Innovation and employment: estimation on a panel of countries using the software stata

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Abstract:

Technological progress and innovation have varying impacts on employment. Recent studies suggest that there is no clear-cut answer, likely due to oscillations in the relationship between innovation and employment. We explored this relationship using a dynamic regression model, incorporating variables of employment through total labor force and innovation through the Innovation Program 5 in OECD countries and by IP5 and the Patent Cooperation Treaty in non-OECD countries. We confirmed the presence of significant positive effects of the IP5 variable on employment in OECD countries and significant positive effects of the PCT variable in non-OECD countries, via the estimation of the two-step SYS-GMM method in stata. Our conclusion was that deploying this methodology enabled us to underscore the oscillations of effects contingent upon the selected innovation proxy, across time, and the classifications applied.

Keywords: Innovation, Employment, Patent, Oscillations, panel data

Résumé:

Le progrès technologique et l'innovation ont des impacts variés sur l'emploi. Des études récentes suggèrent qu'il n'existe pas de réponse définitive, probablement en raison des oscillations dans la relation entre l'innovation et l'emploi. Nous avons exploré cette relation en utilisant un modèle de régression dynamique, intégrant des variables d'emploi à travers la force de travail totale et l'innovation à travers le Programme d'Innovation 5 dans les pays de l'OCDE et par IP5 et le Traité de Coopération en matière de Brevets dans les pays non-OCDE. Nous avons confirmé la présence d'effets positifs significatifs de la variable IP5 sur l'emploi dans les pays de l'OCDE et des effets positifs significatifs de la variable PCT dans les pays non-OCDE, via l'estimation de la méthode SYS-GMM en deux étapes dans stata. Notre conclusion était que le déploiement de cette méthodologie nous a permis de souligner les oscillations des effets en fonction du proxy d'innovation sélectionné, à travers le temps, et les classifications appliquées.

Mots-clés : Innovation, Emploi, Brevet, Oscillations, OCDE

1. Introduction

In the contemporary epoch marked by profound digital interconnectedness, the trajectory of technological advancement has witnessed an exponential rise (Pupillo et al., 2018; Van Roy et al., 2018; World Bank, 2021). This unprecedented technological growth has synergized with economic expansion, serving as a perpetual source of opportunities and resources crucial for the flourishing of nations.

Key stakeholders in both public and private sectors have leveraged such advancements to cater to societal needs, enhance the quality of goods and services, streamline processes, and elevate the standard of living (Geiger and Makri, 2006; Gilchrist, 2016; Agnès, 2022). This symbiosis of technological progress and economic development seemingly advocates for a labor- friendly and a labor- inclusive growth model (Pieroni and Pompei, 2007; Ciriaci et al., 2016). However, the global landscape reveals a stark dichotomy: while technological progress promises economic and labor market benefits, it concurrently plays a pivotal role in exacerbating income disparities, distorting market functionalities, and misaligning economic structures with labor market demands.

Amidst this global backdrop, the specter of technological unemployment looms large, with the OECD (2016) forecasting automation of over 50% of job tasks. Recent trends in the labor market and the advent of automation technologies have sparked a dialogue filled with apprehension. The task model approach to understanding these technologies highlights a shift towards substituting labor with capital across a broad spectrum of activities, influencing both costs and productivity (Restrepo, 2023). Unlike other technological innovations that either introduce new tasks or enhance capital productivity without displacing labor, automation is uniquely characterized by its potential to directly supplant human roles (Acemoglu and Restrepo, 2019; Restrepo, 2023).

The intricate nexus between innovation and employment remains an enigma, despite exhaustive investigations employing a myriad of proxies (Matuzeviciute et al., 2017; Van Roy et al., 2018; Emara, 2021). The academic research delineate various innovation types, each elucidating disparate impacts on the labor market (Vivarelli, 2014, 2015; Matuzeviciute et al., 2017; Adachi et al., 2019; Godin et al., 2021; Restrepo, 2023). This landscape is further complicated by the observation of divergent effects of innovations on employment within identical economic contexts, regions, and even continents (Zhu and al., 2021; Su et al., 2022), necessitating a nuanced theoretical and empirical exploration of these oscillations between researchers.

Acknowledging the complex and multifaceted oscillations of technological advancement on economic and employment landscapes, gauged through inventions, innovations, and R&D expenditures, this study delves into the dynamics of this relationship. It aims to shed light on the oscillatory impacts of innovation across nations, highlighting the global significance of innovation in determining employment outcomes.

The paper unfolds over five sections: following this introduction, Section 2 reviews relevant literature, Section 3 outlines stylized facts, Section 4 details the econometric methodology employed, and Section 5 discusses the findings. The conclusion synthesizes these insights, offering a cohesive understanding of the intricate interplay between innovation and employment.

2. Literature review

2.1 Endogenous growth theory and innovation

Since the beginning of the 20^{th} century, the question of the sources of economic growth has preoccupied considerable economic research. The literature presented by the neoclassicals attests that labor and fixed capital remain the fundamental sources of value creation (Solow 1956). Therefore, economic theory acknowledges that economic progress, as an expression of economic growth, is explained by total factor productivity (Hajek and Toms 1970). The argument has been made by growth models that lean towards neutrality and endogeneity, where technical progress remains exogenous and constant (Daloz 1966; Hajek and Toms, 1970).

