981). In addition, the effect of new products reducing sales of old products can weaken the job creation associated with product innovation (Barbieri et al. 2019; Calvino & Virgillito 2017). The link between technological change and employment is also affected by the business cycle and other economic conditions that shape firms' innovation behavior and their ability to create jobs (Harrison et al. 2014).

Thus, the employment outcomes of technological innovation can vary considerably due to the interplay between direct effects, compensating mechanisms, the challenges of implementing them effectively, and the beneficial effects of product innovation on employment. In short, the impact of technological change on employment is a complex issue for which economic theory does not provide clear answers and which poses challenges for economists. One of the difficulties lies in disentangling the effects of technology from other influencing factors, which can vary depending on the level of aggregation. At the firm level, studies can directly analyze innovation in terms of inputs and outputs, but they may not determine the net effect on employment at the industry level due to competitive factors such as firm selection, entry/exit, and relocation (Dosi et al. 2021). Conversely, industry-level studies provide global trends in technological change and consider sector-specific characteristics, but they may lack a detailed view of firm-level innovation and inter-sectoral or economy-wide complementarities (Bogliacino & Pianta 2010). Finally, macro-level analyses have the advantage of considering all the direct and indirect effects of innovation but are limited by the difficulty of measuring technological change at the aggregate level. Analyses at different levels of aggregation are, therefore, complementary and enrich the ongoing debate on the impact of technology on employment.

2.2 Empirical framework: compensation mechanisms and imported technology impact on employment

For the purposes of this article, only macro-level analyses of the technology-employment relationship are presented. According to Sinclair (1981), using estimates based on US data, positive employment compensation can occur as a result of technological progress if the elasticity of demand and the elasticity of factor substitution are sufficiently high. This study suggests that the "via lower wages" mechanism is effective, as opposed to the "via lower prices" mechanism. However, the study's model assumes a competitive equilibrium among producers and that employment is determined by the demand for labor at a given wage. Thus, if real wages don't rise too much, the risk of a negative effect on employment would be minimized. Similarly, a study by Layard & Nickell (1985) in the United Kingdom highlights the importance of the elasticity of labor demand with respect to real wages and productivity. An increase in productivity due to technological change can offset initial job losses.

Vivarelli (1995) empirically demonstrated the superiority of the "lower prices" mechanism for the two countries studied (Italy and the United States) in an attempt to measure the effectiveness of compensation mechanisms. The other mechanisms proved less efficient. However, the absence of demand constraints, the decision of firms to pass on productivity gains from innovation in the form of lower prices, and the absence of oligopolistic power in the markets concerned are prerequisites for the effectiveness of the "lower prices" channel. These findings were confirmed by Simonetti et al. (2003) in a study of four countries (USA, Italy, France and Japan). According to these results, new technologies can lower prices and improve international competitiveness and output, but this can lead to job losses due to process innovation. Thus, in more product-oriented economies (such as the US or France), the overall relationship between technology and employment is positive. This study shows that, depending on national institutional structures, other compensation mechanisms might not be effective in compensating for process innovation's negative effects on employment. In Italy, for instance, the rigid labor market makes wage cuts ineffective. Tancioni & Simonetti (2002) attribute this inefficiency of the price reduction compensation mechanism in Italy to the absence of a competitive market structure, which leads producers to appropriate the productivity gains resulting from technological change.

This relationship between employment and technology has also been examined in terms of the impact of technological progress on unemployment, including the study by Feldmann (2013) and the more recent ones by Yildirim et al. (2022) and Bouattour et al. (2023a). Feldmann (2013) analyzed the impact of innovation on unemployment in 21 developed countries between 1985 and 2009. The results suggest that technological change initially increases unemployment in the short run, but that this effect diminishes in the long run due to compensation mechanisms such as price and wage reductions.

Similarly, a recent study by Yildirim et al. (2022) focuses on 12 European countries and examines the relationship between technology and unemployment from 1998 to 2015. What makes this study different is that it takes into account the nonlinearity of the relationship between employment and technology. It divided the sample into two groups of countries according to their level of innovation, resulting in low and high innovation regimes. The results show that technological progress has a negative effect on employment. Furthermore, the impact of innovation on unemployment is greater in the low innovation regime than in the high innovation regime in both groups of countries. Although this study is consistent with the analytical framework of this article, it did not provide an in-depth analysis of the results. However, these results indicate the inefficiency of the compensation mechanisms in these countries. Given the period of analysis (1998–2015), a possible explanation for these results could be attributed to the productivity slowdown that began before the global financial crisis of 2007–2008 and worsened thereafter in European countries (Dieppe, Alistair, 2021). Moreover, the fact that the positive impact of innovation on unemployment is reduced in the high innovation regime could be interpreted as a greater efficiency of compensating mechanisms. A more detailed analysis of these results could have important policy implications.

At the end of this review of the empirical literature, three main conclusions can be drawn. First, classical linear models are widely used in previous studies, which are limited to exploring only the direction (positive or negative) of the relationship, assuming that the impact of technological progress on employment is invariant. This assumption of linearity is limiting and may lead to biased results, as the impact of innovation on employment may vary according to several variables, including the intensity of technology used and changing industry dynamics.

Second, these studies emphasize that the positive effects of technological change on employment manifest themselves only in markets characterized by competition and flexibility. Most of these studies point to falling wages and prices as the most effective compensation mechanisms to counteract the direct effects of technological progress on employment. However, these studies often fail to analyze the net effect of technological progress by considering institutional factors that are difficult to control at the aggregate level.

Third, studies of the relationship between technological progress and employment at the macro level are scarce. The methodological difficulties involved explain this scarcity of aggregate studies. That is, the empirical literature at the macroeconomic level raises the problem of the analytical complexity required to represent the various compensating mechanisms, making the interpretation of the empirical results very difficult. Indeed, there are three main methodological problems with empirical macroeconomic analyses of the relationship between innovation and employment. They have the advantage of considering all the direct and indirect effects of innovation but are limited by the difficulty of measuring technological change on an aggregate level. Moreover, the final evolution of employment is influenced by institutional and macroeconomic factors that are difficult to control for. Finally, the choice of an appropriate proxy for technological change proves difficult for such analyses.

Based on this last difficulty and the exploration of the empirical literature, the methodological challenge varies according to a country's level of development. Indeed, a review of the empirical literature shows that R&D expenditures and patents are generally used as technology proxies for developed countries, while technology imports are used for developing countries. However, even developed countries import technologies that they do not produce domestically, especially in the digital age.

Indeed, firms can benefit from many sources to access technologies including imports (Goldberg et al. 2010) providing foreign technology transfer. Such a channel allows countries to access advanced technologies and keep their competitiveness and production levels high (Sharma 2014). To some extent, technology imports stimulate competition by pushing domestic industries to be more competitive. In addition, technology imports improve productivity through technology transfer from advanced countries allowing for better quality inputs (Topalova & Khandelwal 2011; Goldberg et al. 2010).

According to Pianta, (2018), industry-level studies can show direct firm-level and indirect industry-level effects of technology imports. These effects can include the competitive reallocation of jobs and output from low-tech to high-tech firms, as well as the impact of lower prices following innovation on demand and, consequently, on output and employment. This analysis provides a better understanding of the technological strategies of different countries and their impact on the demand dynamics of industrial sectors, while taking into account the different economic structures of countries.

Besides, the use of imported technology to boost industrial employment varies by country and time, but is generally more beneficial when demand is rising, the level of technology is high, and innovation and new product introduction are encouraged. However, slow demand growth within and outside countries limits industrial demand.

Countries that are more technologically advanced can reap the employment benefits of technology, but this is at the expense of countries that are less innovative and face greater job losses (Pianta 2018, 2000; Bogliacino, & Pianta 2010).

Empirical evidence on how imported technology affects employment is scarce and tends to focus on developing countries. To the best of our knowledge, there is only one study by Domini et al. (2021) that concerns developed countries. In this sense, the next review of the empirical literature will be limited to three studies, the one by Domini et al. (2021) for developed countries and those by Sharma and Mishra, (2023) for developing countries and Bouattour et al. (2023a) for both developed and developing countries.

The "Domini et al. (2021) study" serves as a reference in the context of this article, as it used technology imports as a proxy to examine the impact of technology (robotization) on the employment of French firms between 2002 and 2015. According to Domini et al. (2021), imported technology leads to employment growth. However, only industries using advanced technology (robotization) experience this positive effect. They argue that there are job losses in industries where automation is not a factor. That is, increased exposure to advanced technology (robotization) reduces the market share of non-adopters and forces less productive industries to exit, resulting in layoffs.

