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Research article

OSCILLATION EFFECTS OF INNOVATION ON EMPLOYMENT

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Abstract. On the cusp of a promising era of technological progress and innovation that seeks to deeply alter the essence of employment, recent research indicates that there is no straightforward answer to how these changes will affect the total labour force. This study endeavours to clarify the complex oscillations between these forces. It employs a robust methodological fusion of theoretical frameworks and empirical scrutiny to dissect the innovation-employment nexus within both OECD and non-OECD economies. A dynamic regression model was utilized, integrating employment variables through the total labour force, and innovation metrics through the Innovation Program 5 for OECD countries, along with the Patent Cooperation Treaty for non-OECD countries. The analysis favoured the robust two-step SYS-GMM estimator over various estimations, including the DIF-GMM, uncovering a positive relationship effect between innovation and employment. Specifically, the study reveals that the IP5 exerts a significant positive effect on the labour force within OECD countries, endorsing the labour-friendly nature of innovation. Conversely, the PCT demonstrates a marked beneficial effect on employment in non-OECD countries. These insights shed light on the nuanced and favourable interplay between innovation and employment across diverse economies, accentuating the temporal and interdependent nature of their association. The need for in-depth knowledge of innovation and its specific effects on employment is crucial for policy-makers. This entails the development of tailored policies and strategic plans intended for the patenting and exploiting innovations aiming at strengthening employment in its economic environment, in specific business environments and taking account of temporal and contextual factors.

Keywords*:* innovation; employment; patent; oscillations; OECD.

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1. Introduction

At the dawn of a revolutionary era in innovation, the trajectory of technological advancement has witnessed an exponential rise [1–3]. This unprecedented technological progress has synergized with economic growth, 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 raise living standards [4–6]. This symbiosis of technological progress and economic growth seemingly advocates for a labour-friendly and labour-inclusive model [7; 8]. Nevertheless, the global scenario presents a clear dichotomy: while technological progress promises economic and labour market benefits, it concurrently plays a pivotal role in exacerbating income disparities, distorting market functionalities, and misaligning economic structures with labour market demands. Amidst this global backdrop, the spectre of technological unemployment looms large, with the OECD forecasting automation of over 50% of job tasks [9]. Recent trends in the labour market and the advent of automation technologies have sparked a dialogue filled with apprehension. The task model approach emphasizes a shift towards substituting labour with capital across a broad spectrum of activities, influencing both costs and productivity [10]. Unlike other technological innovations that either introduce new tasks or enhance capital productivity without displacing labour, automation is uniquely characterized by its potential to directly supplant human roles [10; 11]. The intricate nexus between innovation and employment remains an enigma, despite exhaustive investigations employing a myriad of proxies [2; 12; 13]. The academic research delineates various innovation types, each elucidating disparate impacts on the labour market [12; 10; 14–17]. This situation is further complicated by the observation of divergent effects of innovations on employment within identical economic contexts, regions, and even continents [18; 19], necessitating a nuanced theoretical and empirical exploration of these oscillations by researchers.

This study presents a meticulous examination of the intricate and multifaceted relationship between innovation and employment, offering a nuanced perspective. Notably, it adopts an analytical framework to explore the oscillations, using diverse proxies for innovation and encompassing the classifications of both OECD and non-OECD nations. Through the implementation of this comprehensive methodology, including dynamic regression modelling, the study delivers a profound investigation into the impacts of innovation on employment. Furthermore, it illuminates temporal and contextual nuances and effects, thereby enriching the discourse surrounding prevailing theories and research in this field. 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, providing a cohesive understanding of the intricate interplay between innovation and employment, and providing crucial recommendations.

2. Literature review

2.1. Endogenous growth theory and innovation

Since the beginning of the 20th century, the question of the sources of economic growth has preoccupied considerable economic research. The literature presented by the neoclassicals attests that labour and fixed capital remain the fundamental sources of value creation [20].

