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DOES REVERSE CAUSALITY EXPLAIN THE RELATIONSHIP BETWEEN ECONOMIC PERFORMANCE AND TECHNOLOGICAL DIVERSITY?

Igam M. MOANIBA[1], Hsin-Ning SU[1*], Pei-Chun LEE[2]

[1]*Graduate Institute of Technology Management, National Chung Hsing University, 250 Kuo Kuang Rd., Taichung, 402, Taiwan*
[2]*International School of Technology and Management, Feng Chia university, No. 100 Wenhwa Rd., Taichung, 407, Taiwan*

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Abstract. Previous studies have highlighted technological innovation as a key instrument for economic development. However, although the relationship between innovation and economic growth has been extensively explored, few studies have investigated the impacts of crucial dimensions of innovation on economic growth. This paper presents one of the first empirical attempts to analyze how the "diversity" aspect of technological progress (or innovation) influences economic performance by considering the possible bidirectional causal effects between these two factors. A series of econometric techniques, including a two-stage-least-squares instrumental variable and dynamic autoregressive distributed lag model, are applied on a dataset of 55 countries. The dataset includes patent data from the United States Patent and Trademark Office and combined macroeconomic data from the World Bank's development indicators and International Monetary Fund's economic outlook databases. The results show that generally, technological diversity does not directly affect economic growth. By contrast, a negative effect of diversity on GDP per capita is observed in non-high-income countries. This study contributes to the macroeconomics and innovation management literature by providing an integrated empirical application of various popular firm management theories and a well-known endogenous economic growth theory.

Keywords: technological diversity, economic performance, patent, reverse causality.

JEL Classification: O33, O11, O38, O50.

Introduction

The innovation–economic performance nexus has long been of significant interest to economists and policymakers. Early well-known growth theories linking economic performance and innovation include the Schumpeterian growth model (Schumpeter, 1934), Solow–Swan growth model (Solow, 1956; Swan, 1956), and endogenous growth theory (Romer, 1994,

*Corresponding author. E-mail: *ning@nchu.edu.tw*

1990, 1986). These pioneering works emphasized the role of technological progress and industrial innovation in driving long-term economic growth (Grossman & Helpman, 1994). With the marked increase in the number of technological breakthroughs in recent years, the world has witnessed a spike in technological diversity.

This study explores the notion that a country's efforts in diversifying technologies may lead to higher economic performance. With the exception of a few studies such as (Mangàni, 2007), the impact of technological diversity on national economies has seldom been investigated, with researchers preferring to focus on technological specialization. Moreover, most diversification studies have been conducted at the firm level, including those that explored the relationships between diversification and firm output factors such as financial performance (Chen, Yang, & Lin, 2013; Chiu, Lai, Lee, & Liaw, 2008; Chun, Ha, & Kim, 2014; Evangelista & Vezzani, 2010). By contrast, studies conducted on a national scale have tended to focus on technological specialization and economic performance (e.g. Archibugi & Pianta, 1992a, 1992b; Attaran, 1986; Cantwell & Vertova, 2004; Evangelista & Vezzani, 2010; Hasan & Tucci, 2010; Mancusi, 2001; Pianta & Meliciani, 1996). Others have indicated that larger countries tend to diversify their technological activities, whereas smaller economies focus on specific fields (Archibugi & Pianta, 1992a, 1992b; Cantwell & Vertova, 2004).

The aforementioned studies have obtained contradictory findings, thereby indicating the need for further investigation. In a more recent study examining how research and development (R&D) specialization within the manufacturing sector affects productivity growth, a concentration index and industrial classification–constructed measures of R&D specialization were employed (Chen et al., 2015). The researchers analyzed 11 member countries of the Organization for Economic Co-operation and Development from 1981 to 2000 and employed a fixed-effect panel data model with cross-sectional dependence to illustrate that concentrating suitable R&D resources within a few industries can stimulate productivity growth. To verify and extend this finding, the present study provides fresh empirical insights from the perspective of technological diversification rather than specialization, which is crucial considering recent developments and attempts to integrate management theories, such as the firm-level strategic resource-based view (RBV) theory (Wernerfelt, 1984), where diversification plays a key role, into economic growth theories such as the endogenous growth model (Romer, 1990).

Understanding the role of technological diversity in economic performance is imperative for assisting decision-makers in formulating policies that can stimulate economic growth. In this context, economic performance encompasses all forms of economic output such as economic growth, aggregate productivity (e.g., total factor productivity), and national innovative capabilities. Previous empirical studies have indirectly analyzed economic performance through various indicators such as GDP (Mancusi, 2001), R&D expenditure (Cantwell & Vertova, 2004), population, and number of patents. However, because of the inconsistency in their findings and the increasing availability of an extensive range of macroeconomic and patent databases, revisiting this topic and exploring it from a different perspective through more advanced and improved econometric models is crucial. Moreover, recently developed features and functions of various popular statistical software packages facilitate conducting investigations from multiple perspectives.

To achieve the present study objective, various indicators of technological diversity and economic performance are constructed and a reverse causality econometric approach is adopted. The uniqueness of this study lies in its novel approach, which is based on a combination of carefully selected econometric models and the assumption that technological diversity has a bidirectional causal effect on economic performance; a relationship caused by reverse causality. Reverse causality asserts that technological diversity and economic performance influence one another. This assumption is based on the famous "Sim's theory" of simultaneous equations (Sims, 1980), which criticizes the heavy restriction on exogeneity often imposed by early macroeconomic models. Since the 1980s, Sim's theory has been the basis of a huge number of empirical studies using simultaneous VAR models in both macroeconomics and microeconomics. To our knowledge, the reverse causality assumption in the present study has not previously been considered in investigating the relationship between technological diversity and economic performance at the national level.

Diversification is among the most researched topics in management literature. From a management perspective, the prevailing theory of diversification is heavily based on the RBV (López Rodríguez & García Rodríguez, 2005; Medcof, 2000; Wernerfelt, 1984) of firms (Steinemann, Veloso, & Wolter, 2004). According to RBV theory, a firm's competitive advantage lies primarily in the accumulation and application of its valuable tangible (or intangible) resources (Eisenhardt & Martin, 2000; Miller, 1960; Montgomery & Wernerfelt, 1988; Penrose, 1995; Rumelt, 1984; Wernerfelt, 1984). Although the findings of previous studies on the relationship between technological diversity and economic performance and related topics have been mixed, we hypothesize that the impact of technological diversification at the national level should be consistent with the notion in RBV theory that the accumulation of diverse technical knowledge within a firm should lead to higher performance.

Our study contributes to the literature by providing an integrated empirical application of firm-level management theories and the economic endogenous growth theory through aggregating firm-level indicators of technological diversity to formulate country-level indicators, employing advanced endogenous econometric methods, and operationalizing a more extensive range of countries data. In contrast to previous related studies, most of which have focused on firm-level technological diversification (Chun et al., 2014), the present study explores a national level perspective of technological diversification and economic performance. Furthermore, it is highly possible that the inconsistency in the results of past similar empirical studies is due to ignoring the reverse causal effects between the two investigated factors (i.e. economic growth and the diversity of technologies). Previous studies that have analyzed the effect of technological diversity on economic growth tended to ignore the reverse-effect of economic growth on technological diversity and thus have led to inconsistent results. In the real world, two macroeconomic factors such as economic growth and technology often simultaneously affect each other (Sims, 1980) i.e. a relationship involving forward and reverse causal effects. To the best of our knowledge, our study is the first empirical attempt to analyze the effect of technological diversity on economic growth that takes into consideration the reverse effect of the latter on the former. This is a much-improved estimation approach as it captures a more realistic nature of the sophisticated relationship between the two. Lastly, the absence of literature on the "reverse-causality between technological diversity and economic growth" is an important gap in economic and innovation management literature.

The remainder of this paper is organized as follows. Section 1 provides a literature review regarding economic growth determinants, the crucial effects of technological diversification on economic performance, and the reverse-causal relationship between economic output and technological progress. Section 2 describes the data. In Section 3, our methodological framework and econometric approach are introduced. Next, the empirical analysis results and a discussion on the key findings are presented in Section 4. Finally, last section concludes the paper.

1. Literature review

1.1. Technological determinants of economic growth

A longstanding question of great importance to economics concerns what drives economic growth. For centuries, theoretical and empirical studies have focused primarily on this question. One of the earliest prominent theories explaining economic growth is neoclassical theory (Solow, 1956; Swan, 1956), which identifies investment in physical capital and labor as the key driver of growth. Many subsequent studies have identified other factors such as technological progress or innovation, government consumption, trade and trade terms, political stability, income distribution, inflation, the rule of law, and fertility (Barro, 1996; Chen & Feng, 2000; Anaman, 2004; Cuaresma, Doppelhofer, & Feldkircher, 2014; Vedia-Jerez & Chasco, 2016; Barro, 1991; Qayum, 2005; Vedia-Jerez & Chasco, 2016; Persson & Tabellini, 1992). All of these studies have confirmed the so-called conditional convergence of firms and nations (Evans & Karras, 1996; Quah, 1996).