Using a large sample of firms in the developing world, Sharma & Mishra, (2023) examine the impact of imported technology on employment and find that the overall impact is positive and significant. They contend that the use of new advanced technologies does not result in labor savings, but rather creates new jobs. The uniqueness of this study lies in examining the impact through three channels of technology (import, adoption of foreign technologies through licensing, and foreign ownership). The results show that each of these channels has a positive impact on employment on its own. However, the interaction between the different channels can lead to a negative impact on employment. Furthermore, when examining how skills are affected, they find that technology matters a great deal. Their findings are not in line with the broader literature, which supports a lopsided impact of technology on skills (see Calvino & Virgillito 2017). The fact that technology imports do not negatively affect temporary or seasonal employment, which is prevalent in developing countries, is another important result of this study. Finally, this study provides empirical evidence that substituting and complementing relationships exist between different technologies available to industries in developing countries. For example, by allowing workers to adapt to new imported technologies, the combination of imported technology and domestic R&D preserves all types of employment. Therefore, according to their findings, these countries need to be aware of which technology channels need to be combined to have a strong positive impact on employment. In the same vein, Bouattour et al. (2023a) confirmed the existence of a non-linear relationship between imported technology and industrial employment for both developed and developing countries over the period 2000 to 2019. Their analysis showed that for different intensities of technology imports, the non-linear impact on industrial employment shows a threshold effect that differs according to the level of development of the countries. Their study also showed a positive impact for both developed and developing countries, with a more pronounced positive effect in the case of developed countries, indicating the relative effectiveness of their compensatory mechanisms compared to those of developing countries.

According to previous studies, not only do technology imports have a direct impact on employment, but the nature and level of these imports can also shape the relationship between technology and employment. Moreover, the level of development of the importing country may determine the extent and nature of these effects.

This review of the empirical literature on the relationship between technology and employment reveals gaps and mixed results. The impact of technology imports in developed countries has been little studied. Analysis at the macroeconomic level is limited, and the relationship between the impact of technology on employment and the level of economic development has been little explored. Moreover, most empirical studies have assumed that this relationship is linear. To fill these gaps, this study examines the nonlinear relationship between imported technology and employment at the macroeconomic level for both groups of countries, thus providing empirical originality.

At the end of this literature review, it is possible to formulate our research hypothesis (H01) as follows: The relationship between imported technology and industrial employment is nonlinear and varies with the level of technology imports.

3 Panel smooth transition regression model

The first step in creating a Panel Smooth Transition Regression (PSTR) model is to test for linearity. If the null hypothesis is not rejected, the testing strategy will be terminated or will have to be rerun with a new hypothesis (a new transition variable). However, if the linearity hypothesis is rejected, the low specification test of Eitrheim & Terasvirta (1996) on the univariate Smooth Transition AutoRegression (STAR) model must be repeated twice. Specifically, two tests adapted by González et al. (2017) for panel data are used to test for misspecification: the parameter constant and the nonlinear residual test. When linearity is rejected, the second step is conducted to calculate the number of transition functions to be used.

3.1 The PSTR model

González et al. (2005) suggested enhancing the Panel Threshold Regression (PTR) models using the Panel Smooth Transition Regression (PSTR) technique, which is analogous to transitioning from abrupt to gradual changes in time series analysis. The PSTR model consists of two regimes and the process ($y_{it}, t \in T$ and $i \in N$) conforms to a two-regime PSTR model if and only if:

$$y_{it} = \mu_i + \beta_0{\prime}X_{it} + \beta_1{\prime}X_{it}G(q_{it}; \gamma, c) + \varepsilon_{it} \tag{1}$$

where μ_i is the vector of the individual fixed coefficients, $G(q_{it}; \gamma, c)$ denotes the transition function relative to the transition variable q_{it}, at threshold parameter c and a smoothing coefficient γ. $X_{it} = \left(X_{it}^1, \ldots, X_{it}^k\right)$ is the matrix of k exogenous variables that do not contain lagged explanatory variables, $\beta = (\beta_1, \ldots, \beta_k)$ and ε_{it} is $iid\left(0, \sigma_\varepsilon^2\right)$. The index $i = 1, \ldots, N$ refers to the individual dimension and the index $t = 1, \ldots, T$ to the temporal dimension.

Similar to time series analysis, the indicator function of the PTR model is modified by a differentiable continuous transition function $G(q_{it}; \gamma, c)$ over the interval 0 to 1. This modification enables a gradual transition of the process from one regime to another. There are two ways to interpret the PSTR model. Firstly, it can be seen as an approach that comprises an infinite number of regimes lying between two extreme regimes. In the case of a linear and heterogeneous panel data model, the coefficients may vary according to the units and dates considered. Secondly, the PSTR approach can be viewed as a nonlinear model where the process slowly transitions between two linear and homogeneous extreme regimes.

To achieve an optimal PSTR model, it is necessary to specify a transition function between regimes that is continuous and differentiable on the interval [0, 1]. González et al. (2005) suggested using a logistic shift function of order m:

$$G(q_{it};\gamma,c) = \left[1 + exp\left(-\gamma\prod_{j=1}^{m}\left(q_{it} - c_j\right)\right)\right]^{-1}, \gamma > 0, c_1 < \cdots < c_m \tag{2}$$

where $c(c_1, \ldots, c_m)$ is a dimension vector $(1, m)$ containing the threshold coefficients and γ symbolizes the presumed positive coefficient.

The focus should be on several key aspects when examining the PSTR model. Firstly, it is important to consider the signs of the slope parameters β_1, which indicate whether the relationship between the exogenous and endogenous variables increases or decreases as a function of the transition variable. Secondly, the temporal evolution of the slope parameters should be taken into account. Finally, it is essential to examine the marginal effect of the exogenous factors X_{it} on the endogenous variable y_{it},

$$\frac{\partial y_{it}}{\partial X_{it}} = \beta_0 + \beta_1 G(q_{it};\gamma,c) \tag{3}$$

The shape of the transition function in the PSTR model is "U"-shaped, as described by Fouquau et al. (2008). This indicates that the extreme regimes located on either side of the threshold coefficients are similar but distinct from the centrally located extreme regime at $q_{it} = \frac{c_1+c_2}{2}$. Consequently, the dynamics in the extreme regimes outside the limits are determined by the sum of the parameters $\beta_0 + \beta_1$, while in the central regime, the dynamics are determined by the sum of the coefficients β_0 and β_1, moderated by a constant value of the transition function ranging from 0 to 1/2. The speed of change between the two regimes depends on the value of the smoothing parameter. As γ approaches infinity, the PSTR model becomes a three-regime PTR model, with the external regimes being similar but distinct from the central one. On the other hand, as γ approaches zero, the PSTR model is reduced to a homogeneous model with fixed effects. This is evident in $G(q_{it};\gamma,c)$, where the outcome is examined for any value of m.

In time series analysis, the logistic change function or the exponential function proposed by Teräsvirta & Anderson (1992) are typically used in STAR models to address similar issues. However, the exponential function has not been widely used in panel data analysis, except in the work of Bessec & Fouquau (2008). This lack of interest may be due to the close relationship between the exponential function and the order 2 logistic function. Nonetheless, the exponential shift function has the advantage of being more parsimonious, requiring estimation of only one threshold, as follow:

$$G(q_{it};\gamma,c) = 1 - exp\left[-\gamma(q_{it} - c)^2\right], \gamma > 0 \tag{4}$$

The exponential function has a U-shaped configuration, which implies that the function approaches 1 as the transition parameter q_{it} moves away from the threshold parameter c, and conversely, it approaches 0 for $q_{it} = c$. This is different from the 2nd order logistic function. In the PSTR model with exponential shift function, the process follows the same dynamics as indicated by the slope coefficients $\beta_0 + \beta_1$. Specifically, when q_{it} equals the threshold parameter c, the dynamics are governed by the parameter β_0. As the smoothing coefficient γ approaches zero or infinity, the exponential form becomes fixed at 0 or 1, respectively, and the PSTR model reduces to a linear model with individual effects rather than a three-regime PTR model.

In the PSTR approach, it is possible to relax the assumption of uncorrelated residuals by allowing for different forms of covariance, but this can complicate the estimation of coefficients. To address this issue, an alternative approach is to include common explanatory variables $z_{1t}, \ldots, z_{kt}$ as additional exogenous factors, which allows for contemporaneous correlations between the errors. Fok et al. (2005) proposed a first-order transition mechanism for the transition function between regimes, which has been described in the previous sub-section:

$$G(q_{it}; \gamma_i, c_i) = \frac{1}{1 + exp\left[-\gamma_i (q_{it} - c_i)^2\right]}, \gamma_i > 0 \tag{5}$$

To ensure that the indicator function does not depend on the individual dimension, it is important to use an indicator that can generate a step function for all units. However, this assumption becomes less realistic as the number of units increases. To address this, Fok et al. (2005) proposed that the threshold and smoothing coefficients vary by unit, denoted as $c_i \neq c_j$ and $\gamma_i \neq \gamma_j$, respectively, where i and $j = 1, \ldots, N$. This allows for a more realistic representation of how contagion operates in economics.