Therefore, economic theory acknowledges that economic progress, as an expression of economic growth, is explained by total factor productivity [21]. The argument has been made by growth models that lean towards neutrality and endogeneity, where technical progress remains exogenous and constant [21; 22]. We posit that technological progress contributes to economic growth, suggesting technological progress and innovation are key predictors of economic expansion. By the end of the 20th 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. [23–27]. Scientific research, more precisely inventions and innovations, has been integrated as independent variables in endogenous growth models [28–31]. It is suggested that including technological changes in endogenous economic growth models reveals a stronger positive relationship with economic growth than models treating technology as exogenous. 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 [32]. 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 [33]. 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, the primary emphasis is given to product and process innovations, as in previous studies, due to their key role in the relationship between employment and technical progress [12]. 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 vehicles) and process innovations which are explained by cost-minimizing production methods (e.g., robotic warehouses) [34; 35]. It is often argued that the distinctions between these innovations are artificial [36]. The mentioned innovations lead to labour-saving by eliminating routine jobs and displacing low to medium-skilled employees [37–39]. It is hypothesized that while innovation initially eliminates routine jobs, it ultimately leads to more job creation, indicating a positive effect on employment. Additionally, based on the literature of Keynes [40] and Leontief [41], who argue that technical progress will replace workers and create technological unemployment, researchers assert that technological innovations contribute to technological unemployment [42; 43]. This deduction has been the objective result of several evaluations of job placement programs, especially in many European countries [44].

2.2 Compensation theory and technological unemployment

The economic theory explains that, in the short term, technological changes generate a replacement effect [45; 46]. Consequently, the compensation theory initiated by K. Marx and D. Ricardo [37] creates an effect to compensate for job losses in the medium to long run. According to the compensation theory, process innovations increase productivity [47; 48] and lead to increased wages [49–51], thereby decreasing prices and costs in the market [52–54]. On one side, lower costs improve firms' profits and increase production through investment, which stimulates the creation of new jobs [55–62]. 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 [14; 58; 63–66]. Although this theory has been advanced through economists have raised strong and significant critiques [37]. 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 labour market [37]. Economists assume that the effect of technological product innovations on job creation is positive [12; 45; 46]. Bringing these new products to the market attracts new demand, stimulating a positive link between technological change and employment [12]. Consequently, product innovations are labour-friendly. In this discourse, a clear-cut answer regarding the effects of innovations on the labour market remains elusive, fuelling the ongoing debate between these two perspectives. Initially, innovations contribute to the rise of technological unemployment within the labour economy. However, the compensation theory argues that the long-term decrease in prices and the consequent increase in demand help alleviate technological unemployment [12; 13; 37; 70].

2.3 Contemporary effects of innovation on employment

The differences between micro and macro-econometric empirical studies in terms of scope, behaviours, assumptions, and variables provide us with a broader coverage of the problem. In this sense, limitations of micro studies are noted, such as the impact of competition between firms [43] and the limit of an indirect effect of the cross-sector [71]. It is emphasized that the study operates at a macroeconomic level, elucidating the impacts of the innovation-employment relationship on a global scale. The works of Acemoglu and Autor [11], Autor [72], and Acemoglu and Restrepo [73] employ an empirical approach to examine the displacement effect of automation on labour 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. [74] 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 [10], 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 (replacement effect) [52; 67]. In the long run, technological innovations have a positive effect on employment (compensation effect) [37; 67–69]. 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 [75; 76], as evidenced by the work of Matuzeviciute et al. [12]. In the context of the empirical study exploring the link between employment and product innovation, several researchers have highlighted the beneficial effects of innovation [12; 77; 78]. Conversely, empirical studies on the link between employment and process innovation offer less conclusive results, presenting ambiguity and posing justification challenges [12; 79; 80]. These results tend to indicate a potentially negative impact of process innovation. Nevertheless, other researchers, such as Lachenmaier and Rottmann [62], suggest a positive impact of process innovation on employment.

3. Effects of innovation on employment: analysis of stylized facts

In this section, the analysis begins with statistical visualization, based on the topics and hypotheses of the study, across 3 proxy variables. The following Fig. 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.

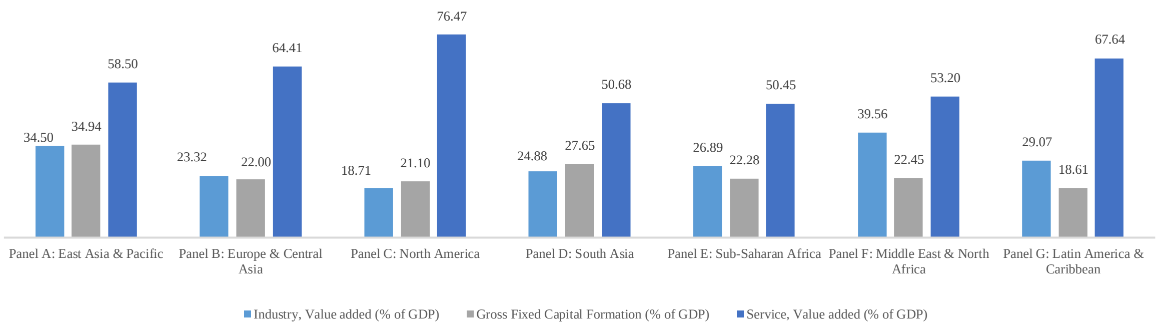

Figure 1. Comparison between industry, service, and GFCF in 2019
Source: developed by the authors, World Bank Data.