A more recent well-known scholar who provided a fresh theoretical extension and empirical perspective on the crucial effects of technological progress on economic growth is Romer (1986). The basic premise of Romer's endogenous growth theory is that technical progress creates a means for unchanging resources to be used in a sophisticated manner. Therefore, as a key driver of economic growth, technological progress should be modelled endogenously. Romer's paper has been followed by many studies that have attempted to unveil the roles and behavioral characteristics of other factors in the endogenous growth model, including several social factors and institutional settings.

The primary focus on the role of institutions in the endogenous growth model concerns institutional structure and how it enables institutions to adapt to new technology. However, because of the viscosity of national specialization profiles, adaptation often requires time and effort (Andrews, Criscuolo, & Gal, 2015; García-Muñiz & Vicente, 2014; Geroski, 2000). Institutions are built on structures that are not easy to change, especially in the short term. Various infrastructures and organizational structures are required for different technological directions, and this explains the difficulty and costs faced by firms attempting to diversify their technological innovations or products.

1.2. Benefits from technological diversification

Products and technological diversification have often been used by firms as strategies to overcome competition. For this reason, diversification has attracted a lot of attention from researchers. Numerous empirical studies have explored the links between technological diversification efforts, competitive strategies, and firm performance (Breschi, Lissoni, & Malerba, 2003; Cantwell & Piscitello, 2000; Penrose, 1995; Piscitello, 2000). One of the most prominent management theories related to the competitive strategies of firms is the RBV. The principal foundation of diversification is heavily influenced by the RBV of a firm (López Rodríguez & García Rodríguez, 2005; Medcof, 2000; Wernerfelt, 1984).

The RBV asserts that firms must accumulate valuable, rare, inimitable, non-substitutable resources to formulate value-creating strategies and sustainable competitive advantages (Wernerfelt, 1984; Eisenhardt & Martin, 2000; Montgomery & Wernerfelt, 1988). It posits that to understand the corporate coherence of firms, knowledge of their technological capabilities is essential. Firms have shown increasing interest in technological diversification as a means of achieving product and market diversification. In addition, a study that analyzed firm data from 1978–1993 from the European Patent Office has observed that firms are more likely to diversify into knowledge-based fields (Breschi et al., 2003). The benefits from diversification demonstrate the principle of economies of scope, where two or more different products are produced using the same sets of equipment (or resources) in order to minimize spending.

Although the importance of diversification for firm survival is widely acknowledged, the equivalent phenomenon at the macro (or national) level has seldom been explicitly explored. Furthermore, in contrast to the relationship between technological diversification and economic growth, the relationship between technological specialization and economic growth (or performance) has recently attracted more interest from scholars than in previous years. Popular specialization research areas include technological specialization and trade (Dosi, Pavitt, & Soete, 1990; Greaney & Karacaovali, 2017; Manwa & Wijeweera, 2016; Mustafa, Rizov, & Kernohan, 2017; Silberberger & Königer, 2016; Soete, 1987; Sokolov-Mladenović, Milovančević, & Mladenović, 2017) and technological specialization with economic growth (Meelen, Herrmann, & Faber, 2017; Murshed & Serino, 2011; Rehner, Baeza, & Barton, 2014; Šipilova, 2015). Moreover, technological diversification patterns are heterogenous across industries and countries, as observed in the United States, Japan, and the United Kingdom (Kodama, 1986; Mowery & Nelson, 1999; Pavitt, Robson, & Townsend, 1989).

1.3. Simultaneous relationships created by reverse causality

In essence, the simultaneous (or bidirectional) causal effects between two economic factors is often created by reverse-causality. Reverse causality is extremely important in studies where economic growth and policy related factors such as decisions to innovate and diversify products or services (Sims, 1980). Ignoring the reverse causal effects in an empirical analysis that involved such factors often leads to biased and inconsistent results.

Although the reverse causality between economic growth and technological diversity has never been investigated empirically, a number of related studies have demonstrated the possibility of the existence of a (reverse) causal effect of economic growth on technological diversity. The studies include those that have investigated drivers of innovation (Barata & Fontainha, 2017; Río, Romero-Jordán, & Peñasco, 2017) and economic growth (Škare, 2011; Snieska & Valodkiene, 2015; Zeng, Xie, & Tam, 2010), the simultaneous relationships between variables like economic growth and others such as public transportation (Duffy-Deno & Eberts, 1991; Eisner, 1991; Garcia-Milà & McGuire, 1992; Moomaw, Mullen, & Williams, 1995), and carbon emissions as evidenced by the continuing increase in carbon emissions alongside economic growth despite the increasing number of environmentally friendly innovations (de Bruyn, van den Bergh, & Opschoor, 1998; Mugableh, 2013; Narayan, P. K. & Narayan, S., 2010; Tucker, 1995). Reverse causality has been observed in the transportation sector and economic output (e.g. Duffy-Deno & Eberts, 1991; Eisner, 1991; Garcia-Milà & McGuire, 1992; Moomaw et al., 1995), and among several indicators of development and public expenditure on highways (Jones, 1990; Mofidi & Stone, 1990) have been empirically observed. While investment in the transportation sector has been found to influence economic growth and development (Boopen, 2006; Devarajan, Swaroop, & Zou, 1996; Easterly & Rebelo, 1993; Zhou, Yang, Xu, & Liu, 2007), various indicators of economic growth have been found to have reverse effects on investment (Crihfield & Panggabean, 1995; Fernald, 1999; Garcia-Milà & McGuire, 1992; Singletary, Henry, Brooks, & London, 1995).

In addition, reverse causal effects of economic growth on technological progress (or innovation) have been observed in several previous studies (Murmann, 2003; Nelson, 1994). Such effects reflect the interactive nature of innovation processes and how such processes rely on wealth and income. In the same context, it is possible that increased technological diversity may have a bidirectional cause–effect relationship with economic growth. This is the basis of our analysis and thus our methodological approach is mainly designed to test this hypothesis.

2. Data and descriptive statistics

2.1. Dataset description

The dataset used in the empirical analysis in the present study consists of patent data, macro data from various countries, and constructed indicators of technological diversity. Patent data from 1976 to 2015 are from the United States Patent and Trademark Office (USPTO) database. A total of 4,662,461 patents granted in 55 countries are used in the analysis. The countries are listed in Table A.1 in the Appendix. Country selection is based on the highest number of patents, availability of GDP and population data, geographical location, and United Nations' categorization of income levels. Countries with very few patents are discarded to avoid truncation bias and estimation inefficiencies. Countries' GDP and population data are gathered from the World Bank World Development Indicators (WDI) database (World Development Indicators, 2017) and International Monetary Fund (IMF) world economic outlook database (IMF, 2016). Data from the WDI and IMF databases include countries' historical annual data from 1960 to 2016. To maintain balance and consistency between the selected data and patent data, this study investigates data only from 1976 to 2015 (Table 1).

Table 1. Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Max
Country	2,200	–	–	1	55
Year	2,200	–	–	1976	2015
GDP per capita	2,172	24,364.8000	20,953.1300	263.2310	115,003.0000
Patents	2,200	2,114.0440	9,663.5130	–	99,714.0000
Citations	2,200	3.8846	4.2934	0.0000	37.3529
Inventors	2,200	2.3733	1.9787	0.0000	29.0000
Claims	2,200	12.3879	6.8836	0.0000	63.0000
Cross citations	2,200	4,847.7550	36,102.2500	0.0000	561,987.0000
IPC	2,200	2.8733	2.0248	0.0000	21.0000
Diversity	2,200	2.8059	1.4410	0.0000	4.3969
Generality	2,200	1.0771	0.4593	0.0000	2.0000
Originality	2,200	1.1682	0.4920	0.0000	2.0000
Income class	2,200	1.8909	1.3169	1.0000	4.0000

2.2. Dependent variable

The main dependent variable in this study is the real annual GDP per capita of a country, obtained by dividing the real GDP by the total population. Real GDP per capita is defined as GDP per capita deflated to the base year, 2010. This variable is operationalized as the natural log of real GDP per capita and used in this study as a proxy for economic performance. GDP is a well-accepted proxy for economic performance or growth and has been used in many previous studies (Crosby, 2000).

2.3. Independent variables

The key independent variables in this study are those that measure a country's technological diversity. Based on previous studies, three key indicators of technological diversity are computed and cross-examined against economic performance. These indicators are described in the following subsections.