Second, we believe that the PSTR model with an exponential transition function should be retained as an alternative assumption:

$$G(q_{it}; \gamma_i, c_i) = 1 - exp\left[-\gamma_i (q_{it} - c_i)^2\right], \gamma_i > 0 \tag{6}$$

The test for no remaining heterogeneity will determine the number of regimes or transition functions needed to capture all of the heterogeneity and nonlinearity in the data. The model used will be specified in error if the null hypothesis is rejected. To capture the remaining heterogeneity, it must include at least the second transition function. The process should then be repeated, with the PSTR model with two transition functions being compared to the model with three regimes.

3.2 Linearity tests

The analysis would not be complete without a linearity test. In fact, the null hypothesis can be represented by two sets of hypotheses:

$H_0 : \beta_1 = 0$ versus $H_1 : \beta_1 \neq 0$ or $H_0 : \gamma = 0$ versus $H_1 : \gamma \neq 0$ (7).

Then, T and N represent, respectively, the number of observations per country and the number of countries.

We will begin this section by conducting a linearity test to determine if the threshold effect is statistically significant and if the relationship between the exogenous and endogenous variables can be modeled using a regime change model. There are two hypotheses that we will test using the Wald Lagrange Multiplier statistic, which follows a chi-square distribution, to determine if there is no regime change:

$$LM = TN[(RSS_0 - RSS_1)/RSS_0] \sim \chi^2(k) \tag{8}$$

Let RSS_0 denote the panel residual sum of squares of a linear panel model with individual effects and let RSS_1 denote the panel residual sum of squares of a nonlinear panel model with two regimes. Under the null hypothesis, the Wald Lagrange Multiplier (LM) statistic follows a chi-square distribution with k degrees of freedom, where k is the number of explanatory variables.

Alternatively, we can also use the Likelihood Ratio (LR) test, which can be expressed as:

$$LR = -2[Ln(RSS_0) - Ln(RSS_1)] \sim \chi^2(k) \tag{9}$$

If the null hypothesis is true, the LR statistic follows a chi-square distribution with k degrees of freedom, where k is the number of explanatory variables.

In addition, we can also use the Fisher Lagrange Multiplier (LMF) statistic, which is defined as follows:

$$LMF = [(RSS_0 - RSS_1)/2]/[RSS_0/(NT - N - 2)] \sim \chi^2(2) \tag{10}$$

In addition, if the null hypothesis holds, this statistic LMF follows a Chi-square distribution with two degrees of freedom.

4 Model presentation and estimation

4.1 Treatment of the econometric model and variables

The literature on the impact of technology on employment is extensive. In this study, we empirically assess the impact of various macroeconomic variables and attempt to validate their effects on employment. These are briefly described below. Based on the availability of data and the theoretical foundations of Conte & Vivarelli (2007), our model will be given as follows:

$$LnEMPLOY\_IND_{it} = \beta_0 + \beta_1 LnIMPORT\_T_{it} + \beta_2 LnCPI_{it} + \beta_3 LnFDI_{it} + \beta_4 LnIAV_{it} + \lambda_i + \varepsilon_{it}$$

4.1.1 (11)

Where β_0 is a constant, $LnEMPLOY\_IND$ is the logarithm of industrial employment (as % of total employment), and $LnIMPORT\_T$ is the logarithm of imports of technology. $LnCPI$ is the logarithm of the consumer price index, $LnFDI$ is the logarithm of foreign direct investment (% of GDP), $LnIAV$ is the logarithm of industrial value added (% of GDP), ε is an error term assumed to satisfy the classical Gauss-Markov assumptions, λ is the unobserved effect, representing the individual effect and the subscripts t and i refer to time and country, respectively.

The current study covers the years 2000 to 2019 and is based on the World Bank's 2020 database. Accordingly, this study included a panel of eight developing and seven developed countries, with countries selected:

■ Developing countries: Turkey, Bahrain, Egypt, Jordan, Morocco, Oman, Tunisia and Saudi Arabia.

■ Developed countries: Canada, France, Germany, Spain, Italy, Israel and Japan.

The selection of countries is based on the 2019 Global Innovation Index (GII), since the purpose of this paper is to analyze technology imports and industrial employment. The large number of countries, the inclusion of input and output measures, and the linkage of GII measures to some key elements of the NIS are several arguments in favor of the choice of the GII. In addition, this diverse sample includes countries that are representative of different rankings according to this criterion, all within the top 100.

Employment in industry ($EMPLOY\_IND$): The percentage of employment in industry will be our dependent variable in the model. Knowing that the industrial sector includes mining and quarrying, manufacturing, construction and utilities (electricity, natural gas and water).

Imports of technology ($IMPORT\_T$): Imports of Technology is considered as a proxy of technological innovation (Bouattour et al. 2023a; Sharma & Mishra 2023; Domini et al. 2021). Based on Schumpeter's theory of innovation (1961), imports of technology can result in either an increase or decrease in employment depending on whether they pertain to process or product innovation. Furthermore, the ultimate effect of importing technology hinges on the compensation mechanisms (Marx 1867; Freeman et al. 1982; Vivarelli 1995; Pianta, 2005; Vivarelli 2014; Calvino & Virgillito 2017) of different countries, both developed and developing.

Consumer Price Index (CPI): The Consumer Price Index can be seen as a control variable for employment in that when prices rise, firms reduce their spending on labor and the unemployment rate rises. A rise in prices also increases labor costs and reduces the demand for labor, which in turn can lead to higher unemployment. Finally, an increase in prices can lead to a decrease in consumption and demand for firms' products, which can decrease the demand for labor and increase the unemployment rate (Feldmann 2013).

Foreign direct investment (FDI): The Foreign direct investment is considered a proxy for technology. FDI is considered an important channel for technology diffusion (Dimelis & Papaioannou 2010). With the objective of creating jobs either directly or indirectly through the movement of labor from foreign companies to other sectors, several economies have developed strategies to attract such investment (Balcerzak & Żurek 2011; Subramaniam & Baharumshah 2011). Thus, from a theoretical perspective, FDI can be seen to be accompanied by improvements in output and employment under the multiplier effect of investment (Keynes 1936) arising from the adoption of new and improved technologies and skills by host countries as well as the creation of linkages between foreign and domestic firms (Gachunga 2019).

Industries Value Added (IAV): The value added of industries can be seen as a control variable for employment. An increase in the value added of industries may indicate a growing demand, which leads to an increase in employment (Feldmann 2013).

Industry (including construction) corresponds to ISIC divisions 05–43 and includes manufacturing (ISIC divisions 10–33). It comprises value added in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 4. Note: For VAB countries, gross value added at factor cost is used as the denominator.

We summarize all the variables in Table 1 as follows:

4.2 Statistical description of variables

Before delving into an economic and empirical examination of the relationship between industrial employment and technology, it is essential to conduct a descriptive study of the main crises variables. Table 2 provides descriptive statistics for the eight developing countries and seven developed countries, giving an overview of the characteristics of these variables. This preliminary analysis will help in understanding the distribution and key features of the data, setting the foundation for the subsequent investigation into the link between industrial employment and technology.

In developing countries, industrial employment exhibits a consistent upward trend, with an average of 3.24 and a standard deviation of 0.22. The 160 observations all fall within a narrow range of 2.41 to 3.60. On the other hand, for developed countries, the total value of this variable experienced a substantial increase, reaching a peak of 3.51. The average industrial employment in developed countries is 3.19, with a standard deviation of 0.17. The 140 observations in this case are confined within the range of 2.83 to 3.51.

Both sets of countries exhibit a left-skewed (Skewness < 0) and leptokurtic (Kurtosis > 0) distribution in the sample. Over the study period, developing countries had an average value of 1.52 for the IMPORT_T variable. Consequently, in developing countries, the minimum value of IMPORT_T must be at least 0.34. Notably, this variable has experienced a significant increase since 2005, peaking at 2.38% of total imports. Similarly, in developed countries, the IMPORT_T rate increased from 1.51 to 2.78 during the study period, with an average of 2.11 and a dispersion of 0.29. These findings indicate a notable variation in the import intensity of technology across both sets of countries.