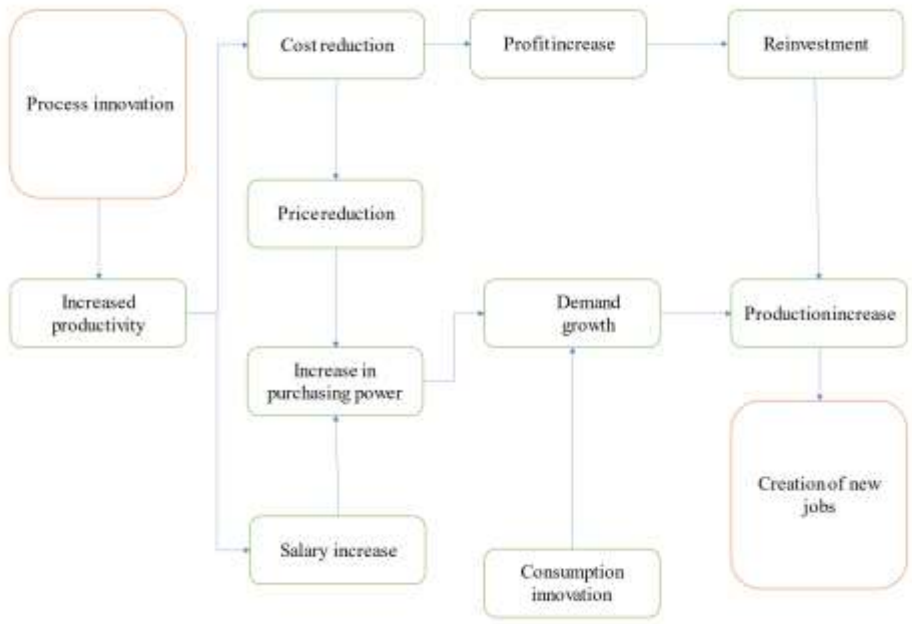
By the end of the 20^{th} century, the economic landscape underwent significant changes marked by exponential economic growth, the rise of industrialization, and the increase in free trade flows. The explanations provided by neoclassical economic theory have shown their limitations. Moreover, it has become imperative to explicitly incorporate technological changes into explanatory models. (Romer 1986, 1990, 1994; Lucas 1988; Godin 2004). Thus, scientific research, more precisely inventions and innovations, has been integrated as independent variables in endogenous growth models (Godin 2008, 2015, 2019, 2020).

In fact, the concept of innovation was introduced by the author J. A. Schumpeter to explain the technological changes affecting economic structures, as a process of creative destruction. (Lakomski-Laguerre 2006). The author explains that innovation, the key to economic growth, destroys old economic structures and creates new ones, which generates new jobs. This theory has influenced economic researchers to adopt different approaches for categorizing forms of innovation (OECD 2005). Therefore, the differentiation primarily resulted in four types of innovations, as outlined in the Oslo manual: Product, Process, Marketing, and Organizational innovation. In this literature, we emphasized product and process innovations, following previous studies, due to their primary roles in the relationship between employment and technical progress (Matuzeviciute et al. 2017). More precisely, product and process innovations anticipate increases in productivity, the creation of opportunities, and improvements in social welfare. In this sense, product innovations are driven by new breakthroughs (e.g., Self-driving vehicle) and process innovations which are explained by cost-minimizing production methods (e.g., robotic warehouses) (Ramanauskienė 2010; Hoover 2012). It is often argued that the distinctions between these innovations are artificial (Flichy 2007). The mentioned innovations lead to labor-saving by eliminating routine jobs and displacing low- to medium-skilled employees (Piva and Vivarelli 2017; Hidalgo et al. 2014; Bratti et al., 2022). Additionally, based on the literature of Keynes (2010) and Leontief (1953), who argue that technical progress will replace workers and create technological unemployment, researchers assert that technological innovations contribute to technological unemployment (Aguirregabiria and Alonso-Borrego 2001; Feldmann 2013). This deduction has been the objective result of several evaluations of job placement programs, especially in many European countries (Bal-Domańska 2021).

2.2 Compensation theory and technological unemployment

The economic theory explains that, in the short term, technological changes generate a replacement effect (Freeman 1982, 1994). Consequently, the compensation theory initiated by K. Marx and D. Ricardo creates an effect to compensate for job losses in the medium to long run (Piva and Vivarelli 2017). According to the compensation theory, process innovations increase productivity (Say 1964; Lorenzi and Bourlès 1995) and lead to increased wages (Pigou 1933b; Wicksell 2022; Hicks 1963), thereby decreasing prices and costs in the market (Vivarreli 1995; Clark 2010; Pigou 1933a). On one side, lower cost improve firms profits and increase production through investment, which stimulates the creation of new jobs. (Ricardo 1981; Marshall 1961; Hicks 1973; Stoneman 1983; Samuelson 1988, 1989; Van Reenen 1997; Lachenmaier and Rottmann 2011). On the other side, lower prices lead to increased purchasing power, which triggers the process of economic growth and thus stimulates the creation of new jobs (Neary 1981; Stoneman 1983; Nickell and Komg 1989; Smolny 1998; Harrison et al. 2008; Vivarelli 2014). Figure 1 illustrates this concept.

Figure 1: The compensation theory



Source: Authors – Based on (Saafi 2008).

Although this theory has been advanced through economists have raised strong and significant critiques (Piva and Vivarelli, 2017). Such criticisms include: (A) the delay in compensation that generates technological unemployment may persist over time; (B) in the case of unemployment linked to effective demand, technological innovations do not necessarily lead to increased productivity, and a decrease in employment may be expected; (C) the accumulation of profits allocated for reinvestment is not necessarily applied in reality, which may lead to accumulated unemployment.

Moreover, product innovations imply effects, albeit positive, on the labor market (Piva and Vivarelli, 2017). Economists assume that the effect of technological product innovations on job creation is positive (Freeman, 1982, 1994; Matuzeviciute et al., 2017). Bringing these new products to market attracts new demand, stimulating a positive link between technological change and employment (Matuzeviciute et al., 2017). Consequently, product innovations are labor-friendly.