2.3.1. Diversity index

Our main indicator of technological diversity is the diversity index, which is adapted from a popular measure of technological diversification used in previous studies (Wang, Pan, Li, & Ning, 2016; Zander, 1997). This measure employs the entropy index and considers the number of active patents in a country and relative distribution of patents across the 35 technological industries analyzed by (Schmoch, 2008). The diversity index is calculated as follows:

$$Diversity\ index = \sum_{i=1}^{35} P_i ln \frac{1}{P_i},$$

where P_i represents the share of a country's patents accounted for by the *i*th patent. The value of the entropy measure ranges between 0 and *ln n*, where 0 indicates that the country in question concentrates on one technology only and a value approaching *ln n* indicates that the country has an even distribution of patents across *n* technologies. The 35-technology classification is used in this calculation.

One of the main objectives of this study is to link well-known firm level management theories with popular country level economic theories. In particular, to link the RBV theory (of how firms or organizations within a country utilize their resources to come up strategic goals) to several macroeconomic theories such as the endogenous growth model. This is based on the fact that economic growth in a country is immensely dictated by the outputs and performances of firms and organizations in such country (Schumpeter, 2013, 1934; Sims, 1980; Solow, 1956). For instance, the more productions at firm level often leads to higher GDP, and *vice versa*. In fact, a country's GDP is measured or calculated by aggregating the economic value of all firm level and organizational level productions. In a similar context, the growth in technological capability of a country depends entirely on the technological and R&D activities of firms and organizations in such country. For this reason, we derive our main independent variable of interest (i.e. technological diversity) by aggregating all diversification efforts of firms and organizations in a country. A firm's diversification effort is measured by a popular entropy technological diversification index (Wang et al., 2016; Zander, 1997). This is done by measuring the diversity of the firm's patents. To measure a country's diversification index, we simply consider all firm (including organizational) diversity indices derived from all patents granted to firms in that country.

Figure 1 shows that the aforementioned 35 technological fields are categorized into the following five main industries: chemical, electrical engineering, instruments, mechanical engineering, and others (Van Looy, Du Plessis, & Magerman, 2006). Figure 1 shows the distribution or share of each technological field relative to the overall number of patents granted by the USPTO between 1975 and 2015. Of the five industries, the chemical industry has the highest share followed by the electrical engineering industry. From the 35 fields, computer technology has the highest share with approximately 8.7%.

To check for robustness and sensitivity, we construct and use two other indices as proxies for technological diversity – generality index and originality index. The entire analysis is repeated twice using one of these indices in each repeated iteration.

2.3.2. Generality index

The generality index was proposed by Trajtenberg, Henderson, and Jaffe (Trajtenberg et al., 1997) to indicate the generality of a patented technology. The present study was conducted on a country basis rather than a per patent basis, and thus the generality index is adapted to the national level by calculating the annual average of all the generality indices of a country's patents. The country generality index is expressed as follows:

$$Generality\,index_i = \frac{1}{M}\sum_{p=1}^{M}\left(1-\sum_{j}^{n_i} SF_{ijk}^2\right),$$

where SF_{ijk} is the percentage of patent citations received by patent i and belonging to patent

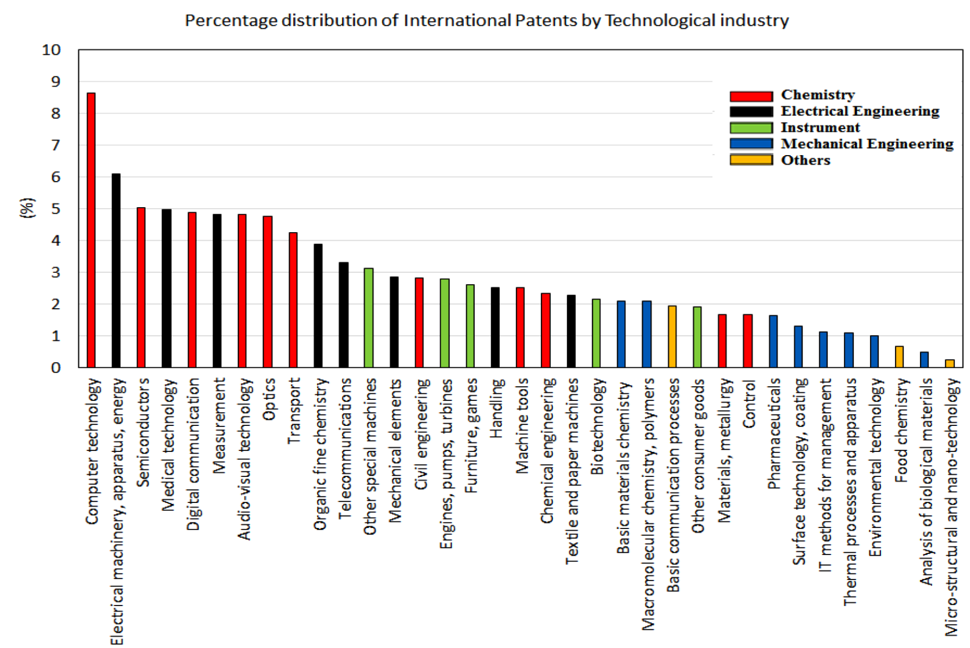


Figure 1. Percentages of the 35 technological industries

class j out of $n_i = 35$ patent classes, where patent i is from country k. The generality index ranges from 0 to 1. If a patent is cited by a number of forward patents belonging to the same technological field, the generality index is low. If most forward patents belong to various technological fields, the generality index is high. A higher generality index indicates that the patent in question influences many technological fields, and thus exerts a heavier general impact. Four-level international patent classification (IPC) was used to define technological fields. In cases of multiple IPCs being assigned to a single patent, the first and primary IPC is used.

2.3.3. Originality index

The originality index was proposed by Trajtenberg, Henderson, and Jaffe (Trajtenberg et al., 1997) to indicate the originality of a patented technology. Similarly, the index is adapted to the national level in the present study by considering the annual average of all the originality indices of a country's patents. The country originality index is expressed as follows:

$$Originality\,index_i = \frac{1}{M}\sum_{p=1}^{M}\left(1 - \sum_{j}^{n_i} SB_{ijk}^2\right),$$

where SB_{ijk} is the share of previous patents cited by patent i and belonging to patent class j out of $n_j = 35$ patent classes, where patent i is from country k. The originality index ranges from 0 to 1. If a patent cites a number of prior patents belonging to the same technological field, the originality index is low. If most prior patents belong to many technological fields, the originality index is high. A higher originality index indicates that the patent in question is more original and not directly derived from prior patents. Like in the generality index, a four-level IPC was used to define technological fields. For patents assigned to multiple IPCs, the first and primary IPC is used.

2.4. Control variables

Our basic approach is to ensure control for technological factors known to influence economic performance. The following variables are selected based on literature.

2.4.1. Knowledge transfer via the flow of technical knowledge

A commonly employed indicator of knowledge transfer is forward citation. Under specific circumstances, patent citation can be interpreted as knowledge transfer from one invention to another and used to identify innovations with breakthrough impacts. Patent citation has been shown in past studies to strongly influence economic and technological performance (Duguet & MacGarvie, 2005; Jaffe, Trajtenberg, & Henderson, 1993; Su & Moaniba, 2017a). In the present study, the average number of forward citations of a patent from country i in year t is considered as a proxy for knowledge transfer. The value of this variable ranges from 0 to 37.35, where 0 indicates that no patent is granted to country i in year t.

2.4.2. Collaborations between countries

In this study, we control for the degree of international technical collaboration based on the number of countries involved in the (patented) invention. We propose that greater collaboration between inventors should have a more positive impact on economic performance. Therefore, we consider the average number of inventors per patent in country *i* in year *t* as a proxy for the degree of technical collaboration.

2.4.3. Legal protection of technologies and inventions

Because of the need to protect intellectual property, economic agents are likely to file patents and claim property rights to their inventions and their features. Therefore, the number of claims for a single patent is often used to indicate a country's degree of protection. In this study, the average number of claims per patent in country *i* in year *t* is considered a proxy for the extent to which a country protects its technologies.

2.4.4. Technological capability of a country

Previous studies have proposed that patent data is a measure of innovation (Jaffe et al., 1993; Jaffe & Trajtenberg, 1999). The present study adopts patent count as a proxy and means of control for a country's technological capability. Therefore, a variable called *patents* is added in our model specifications to denote the natural log of the total number of patents granted to country *i* in year *t*.