Table 1 Variable Descriptions

Variable type	Symbol	Variable name	Indicator	Source
Explained variable	EMPLOI_IND	Industrial employment	% of industrial employment	WDI
Explanatory variable	IMPORT_T	Imports of technology	% of technology imports in total importation	ISIC
Explanatory variable	FDI	Foreign direct investment	% of GDP	WDI
Threshold variable	IMPORT_T	Imports of technology	% of technology imports in total importation	ISIC
Control variable	CPI	Consumer Price Index	base 100 = 2010	WDI
Control variable	IAV	Industrial Value Added	% of GDP	WDI

WDI refers to World Development Indicators—DataBank. ISIC refers to International Standard Industrial Classification

Table 2 Descriptive statistics of the variables

Variables	LnEMPLOY_IND	LnIMPORT_T	LnCPI	LnFDI	LnIAV
Developing countries					
Observations	160	160	160	160	160
Mean	3.242	1.525	4.560	0.764	3.563
Standard Deviation	0.221	0.343	0.335	1.147	0.330
Minimum	2.415	0.332	3.025	−4.540	3.124
Maximum	3.607	2.388	5.605	3.145	4.270
Skewness statistic	−0.419	−0.430	-0.446	−1.228	−0.611
Kurtosis statistic	3.696	3.557	6.558	6.183	1.980
Coefficient of variation	0.683	0.224	0.073	1.500	0.927
Jarque–Bera statistic (JB) statistic	9.68	7.009	89.69	107.8	16.9
JB probability	0.014	0.033	0.000	0.000	0.000
Born and Breitung (BN) statistic	5.47	32.12	6.23	9.08	24.17
BN probability (lags p = 2)	0.065	0.000	0.044	0.011	0.000
Developed countries					
Observations	140	140	140	140	140
Mean	3.195	2.110	4.589	0.363	4.589
Standard Deviation	0.177	0.295	0.093	1.317	0.093
Minimum	2.832	1.513	4.330	−6.395	4.329
Maximum	3.512	2.784	4.760	2.547	4.760
Skewness statistic	−0.158	−0.038	−0.637	-2.021	−0.636
Kurtosis statistic	1.920	2.458	2.495	9.036	2.495
Coefficient of variation	0.055	0.140	0.020	3.630	0.020
Jarque–Bera statistic (JB) statistic	7.381	1.747	10.95	307.8	8.181
JB probability	0.000	0.284	0.008	0.000	0.000
Born and Breitung (BN) statistic	33.59	77.47	30.62	11.55	24.25
BN probability (lags p = 2)	0.000	0.000	0.000	0.003	0.000

JB represents the Jarque & Bera (1987) statistic; BB represents the Born & Breitung (2016) statistic

Between 2008 and 2015, there was a noticeable upward trend in the industrial value added in developing countries. The overall increase in this variable was significant, with a maximum value of 4.27, a mean of 3.56, and a standard deviation of 0.33. All 160 observations during this period were confined within the range of 3.12 and 4.27, indicating a relatively narrow spread of data. In contrast, industrialized countries experienced a more consistent and gradual progression in their industrial value added. The range of IAV values for this group ranged from 4.32 to 4.76, with an overall mean of 4.58 and a standard deviation of 0.093.

Based on the outcomes of the Jarque & Bera (1987) test, the probability of obtaining the observed statistics is less than 10% for all the variables examined in both groups of nations, which leads us to reject the null hypothesis of normality. Furthermore, the autocorrelation test of Born & Breitung (2016) reveals that there is a significant serial correlation with a probability less than 5%. This suggests that the data points are not independent, and there are systematic dependencies between consecutive observations in the dataset.

After conducting a descriptive analysis of the variables used in this study, it becomes evident that their levels often exhibit non-stationarity. Due to this, we employ several methods to investigate their stationarity. Additionally, most of the series display breaks and alterations that are not consistent over time, resulting in non-symmetric distributions spread out on either the left or right.

The next phase involves conducting the unit root test for the variables included in the model. During this step, we will interpret the unit root tests using two generations. The first-generation tests rely on the assumption of inter-individual independence of the residuals. This assumption allows us to establish the statistical distributions of the tests easily and generally obtain asymptotic or semi-asymptotic normal distributions. From this perspective, any correlations between individuals are considered nuisance parameters and are not explicitly accounted for in these tests.

As a result, we employ three different types of first-generation tests: Levin et al. (LLC, 2002), Im et al. (IPS, 2003), and Hadri (LM, 2000). These tests aim to detect any potential structural breaks and will be further elaborated on in the subsequent section. Table 3 presents the outcomes of the unit root tests conducted on our panel data using LLC, IPS, and LM methods for the eight developing and seven developed countries. Based on these results, the three first-generation unit root tests using panel data for both country groups indicate a failure to reject the null hypothesis of non-stationarity at the level. Therefore, we can classify the variables as non-stationary in terms of level. However, when we perform the tests on the first difference series, the results demonstrate stationarity. Thus, with reference to the first-generation tests, we can conclude that all variables are integrated of order 1 [I(1)] for both developing and developed countries.

In more recent times, the second generation of tests has emerged, challenging the assumption of inter-individual independence. These tests take a different perspective compared to the first-generation tests. Instead of considering correlations between individuals as nuisance parameters, they propose to utilize these co-movements to define new test statistics. The results of these second-generation tests are presented in Table 4. The findings from the second-generation unit root tests conducted by Pesaran (2003) and Pesaran (2007) indicate that all variables, except for the variable LnFDI, are stationary in their first differences for both groups of countries. This contradicts the results

Table 3 Panel first-generation unit root test results

Variables	In Level			In First Difference		
	LLC	IPS	LM	LLC	IPS	LM
Developing countries						
LnEMPLOY_IND	−2.953*	−0.629***	26.961***	−3.617***	−4.290***	10.181***
LnIMPORT_T	−2.029**	−1.988**	13.927***	−4.901***	−6.395***	−0.679
LnCPI	1.789	5.097	31.363***	−6.258***	−4.506***	0.805
LnFDI	−2.784***	−3.239***	6.496***	−1.290*	−7.614***	−2.070
LnIAV	−1.009	−0.286	9.995***	−4.271***	−5.126***	−0.035
Developed countries						
LnEMPLOY_IND	−3.208***	0.247	29.592***	−3.254***	−4.261***	−2.012**
LnIMPORT_T	−2.988**	−2.697**	20.243***	−6.466***	−4.737***	0.856
LnCPI	−3.805***	−1.502*	29.757***	−4.436***	−3.642***	0.3680
LnFDI	−3.615***	−4.433***	0.947*	−6.284***	−6.800***	−2.136
LnIAV	−2.262	−1.157	25.630***	−2.403*	−4.176***	0.336

*, **, and *** significant at 10%, 5%, and 1%

Table 4 Panel second-generation unit root test results

Variables	LnEMPLOY_IND	LnIMPORT_T	LnCPI	LnFDI	LnIAV
Developing countries					
Pesaran (2003)					
In Level					
Constant	−2.079	−2.295*	−1.604	−3.234***	−1.523
Constant & Trend	−3.289***	−2.509	−1.762	−3.345**	−2.413
Decision	Non-stationary	Non-stationary	Non-stationary	Stationary	Non-stationary
In First Difference					
Constant	−3.587***	−4.279***	−2.363**	−5.677***	−3.440***
Constant & Trend	−3.878***	−4.369***	−3.441**	−5.837***	−3.162**
Decision	Stationary	Stationary	Stationary	Stationary	Stationary
Pesaran (2007)					
In Level					
Constant	0.041	−1.552	−0.160	−3.537***	1.323
Constant & Trend	−0.431	−0.641	1.449	−3.782***	−0.374
Decision	Non-stationary	Non-stationary	Non-stationary	Stationary	Non-stationary
In first difference					
Constant	−4.858***	−7.000***	−3.738***	−10.839***	−4.653***
Constant & Trend	−4.140***	−5.851***	−3.451**	−9.961	−3.404**
Decision	Stationary	Stationary	Stationary	Stationary	Stationary
Developed countries					
Pesaran (2003)					
In Level					
Constant	−2.612**	−2.781***	−0.684	−3.239***	−2.246*
Constant & trend	−3.288***	−2.611	−1.630	−3.563***	−2.148
Decision	Stationary	Non-Stationary	Non-Stationary	Stationary	Non-Stationary
In first difference					
Constant	−3.810***	−4.019***	−2.876***	−5.156***	−3.083***
Constant & Trend	−3.860***	−3.942	−3.152**	−5.066***	−3.198***
Decision	Stationary	Stationary	Stationary	Stationary	Stationary
Pesaran (2007)					
In Level					
Constant	−1.813	−2.699***	2.688	−3.875***	−1.809
Constant & Trend	−1.776	−0.868	1.702	−3.361***	0.477
Decision	Non-Stationary	Non-Stationary	Non-Stationary	Stationary	Non-Stationary
In First Difference					
Constant	-5.342***	-5.879***	−2.944***	−8.802***	−3.476***
Constant & Trend	−4.138***	−4.353***	−2.284**	−7.298***	−3.404**
Decision	Stationary	Stationary	Stationary	Stationary	Stationary

All tests use Schwarz Information Criteria (SIC) for lag selection. In the first-generation tests, for the case with constant, critical values for Pesaran CIPS test are -2.18, -2.33 and -2.64 for 10%, 5% and 1% significance levels, respectively. For the case with drift and trend, critical values are -2.82, -3.02 and -3.46 for 10%, 5% and 1% significance levels, respectively. ***, ** and * denote significance at 10%, 5% and 1%, respectively

obtained from the first-generation tests, where strong dependence was observed. These second-generation tests suggest that the variables tend to exhibit stationarity once the inter-individual co-movements are considered, highlighting the importance of accounting for such dependencies in the analysis.