In this discourse, a clear-cut answer regarding the effects of innovations on the labor market remains elusive, fueling the ongoing debate between these two perspectives. Initially, innovations contribute to the rise of technological unemployment within the labor economy. However, the compensation theory argues that the long-term decrease in prices and the consequent increase in demand help alleviate technological unemployment (Matuzeviciute et al. 2017; Piva and Vivarelli 2017; Oware and Mallikarjunappa 2021; Emara, 2021).

2.3 Contemporary effects of innovation on employment

The differences between micro and macro econometric empirical studies in terms of scope, behaviors, assumptions, and variables provide us with a broader coverage of the problem. In this sense, we note limitations of micro studies, such as the impact of competition between firms (Feldmann 2013) and the limit of indirect effect of the cross-sector (Bogliacino and Vivarelli 2012). We emphasize that our study operates at a macroeconomic level, elucidating the impacts of the innovation-employment relationship on a global scale.

The works of Acemoglu and Autor (2011), Autor (2015), and Acemoglu and Restrepo (2019) employ an empirical approach to examine the displacement effect of automation on labor markets. In particular, they have utilized econometric analyses to study how jobs and wages are affected, focusing on job polarization. They have also explored the consequences of technological substitution on skills jobs. These authors find that automation has contributed to job polarization, with growth in highly skilled and low-skilled jobs to the detriment of medium-skilled jobs. They also emphasize the importance of education and training in adapting to these changes. Manyika et al. (2017) build on assessing the potential impact of automation on different sectors and jobs worldwide. They estimate that up to a third of work activities in advanced economies could be automated, highlighting the urgency of developing strategies to manage this transition. Finally, as outlined in the task model (Restrepo 2023), automation stands apart from other forms of technological progress that don't lead to displacement effects. These include the introduction of new tasks and products, as well as improvements in capital productivity at the intensive margin.

Turning to the next key element, authors argue that technological innovations increase unemployment in the short run (Vivarelli 1995; Saafi 2008; replacement effect). In the long run, technological innovations have a positive effect on employment (Piva and Vivarelli 2017; Saafi 2008; compensation effect).

Moreover, researchers have explored the impact of innovations on unemployment in response to findings that fail to demonstrate a positive significant effect between innovation and employment (Piva et al., 2006; Meschi et al., 2016), as evidenced by the work of Matuzeviciute et al. (2017).

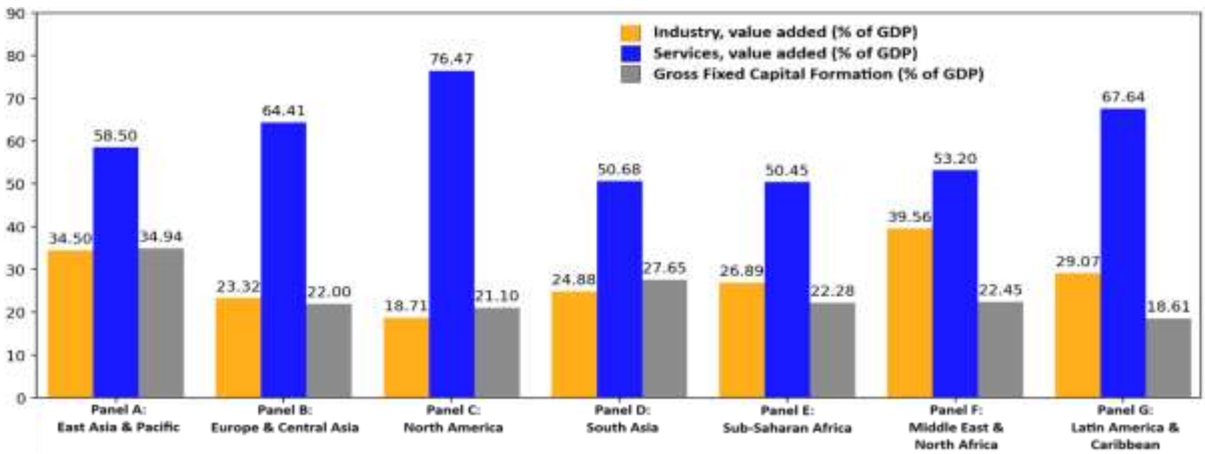
In the context of our empirical study exploring the link between employment and product innovation, several researchers have highlighted the beneficial effects of innovation (see, for example: Greenhalgh et al. 2001; Hall et al. 2008; Matuzeviciute et al. 2017). Conversely, empirical studies on the link between employment and process innovation offer less conclusive results, presenting ambiguity and posing justification challenges (see, for example: Dachs and Peters 2014; Kwon et al. 2015; Matuzeviciute et al. 2017). These results tend to indicate a potentially negative impact of process innovation. Nevertheless, other researchers, such as Lachenmaier and Rottmann (2011), suggest a positive impact of process innovation on employment.

2.4 Effects of innovation on employment: analysis of stylized facts

In this section, we start by analyzing statistical visualization, based on the topics and hypotheses of our study, across 3 proxies variables. The following graph 1 provides an insightful overview of the interplay between Industry, Services, and Gross Fixed Capital Formation (GFCF) in various regions.

Noteworthy trends emerge, revealing diverse economic dynamics. Within Panels C, G, and B, the services sector emerges as an important influential contributor to GDP, displaying higher percentages compared to other sectors.