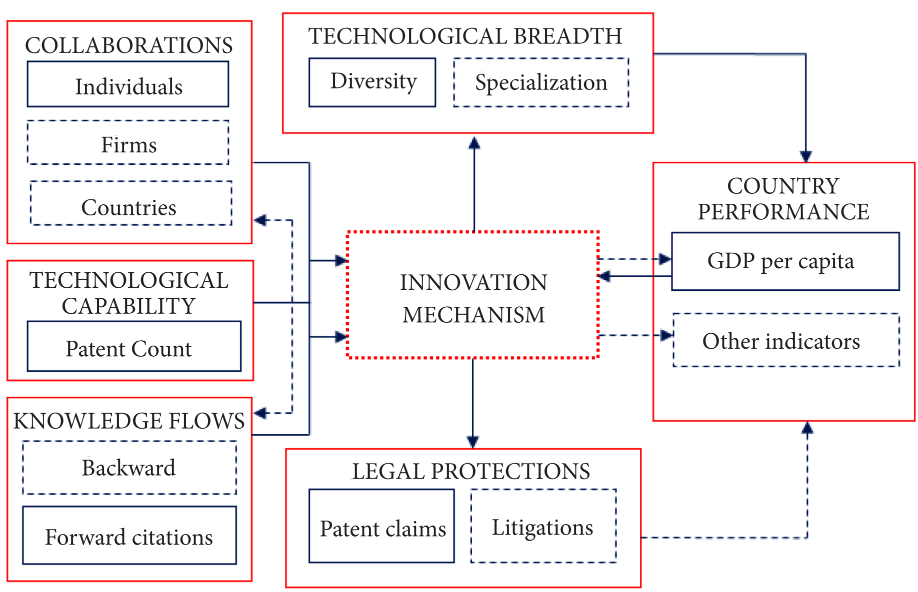
3. Methodology

3.1. Methodological framework

This section introduces our methodological framework called technological determinants of economic performance (TDEP) (Figure 2), which is constructed by combining five technological dimensions of innovation identified in the literature review (i.e., within the traditional framework of existing empirical studies on diversification, innovation, and economic growth theories). However, the present study focuses on the dynamics of technological diversity and how these dynamics influence economic performance. The five key dimensions of innovation (or technological progress) are the technological breadth of a country's innovative progress; technical collaborations between inventors, firms, or countries; a country's technological capability; technical knowledge flow; and strength of a country's legal protection system.

Each component has several subcomponents for example, technological collaboration refers to any collaboration between inventors, among firms or across countries. The key point of interest in this study is a country's technological breadth of innovation and how it affects its economic performance. Although most related studies have analyzed the "specialization" aspect of breadth of technological progress, our study focuses on diversity. The box in Figure 2 labeled "innovation mechanism" indicates the complex and integrated processes of an innovation system.

The solid blue lines refer to the selected indicators included and tested in our analysis. The dashed blue lines indicate other indicators of the five dimensions of innovation identi-



Note: 1) solid blue line = investigated in this study; 2) dashed blue line = investigated in previous studies but not the present study; 3) dotted red line = conceptual mechanism.

Figure 2. Methodological framework of TDEP

fied from previous studies but not investigated in the present study. The dotted red lines represent conceptual mechanisms where various complex technological processes collaborate with one another.

3.2. Data issues and diagnostic tests

Because of the panel (or longitudinal) nature of our dataset, several problems are likely to cause bias in our estimations. Therefore, we conduct several diagnostic tests to check for common panel data issues such as heteroskedasticity, autocorrelation, and cross-sectional dependence. The tests include the Pesaran cross-sectional dependence test, B-P/LM test of independence, modified Wald statistic, and Wooldridge test for serial correlation. In addition, unit root tests such as the Levin-Lin-Chu test, Harri-Tzavalis, Breitung, lm-Pesaran-Shin test, Fisher-type test, and Hadri LM stationarity test are conducted; as well as Pedroni co-integration test. The results of our stationarity tests and cointegration tests are provided in Tables B.1, B.2, and B3 in Appendix B.

Pairwise correlation test results (Table 2) indicate no major collinearity issues except for the correlation between the number of patents and diversity index, which is relatively high (0.8564). Our main analysis utilizes a two-stage-least-squares (2SLS) method, where the diversity index estimates are used as opposed to actual values. The correlation check results for the diversity index estimates against those of all other variables are reported in Table 3. The correlations are considerably lower than those in Table 2. Furthermore, our estimation results (especially the standard errors, discussed in Section 5) are well within the reasonable range, and thus collinearity is not an issue.

Other critical tests are performed during and after the estimations. The overidentifying test and weak instrument tests are conducted as part of the 2SLS method and during the dynamic autoregressive estimations to validate the use of the selected instruments. The endogeneity test in the form of the Durbin–Wu–Hausman test is applied to suspected endogenous variables such as the diversity index, generality index, and originality index. In addition, we perform the Hausman test to compare estimates using ordinary least squares (OLS) and instrumental variables. The results are robust. To address data issues, an instrumental variable approach using the 2SLS method (combined with panel data techniques) and a dynamic Generalized method of moments (GMM) that uses lags as instrumental variables are employed to reduce potential bias due to endogeneity and reverse causality (Wooldridge, 2015).

In summary, heteroskedasticity, autocorrelation, cross-residual dependence, endogeneity, and unit roots are all present in our data. All the variables are stationary only at the first difference with no cointegration found at levels.

Apart from the diagnostic tests, several data transformations are also carried out. The diversity index, generality index, and originality indices with values of zero refer to special conditions, rather than literally "nothing". For this reason, all three indices are increased by 1 unit[1].

[1] In this transformation, all diversity, generality, and originality indices with a value of 0 will get 1. Countries without patents in a given year will now get 0 values for all three indices in such year.

Table 2. Pairwise correlations

	Variable	1	2	3	4	5	6	7	8	9	10
1	GDP per capita	1.0000									
2	Patents	0.5510*	1.0000								
3	Citations	0.2136*	0.2506*	1.0000							
4	Inventors	0.1416*	0.3347*	–0.0710*	1.0000						
5	Claims	0.3578*	0.4294*	0.3906*	0.4126*	1.0000					
6	Diversity index	0.5376*	0.8564*	0.3032*	0.3641*	0.5616*	1.0000				
7	Cross-citation	0.1226*	0.3116*	0.0495*	0.1187*	0.1038*	0.1263*	1.0000			
8	IPC	0.2185*	0.3484*	0.4678*	0.0529*	0.4131*	0.4724*	–0.0062	1.0000		
9	Generality index	0.3086*	0.4692*	0.5356*	0.2971*	0.6317*	0.6873*	0.0385	0.6219*	1.0000	
10	Originality index	0.3425*	0.5073*	0.3636*	0.4597*	0.7509*	0.7208*	0.0800*	0.5221*	0.8450*	1.0000

* indicates significance at 95%. GDP per capita and patents are in natural log.

Table 3. Pairwise correlations (with 2SLS first stage diversity index estimates)

	Variable	1	2	3	4	5	6	7	8	9	10
1	GDP per capita	1.0000									
2	Patents	0.5510*	1.0000								
3	Citations	0.2136*	0.2506*	1.0000							
4	Inventors	0.1416*	0.3347*	–0.0710*	1.0000						
5	Claims	0.3578*	0.4294*	0.3906*	0.4126*	1.0000					
6	Diversity index	0.2804*	0.4843*	0.1990*	0.4272*	0.6394*	1.0000				
7	Cross-citation	0.1226*	0.3116*	0.0495*	0.1187*	0.1038*	0.2964*	1.0000			
8	IPC	0.2185*	0.3484*	0.4678*	0.0529*	0.4131*	0.5287*	–0.0062	1.0000		
9	Generality index	0.3086*	0.4692*	0.5356*	0.2971*	0.6317*	0.4322*	0.0385	0.6219*	1.0000	
10	Originality index	0.3425*	0.5073*	0.3636*	0.4597*	0.7509*	0.6261*	0.0800*	0.5221*	0.8450*	1.0000

* indicates significance at 95%. GDP per capita and patents are in natural log.

3.3. Econometric approach

This section explores the integrated patent–country macroeconomic data described in Section 3 to analyze the impact of the technological progress dimensions on economic performance and in particular, the economic impact of technological diversity. In the analysis, the dataset is subdivided into "high-income" countries and "non-high-income" countries in order to cross-examine the effects of diversity across countries with different income levels. The first group consists of countries classified as high-income countries in the UN's categorization of income levels. The latter group consists of those that are categorized by the UN as low income, lower-middle income, and upper-middle income countries.