To enhance the validity and reliability of our findings, we plan to utilize the unit root test with break, a method introduced by Karavias & Tzavalis (2014). Our goal is to ensure that the insights derived from the Pesaran tests remain robust and to verify the stability of the dataset across various analytical approaches. As indicated in Table 5, the results affirm that all the variables exhibit stationarity when analyzed in their first differences, taking into account the occurrences of breaks associated with economic and financial shocks in the years 2001, 2008, and 2011. As regards developing countries, the decline in industrial employment in 2011, timed to coincide with the Arab Spring, is attributable to the slowdown in economic growth in most of the developing countries in the study sample (Ghanem 2016). Furthermore, the breaks in 2001 can be explained by the 2001 recession coinciding with the information technology (IT) boom. The decline in industrial employment can be explained by the fall in TFP growth, which began with the 2001 recession and worsened with the 2008 crisis (Bianchi, 2019; Fernald 2014). Indeed, the results show the negative and significant effect of the 2008 global financial crisis on industrial employment mainly linked to the slowdown in total factor productivity in developed countries (Bouattour et al. 2023b; Ollivaud et al. 2018).

Consequently, it becomes imperative to investigate the cointegration between the variables in our model.

As a next step, we will investigate individual dependence in the panel data. The presence of repeated measures over time can challenge the assumption of independence between individuals. To examine if there is residual dependence in our model, we employ specific tests that have been developed for this purpose. The tests presented in this article include those proposed by Friedman (1937), Frees (1995 & 2004), Pesaran et al. (2008), and Pesaran (2006 & 2015). These tests are designed to assess the correlations and residuals to determine if there is any residual dependence among individuals.

Table 6 displays the results of the various tests, and they consistently confirm the presence of dependence between individuals, with all probabilities from these tests falling below 1%. This suggests that there is significant intra-individual dependence in the panel data, which can be attributed to unobserved heterogeneity. The persistent dependence observed in our results underscores the importance of considering and addressing this unobserved heterogeneity in the analysis of the data.

To further validate the aforementioned findings, we conducted the Breusch & Pagan (1980) test to assess cross-sectional independence in the residuals of a fixed-effects regression model. Additionally, Breusch & Pagan (1979) and White (1980) tests are used based on the Wald statistic to examine groupwise heteroscedasticity in the residuals of the fixed-effects regression model. The results presented in Table 7 provide compelling evidence of strong cross-sectional independence in the residuals, reinforcing the

Table 5 Unit root test with break

Variables	Developing countries		Developed countries	
	In level	In first difference	In level	In first difference
LnEMPLOY_IND	−5.495*** (2001)	−9.027*** (2011)	−10.563*** (2008)	−9.824*** (2001)
LnIMPORT_T	−3.656*** (2018)	−13.999*** (2001)	−11.004*** (2008)	−13.130*** (2001)
LnCPI	−9.807*** (2001)	−9.960*** (2002)	−11.545*** (2001)	−9.383*** (2017)
LnFDI	−10.809*** (2018)	−19.432*** (2017)	−11.895*** (2018)	−17.550*** (2001)
LnIAV	−6.968*** (2018)	−13.370 (2001)	−7.810*** (2018)	−13.532*** (2001)

Table 6 Results of the Cross-section dependence test

Tests	Value	Probability	Decision
Developing countries			
Friedman (1937)	14.886	0.038	Dependence
Frees (1995 & 2004)	5.133	0.000	Dependence
Pesaran (2006)	19.162	0.000	Dependence
Pesaran et al. (2008)	8.872	0.000	Dependence
Pesaran (2015)	-2.578	0.010	Dependence
Developed countries			
Friedman (1937)	16.641	0.011	Dependence
Frees (1995 & 2004)	5.229	0.000	Dependence
Pesaran (2006)	25.635	0.000	Dependence
Pesaran et al. (2008)	9.668	0.000	Dependence
Pesaran (2015)	-3.033	0.006	Dependence

Table 7 Cross-sectional independence & Groupwise heteroscedasticity Tests

Tests	Statistic	p-value
Developing countries		
Groupwise heteroscedasticity	10,495.790	0.000
Cross-sectional independence	83.022	0.000
Developed countries		
Groupwise heteroscedasticity	215.92	0.000
Cross-sectional independence	100.863	0.000

presence of significant individual heteroscedasticity. These results offer additional support to our previous observations regarding the presence of dependence between individuals and highlight the need to account for such heteroscedasticity in our analysis.

Given that most of the variables are stationary in first difference, it becomes crucial to investigate the possibility of cointegration among these variables. Granger (1981) demonstrated that when a series is integrated of order one (i.e., it becomes stationary after the first difference), and its linear combination is already stationary without differencing, it is considered to be cointegrated. This suggests the existence of a long-term relationship among the series (Azmi et al. 2023). To explore this further, we will apply two sets of tests: the first-generation tests, namely Kao (1999) and Pedroni (2004), and the second-generation test, namely Persyn & Westerlund (2008).

The results of the two first-generation Panel cointegration tests, presented in Table 8, indicate the presence of at least one cointegration relationship. All the probabilities associated with these three statistics are below 5%. As a result, we can confidently reject the null hypothesis of no cointegration. This confirms the existence of long-term relationships among the variables studied, indicating that they are co-movements with a stable equilibrium in the long term.

Based on the results of the second-generation cointegration test, specifically the Persyn & Westerlund (2008) test, as presented in Table 9, it is evident that there is at least one cointegration relationship among the different variables for both groups of countries.

Table 8 First-generation Panel cointegration tests

Tests	Developing countries		Developed countries	
	Statistic	Probability	Statistic	Probability
Kao (1999)	−1.724**	0.042	2.245**	0.027
Pedroni (2004)	Constant	Constant & Trend	Constant	Constant & Trend
Panel v-statistic	2.754***	2.531***	1.732*	0.015
Panel rho-statistic	-0.384	−3.048***	−2.304**	−0.122
Panel PP-statistic	−2.239**	−2.519***	−2.840***	-2.765***
Panel ADF-statistic	−2.074**	−2.559***	−3.063***	-3.345***
Group rho-statistic	2.296**	2.968***	−0.233	0.916
Group PP-statistic	−2.620**	−2.166**	−3.091***	-2.373**
Group ADF-statistic	−2.555***	−2.207**	−3.218***	-3.106***

Notes: All test statistics are distributed N(0,1), under a null of no cointegration; *, **, *** refer to significant at 10%, 5%, and 1%, respectively

Table 9 Second-generation Panel cointegration test

Persyn & Westerlund (2008) test	Developing countries		Developed countries	
	Constant	Constant & Trend	Constant	Constant & Trend
G_t	−7.532***	−6.479***	−3.465*	−4.556**
G_a	−4.896***	−2.962*	−3.985**	−5.632***
P_t	−8.196***	−10.437***	−4.296**	−9.364***
P_a	−7.810***	−6.692***	−3.569**	−7.362***

*, **, *** significant at 10%, 5%, and 1%, respectively

This further supports the notion of long-term relationships and co-movements among the variables studied, confirming the presence of stable equilibrium associations in the long term.

In concluding this section, we conducted an examination of Pearson linear correlations and the multicollinearity in the regression analysis using the Variance Inflation Factor (VIF) measure of Marquaridt (1970). For the Pearson linear correlations between the different variables of the model in both developing and developed countries, the findings presented in Table 10 reveal that, for both groups, the linear correlations are statistically significant but weak at a 5% level.

To ensure the model is properly specified and functioning correctly, there are tests that can be run for multicollinearity. The VIF is one such measuring tool. Multicollinearity arises when there is a correlation among multiple independent variables in a multiple regression model. The results of the statistical analyses revealed a VIF value of 1.08 for developing countries and 1.37 for developed countries. These values indicate that the model is highly robust, as the factors are not significantly affected by correlations with other variables. Therefore, the regression model demonstrates a satisfactory level of independence among the predictor variables, enhancing the reliability of the findings.

4.3 Empirical estimation

Previous research has shown that the most effective method for modelling non-linearity is the regime transition model (Ben Cheikh & Ben Zaied 2020; Helali & Kalai 2021).