Graph 1: Comparison between industry, service, and GFCF in 2019



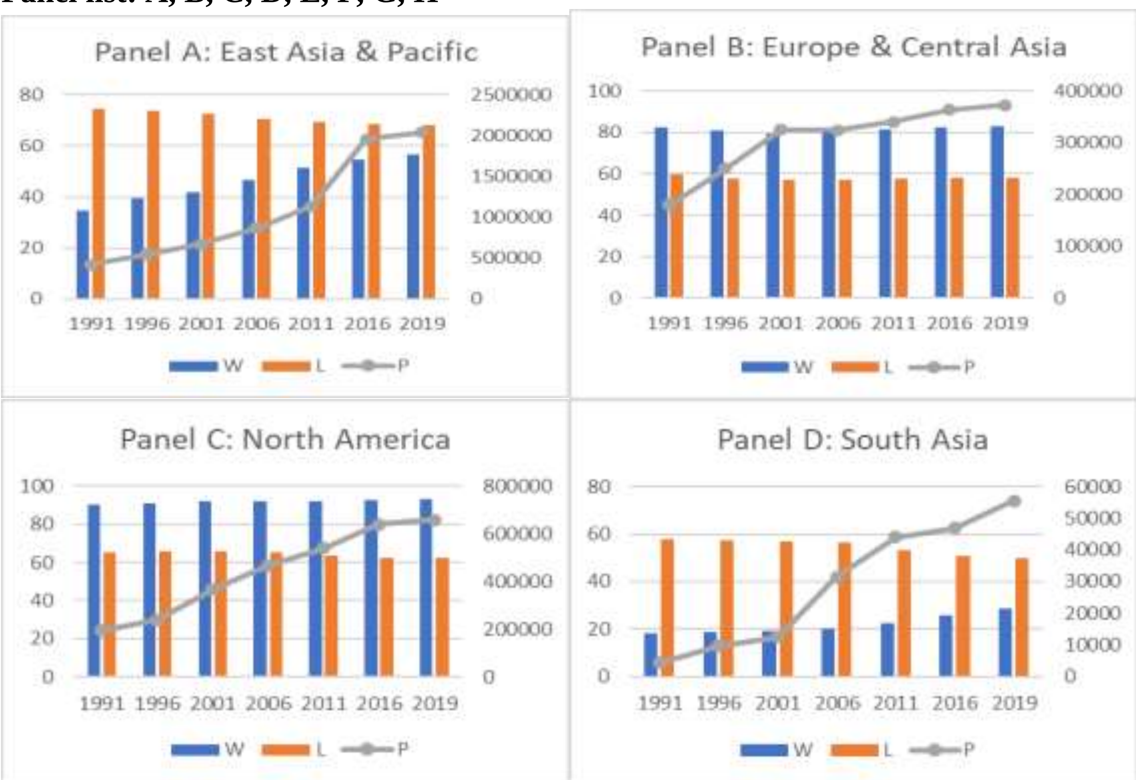
Source: authors, World Bank data.

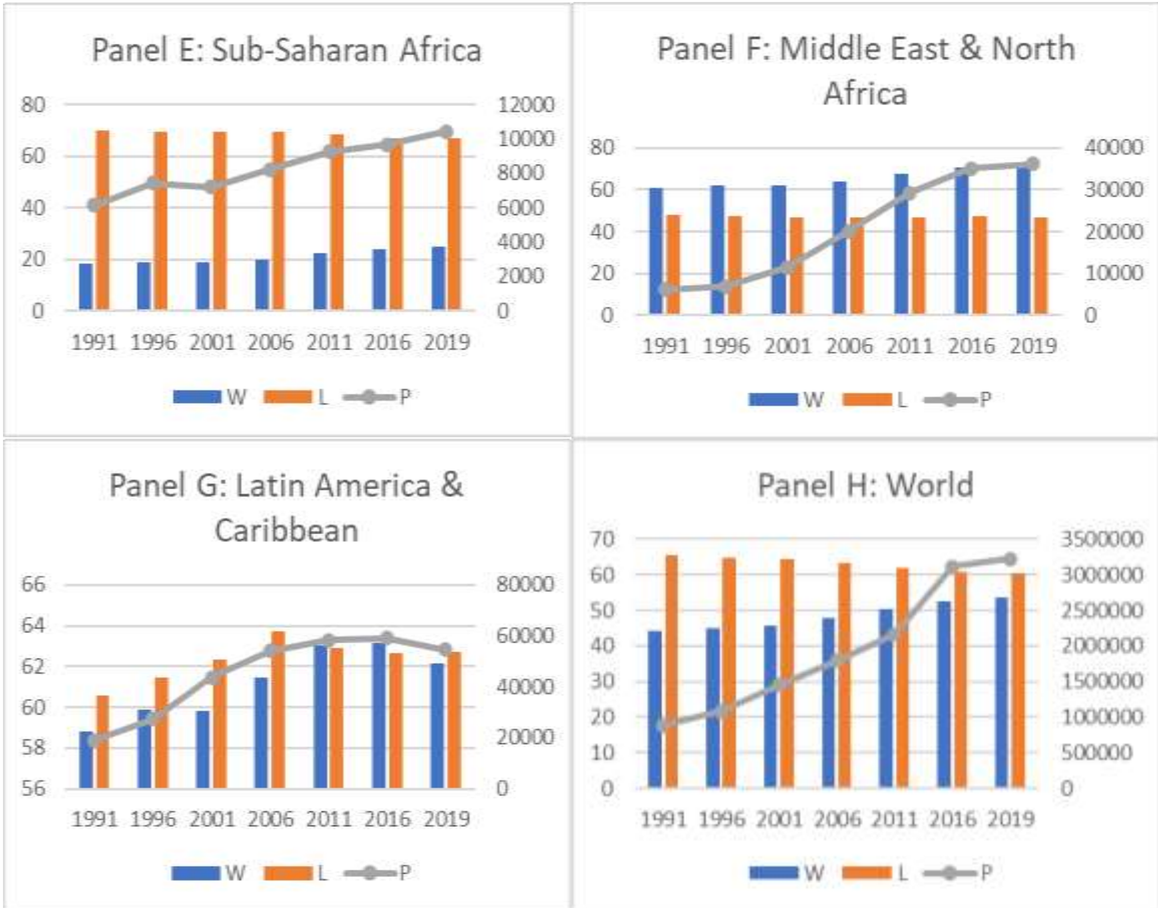
We emphasize that the difference between the value added by services and industry in each region expresses the gap between the two variables. This gap indicates a strong economic orientation, wherein, with similar investment levels across regions, nations produce a high value added. Particularly, the gaps in Panels C (57.75) and B (41.09) provide evidence of a high GDP per capita (thousands of US$ Panels C (63,203) and B (24,892), Word Bank data 2019).