It should be noted 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. 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 [12; 13; 37]. Companies seek patenting from various organizations, underscoring how innovation serves as a key driver for both national and international competition [2; 13]. The effects of innovation manifest in various ways within the labour market [12; 2; 37]. The following panel list illustrates the relationship between innovation, employment, and wages, across these regions. Thus, a geographical trends visualization of regions (Panels B, C, D, E, F, G) is presented alongside a global overview (Panel H). In Panels A, C, and B, similar stability has been 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 show notable growth between 2011 and 2016, followed by a maturation phase until 2019. From these panels, a multitude of interpretations can be derived; however, the analysis is limited to the chosen topic and research hypotheses.

Figure 2. Panel list. A, B, C, D, E, F, G, H
Note: W: Wage and salaried workers; L: Labour force participation rate; P: Patent applications
Source: developed by the authors, World Bank Data.

4. Methodology and Data

4.1 Description of data

There is a taxonomy of definitions and methods for measuring and classifying innovations [81]. Previous studies have primarily been based on patents as a measurement output and R&D expenditures as a measurement input of innovations [14; 15; 82–84). Comparing patented innovations faces challenges due to variations in technical and economic significance, country preferences, and differences between patent offices [12; 43; 85]. In this regard, IP5 patent families are employed as a preferable and expanded measurement approach, following the methodologies of previous literature [12; 86–90]. The IP5, registered at 5 renowned organizations, pose additional limitations in this 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, the database has been collected and constructed according to the World Bank, ILO, and OECD. Table 1 shows the variables mobilized in this study.

Table 1. Descriptive statistics

Variables		Panel OECD						Panel Non-OECD				
		Acr	**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: the authors' estimate.

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, limited geographic accessibility and administrative simplicity for inventors in developing economies are suspected. Consequently, the use of International Patent System (PCT) data allows for valuable insights into the effects in non-OECD countries. As Table 2 illustrates the difference between these countries in terms of labour and innovation, it is noteworthy that choice is highly justifiable to address the issue of the effects of innovation on employment by examining patent applications in these countries. This study includes 40 OECD countries and 52 non-OECD countries. The classification of OECD countries (Panel 1) and non-OECD countries (Panel 2), covering the period from 1990 to 2019, was pivotal in achieving the study's outcomes.

Table 2. Labour force and innovation spread (log unit)

OECD	**Labour**	**IP5**	**Non-OECD**	**Labour**	**IP5**	**PCT**
	Mean				**Mean**	
JP	18.711	11.432	CN	21.112	8.431	8.115
US	19.512	11.181	IN	20.514	6.647	6.484
DE	18.224	10.619	RU	18.812	6.450	7.134
KR	17.687	9.779	SG	15.387	6.365	6.076
FR	17.860	9.579	BR	18.951	6.040	6.237
UK	17.942	9.257	HK	15.759	5.902	5.649
IT	17.701	8.864	ZA	17.483	5.724	5.971
CA	17.367	8.653	MY	16.880	4.969	4.630
NL	16.631	8.486	AR	17.350	4.642	3.894