Table 10 Correlation matrix

Correlation (Probability)	Developing countries					Developed countries				
	LnEMPLOY_IND	**LnIMPORT_T**	**LnCPI**	**LnFDI**	**LnIAV**	**LnEMPLOY_IND**	**LnIMPORT_T**	**LnCPI**	**LnFDI**	**LnIAV**
LnEMPLOY_IND	1.000					1.000				
LnIMPORT_T	-0.314 (0.000)	1.000				0.203 (0.016)	1.000			
LnCPI	0.341 (0.000)	-0.082 (0.304)	1.000			-0.449 (0.000)	-0.330 (0.000)	1.000		
LnFDI	0.272 (0.001)	-0.153 (0.054)	0.084 (0.292)	1.000		-0.251 (0.003)	-0.162 (0.056)	-0.211 (0.012)	1.000	
LnIAV	-0.346 (0.062)	-0.240 (0.002)	0.039 (0.627)	-0.161 (0.042)	1.000	0.512 (0.000)	0.559 (0.000)	-0.221 (0.009)	-0.216 (0.011)	1.000
VIF	1.08					1.37				

VIF refers to Variance Inflation Factor measure of Marquaridt (1970)

The reason for this choice is simple: in addition to providing an economic explanation for this non-linearity, these models can also ensure that economic series have different dynamics across the institutions or the states of the world. Below a two-regime threshold, the linear equation above becomes a non-linear equation, resulting in the regression model, which can be written as follows:

$$\begin{aligned} LnEMPLOY\_IND_{it} = & \left(\beta_0{}^1 + \beta_1{}^1 LnIMPORT\_T_{it} + \beta_2{}^1 LnCPI_{it} + \beta_3{}^1 LnFDI_{it} + \beta_4{}^1 LnIAV_{it}\right) \\ & + \left(\beta_0{}^2 + \beta_1{}^2 LnIMPORT\_T_{it} + \beta_2{}^2 LnCPI_{it} + \beta_3{}^2 LnFDI_{it} + \beta_4{}^2 LnIAV_{it}\right) \\ & \times \mathrm{G}(q_{it}; \gamma, \mathrm{c}) + v_{it} \end{aligned} \tag{12}$$

where c is the optimal threshold of $LnIMPORT\_T$ and v is the new error term of the nonlinear model.

Let us shift our focus to the examination of inflection in panel data models. Our initial steps involve conducting tests to assess linearity and determine the appropriate model specification for addressing non-linearity. These tests take precedence and help us determine which specification to use to account for non-linearity. Specifically, failure to reject the null hypothesis of linearity may lead us to believe that either the test process is in fact linear, or the alternative hypothesis is ill-defined.

The linearity tests will come first. The test reveals that the regime-switching model can be used to explain the relationship between the explanatory factors and the explanatory variables, and that the threshold effect is statistically significant. The null hypothesis, that there is no regime shift. The order m must be equal to one to pass the linearity test. The results of the specification tests are presented in Table 11. This table presents the p-values of the Lagrange Multiplier (LM) test, the Fisher (LMF) test and the Likelihood Ratio (LR) test for the null hypothesis of linearity against the alternative logistic PSTR specification ($m=1$) for developing and developed countries, respectively. At the 1% significance level, we find that the null hypothesis of linearity is rejected. The results suggest that in both developed and developing countries there is a non-linear relationship between technical change and EMPLOY_IND. Therefore, we use PSTR estimation to estimate the non-linear industrial employment model.

A second step in the final estimation of the PSTR model is to establish the optimal number of transition functions, thus determining the number of regimes that characterize the dynamics of the link between technological change and industrial employment. However, to respect the lessons of the theoretical model, the maximum number of establishments is limited to 2.

Table 11 LM, LMF and LR digitization linearity tests with PSTR (r = 1, m = 1)

H_0: r = 0 versus H_1: r = 1	Developing countries		Developed countries	
Tests	**Statistic**	**p-value**	**Statistic**	**p-value**
Lagrange multiplier (LM)	10.633	0.031**	14.821	0.005***
Fisher (LMF)	2.634	0.036**	3.582	0.008***
Likelihood test (LR)	11.003	0.027**	15.666	0.004***

*, **, *** significant at 10%, 5%, 1%, respectively. *r* represents number of thresholds

Table 12 Remaining linearity tests with PSTR (m = 1)

Hypotheses	Tests	Developing countries		Developed countries	
H_0: r = 1 versus H_1: r = 2	Lagrange multiplier (LM)	1.717	0.788	4.821	0.306
	Fisher (LMF)	0.380	0.823	3.582	0.676
	Likelihood test (LR)	1.726	0.786	5.666	0.226

Table 13 Optimal PSTR threshold value results

Regions	Optimal threshold value	Transition Parameter	RSS	AIC	BIC
Developing countries	1.236	21.861	2.364	-4.019	-3.826
Developed countries	2.615	26.152	0.177	-6.447	-6.237

The PSTR estimate should then be used to test for the remaining non-linearity in Table 12. All three tests accept the null hypothesis of a threshold ($r=1$) with a significance of 1%. This suggests that the relationship between technical change and industrial employment in the two groups of countries has only one threshold; therefore, there are two regimes independently of the two sets of countries.

Finally, in the next phase, we start the grid search to acquire the threshold values "c" of the PSTR model. Indeed, the best threshold is the one that minimizes the residual sum of squares (RSS) sequence. Table 13 provides information on the transition parameters as well as the results of the threshold existence tests.

Indeed, to address the issue of individual effects and to mitigate the endogenous bias caused by the presence of dummy variables (representing fixed-country effects) influencing the dependent variable throughout the entire period, the PSTR estimation model is employed. This model involves applying the nonlinear least squares method to the data, allowing us to eliminate individual effects. By doing so, we can obtain more accurate and reliable estimates while capturing the nonlinearity and threshold effects that may exist in the relationship between the variables under investigation.

For developing countries, the optimal threshold value of LnIMPORT_T is equal to $\widehat{c} = 1.236$ (i.e., IMPORT_T equal to 3.442%), and the values minimizing RSS, AIC and BIC are respectively 2.364, -4.019 and -3.826. The optimal threshold value for developed countries is equal to $\widehat{c} = 2.615$ (i.e., IMPORT_T equal to 13.667%), and the values minimizing RSS, AIC and BIC are, respectively, 0.177, -6.447 and -6.237. These results show that the transition from a weak to a strong technology import regime is smoother for developing countries compared to developed ones.

Next, we gave the estimated transition function of the PSTR model for industrial employment in country employment. For developing countries, despite the large value of $\widehat{\gamma}$ (21.861), the transition function is almost smooth, showing that the transition from a weak to a strong regime is not abrupt (see Fig. 1).

In Fig. 2, we have just provided the estimated transition function of the PSTR model for industrial employment in developed countries. Also, despite the large value of $\widehat{\gamma}$

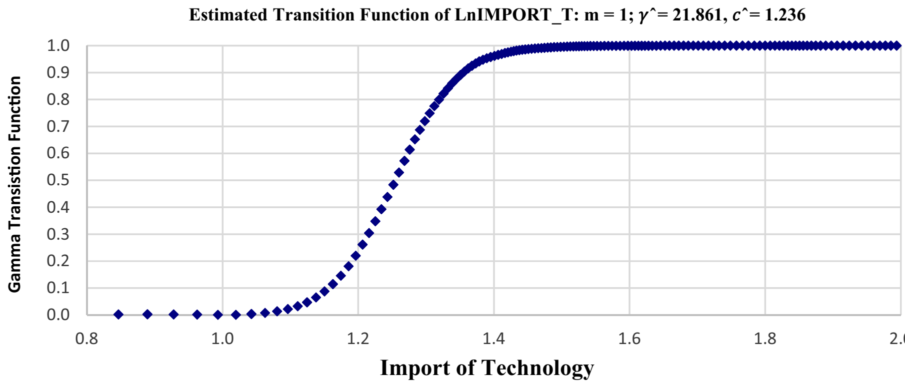

Fig. 1 Estimated transition function of the Developing countries

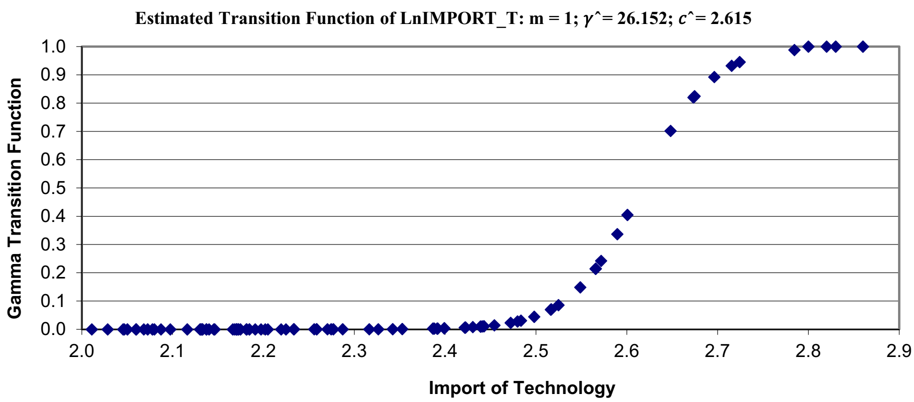

Fig. 2 Estimated transition function of Developed Countries

Table 14 PSTR estimation results of the effect of technology on industrial employment