Innovation within these sectors stands as the cornerstone of this phenomenon, with the economic orientation in these regions being shaped by their capacity for creative production (Matuzeviciute et al., 2017; Piva and Vivarelli, 2017; Emara 2021;). Companies seek patenting from various organizations, underscoring how innovation serves as a key driver for both national and international competition (Van Roy et al., 2018; Emara 2021). The effects of innovation manifest in various ways within the labor market (Matuzeviciute et al., 2017; Van Roy et al., 2018; Piva and Vivarelli, 2017). In Section 2, we outlined the theoretical framework aiming to elucidate the pivotal role of innovation in fostering national growth and prosperity.

The following panel list illustrates the relationship between innovation, employment, and wages, across these regions. Thus, we present a geographical trends visualization of regions (Panels B, C, D, E, F, G, H) alongside a global overview (Panel H).

Panel list: A, B, C, D, E, F, G, H





W: Wage and salaried workers, total; L: Labor force participation rate, total; P: Patent applications, total - Source: authors, World Bank data.

In Panels A, C, and B, similar stability is observed in employment and salary trends since 1991, with high salaries in C and B, and important patent applications. Meanwhile, Panels D and F show declining employment alongside rising salaries in the region, with an increase in patent applications since 2006. However, Panels E and G reveal marked disparities between employment and salaries, with oscillation patent applications over time.

Finally, Panel H illustrates an overall trend where employment is decreasing while salaries are gradually increasing, and patent applications shows notable growth between 2011 and 2016, followed by a maturation phase until 2019. From these panels, we can derive a multitude of interpretations from these panels; however, we limit our analysis to the chosen topic and research hypotheses.

4. Methodology and Data

4.1. Description of data

There is a taxonomy of definitions and methods for measuring and classifying innovations (Coccia 2006). Previous studies have primarily been based on patents as a measurement output and R&D expenditures as a measurement input of innovations (Fai and Von Tunzelmann 2001; Kromann and et al. 2011; Bonanno 2016; Vivarelli 2014, 2015). Comparing patented innovations faces challenges due to variations in technical and economic significance, country preferences, and differences between patent offices (Dernis and Khan 2004; Feldmann 2013; Matuzeviciute et al. 2017).

In this regard, we employ IP5 patent families as a preferable and expanded measurement approach, following the methodologies of previous literature (Robitaille et al. 2009; Sternitzke 2009; OECD 2009; Matuzeviciute et al. 2017; OECD 2020, 2021). The IP5, registered at 5 renowned organizations, pose additional limitations in our study: (A) inability to distinguish between product and process innovations, (B) patent registration costs, risking loss for low-value patents, and (C) patents not definitively registered or counted due to legal constraints.

In short, we have collected and constructed our database according to World Bank, ILO and OECD, the following Table 1 shows the variables mobilized in this study.

Table 1: Descriptive statistics variables

			Panel OECD					**Panel Non-OECD**				
		Acronym	Obs	Mean	S.dev	Min	Max	Obs	Mean	S.dev	Min	Max
Dep. Variable	Labor force	**L**	1140	16,280	1,489	12,563	19,627	1500	16,430	1,680	12,512	21,169
Ind. Variables	IP5 Offices	**IP5**	1140	6,471	2,630	0,000	11,815	1497	2,685	2,131	0,000	11,136
	Patent Cooperation Treaty	**PCT**						1499	2,901	2,211	0,000	11,712
Cont.Variables	Wage and salaried workers	**W**	1102	5,080	0,147	4,530	5,259	1450	4,780	0,393	3,394	5,290
	Gross Domestic Product	**GDP**	1114	26,965	1,691	22,921	31,387	1479	25,440	1,687	21,153	30,983
	Trade	**T**	1109	4,992	0,053	3,455	6,628	1454	4,983	0,602	3,316	6,786
	Final Consumption Expenditure	**FCE**	1121	26,652	1,711	22,563	31,181	1450	25,195	1,597	20,705	30,404

Source: authors.

While patents may not fully capture innovation in non-OECD countries due to their limited capabilities and reliance on imported technological change, utilizing IP5 data in these regions remains valuable. Despite their limitations, patents still provide a tangible measure of technological advancement and are widely recognized as indicators of innovation. Additionally, IP5 data offers a standardized and internationally comparable dataset, enabling meaningful cross-country comparisons. Moreover, we suspect limited geographic accessibility and administrative simplicity for inventors in developing economies.

Consequently, by using International Patent System (PCT) data, we can still glean valuable insights into the effects in non-OECD countries.