3.3.1. OLS regression approach

Following the logic described in Section 2.3, the relationship between technological diversity and the proxy for economic performance, GDP per capita, is expected to be bidirectional (i.e., having a reverse causality effect). Such a relationship is commonly known as a simultaneous relationship. In our analysis, we initially conducted OLS regressions with adjusted standard errors to ensure robustness under heteroskedasticity, serial correlation, and cross-residual dependence. All estimates control for the unobserved year and fixed effects of countries. Our OLS model specification is expressed as follows:

$$GDPpc_{it} = \beta Div_{it} + \delta Pat_{it} + \gamma Cit_{it} + \lambda_1 Inv_{it} + \lambda_3 Claim_{it} + C_t + \varepsilon_{it}, \tag{1}$$

where $GDPpc_{it}$ denotes GDP per capita (in natural log), $\mathrm{Div}_{\mathrm{it}}$ denotes the observed values of the diversity index, Pat_{it} denotes the (natural log) number of patents granted to country i in year t, Cit_{it} denotes the average number of forward citations per patent in country i in year t, Inv_{it} denotes the number of inventors, $Claim_{it}$ denotes the average number of patent claims, C_t controls for the unobserved country effects, and d_t controls for the fixed effects of the unobserved year.

OLS estimates are biased and inconsistent when a model specification contains reverse and dynamic effects. A dynamic model refers to a specification where the current values of the dependent variable are influenced by its previous values. A reverse relationship and dynamic effects often lead to endogeneity bias if estimated by OLS regression. Furthermore, our unit root test results indicate that all our variables are stationary only at the first difference. Because of the unit roots in our variables, the OLS estimates are likely to result in further bias.

To address these problems, several known and widely recognized econometric techniques are considered. The following two techniques are employed in the subsequent model specifications: 1) an instrumental variable (IV) approach using a 2SLS estimator (Schaffer, 2015; Wooldridge, 2015); and 2) a dynamic autoregressive distributed lag (ADL) model using a two-step system GMM to account for dynamic and reverse causality effects (Blundell & Bond, 1998). In the first technique, 2SLS analysis is conducted to analyze the relationship between diversity and economic performance (GDP per capita) based on the assumption that there is no cross-equation dependency and no dynamic (or lag) effect of GDP per capita.

The second technique employs a GMM that considers cross-equation dependencies and the dynamic effect. But their main advantage is that they enable the independent variable of interest (diversity) to be treated as an endogenous variable, which corrects the simultaneity (or reverse-causality) bias.

3.3.2. Instrumental variable approach using a 2SLS estimator

Because of the potential reverse causality effect of GDP per capita on technological diversity, endogeneity problems are likely to distort the OLS estimation. Therefore, a 2SLS approach is employed. The first of the two stages in a 2SLS relates the technological diversity index (Section 3.3.1) of a country to its instruments – cross-citation and IPC variables. The linear relationship[2] between such instrumental variables and the diversity index is expressed as follows:

$$Div_{it} = \gamma Cross_{it} + \delta IPC_{it} + C_t + d_t + u_{it}, \tag{2a}$$

where Div_{it} denotes a country's technological diversity index; $Cross_{it}$ denotes a country's cross citation index and is included as a key instrumental variable, IPC_{it} indicates the average number of IPC classes a patent belongs to and is included as a control variable. C_t denotes a country intercept and is included as a control for unobserved country heterogeneity, and d_t controls for the year fixed effects. u_{it} stands for the error term. Cross citation refers to the average number of citations involving one patent citing a patent from a different technological field. We propose that cross citation is a form of knowledge flow across various technological domains that leads to technological diversification.

In the second 2SLS stage, the estimated diversity values ($\widehat{\mathrm{Div}_{\mathrm{it}}}$) from Eq. (2a) are included as predictors (or independent variables) alongside the other known technological determinants of GDP in Eq. (2b). This second stage model is expressed as follows:

$$\Delta GDPpc_{it} = \hat{\beta}\Delta\widehat{Div_{it}} + \delta\Delta Pat_{it} + \gamma\Delta Cit_{it} + \lambda_1\Delta Inv_{it} + \lambda_3\Delta Claim_{it} + d_t + C_t + \varepsilon_{it}, \tag{2b}$$

where $GDPpc_{it}$ denotes *GDP* per capita (in natural log), $\widehat{Div_{it}}$ denotes the diversity index estimates from Eq. (2a), Pat_{it} denotes the (natural log) number of patents granted to country *i* in year *t*, Cit_{it} denotes the average number of forward citations per patent in country *i* in year *t*, Inv_{it} denotes the number of inventors, and $Claim_{it}$ denotes the average number of patent claims. Similarly, C_t controls for the effects of country size and d_t controls for the fixed effects of a year. ε_{it} is the error term.

Our variable cross citation used in the first stage Eq. (2a) is proposed as a valid instrument because it meets the two vital instrument conditions of relevance (i.e. $E\left(Cross_{it}Div_{it}\right) \neq 0$) and exogeneity (i.e. $E\left(Cross_{it}\varepsilon_{it}\right) = 0$) (Wooldridge, 2015; Schaffer, 2015). In other words, the instrument (cross citation) is correlated with the dependent variable (GDPpc) in Eq. (2b) exclusively through the endogenous explanatory variable (diversity). The rationale behind this is that when the two conditions hold, the probability limit of the IV estimator β in Eq. (2b) should converge to the true estimator (of diversity index) β i.e.:

[2] Since the variables Cross and IPC are uncorrelated with ε_{it}, their linear combination is also uncorrelated with ε_{it}, and therefore a valid IV (Wooldridge, 2015).

$$p\lim\hat{\beta} = \frac{E\left(Cross_{it} GDPpc_{it}\right)}{E\left(Cross_{it} Div_{it}\right)} = \beta + \frac{E\left(Cross_{it} \varepsilon_{it}\right)}{E\left(Cross_{it} Div_{it}\right)},$$

which equals to β if and only if $E(Cross_{it}\ GDPpc_{it}) = 0$ and $E(Cross_{it}\ Div_{it}) \neq 0$.

3.3.3. Dynamic GMM approach using lags as instruments

Another popular method that can be used to estimate a reverse-causal relationship between technological diversity and GDP per capita is the dynamic ADL model, which is commonly employed in country-level studies (e.g. Hasan & Tucci, 2010; Siddiqui & Ahmed, 2013; Su & Moaniba, 2017b) and sectoral-level analysis (e.g. Bertoni, Colombo, & Grilli, 2011; Colombo, Croce, & Guerini, 2013; Dosi et al., 2015; Onishi, 2013). The advantage of the ADL model is its abilities to correct problems related to autocorrelation and heteroskedasticity, and control for the unobserved heterogeneity and endogeneity of all the main regressors through two-step system GMM estimation (Blundell & Bond, 1998; Roodman, 2009). Furthermore, the ADL model considers dynamic effects of GDP per capita by integrating its lag values as predictor variables. The dynamic ADL model is expressed as follows:

$$GDPpc_{it} = \sum_{l=1}^{L=3} \alpha_l GDPpc_{it-1} + \beta Div_{it-1} + \delta Pat_{it-1} + \gamma Cit_{it-1} + \lambda Inv_{it} + \Omega Claim_{it} + C_t + \varepsilon_{it}, \quad (3)$$

where $GDPpc_{it}$ denotes GDP per capita (in natural log), Div_{it} denotes the generality index, Pat_{it} denotes the (natural log) number of patents granted to country i in year t, and Cit_{it} denotes a patent's average number of forward citations. C_t refers to the number of countries and controls for the effects of country size, and $\mathrm{d_t}$ controls for the year fixed effects. In this baseline specification, the (1-year lagged) technological diversity indices and control variables are related to the main dependent variable. ε_{it} is the error term. The optimal lag ($\underline{L} = 3$) is selected based on the Akaike information criteria (AIC) (Akaike, 1969), the Bayesian information criteria (BIC) (Rissanen, 1978; Schwarz, 1978), and the Hannan-Quinn information criteria (HQIC) (Hannan & Quinn, 1979).

4. Results

4.1. OLS estimation results

The OLS regression results are presented in Table 4. Diversity has a negative influence on a country's *GDP* per capita, especially in high-income countries. By contrast, in non-high-income countries, economic performance is unaffected by technological diversity. Furthermore, the significance of the impact of diversity appears to increase positively over time, demonstrated by the increased coefficient of diversity in 1996–2005 compared with that in 1986–1995. These findings may validate those of related empirical studies that indicate that as countries develop, they tend toward specializing in specific technologies.