OECD	Labour	IP5	Non-OECD	Labour	IP5	PCT
	Mean				Mean	
CH	15.961	8.386	SA	16.667	4.126	4.020
SE	16.077	8.295	UA	17.632	4.112	4.871
AT	15.917	7.844	TH	18.102	3.891	3.770
FI	15.473	7.721	RO	16.847	3.659	4.001
AU	16.858	7.713	HR	15.164	3.557	3.904
IL	15.609	7.621	BG	15.761	3.504	3.849
BE	16.026	7.612	PH	18.002	3.292	3.344
ES	17.501	7.405	ID	19.164	2.934	2.754
DK	15.569	7.369	VE	16.907	2.752	2.129
NO	15.412	6.690	AE	15.550	2.734	3.063
IE	15.184	6.077	BY	16.093	2.715	3.222
NZ	15.270	5.844	EG	17.658	2.700	3.259
HU	15.975	5.506	MT	12.744	2.314	1.935
CZ	16.157	5.393	CY	13.813	2.309	2.547
PL	17.386	5.372	IR	17.556	2.307	2.431
MX	18.245	5.202	UY	14.954	2.143	2.074
TR	17.704	4.814	MA	16.822	2.036	2.773
GR	16.066	4.799	JO	14.862	1.881	1.409
LU	12.971	4.755	LB	14.899	1.807	1.996
SI	14.494	4.686	LK	16.571	1.783	2.312
PT	16.155	4.622	TN	15.751	1.730	2.015
CL	16.440	3.788	PE	17.077	1.722	2.015
SK	15.478	3.728	PK	18.414	1.605	1.486
IS	12.773	3.549	KZ	16.617	1.539	2.785
CO	17.476	3.242	KE	17.163	1.365	1.745
EE	14.150	3.078	KW	14.691	1.349	1.123
LT	14.990	2.591	PA	14.839	1.346	1.661
LV	14.607	2.445	EC	16.276	1.337	1.652
CR	15.097	1.888	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: developed by the authors, World Bank data.

4.1. 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, a dynamic regression model is adopted as follows:

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

In this model (1), where a set of variables is analysed, 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 the model. The initial estimation involves applying two statistical methods: OLS in columns (I) and FE in columns (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:

$$L_{i,t} = \alpha L_{i,t-1} + \beta_1 IP5_{i,t-1} + \beta_2 IP5_{i,t} + \gamma_3 GDP_{i,t} + \gamma_4 W_{i,t} + \gamma_5 FCE_{i,t} + \gamma_5 T_{i,t} + \delta + \mu_i + \rho_t + \epsilon_{i,t} \quad (2)$$

In model (2), the IP5 variable and the IP5(-1) variable are used 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 [91]. 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, the two-step SYS-GMM estimation is employed. 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. The model is estimated using both DIF-GMM and SYS-GMM methods in columns (III) and (IV) respectively. SYS-GMM is simultaneously estimated with reference to Roodman [92] and Kripfganz and Schwarz [93], driven by two endogenous variables, IP5 and GDP. The SYS-GMM estimation is validated using both the Hansen and AR(2) tests. In the two-step SYS-GMM estimation, dummy variables were utilized across columns (V) for 1990-2000, (VI) for 2000-2010, (VII) for 2010-2019, and (VIII) for 2015-2019. Their implementation facilitates the control of unobservable fixed effects, correction of endogeneity bias, and harnessing of both temporal and individual variation, ensuring the model yields reliable and unbiased results.

5. Results and Discussion

The estimation results are presented in Table 3. It is highlighted in Panel 2: Non-OECD / PCT patents that the same estimation approach was used, replacing the variable IP5 with PCT. According to the estimation in Panel 1, it is confirmed 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.

