The linkage between productivity and innovation: global evidence from 97 economies

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Abstract. This study investigates the linkage between productivity and innovation. We employ the panel vector autoregression to model the country-level interactions between total factor productivity and global innovation index of 97 economies from 2013 to 2019. We find that innovation has no significant impact on productivity but inversely, the past performance of productivity affects the innovation index negatively. This result states that innovation is not a cause, but a consequence of productivity. This finding implies that relevant literature might have ignored the trans-economic interactions between productivity and innovation. Hence, future studies are supposed to innovate their research designs to elaborate the relationship between total factor productivity and innovation.

Keywords: Productivity, Innovation, Panel vector autoregression.

1 Introduction

Technology and innovation in terms of process change facilitates productivity in pursuit of economic growth [1]. Accordingly, innovation is considered an inevitable resource of long-term growth [2]. The impact of innovation on productivity is robustly found across regions [3], economies [4], industries [5], and firms [6]. In which, the representative of innovation diversifies, including information technology [6], workplace innovation [7], technological activities [5], knowledge spillovers [3], and patent citations [4]. As innovation is represented by various factors, there may arise arguments relating to empirical findings. This issue drives the world create a sufficient and consistent proxy for innovation. This index shall reflect the innovative capabilities of economies [8]. This context motivates the making of the global innovation index, which is designed to measure the innovation process all over the world [9]. In which, the output shall be knowledge, technology, and creativity.

The global innovation index facilitates to seek any potential linkages between productivity and innovation, due to the correspondingly panel characteristic of the two datasets. Recent studies have found multiple perspectives of innovation thanks to the global dataset. An application of this index is the comparative analysis between economies, for example, knowledge spillovers [10], driving factors [11], and efficiency

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assessment [12]. In terms of statistics and regression, the panel innovation index data have previously been exploited as a cross section [13] and timeseries [14]. In specific, challenges appear when space and time directions of the innovation data is not jointly used in analytics. This issue requires solutions such as the structural equation model [13]. In relation to the relationship between innovation and productivity, a feasible approach comes from contemporaneous causality [4]. However, this study uses patents as a proxy for innovation. It is noticeable that inputs of the innovation consist of institutions, human capital and research, infrastructure, market sophistication, and business sophistication [9].

The above preliminary review states that previous literature leaves a gap in relation to the direct linkage between productivity and innovation. This circumstance motivates us to investigate the relation between total factor productivity and innovation using the panel vector autoregression. This modeling strategy is expected to reveal any connectedness between the two variables due to their corresponding datasets. This study expects to seek any significant impacts of innovation on productivity and vice versa, reliable evidence that productivity drives innovation. On the other hand, the novelty of this study is that we examine productivity as both input and output of innovation. This approach is expected to elaborate the structure of innovation as previously evaluated under the simultaneous equation model [13].

The remainder of this study is structured as follows. Section 2 presents methods. Section 3 reports findings. Section 4 concludes.

2 Methods

2.1 Data

This study uses the total factor productivity[1] (TFP) and the global innovation index[2] (INN) as main variables. Databases provide productivity from 1954 to 2019 and innovation from 2013 to 2022. The combined material for this study includes 97 economies (as detailed in Table 1) from 2013 to 2019, generating 679 observations. An alternative source is the multifactor productivity as provided by OECD[3] whose availability is 24 economies from 1985 to 2021. Hence, we choose the TFP dataset based on the number of economies even though two years are missing. The selected 2013-2019 period coincidently excludes the volatility, uncertainty, complexity, and ambiguity associated with the Covid-19 pandemic.

Table 2 presents descriptive statistics of the used data. It is noticed that the two variables correlate to each other negatively (-0.0362). The panel dataset is characterized that $N >> T$, in which $N = 97$ economies and $T = 7$ years.

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[1] Source: Our World in Data, retrieved from https://ourworldindata.org/.

[2] Source: World Intellectual Organization (WIPO), retrieved from https://www.wipo.int/portal/en/index.html.