Developing countries				
Variables	**Regime 1: LnIMPORT_T$_{it-1} \leq 1.236$**		**Regime 2: LnIMPORT_T$_{it-1} > 1.236$**	
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**
LnIMPORT_T$_{it}$	0.050	2.375**	−0.004	−2.026**
LnCPI$_{it}$	0.114	2.603***	0.085	2.447**
LnFDI$_{it}$	0.118	2.601***	−0.102	−2.110**
LnIAV$_{it}$	0.143	0.687	−0.112	−0.530
Observations	64		96	
Developed countries				
Variables	**Regime 1: LnIMPORT_T$_{it-1} \leq 2.615$**		**Regime 2: LnIMPORT_T$_{it-1} > 2.615$**	
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**
LnIMPORT_T$_{it}$	−0.014	−2.018**	0.876	6.356***
LnCPI$_{it}$	−0.688	−7.652***	0.066	0.543
LnFDI$_{it}$	−0.004	−1.810*	−0.051	−3.648***
LnIAV$_{it}$	0.562	5.821***	−0.770	−3.570***
Observations	90		50	

*, **, and *** significant at 10%, 5%, and 1%, respectively

(26.152), we see a smooth function without outliers. Moreover, this function is distinguished by a smooth transition from a low to a high regime.

From 2000 to 2019, Table 14 shows the estimated values of the PSTR for the two regimes in the two country groups.

Before interpreting the results of the two regimes for each group of countries, we conducted several diagnostic tests on the panel data to analyze the presence of conditional temporal heteroscedasticity, serial autocorrelation, and model specification issues. Specifically, we applied the ARCH test for self-regressive conditional heteroscedasticity, the Lagrange Multiplier Test of Breusch-Godfrey for serial correlation, and the RESET test of Ramsey to check for omitted variables and model misspecification.

The results of these diagnostic tests, as shown in Table 15, have confirmed that the error terms in all four regions (two regimes for each group) are free from individual-specific temporal heteroscedasticity and do not exhibit serial autocorrelation or specification errors. This indicates that our model is appropriately specified, and the estimation is reliable for further interpretation and analysis of the relationships between the variables in each regime and country group.

5 Discussion

Regarding the consumer price index (CPI), his impact on employment (negative impact of consumer price increase) is in line with the literature (Feldmann 2013) for all developed and developing countries (in both scenarios). As regards the value-added variable, only the industrial value added for the case of developed countries are significant. These results show that beyond the threshold, the increase in industrial value added translates into a statistically significant loss of employment. Indeed, under a strong regime (LnIMPORT_T > 2.615 or IMPORT_T > 13.667%) the elasticity coefficient of IAV is estimated at -0.770, thus a statistically significant and negative impact of industrial value added on employment. This result is consistent with previous studies (Topalova & Khandelwal 2011; Goldberg et al. 2010) which states that technology imports improve productivity-leading industries, through strategic optimization and restructuring processes, to significantly reduce the number of jobs to be filled.

Regarding FDI, these results show a negative impact of FDI on employment in the second regime (for developing countries) and in both regimes (for developed countries). For developing countries, the effect of FDI on employment is positive in regime 1 (0.118).

Table 15 Diagnostic tests

	Developing countries			**Developed countries**		
	Regime 1	**Regime 2**	**Decision**	**Regime 1**	**Regime 2**	**Decision**
	Value (p-value)	**Value (p-value)**		**Value (p-value)**	**Value (p-value)**	
ARCH test	1.826 (0.177)	1.306 (0.253)	No heteroscedasticity	1.978 (0.160)	1.347 (0.246)	No heteroscedasticity
Serial correlation LM test	5.896 (0.207)	4.003 (0.406)	No serial autocorrelation	2.321 (0.128)	2.556 (0.110)	No serial autocorrelation
Ramsey test	0.621 (0.648)	2.036 (0.159)	No specification error	2.113 (0.150)	2.188 (0.145)	No specification error

p-value between brackets

Thus, when technology import intensity is below the optimal range, the effect of FDI is positive in line with the literature explaining this impact by the investment multiplier effect (Keynes 1936). This multiplier effect of FDI is in fact a function of the adoption of new and improved technologies and skills by host countries as well as the creation of linkages between foreign and domestic firms (Gachunga 2019). In contrast, when the technology import intensity is in the optimal range (regime 2), the impact becomes negative (-0.102). This negative impact is consistent with previous studies (Jude & Silaghi 2016). Indeed, industries in developing countries reduce their workforce to remain competitive in the face of the arrival of FDI, thus provoking a change of profession for workers who integrate new structures. Moreover, since developing countries' low-skilled or unskilled workers are not able to adapt to the new environment, they risk losing their jobs. For developed countries, the results show that FDI inflows, regardless of import dynamics, are not able to create more jobs in host countries as indicated by previous empirical literature (Jude & Silaghi 2016). This negative effect is relatively small (-0.004 and -0.051) as indicated by the literature (Johnny et al. 2018; Tadesse 2014).

About the impact of imported technology on industrial employment, the results will be analyzed at two levels to respond to the problem posed. The first level of analysis will concern the interpretation of the impact of imported technology on industrial employment, which will allow validating or invalidating the hypothesis of our research: The relationship between imported technology and industrial employment is nonlinear and varies with the level of technology imports. The second level of interpretation of the results aims to determine whether the nature of the transition and the threshold of imported technology depend on the level of development country.

5.1 Nonlinear relationship between technology imports and industrial employment

For developing countries, the elasticity of IMPORT_T is estimated at 0.05 for a low technology import regime ($LnIMPORT\_T \leq 1.236$, or $IMPORT\_T \leq 3.44\%$). However, we found a negative effect on employment when the import intensity of technologies is in the optimal range (regime 2). Indeed, the elasticity coefficient of IMPORT_T is estimated at -0.004 in a strong regime ($LnIMPORT\_T > 1.236$, i.e. $IMPORT\_T > 3.44\%$), which is negative and statistically significant. The results show that the relationship between technology and employment is not monotonically linear. In fact, the coefficients of the regression of the variables change sign and trend during the transition from the low to the high regime of technology imports. In fact, it is observed that technology imports have a positive and significant effect on employment when the level of imports is lower than the estimated threshold, while its effect becomes negative and significant when the level exceeds the threshold.

For developed countries, the results are opposite. Indeed, under a weak regime ($LnIMPORT\_T \leq 2.615$ or $IMPORT\_T \leq 13.667\%$), the elasticity of IMPORT_T is evaluated at -0.014, thus a statistically significant and negative impact of imports on employment. However, under a strong regime ($LnIMPORT\_T > 2.615$ or $IMPORT\_T > 13.667\%$), the elasticity of IMPORT_T is evaluated at 0.876, implying a statistically significant and positive impact of imports on employment. The results again show that the relationship between technology and employment is not monotonically linear for developed countries. In fact, the coefficients of the regression of the variables change in sign and trend during the transition from the low to the high regime of technology imports. In fact, it is found that technology imports have a negative and significant impact on employment when the level of imports is below the estimated threshold, while its impact becomes positive and significant when the level exceeds the threshold.

These results show that the impact of technological progress on industrial employment is nonlinear and varies with the intensity of technology imports for both developed and developing countries. These results are consistent with the previously cited empirical study (Yildirim, et al. 2022; Bouattour, et al. 2023a) and confirm the research hypothesis: The relationship between imported technology and industrial employment is nonlinear and varies with the level of technology imports.

5.2 Threshold and transition speed according to country level of development

For advanced economies, technology imports have a negative and significant effect on industrial employment when the level of imports is below the estimated threshold, while the effect becomes positive and significant when the level exceeds the threshold.

These results can be interpreted in terms of industry compensation mechanisms. When the intensity of technology imports is in the optimal range, the effect of imported technologies on industrial employment becomes positive, showing overall the effectiveness of compensation mechanisms in offsetting the negative effects of process innovation, in line with the literature cited above (Domini et al. 2021). Moreover, this positive effect could find an explanation in the product innovation that characterizes these countries industry thanks to the increase in technology imports (strong regime), whose impact on industrial employment is positive, in line with the theoretical framework previously outlined (Schumpeter 1934; Piva & Vivarelli 2018). Nevertheless, it is important to note that this observation is global in nature and does not necessarily apply to each country in the sample. Indeed, referring to the classification according to the Global Innovation Index (GII), it is possible to argue that some countries, such as Spain and Italy (which rank behind the other countries in the sample), may have less effective industry compensation mechanisms than other countries, such as Germany, France, Israel, Canada, and Japan, as suggested by the previously cited literature (Vivarelli 1995; Simonetti et al. 2003; Tancioni & Simonetti 2002; Dauth et al. 2021).