Table 3. Estimation results (log variables)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
PANEL 1: OECD / IP5 PATENT								
L (-1)	0,996 0,000***	0,964 0,000***	0,760 0,000***	0,970 0,000***	0,971 0,000***	0,970 0,000***	0,959 0,000***	0,963 0,000***
IP5	-0,001 0,574	-0,001 0,734	0,000 0,949	0,012 0,001***	0,012 0,001***	0,009 0,003***	0,053 0,003***	0,049 0,001***
IP5(-1)	-0,001 0,542	0,000 0,904	0,009 0,023**	-0,020 0,001***	-0,021 0,000***	-0,019 0,002***	-0,059 0,000***	-0,054 0,000***
GDP	0,052 0,000***	0,069 0,000***	0,240 0,002***	0,212 0,012**	0,201 0,015**	0,167 0,061*	0,147 0,104	0,195 0,029**
FCE	-0,047 0,001***	-0,064 0,001***	-0,218 0,003***	-0,184 0,021**	-0,171 0,035**	-0,135 0,113	-0,111 0,209	-0,166 0,055*
W	-0,026 0,007***	0,008 0,711	0,031 0,700	-0,056 0,073*	-0,052 0,138	-0,043 0,240	-0,076 0,147	-0,075 0,090*
T	-0,006 0,054*	-0,002 0,655	0,008 0,472	-0,036 0,011**	-0,033 0,023**	-0,033 0,018**	-0,029 0,044**	-0,039 0,009***
Cst,	0,093 0,132	0,414 0,002***		0,188 0,409	0,111 0,608	0,044 0,858	0,251 0,486	0,374 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 0,000***	0,973 0,000***	0,738 0,000***	0,943 0,000***	0,931 0,000***	0,928 0,000***	0,902 0,000***	0,936 0,000***
IP5	0 0,791	0 0,532	0,017 0,011**	0,009 0,140	0,021 0,002***	0,005 0,348	0,027 0,021**	0,021 0,076*
IP5(-1)	-0,003 0,003***	-0,001 0,318	0,008 0,027**	0,000 0,983	-0,007 0,182	0,001 0,76	-0,007 0,445	-0,007 0,394
GDP	0,033 0,008***	0,028 0,213	-0,004 0,929	0,171 0,000***	0,175 0,001***	0,184 0,000***	0,165 0,001***	0,169 0,000***
FCE	-0,025 0,044**	-0,023 0,318	0,024 0,576	-0,152 0,000***	-0,149 0,002***	-0,153 0,000***	-0,124 0,004***	-0,15 0,000***
W	-0,009 0,066*	-0,039 0,000***	0,041 0,502	-0,088 0,026**	-0,105 0,016**	-0,107 0,013**	-0,128 0,005***	-0,09 0,037**
T	-0,001 0,895	-0,002 0,588	0,003 0,671	-0,052 0,002***	-0,053 0,025**	-0,056 0,001***	-0,083 0,002***	-0,064 0,008***
Cst,	-0,034 0,63	0,524 0,000***		1,085 0,005***	1,166 0,008***	1,133 0,002***	1,536 0,002***	1,243 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 0,000***	0,973 0,000***	0,672 0,000***	0,972 0,000***	0,991 0,000***	0,968 0,000***	0,94 0,000***	0,968 0,000***
PCT	-0,002 0,043**	0,001 0,344	0,019 0,002***	-0,032 0,004***	-0,056 0,000***	-0,05 0,000***	-0,025 0,013**	-0,031 0,004***
PCT (-1)	-0,004 0,000***	-0,001 0,201	0,008 0,004***	0,02 0,020**	0,029 0,006***	0,028 0,011**	0,02 0,009***	0,02 0,021**
GDP	0,027 0,017**	0,028 0,218	-0,012 0,788	0,12 0,000***	0,096 0,022**	0,09 0,029**	0,123 0,001***	0,114 0,000***
FCE	-0,017	-0,023	0,033	-0,092	-0,066	-0,049	-0,077	-0,083

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
	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: P-value are presented coefficient (*** p<0.01, ** p<0.05, * p<0.1)
Source: The authors’ estimations

A moderate effect of Trade and GDP, besides a modest effect of Wage and FCE on employment, are also observed. In Panel 2, an effort was made to assess whether innovation, approximated by IP5, affects the labour force. It was found that only the IP5 variable shows a weak effect when employing time dummies, and the IP5(-1) variable has no impact on employment. However, significant effects from the variables GDP, FCE, Wage, and Trade are clearly observable. Following the rationale for selecting the PCT variable, the statistically significant positive effect of the IP5 variable and the same lagged variable on employment is confirmed. This indicates that innovation plays a significant role in explaining the labour force in non-OECD countries. Significant effects of GDP and FCE, along with modest effects of Wage and Trade when using time dummies, are also emphasized. The previous results that did not confirm a decisive effect of innovation on employment are explained through an oscillation effect of innovation. This oscillation is attributed to the types of innovation studied in each analysis, sparking a debate among researchers regarding the role of technology, R&D, and innovation in employment. The presence of explanations from compensation theory (compensation effects) is confirmed, highlighting that time plays a crucial role in compensating for the effects of innovation, which tends to accumulate towards a positive and significant impact. Additionally, it is explained that the limitation of patent registration with IP5 offices affects the ability of developing economies to register patents.

6. Conclusion

The 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. The quest for a robust response involved a thorough examination of existing literature, incorporating a wide array of interpretive insights and econometric analyses. This current research has allowed us to navigate precisely the roles of endogenous and exogenous variables by exploiting instrumental variables, thereby validating propositions and empirical findings regarding oscillations. Notably, the 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, underline 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 its pivotal role in explanation, which collectively suggests 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, policymakers must implement public policies that support innovation, especially in emerging economies, to boost employment and economic growth. It is also critical to reform patenting and exploitation processes to ensure fair access to innovation. Reforms should align with each nation's business environment. This underscores the legitimate role of public action in leveraging innovation for long-term employment, contributing to the social and economic well-being of communities.

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