[3] See: https://data.oecd.org/lprdty/multifactor-productivity.htm.

Table 1. List of economies

No.	Code	Economy	No.	Code	Economy
1	ARG	Argentina	44	ITA	Italy
2	ARM	Armenia	45	JAM	Jamaica
3	AUS	Australia	46	JOR	Jordan
4	AUT	Austria	47	JPN	Japan
5	BEL	Belgium	48	KAZ	Kazakhstan
6	BFA	Burkina Faso	49	KEN	Kenya
7	BGR	Bulgaria	50	KGZ	Kyrgyzstan
8	BHR	Bahrain	51	KWT	Kuwait
9	BOL	Bolivia	52	LKA	Sri Lanka
10	BRA	Brazil	53	LTU	Lithuania
11	BWA	Botswana	54	LUX	Luxembourg
12	CAN	Canada	55	LVA	Latvia
13	CHE	Switzerland	56	MAR	Morocco
14	CHL	Chile	57	MDA	Moldova
15	CHN	China	58	MEX	Mexico
16	CIV	Cote d'Ivoire	59	MLT	Malta
17	CMR	Cameroon	60	MNG	Mongolia
18	COL	Colombia	61	MOZ	Mozambique
19	CRI	Costa Rica	62	MUS	Mauritius
20	CYP	Cyprus	63	MYS	Malaysia
21	CZE	Czechia	64	NAM	Namibia
22	DEU	Germany	65	NER	Niger
23	DNK	Denmark	66	NGA	Nigeria
24	DOM	Dominican Republic	67	NLD	Netherlands
25	ECU	Ecuador	68	NOR	Norway
26	EGY	Egypt	69	NZL	New Zealand
27	ESP	Spain	70	PAN	Panama
28	EST	Estonia	71	PER	Peru
29	FIN	Finland	72	PHL	Philippines
30	FRA	France	73	POL	Poland
31	GBR	United Kingdom	74	PRT	Portugal
32	GRC	Greece	75	PRY	Paraguay
33	GTM	Guatemala	76	QAT	Qatar
34	HKG	Hong Kong	77	ROU	Romania
35	HND	Honduras	78	RUS	Russia
36	HRV	Croatia	79	RWA	Rwanda
37	HUN	Hungary	80	SAU	Saudi Arabia
38	IDN	Indonesia	81	SEN	Senegal
39	IND	India	82	SGP	Singapore
40	IRL	Ireland	83	SRB	Serbia
41	IRN	Iran	84	SVK	Slovakia
42	ISL	Iceland	85	SVN	Slovenia
43	ISR	Israel	86	SWE	Sweden

Table 2 (continued). List of economies

No.	Code	Economy	No.	Code	Economy
87	TGO	Togo	93	UKR	Ukraine
88	THA	Thailand	94	URY	Uruguay
89	TJK	Tajikistan	95	USA	United States
90	TUN	Tunisia	96	ZAF	South Africa
91	TUR	Turkey	97	ZMB	Zambia
92	TZA	Tanzania			

Table 2. Summary statistics

	Mean	Std deviation	Minimum	Maximum
Productivity	0.9955	0.0476	0.7425	1.3582
Innovation	39.8888	11.6273	17.6	68.4

2.2 Modeling strategy

This study employs the bivariate simultaneous equation model [15] to evaluate the linkage between productivity and innovation as follow:

$$y_{it} = \sum_{j=1}^{l} A_j y_{i(t-j)} + u_i + \epsilon_{it} \tag{1}$$

In (1), $y_{it} = (y_{it}^{TFP} \quad y_{it}^{INN})'$ is the vector expressing total factor productivity and innovation index of economy i in year t. A_j is the jth lagged matrix of coefficients. The lag of estimation is denoted by l. Table 3 presents the lag selection procedure associated with the panel vector autoregression [16]. In which, the optimal lag is either two (under MAIC) or three (under MBIC and MQIC). As the studied data is across seven years, we select the two-lagged modeling ($l = 2$) to prevent the potential result from loss of observations. Errors are presumed that $E(\epsilon_{it}) = E(\epsilon_{it}'\epsilon_{it}) = E(\epsilon_{it}'\epsilon_{is}) = 0$ for $t > s$. This modeling framework shall be additionally tested with causality [17] and stability [18].