Thus, the adoption of new technologies could lead to lower prices and improved international competitiveness and output, but it could also lead to job losses due to process innovation. In more product-oriented economies (such as Germany or France industry), the correlation between employment and technology is generally positive. In other economies, however, various industry compensation mechanisms may prove ineffective in counteracting the negative effects of process innovation on employment, as is the case in the Italian economy.

The positive impact of technological progress is thus observed globally for developed countries, but it hides disparities in productivity and technology reintegration effects across countries industries, as mentioned in the empirical literature (Arntz et al. 2020). These effects are closely related to institutional factors, which vary across countries. For example, in countries such as Germany or France, stricter industry regulations encourage an increase in technology imports and allow the industry technological progress thus incorporated to be translated into higher wages, thanks to training that leads to improved skills and productivity. However, this macroeconomic analysis cannot capture other factors that may differ from one country to another and have an impact on compensation mechanisms. These include international openness, the role of organizational innovation, and changes in work practices. These elements play a crucial role in the way countries deal with the effects of technological innovation on employment and productivity, but they are not always taken into account in global analysis.

For developing countries, the impact of imported technology on industrial employment is positive but limited to cases below the threshold. This positive effect is consistent with the empirical literature mentioned above (Sharma & Mishra 2023). The explanation for this result lies in the unique characteristics of these countries, which face various challenges such as insufficient spending on research and development (R&D) and slow technological innovation of their industry. These challenges make the imported technology channel particularly important for developing countries industry, as it allows them to access advanced technologies and maintain their competitiveness (Mitra & Sharma 2020). By adopting these technologies, developing countries industry can increases productivity and output without incurring higher wages, given the availability of abundant cheap labor. This mechanism helps to offset the negative direct effect of technological progress on industrial employment, but the efficiency of industry compensation mechanisms is lower when the intensity of technology imports is above the threshold.

As with the developed countries, however, these interpretations must be treated with caution because of the aggregate nature of the results. The diverse sample of developing countries includes countries with institutional factors (e.g., Turkey) that may favor industry compensation mechanisms, and others (e.g., Egypt) where such institutional factors may hinder these mechanisms. For example, in Turkey, relatively strict regulations (ranked 102 in the GII 2019) and high dismissal costs (ranked 115 in the GII 2019) might be offset by efforts in training and R&D (ranked 39 in the GII 2019), which would likely increase the effectiveness of industry compensation mechanisms. On the other hand, Egypt's institutional framework (ranked 112 in GII 2019) and weaknesses in training and R&D efforts (ranked 101 in GII 2019) could hinder the effectiveness of industry compensation mechanisms in the country. Thus, macro-level analysis always masks disparities that can only be captured by micro-level analysis.

As for the negative effect of imported technology on industrial employment observed in Regime 2 (strong regime), the explanation may lie in the inability of developing countries industry to benefit from the positive effect of product innovation as in the case of developed countries industry. Moreover, at higher levels of technology import intensity, industry compensation mechanisms prove ineffective in offsetting the negative effect of process innovation. In fact, several factors, such as restrictive regulations, unfavorable and cyclical macroeconomic conditions, and labor market rigidities, interact to reduce the effectiveness of these mechanisms in these countries.

The conclusion of this discussion is that the transition from a weak technology import regime to a strong technology import regime is smooth for both developed and developing countries. This smooth transition requires rapid policy action to improve the efficiency of industry compensation mechanisms and to counteract the negative effects of the innovation process following more intensive technology imports.

6 Conclusions and policy implications

The main objective of this article was to investigate the non-linear relationship between imported technology and industrial employment, taking into account threshold effects established by the level of technology imports. To this end, unlike previous empirical studies using traditional parametric estimation methods, the PSTR nonlinear regression model was used to detect nonlinear dynamics between variables and to demonstrate the existence of threshold effects resulting from the transition function, which depends on the speed of transition from one regime to another.

Depending on the test used to estimate the number of thresholds, the single-threshold model or the two-regime model adequately captures this relationship. For both developed and developing countries, the estimated results clearly show that the relationship between imported technology and industrial employment is not linear.

Overall, the results are consistent with the theoretical framework and confirm the existence of a nonlinear dynamic between imported technology and industrial employment, proving the existence of threshold effects caused by the speed of transition, leading to regime switching behavior. These results could, therefore, provide elements of explanation to the controversies in the literature on the relationship between technology and employment.

The results also show that technology has a positive impact on industrial employment in developed countries and a negative impact in developing countries (for the regime with high technology imports). This difference arises because advanced countries have relatively efficient industry compensation mechanisms and the skills needed to adapt to and benefit from these technologies. Technologically advanced countries industry reaps more of the employment benefits of technology through product innovation.

For developing countries, the impact on industrial employment is negative when the intensity of technology imports is within the optimal range (regime 2). Although this channel is particularly important for developing countries, it remains limited by the characteristics of these economies industry (insufficient R&D spending, lack of financing and skills), which mean that their adaptation to new technologies is rather slow and job-destroying.

For developed countries, the results are reversed: the impact becomes positive only when technology importing intensity falls into the optimal range. Thus, it is increasing technology import intensity that allows industry compensation mechanisms to offset the direct negative effects of process innovation. Moreover, the positive effects of product innovation can be exploited through technology import intensity.

However, it is important to note that the macro-level analysis is subject to certain methodological limitations and, therefore, our results should be interpreted with caution. The relationship between technology and industrial employment involves both partial equilibrium adjustments and general equilibrium compensating mechanisms, which are complex and difficult to identify accurately at the macro level.

Moreover, our time frame covers a period characterized by significant technological restructuring following the Great Recession and the development of international competition. Combined with institutional factors specific to each country or region, these factors may explain the relative ineffectiveness of some compensation mechanisms in generating a more substantial positive impact of technology on employment.

In sum, the results underscore the importance of efficient industry compensation mechanisms to offset the negative direct effects of process innovation resulting from technology imports. This efficiency depends largely on institutional and economic factors that vary across countries and levels of economic development. Therefore, special attention must be paid to these factors when formulating economic policies and innovation strategies.

For developed countries, consideration of the existence of an import technology threshold should prompt a review of their industrial policies by addressing factors that hinder industry compensatory mechanisms. These countries should design industrial innovation policies that focus on improving price and income compensation mechanisms, primarily by enhancing market competition and demand elasticity. In addition, policymakers need to examine the cyclical conditions that affect this efficiency to mitigate their negative effects.

With regard to developing countries, targeted economic policies should be pursued to improve the industry compensation mechanisms. Policymakers should take the necessary measures to improve the regulatory framework. In addition, innovation policies should aim to increase productivity and labor market flexibility to promote growth and minimize the labor-saving effects of process innovation in the industry. In addition, efforts should be made to develop training and R&D capacities so that the industry can reap the full benefits of product innovation.

Finally, in the digital age, countries that do not innovate will remain on the periphery and risk not only increasing unemployment but also recession and worsening macroeconomic imbalances (Cefis, et al. 2023). This is why innovation is a priority. In this respect, we can mention green innovation in the context of sustainable development, which is gaining increasing awareness among academic actors, companies and policy makers (Takalo & Tooranloo 2021). These studies provide avenues for future research.

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Author contributions
All authors participated in the methodology and the writing of the different sections of the article. Professor KH carried out the empirical part on the basis of the available data.

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Availability of data and materials
The study estimates are based on annual data covering a 20-year sample (2000–2019) for eight developing (Turkey, Bahrain, Egypt, Jordan, Morocco, Oman, Tunisia and Saudi Arabia) and seven developed (Canada, France, Germany, Spain, Italy, Israel and Japan) countries. The selection of countries is based on the 2019 Global Innovation Index (GII), since the purpose of this paper is to analyze technology imports and industrial employment. The large number of countries, the inclusion of input and output measures, and the linkage of GII measures to some key elements of the NIS are several arguments in favor of the choice of the GII. In addition, this diverse sample includes countries that are representative of different rankings according to this criterion, all within the top 100.
The study aimed at presenting the estimated model and the relative variables knowing that they were collected from the databases of the World Development Indicators (WDI) and the International Standard Industrial Classification (ISIC). We use Stata 17.0 and Matlab R2021a softwares to run different programs. The data are available on request from the corresponding author.

Declarations

Competing interests

We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. We confirm that the manuscript has been read and approved by all named authors and that are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the Corresponding Author is the sole contact for the Editorial process. We are responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. Authors are responsible for correctness of the statements provided in the manuscript.

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