As Table 2 illustrates the difference between these countries in terms of labor and innovation, it is noteworthy that our choice is highly justifiable to address the issue of the effects of innovation on employment by examining patent application in these countries. This study includes 40 OECD countries and 52 non-OECD countries. We work on two panels, the first for OECD countries (Panel 1) and the second for non-OECD countries (Panel 2), covering the period 1990-2019.

Table 2: Labor force and innovation spread (log unit)

OECD	**Labor**	**IP5**
	Mean	
JP	18,711	11,432
US	19,512	11,181
DE	18,224	10,619
KR	17,687	9,779
FR	17,860	9,579
UK	17,942	9,257
IT	17,701	8,864
CA	17,367	8,653
NL	16,631	8,486
CH	15,961	8,386
SE	16,077	8,295
AT	15,917	7,844
FI	15,473	7,721
AU	16,858	7,713
IL	15,609	7,621
BE	16,026	7,612
ES	17,501	7,405
DK	15,569	7,369
NO	15,412	6,690
IE	15,184	6,077
NZ	15,270	5,844
HU	15,975	5,506
CZ	16,157	5,393
PL	17,386	5,372
MX	18,245	5,202
TR	17,704	4,814
GR	16,066	4,799
LU	12,971	4,755
SI	14,494	4,686
PT	16,155	4,622
CL	16,440	3,788
SK	15,478	3,728
IS	12,773	3,549
CO	17,476	3,242
EE	14,150	3,078
LT	14,990	2,591
LV	14,607	2,445
CR	15,097	1,888

Non-OECD	**Labor**	**IP5**	**PCT**
		Mean	
CN	21,112	8,431	8,115
IN	20,514	6,647	6,484
RU	18,812	6,450	7,134
SG	15,387	6,365	6,076
BR	18,951	6,040	6,237
HK	15,759	5,902	5,649
ZA	17,483	5,724	5,971
MY	16,880	4,969	4,630
AR	17,350	4,642	3,894
SA	16,667	4,126	4,020
UA	17,632	4,112	4,871
TH	18,102	3,891	3,770
RO	16,847	3,659	4,001
HR	15,164	3,557	3,904
BG	15,761	3,504	3,849
PH	18,002	3,292	3,344
ID	19,164	2,934	2,754
VE	16,907	2,752	2,129
AE	15,550	2,734	3,063
BY	16,093	2,715	3,222
EG	17,658	2,700	3,259
MT	12,744	2,314	1,935
CY	13,813	2,309	2,547
IR	17,556	2,307	2,431
UY	14,954	2,143	2,074
MA	16,822	2,036	2,773
JO	14,862	1,881	1,409
LB	14,899	1,807	1,996
LK	16,571	1,783	2,312
TN	15,751	1,730	2,015
PE	17,077	1,722	2,015
PK	18,414	1,605	1,486
KZ	16,617	1,539	2,785
KE	17,163	1,365	1,745
KW	14,691	1,349	1,123
PA	14,839	1,346	1,661
EC	16,276	1,337	1,652
GE	15,250	1,298	2,095
AM	14,888	1,221	2,109
MD	14,625	0,979	1,743
UZ	16,848	0,923	1,320
SV	15,366	0,916	0,665
DZ	16,759	0,872	1,785
BA	14,852	0,807	1,825
JM	14,709	0,670	0,613
MN	14,547	0,632	0,409
NG	18,344	0,587	0,862
ZW	16,033	0,556	0,808
GT	16,034	0,469	0,903
MK	14,386	0,464	1,512

Source: Authors

4.2. Specification of the model and estimation

Following the previous studies mentioned in sections 2 and 3, and in line with the nature of the data collected in this study, we adopt a dynamic regression model as follows:

$$Y_{i,t} = \alpha Y_{i,t-1} + \beta_i X_{i,t} + \gamma_i Z_{i,t} + \delta + \mu_i + \rho_t + \varepsilon_{it}$$

In this context, where we analyze a set of variables, the symbols Y and Y (-1) correspond to the dependent variable and its lagged value. The index (i, t) is used to identify specific cross-sectional units, while X represents the primary independent variable associated with core innovation. Z represents a matrix of control variables, and μ captures unobservable time-invariant cross-sectional heterogeneity. The symbol ρ signifies time effects that remain constant across cross-sectional observations. Attributes denoted by (α, δ, γ) are to be estimated, and ε represents the error term, while δ serves as the constant term in our model.

Our initial estimation involves applying two statistical methods: OLS and FE. These results are presented in columns (I) and (II). Nevertheless, it's important to acknowledge that both of these methods come with biases and do not satisfy the assumptions of autocorrelation, heteroskedasticity, and endogeneity. The equation used for this analysis is as follows:

$$L_{i,t} = \alpha L_{i,t-1} + \beta_1 IP5_{i,t-1} + \beta_2 IP5_{i,t} + \gamma_3 GDP_{i,t} + \gamma_4 W_{i,t} + \gamma_5 FCE_{i,t} + \gamma_5 T_{i,t} + \delta + \mu_i + \rho_t + \epsilon_{i,t}$$

In this model, we use the IP5 variable and the IP5(-1) variable to capture past effects and explanatory precision for both Panels. Two distinct GMM estimation techniques are commonly employed in statistical analysis: the Difference GMM (DIF-GMM), initially introduced by Arellano and Bond in 1991, and the System GMM (SYS-GMM), introduced by Arellano and Bover in 1995 and further developed by Blundell and Bond (1998). These estimation methods are tailored for dynamic panel datasets characterized by either a limited number of time periods (small-T) or a substantial number of individual entities (large-N). These datasets may encompass fixed effects or exhibit heteroskedasticity and correlated idiosyncratic errors within individual observations.