Table 3. Lag selection

Lags	CD	J-stat	J-value	MBIC	MAIC	MQIC
1	1 .9998	17.4672	0.1329	-45.7471	-6.5328	-22.4118
2	2 .9998	6.0433	0.6424	-37.0100	-9.9567	-20.5427
3	3 .9997	1.3886	0.8462	-19.6828	-6.6114	-11.9044

CDs are coefficients of determination. MBIC, MAIC, and MQIC are respectively Schwarz-Bayes, Akaike, and Hannan-Quinn information criteria.

3 Findings

Table 4 presents the panel vector autoregression between productivity and innovation of chosen economies from 2013 to 2019. This empirical result is estimated based on the Stata package [19] accompanying the generalized method of moments [20]. Along the interaction between productivity and innovation, Table 3 presents the Granger causality [17] between the two variables.

We find statistically significant evidence on the interaction between the two variables under the panel vector autoregression. In which, TFP is explained by its own first-lagged performance and innovation is positively influenced by its first and second lags. It is noticeable that past productivity negatively affects innovation, as reflected in the first lag (-33.7533). Reversely, the impact of innovation on productivity is insignificant. This finding is affirmed in terms of impulse response functions, as illustrated in Fig. 1. The negative impact of productivity on innovation matches their unconditional correlation (-0.0362), as shown in Table 1 and Table 2. Besides, main results shall ensure the stability condition [18]. Fig. 2 states that eigenvalues are inside the unit circle ($0.8084 \pm 0.1145i$ and $-0.1212 \pm 0.0791i$), whose corresponding moduli (0.8164 and 0.1447) confirm that the estimation is stable.

Table 4. Panel vector autoregression result

	y_t^{TFP}	y_t^{INN}		y_t^{TFP}
y_{t-1}^{TFP}	0.6753***	(0.2167)	y_{t-1}^{TFP}	0.6753***
y_{t-2}^{TFP}	0.1209	(0.1451)	y_{t-2}^{TFP}	0.1209
y_{t-1}^{INN}	0.0016	(0.0014)	y_{t-1}^{INN}	0.0016
y_{t-2}^{INN}	-0.00004	(0.0007)	y_{t-2}^{INN}	-0.00004
	Productivity		Innovation	
Wald test	Innovation	1.242	Productivity	4.896*

Standard errors are in parentheses. P-value < 0.1, 0.05, and 0.01 are denoted by *, **, and ***, respectively. The Wald test indicates that productivity Granger-causes innovation but finds no statistically significant evidence that innovation Granger-causes productivity.