Table 4. OLS regression results

		All 55 countries	High income countries	Non-high-income countries	Period 1 1976–1985	Period 2 1986–1995	Period 3 1996–2005	Period 4 2006–2015
Diversity		–0.0672*	–0.1040*	–0.0645	–0.0235	–0.0753***	–0.0529**	–0.0142
		(–2.2296)	(–2.0856)	(–1.3228)	(–0.7227)	(–4.1729)	(–2.8164)	(–1.0782)
Patents		0.1890***	0.1670***	0.2610***	0.0775**	0.1480***	0.1200***	–0.0095
		–8.0574	–8.7576	–4.3730	–2.8797	–7.9617	–5.5357	(–1.1351)
Citations		–0.00354	0.00109	–0.0107**	0.0124**	0.00336*	–0.00390***	–
		(–1.4792)	–0.4972	(–3.0664)	–2.7622	–2.1184	(–3.7257)	–
Inventors		0.0412***	0.0555***	0.0224	–0.0174	–0.000908	0.0225**	0.0073+
		–3.9822	–6.9630	–1.5971	(–1.1028)	(–0.0629)	–3.2465	(1.9074)
Claims		0.00193	0.0045	–0.000676	0.00106	–0.00192	0.000295	–0.0011
		–0.6327	–1.5676	(–0.1555)	–0.7100	(–1.5759)	–0.2935	(–1.2705)
Constant		8.9370***	9.5800***	7.8200***	9.1090***	9.1670***	9.2900***	9.9698***
		–97.2091	–71.5331	–129.557	–153.0873	–174.3374	–159.8124	(266.5046)
N		2172	1465	707	527	550	550	545

t statistics in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. GDP per capita and patents are in natural log. The actual observed values of diversity index are used in this regression as opposed to the estimated values (used in 2SLS estimation; Table 5). To avoid truncation bias, forward citation for the period 200–2015 is dropped.

Another crucial finding is the positive coefficients of patents in all regression categories, which could imply a positive contribution of innovation on GDP per capita as expected. However, a reverse effect of GDP per capita on the number of patents – a concept illustrated by the Solow endogenous growth model (Solow, 1956) and Sims' theory (Sims, 1980) – is a possibility. Such a reverse effect could inflate the estimated coefficients of patents, resulting in bias. Among the other major findings, notably, forward citation has a negatively significant effect on GDP per capita in non-high-income countries and its coefficients tend to decrease over time, as shown by the reductions in coefficients from Periods 1 and 2 to Period 3. These reductions yield the unexpected finding that technical knowledge flow with forward citations as proxies may not directly contribute to economic development, especially in non-high-income countries. Collaborations between inventors tend to positively influence GDP per capita. Table 4 shows that an increase in the number of individuals involved in such technical collaborations could yield an overall 4% increase in GDP per capita and 5.6% increase in GDP per capita for high-income countries.

4.2. Results of 2SLS IV estimation

The 2SLS estimation results are reported in Table 5. A negative but unusually significant coefficient of diversity is observed, denoting that diversity is significant only in the categories of all 55 countries, non-high-income countries, and Period 3 (1996–2005). Nonetheless, the key finding is that diversity generally appears to negatively influence a country's GDP per capita, which is consistent with the OLS results. Another similar finding is that in high-income countries, economic performance is not influenced by technological diversity. This finding is confirmed by the nonsignificant coefficients of diversity for high-income countries. Furthermore, the significant coefficient of diversity in 1996–2005 could imply that diversity is slowly becoming an influential negative contributor to GDP per capita. These results further validate previous empirical findings indicating that as countries develop, they tend to further focus on and specialize in specific technologies.

Table 5. Results of the 2nd stage of 2SLS regression

	All 55 countries	High income countries	Non-high-income countries	Period 1 1976–1985	Period 2 1986–1995	Period 3 1996–2005	Period 4 2006–2015
Diversity	–0.0303+	0.0039	–0.1081*	–0.0513	–0.0625	–0.0494+	–0.0820
	(–1.8153)	(0.2469)	(–2.4986)	(–0.6591)	(–1.1164)	(–1.6697)	(–0.9352)
Patents	0.0309*	0.0057	0.1061**	0.0530	0.0730	0.0542*	0.0425
	(2.5370)	(0.5981)	(2.7896)	(0.8423)	(1.4155)	(2.0394)	(0.9783)
Citations	0.0000	0.0001	0.0008	0.0015	0.0002	–0.0002	–
	(0.0619)	(0.6093)	(1.1342)	(0.5293)	(0.3755)	(–0.4256)	–
Inventors	–0.0001	–0.0027	0.0009	0.0003	0.0001	0.0010	0.0016
	(–0.1107)	(–1.6253)	(0.6906)	(0.0377)	(0.0485)	(0.3531)	(0.6030)
Claims	0.0003	–0.0001	0.0013+	0.0008	0.0001	0.0002	0.0014
	(0.9748)	(–0.3691)	(1.7438)	(0.9543)	(0.0590)	(0.4632)	(0.9128)
Constant	0.0201***	0.0194***	0.0218***	0.0183***	0.0187***	0.0210***	0.0145***
	(19.4966)	(16.8277)	(9.4391)	(5.5094)	(5.9790)	(10.1943)	(5.2620)
N	2117	1428	689	472	550	550	545

t statistics in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in first order difference. GDP per capita and patents are in natural log. To avoid truncation bias, forward citation for the period 2006–2015 is dropped. The results of the first stage of the 2SLS are not reported here since we are only interested in the diversity-GDP per capita results.

The coefficients of Patents are again positive although significant only in the All 55 countries, non-high-income countries, and period 3 categories. These are consistent with the results of the OLS regressions in Table 4 and thus confirm previous studies' finding that innovation contributes positively to economic growth (GDP per capita). Furthermore, the coefficients of Inventors and Citations are no longer significant. This might indicate that the linear instruments of diversity (i.e. estimates of diversity from Eq. (2a) – first stage of 2SLS) have no direct significant influence on GDP per capita. Technically speaking, correcting for the reverse-effect bias (using 2SLS) shows that our results for Inventors and Citations in OLS are biased. In addition, as previously mentioned, a dynamic effect caused by a past value of GDP per capita (on its current value) is likely and could yield biased coefficients. Such effect

Table 6. Dynamic model results for high-income and non-high-income countries

	High income countries					Non-high-income countries				
	All periods	1976–1985	1986–1995	1996–2005	2006–2015	All periods	1976–1985	1986–1995	1996–2005	2006–2015
L1.GDPpc	1.4141***	1.4116***	1.4056***	1.4258***	1.4370***	1.3718***	1.3829***	1.3827***	1.3718***	1.3901***
	(45.6463)	(46.5772)	(46.5099)	(46.8531)	(46.7912)	(32.6836)	(33.4572)	(33.5903)	(33.1199)	(33.4006)
L2.GDPpc	−0.4310***	−0.5258***	−0.5193***	−0.5422***	−0.4995***	−0.3393***	−0.3903***	−0.3867***	−0.3514***	−0.3850***
	(−7.2304)	(−9.3812)	(−9.2078)	(−9.5343)	(−8.3851)	(−4.3971)	(−5.0834)	(−5.1168)	(−4.5434)	(−4.8807)
L3.GDPpc	0.0056	0.1004**	0.0994**	0.1023**	0.0515	−0.0360	0.0049	0.0013	−0.0224	−0.0068
	(0.1480)	(2.7889)	(2.7415)	(2.8314)	(1.3605)	(−0.7383)	(0.1010)	(0.0271)	(−0.4561)	(−0.1339)
Diversity	0.0013	0.0023	0.0013	0.0023	0.0008	−0.0062+	−0.0058	−0.0052	−0.0056	−0.0073*
	(0.8346)	(1.3706)	(0.7684)	(1.3494)	(0.5103)	(−1.7420)	(−1.5548)	(−1.3847)	(−1.5046)	(−2.0216)
Patents	0.0015*	0.0006	0.0011	0.0006	0.0018*	0.0074**	0.0076**	0.0076**	0.0078**	0.0083***
	(1.9910)	(0.7065)	(1.3286)	(0.7356)	(2.3378)	(3.0206)	(2.9686)	(2.9641)	(3.0915)	(3.3291)
Citations	0.0003	0.0010***	0.0010***	0.0008**	–	0.0001	−0.0001	−0.0000	−0.0002	–
	(0.8526)	(3.8958)	(3.7673)	(2.8436)	–	(0.1220)	(−0.1747)	(−0.0765)	(−0.3963)	–
Inventors	−0.0011	0.0004	0.0006	0.0004	−0.0011	−0.0013	−0.0009	−0.0007	−0.0007	−0.0009
	(−1.1738)	(0.6289)	(0.9778)	(0.6711)	(−1.0646)	(−1.4119)	(−0.9615)	(−0.7403)	(−0.7695)	(−0.9191)
Claims	−0.0001	−0.0004*	−0.0002	−0.0003	0.0001	0.0001	0.0002	0.0001	0.0000	0.0004
	(−0.2925)	(−2.2367)	(−1.1964)	(−1.6292)	(0.5009)	(0.3893)	(0.4023)	(0.2623)	(0.0959)	(1.0187)
Constant	0.0000	0.1440***	0.1467***	0.1449***	0.1147***	0.0000	0.0329+	0.0313+	0.0267	0.0231
	(.)	(5.5579)	(5.6836)	(5.6340)	(4.6067)	(.)	(1.7649)	(1.6866)	(1.4849)	(1.2461)
N	1354	1354	1354	1354	1354	653	653	653	653	653

t statistics in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All estimations are done using Blundell Bond two-step system GMM with year dummies included. To avoid truncation bias, forward citation for the period 2006–2015 is dropped.

is not considered and corrected for in our 2SLS results. The next estimation results take into account these dynamic effects.