The DIF-GMM encounters the following issues: (1) when the dependent variable is close to a probability of a random walk, as past levels do not provide sufficient information on future changes; (2) it can be unreliable for transformed variables; (3) explanatory variables are persistent over time, and observation periods are short. To address these limitations, we employ the two-step SYS-GMM estimation. If the DIF-GMM estimate for the coefficient of a lagged dependent variable is near or below that of the fixed effect model, it implies that the former estimate may be underestimated due to weak instrumental variables. In such cases, SYS-GMM should be utilized for more accurate results.

The two-step SYS-GMM is more robust than the one-step SYS-GMM, particularly when the sample size is small, as it helps to mitigate dynamic panel bias in the estimates. Subsequently, we estimate the model using both DIF-GMM and SYS-GMM methods in columns (II) and (IV) respectively. We simultaneously estimate SYS-GMM with reference to Roodman (2009) and Kripfganz and Schwarz (2019), driven by two endogenous variables, IP5 and GDP. We validate the SYS-GMM estimation using both the Hansen and AR(2) tests.

5. Results and discussion

We present the estimation results in Table 3. We highlight in Panel 2: Non-OECD / PCT patents that we have used the same estimation approach, replacing the variable IP5 with PCT.

Table 3: Estimation results (log variables)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
PANEL 1: OECD / IP5 PATENT								
L (-1)	0,996	0,964	0,760	0,970	0,971	0,970	0,959	0,963
	0,000* **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **
IP5	-0,001	-0,001	0,000	0,012	0,012	0,009	0,053	0,049
	0,574	**0,734**	**0,949**	**0,001*** **	**0,001*** **	**0,003*** **	**0,003*** **	**0,001*** **
IP5(-1)	-0,001	0,000	0,009	-0,020	-0,021	-0,019	-0,059	-0,054
	0,542	**0,904**	**0,023** **	**0,001*** **	**0,000*** **	**0,002*** **	**0,000*** **	**0,000*** **
GDP	0,052	0,069	0,240	0,212	0,201	0,167	0,147	0,195
	0,000* **	**0,000*** **	**0,002*** **	**0,012** **	**0,015** **	**0,061***	**0,104**	**0,029** **
FCE	-0,047	-0,064	-0,218	-0,184	-0,171	-0,135	-0,111	-0,166
	0,001* **	**0,001*** **	**0,003*** **	**0,021** **	**0,035** **	**0,113**	**0,209**	**0,055***
W	-0,026	0,008	0,031	-0,056	-0,052	-0,043	-0,076	-0,075
	0,007* **	**0,711**	**0,700**	**0,073***	**0,138**	**0,240**	**0,147**	**0,090***
T	-0,006	-0,002	0,008	-0,036	-0,033	-0,033	-0,029	-0,039
	0,054*	**0,655**	**0,472**	**0,011** **	**0,023** **	**0,018** **	**0,044** **	**0,009*** **
Cst,	0,093	0,414		0,188	0,111	0,044	0,251	0,374
	0,132	**0,002*** **		**0,409**	**0,608**	**0,858**	**0,486**	**0,200**
Obs,	1078	1078	1034	1072	1072	1072	1072	1072
F-Stat/chi2	99999.00***	8140.15***		4.97e+06***	5.75e+07***	3.85e+07***	3.73e+07***	3.06e+07***
AR (2)			-1.66	-0.29	-0.23	-0.28	1.20	1.09
Hansen			34.46	34.90	32.19	27.47	29.48	33.69
PANEL 2: NON-OECD / IP5 PATENT								
L (-1)	0,994	0,973	0,738	0,943	0,931	0,928	0,902	0,936
	0,000* **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **
IP5	0	0	0,017	0,009	0,021	0,005	0,027	0,021
	0,791	**0,532**	**0,011** **	**0,140**	**0,002*** **	**0,348**	**0,021** **	**0,076***
IP5(-1)	-0,003	-0,001	0,008	0,000	-0,007	0,001	-0,007	-0,007
	0,003* **	**0,318**	**0,027** **	**0,983**	**0,182**	**0,76**	**0,445**	**0,394**
GDP	0,033	0,028	-0,004	0,171	0,175	0,184	0,165	0,169
	0,008* **	**0,213**	**0,929**	**0,000*** **	**0,001*** **	**0,000*** **	**0,001*** **	**0,000*** **
FCE	-0,025	-0,023	0,024	-0,152	-0,149	-0,153	-0,124	-0,15
	0,044 **	**0,318**	**0,576**	**0,000*** **	**0,002*** **	**0,000*** **	**0,004*** **	**0,000*** **
W	-0,009	-0,039	0,041	-0,088	-0,105	-0,107	-0,128	-0,09
	0,066*	**0,000*** **	**0,502**	**0,026** **	**0,016** **	**0,013** **	**0,005*** **	**0,037** **
T	-0,001	-0,002	0,003	-0,052	-0,053	-0,056	-0,083	-0,064
	0,895	**0,588**	**0,671**	**0,002*** **	**0,025** **	**0,001*** **	**0,002*** **	**0,008*** **
Cst,	-0,034	0,524		1,085	1,166	1,133	1,536	1,243
	0,63	**0,000*** **		**0,005*** **	**0,008*** **	**0,002*** **	**0,002*** **	**0,009*** **
Obs,	1398	1398	1344	1395	1395	1395	1395	1395
F-Stat/chi2	99999.00***	8517.57***		601193.92***	7.88e+06***	6.26e+06***	5.38e+06***	4.26e+06***
AR (2)			-1.11	-1.14	-0.10	-0.85	-0.17	-0.38
Hansen			38.51*	35.50	36.03	40.34*	30.17	32.64
PANEL 2: NON-OECD / PCT PATENT								
L (-1)	0,995	0,973	0,672	0,972	0,991	0,968	0,94	0,968
	0,000* **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **	**0,000*** **
PCT	-0,002	0,001	0,019	-0,032	-0,056	-0,05	-0,025	-0,031
	0,043 **	**0,344**	**0,002*** **	**0,004*** **	**0,000*** **	**0,000*** **	**0,013** **	**0,004*** **
PCT (-1)	-0,004	-0,001	0,008	0,02	0,029	0,028	0,02	0,02
	0,000* **	**0,201**	**0,004*** **	**0,020** **	**0,006*** **	**0,011** **	**0,009*** **	**0,021** **
GDP	0,027	0,028	-0,012	0,12	0,096	0,09	0,123	0,114
	0,017 **	**0,218**	**0,788**	**0,000*** **	**0,022** **	**0,029** **	**0,001*** **	**0,000*** **
FCE	-0,017	-0,023	0,033	-0,092	-0,066	-0,049	-0,077	-0,083
	0,138	**0,321**	**0,428**	**0,003*** **	**0,115**	**0,28**	**0,023** **	**0,001*** **
W	-0,007	-0,039	0,038	-0,018	0,023	-0,02	-0,078	-0,029
	0,181	**0,000*** **	**0,531**	**0,501**	**0,491**	**0,522**	**0,021** **	**0,209**
T	0,003	-0,002	-0,006	-0,012	0,015	0	-0,035	-0,015
	0,466	**0,583**	**0,529**	**0,257**	**0,363**	**0,985**	**0,017** **	**0,163**
Cst,	-0,12	0,52		-0,058	-0,714	-0,356	0,386	-0,01
	0,076*	**0,000*** **		**0,787**	**0,005*** **	**0,157**	**0,19**	**0,963**
Obs,	1400	1400	1346	1397	1397	1397	1397	1397
F-Stat/chi2	99999.00***	8959.27***		2.22e+06***	3.37e+07***	2.25e+07***	1.09e+07***	1.88e+07***
AR (2)			0.61	1.51	1.74*	1.65	1.37	1.48
Hansen			33.73	35.54	30.45	31.36	34.17	33.99