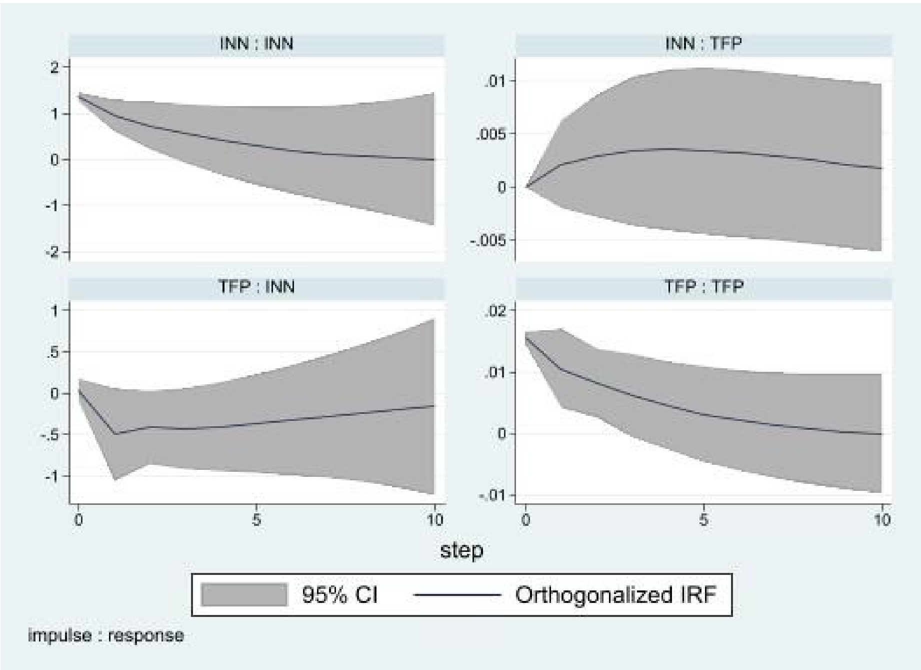

Fig. 1. Impulse response functions

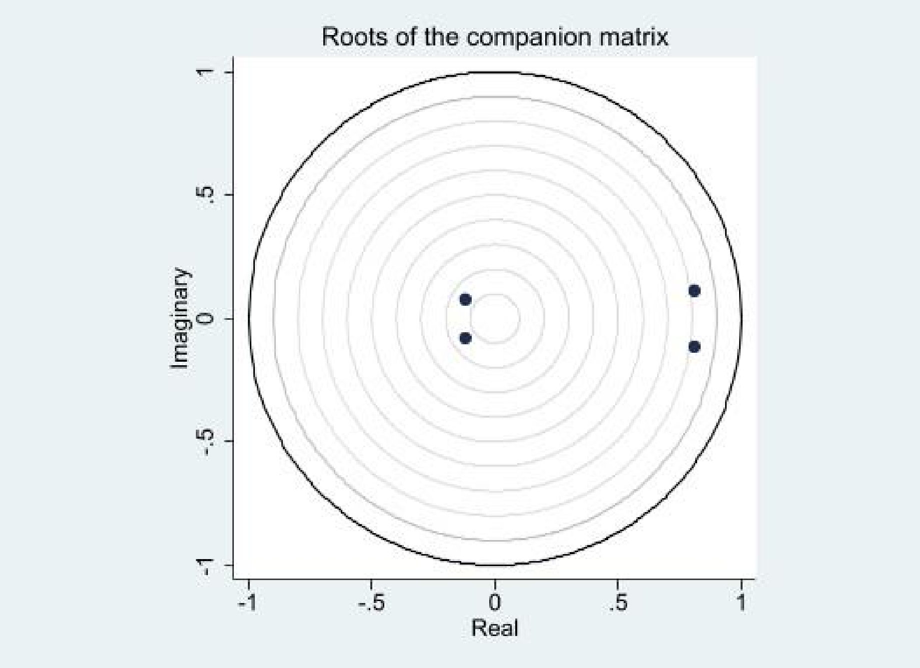

Fig. 2. Eigenvalue stability condition

In terms of economic meaning, our findings indicate that the global innovation is challenged through its insignificant impact on productivity. The case becomes more complicated as the improvement in productivity drives the innovation score decrease. Furthermore, our result does not capture the Covid-19 outbreak. The linkage between productivity and innovation may be increasingly challenged in the post-pandemic world along the global volatility context.

4 Conclusion

This study finds that innovation is a consequence, instead a cause, of total factor productivity. It is surprising that productivity negatively influences innovation within an economy. On the other hand, this empirical finding matches the inherent trade-off principle of economics, which can be understood that an economy is supposed to optimize productivity and innovation with limited resources. This study innovates the cross-sectional approach [13] and supplements a new perspective as compared to the analysis of patents [4]. In terms of methodological framework, this study, as well as previous literature, seems to ignore the scenario that the innovation of this economy affects the productivity of another economy. As a result, the novelty in approaches, datasets, and empirical methods are expected to clarify the relationship between productivity and innovation in future studies.

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