4.3. Dynamic GMM model results

In the previous section, we assume that the causal effect of diversity is homogeneous over time. To control for possible structural breaks, particularly changes caused by major technological breakthroughs, we apply an estimation technique suitable for dealing with the dynamic and endogenous nature of our models on 10-year period samples for each income country group. The results (Table 6) are similar to those presented in previous subsections, with a few minor exceptions.

A similar negative but unusually significant coefficient of diversity is observed. Diversity is now significant in only two columns for non-high-income countries. Nonetheless, the key finding is that, generally, diversity still appears to negatively influence a country's GDP per capita, which is consistent with the OLS and 2SLS results. In particular, the significant coefficient of diversity in 2006–2015 for non-high-income countries could imply that diversity is slowly becoming an influential negative contributor to GDP per capita in developing countries. Furthermore, in high-income countries, economic performance is still not influenced by technological diversity, confirmed by the nonsignificant coefficients of diversity for high-income countries. These results further validate previous empirical findings indicating that as countries develop, they tend to further focus on and specialize in specific technologies.

4.4. Sensitivity analysis: Panel VAR and Granger tests

Several strategies are employed to test the sensitivity and robustness of the results. First, a panel vector autoregression (VAR) model is used to confirm the results in the previous subsections by validating the estimated coefficients of diversity. Second, postestimation Granger causality tests are carried to enable us to confirm the directions of the causality effects between GDP per capita and diversity index (Abrigo & Love, 2016).

Granger causality testing is a widely accepted method for testing the reverse causality effect and has been used extensively in many empirical studies (e.g., Al-mulali, 2014; Beyzatlar, Karacal, & Yetkiner, 2014; Chang et al., 2014; Florens & Mouchart, 1982; Law, Lim, & Ismail, 2013). The version of Granger causality testing used in our analysis is called the Toda–Yamamoto and Dolado and Lutkepohl (TYDL) Granger test. This test has been found to be consistent and unbiased when variables are non-stationary at level making it appropriate for our I(1) variables (Dolado & Lütkepohl, 1996; Toda & Yamamoto, 1995).

The baseline model specification for our TYDL Granger non-causality test for *GDP* per capita and our primary proxy for diversity is as follows:

$$GDPpc_{i,t} = \sum_{j=1}^{k+s} \gamma_j GDPpc_{i,t-1} + \lambda GDPpc_{i,t-k+s} + \sum_{j=1}^{k+s} \omega_j Div_{i,t-1} + \beta Div_{i,t-k+s} + a_t + \in_{i,t}; \quad (4)$$

$$Div_{i,t} = \sum_{j=1}^{k+s} \eta_j Div_{i,t-1} + \Omega Div_{i,t-k+s} + \sum_{j=1}^{k+s} \delta_j GDPpc_{i,t-1} + \varphi GDPpc_{i,t-k+s} + a_t + \in_{i,t}, \quad (5)$$

where $GDPpc_{i,t}$ denotes the (natural log of) GDP per capita for country *i* in year *t*, and $Div_{i,t}$ denotes its diversity index. k is the optimal lag integration order of $GDPpc_{i,t}$ and $Div_{i,t-1}$ in a VAR model; and *s* is the highest order of integration for the two variables; α_t is the constant term and $\in_{i,t}$ is the error term. i stands for a given country and t for year. Note, although not shown in Eq. (4) and (5), control variables are also included in the tests. Our Granger test results (see Table C.1 in Appendix C) confirm the absence of the causal effect of diversity on GDP per capita.

Table 7 shows the estimation results of our panel VAR model. The coefficients for diversity lags are all nonsignificant in relation to GDP per capita, which implies that diversity has no direct causal effect on GDP per capita. By contrast, the lags of GDP per capita have significantly positive coefficients for diversity (especially Lag 1), which implies that GDP per capita has a direct causal effect on diversity. The most crucial finding in Table 7 is the absence of a bidirectional cause-effect relationship between diversity and GDP per capita, as predicted earlier in this paper. This absence confirms our main finding that diversity does not significantly influence GDP per capita, especially in high-income countries.

Table 7. Panel VAR results

	All	High income countries	Non-high-income countries	1976–1985	1986–1995	1996–2005	2006–2015
GDP per capita							
L1. GDPpc	0.4027***	0.4833***	0.3243***	0.3597**	0.4806***	0.3558***	0.3864***
	(11.0505)	(7.7524)	(5.1349)	(2.8940)	(5.5346)	(4.7911)	(5.7850)
L2. GDPpc	−0.0392	−0.0374	−0.0569	−0.2651*	0.0362	0.0161	−0.0363
	(−1.1463)	(−0.6999)	(−1.0887)	(−2.3760)	(0.6108)	(0.2096)	(−0.6455)
L1. Div	−0.0016	−0.0008	−0.0026	−0.0064	0.0009	−0.0050	0.0073
	(−0.7720)	(−0.2334)	(−0.8509)	(−0.8672)	(0.2626)	(−1.5212)	(1.5381)
L2. Div	−0.0010	0.0014	−0.0031	0.0056	0.0003	−0.0012	−0.0016
	(−0.4657)	(0.4159)	(−1.0168)	(0.8537)	(0.0822)	(−0.3638)	(−0.4031)
Diversity							
L1. GDPpc	2.7581***	1.9292***	3.3973***	1.9138+	1.2942	4.3532***	3.4500**
	(6.2183)	(4.1264)	(3.4146)	(1.9103)	(1.3208)	(3.9308)	(2.8232)
L2. GDPpc	1.0671*	0.6799	1.6322*	−0.4210	0.4445	3.0477*	1.9930
	(2.4852)	(1.4316)	(1.9892)	(−0.3721)	(0.5331)	(2.5106)	(1.3460)
L1. Div	−0.4866***	−0.4973***	−0.4784***	−0.4450***	−0.4654***	−0.5604***	−0.2217+
	(−11.8167)	(−8.4930)	(−7.8751)	(−5.2764)	(−7.1474)	(−7.2041)	(−1.8211)
L2. Div	−0.1862***	−0.2170***	−0.1652**	−0.3054***	−0.0658	−0.1959**	−0.1760
	(−4.6672)	(−3.7425)	(−2.9924)	(−3.3901)	(−0.8789)	(−2.8065)	(−1.3807)
N	1897	1280	617	307	550	550	490

t statistics in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In summary, the most crucial implication of our findings is that the results evidently indicate that technological diversity plays no direct critical role in economic growth. These results appear not to oppose the crucial findings of most previous studies (e.g. Chen et al., 2015; Mancusi, 2001; Pianta & Meliciani, 1996); explaining why countries tend to further focus on and specialize in specific technologies as they develop. This implies that technological progress is imperative to economic growth, no matter diverse or not, and thus clearly proved that our reverse-causality (from economic growth to technological diversity) assumption is false.

Furthermore, the Granger tests further validate these results as indicated by the absence of the causal effect of diversity on GDP per capita – even when using the other two indicators (i.e. the generality and originality indices) of technological diversity instead of diversity index (see the results in Table C.2 and C.3 in Appendix C). Note, our dataset sample varies with the type of index used. The originality index uses a 10-year backward citation window, thereby excluding data from the earliest 10-year period (1976–1985) to avoid truncation bias. On the other hand, the generality index uses a 10-year forward citation window, thereby excluding data from the most recent 10-year period (2006–2015).

Conclusions

This study investigates the possibility of a bidirectional cause-effect relationship between technological diversity and economic performance at the national level. With the underlying assumption that economic output exerts a reverse effect on technological progress, based on the dynamics of technological progress (or innovation) and its relationship with economic growth as theorized in the endogenous growth theory (Romer, 1994, 1986), this study explores the key dimensions of technological progress by examining their impacts on GDP per capita. The primary focus is to evaluate the directionality of the relationship between a specific dimension (in this case, technological diversity with the diversity index as a proxy) and economic performance (with real GDP per capita as a proxy). Specifically, we analyze whether a bidirectional causal effect is present between the two. Several data-mining techniques and econometric models are adopted, including the construction of country indicators such as the technological diversity index, technical knowledge flow indicator based on forward citations, strength of legal protections indicator, and inventor collaboration index. These indicators are adopted based on countries' patent data and patent citation analysis. The econometric methods employed include diagnostic techniques involving panel data combined with IV and dynamic ADL model estimation. In summary, although technological diversity does not play a significant role in a country's economic growth or performance, it negatively influences economic development in non-high-income countries.