Note: We used log variables. P-value are presented coefficient (*** p<0.01, ** p<0.05, * p<0.1). Estimates from (V) to (VIII) include time dummies - Source: Authors estimations

According to the estimation in Panel 1, we confirm that in OECD countries, both the variables IP5 and IP5(-1) have statistically significant effects. The negative coefficient of IP5(-1) indicates that there is a certain time lag between innovation and its impact on employment, suggesting that IP5 and IP5(-1) have a cumulative and increasing impact on employment over time. We also observe a moderate effect of Trade and GDP, as well as a modest effect of Wage and FCE on employment.

In Panel 2, we endeavored to assess if innovation, approximated by IP5, has effects on the labor force. We discovered that only the variable IP5 indicates a weak effect when using time dummies, and there is no effect from the IP5(-1) variable on employment. Conversely, we can clearly observe significant effects from the variables GDP, FCE, Wage, and Trade.

Similarly, following the rationale for selecting the PCT variable, we confirm the statistically significant positive effect of the IP5 variable and the same lagged variable on employment. This suggests that innovation plays a significant role in explaining the labor force in non-OECD countries. We can also emphasize the significant effects of GDP and FCE, along with the modest effects of Wage and Trade when using time dummies.

We explain the previous results that failed to confirm a decisive and final effect of innovation on employment through an oscillation effect of innovation. This oscillation and variation are attributed to the types of innovation studied in each analysis. This creates a debate among researchers regarding the role of technology, R&D, and innovation in employment. We confirm the presence of explanations from compensation theory (compensation effect), as we have observed that time plays a crucial role in compensating the effects of innovation, which tends to cumulate towards a positive and significant impact. Additionally, we explain that patent registration with IP5 offices limits the ability of developing economies to register patents.

6. Conclusion

Our study contributes to the scientific research on the complex relationship between technological progress, innovation, and employment. It is imperative to acknowledge that challenges such as limited access to data have restricted the ability to comprehensively explore nuances among different types of patents.

In our quest to build a robust response, we have thoroughly examined the existing literature, incorporating a wide array of interpretive insights and econometric analyses. This preparatory work has allowed us to navigate precisely the roles of endogenous and exogenous variables by exploiting instrumental variables, thereby validating our propositions and empirical findings regarding oscillations.

Notably, our application of the dynamic model has illuminated the nuanced temporal effect between patenting and employment. The oscillations, conditioned by the division of the Panel into OECD and non-OECD countries, underlines the diverse nature of patents and their differential effects observed in various empirical studies.

The effect between innovation and its outcomes on employment, particularly indicated by the IP5(-1) and PCT variables, points towards a progressive and cumulative effect of innovation. This model emphasizes the relevance of the compensation theory and the pivotal role in explanation, which collectively suggest a significant gradual positive shift in employment attributable to innovation in the long term. Furthermore, the study sheds light on the specific challenges faced by developing economies in patent registration, highlighting a critical area for policy intervention.

Ultimately, we wish to underscore the nuanced perspective presented in this article, emphasizing that policy-makers should prioritize policies that enhance and support innovation, particularly within developing economies, to gain the long-term positive effects of technological progress and patenting activities on employment. Furthermore, it is imperative to implement targeted interventions to refine patent registration processes, ensuring that the benefits of innovation are broadly and equitably distributed.

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