These findings confirm the results of most related empirical studies that high-income countries focus on technological specialization, which suggests that smaller countries are more open to diversification because their domestic markets are capable of absorbing a wider range of competitive and diversified products. However, our findings indicate that diversification in smaller countries negatively effects economic growth. These findings validate those of several previous studies that have observed an inverse relationship between a country's economic performance and technological diversity (Hummels & Klenow, 2005). These empirical findings are crucial because of the recent development of macroeconomic growth theories and attempts to integrate them into microlevel firm management strategy theories.

Contribution to theory

The contribution of this study to innovation management and economic theory is threefold. First, we provide a novel methodological framework for visualizing the key components of technological progress and innovation (TDEP framework in Figure 2) and their links with economic performance, as indicated by the arrows in Figure 2. These components represent the main technological dimensions of innovation; for instance, how a country's legal protection system is vital for economic development can be explored empirically through analyzing the link between the average claims per patent in a country and GDP per capita, how technological collaborations between inventors directly influence economic performance can be investigated empirically through patent inventor counts and GDP per capita, and how a country's innovation capability can support economic development by estimating the impacts of patents produced in a country on GDP per capita. The second contribution of this study relates to the primary study objective: determining how technological diversity influences a country's economic performance. The key finding of this paper is that technological diversity does not significantly affect economic growth, particularly in non-high-income countries, for which the results are negative. Third, the sensitivity of forward citation to time and how future citations are likely to be influenced by current and past citations are causes for concern. These phenomena occur because citation of previous patents may facilitate the promotion of previous patents for future patents, a phenomenon known as the lag effect. To the best of our knowledge, previous studies using forward citation have overlooked the lag citation effect, thereby undermining the reliability of their results. The present study is one of the first to consider the lag effect of forward citations. Fourth, the absence of past studies on the reverse causality of economic growth on technological diversity is an important gap in the literature of the economics of innovation. Our study is the first attempt to fill this gap.

Policy and managerial implications

Several key management and policy implications can be drawn based on the study findings. First, our inability to find empirical evidence of a reverse-causal effect between GDP per capita and the diversity index may indicate the absence of a bidirectional relationship between a country's economic performance and technological diversity, which evidently leads to the strong managerial implication that countries and firms should not overemphasize diversifying their innovations or technologies. Although diversification could be crucial in enabling a firm to survive or gain competitive advantages, it may not yield economic benefits for a whole country. As growth moderators, governments should seek methods to control and regulate the diversification processes of firms. The second implication is that a positive relationship between number of patents and GDP per capita provides strong empirical validation for the positive contribution of a country's innovation capability on its economy. This reflects the importance of public R&D spending by governments and government policies that facilitate innovation. In other words, governments should invest more in R&D programs and technology-based entrepreneurships, as well as other forms of public spending that can accelerate technological progress.

Limitations

This study has several limitations. First, despite its use in many studies on research innovation and economics, patent data is occasionally criticized for their inability to explicitly reflect the technological activities of countries. Therefore, our use of patent data to construct the main variables of interest, such as the diversity index, might not be justifiable. Second, the accuracy with which the USPTO categorizes each patent into one of 35 technology fields is unknown and cannot adequately be validated by researchers. Third, the use of patent citations can lead to truncation bias. The use of 10-year windows at the beginning and end of the investigation period could be unreliable because the numbers of citations outside these 10-year windows are highly likely to be sufficiently large for some countries, and thus the results may be exposed to truncation bias. Last, our econometric approach relies heavily on critical data tests such as the Breitung and Hadri LM stationary tests, and the Pedroni cointegration test. These tests require fully balanced panel datasets thus making it difficult for us to have more control variables. For instance, the lack of balanced country data for some important variables such as R&D expenditure prevents us from adding them as controls in our estimation analysis.

Future research

Based on some of the crucial findings of this study, several potential research topics could be explored either as extensions to this study or as diverted research streams from the topic of this study. These include the following: 1) examining how the dynamics of technological progress in our TDEP framework influence firm performance; 2) investigating the reverse effect of GDP per capita on each of the other technological dimensions of innovation in the TDEP framework; and 3) repeating this study with other known indicators (or indices) of technological diversity; 4) extending this study to explore the technology push and demand push models through the use R&D expenditure data for most countries as soon as they are sufficiently available.

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APPENDIX A

Table A.1. Countries investigated in this study

1	United States	20	Austria	39	Bahamas, The
2	Japan	21	Bermuda	40	Argentina
3	Germany	22	Norway	41	Turkey
4	Korea, Rep.	23	India	42	Portugal
5	France	24	Ireland	43	Chile
6	Taiwan	25	Spain	44	Greece
7	United Kingdom	26	Hong Kong SAR, China	45	Thailand
8	Canada	27	Luxembourg	46	Panama
9	Switzerland	28	New Zealand	47	Mauritius
10	Netherlands	29	Barbados	48	Malta
11	Sweden	30	South Africa	49	Seychelles
12	Italy	31	Brazil	50	Cuba
13	China	32	Saudi Arabia	51	United Arab Emirates
14	Finland	33	Mexico	52	Colombia
15	Australia	34	Malaysia	53	Philippines
16	Israel	35	Iceland	54	Niger
17	Belgium	36	Bulgaria	55	Samoa
18	Denmark	37	Venezuela, RB		
19	Singapore	38	Cyprus		

APPENDIX B

Table B.1. Stationary test results (using Breitung unit-root test)

Variable	At	Type	Statistic	p–value
GDP per capita	Level	lambda*	3.0874	0.999
Diversity index	Level	lambda*	–0.5987	0.2747
Patents	Level	lambda*	3.7431	0.9999
Citation	Level	lambda*	–0.993	0.1604
Inventors	Level	lambda*	12.5505	1
Claim	Level	lambda*	–1.9882	0.0234
GDP per capita	First difference	lambda*	–5.9792	0.0000
Diversity index	First difference	lambda*	–8.1330	0.0000

Variable	At	Type	Statistic	p–value
Patents	First difference	lambda*	–6.0426	0.0000
Citation	First difference	lambda*	–9.7536	0.0000
Inventors	First difference	lambda*	–4.0283	0.0000
Claim	First difference	lambda*	–6.4362	0.0000

Note: Ho: Panels contain unit roots; Ha: Panels are stationary; Tests using Hadri LM unit root test (not shown here but also conducted) report the same stationary results for all the above variables except GDP per capita. These two tests are selected because they are valid and consistent in the presence of cross-residual dependency i.e. lambda* is robust to cross-sectional correlation.

Table B.2. Cointegration test results for high income countries sample

Pedroni's cointegration tests:

No. of panel units: 18 Regressors: 4
No. of obs. : 558 Avg obs. per unit: 31
Data has been time-demeaned.
A time trend has been included.

Test Stats.	Panel	Group
v	–.7071	.
rho	2.854	3.612
t	.4192	.1637
adf	1.047	1.64

All tests statistics are distributed N(0, 1), under null of no cointegration, adn diverge to negative infinity (save for panel v).

Table B.3. Cointegration test results for non-high income countries sample

Pedroni's cointegration tests:

No. of panel units: 37 Regressors: 4
No. of obs. : 1147 Avg obs. per unit: 31
Data has been time-demeaned.
A time trend has been included.

Test Stats.	Panel	Group
v	–.2787	.
rho	3.434	4.822
t	.3733	.4674
adf	1.364	.87

All tests statistics are distributed N(0, 1), under null of no cointegration, adn diverge to negative infinity (save for panel v).

APPENDIX C

Table C.1. Granger causality test results for GDP per capita and diversity index

Sample	Dependent	Independent	Chi2	df	Prob
High income countries	GDP per capita				
		Lags of GDP per capita	1.15	3	0.765
		ALL	1.15	3	0.765
	Diversity index				
		Lags of GDP per capita	0.416	3	0.937
		ALL	0.416	3	0.937
Non-high income countries	GDP per capita				
		Lags of Diversity	0.34	3	0.952
		ALL	0.34	3	0.952
	Diversity index				
		Lags of Diversity	0.41	3	0.938
		ALL	0.41	3	0.938

Table C.2. Granger causality test results for GDP per capita and originality index

Sample	Dependent	Independent	Chi2	df	Prob
High income countries	GDP per capita				
		Lags of GDP per capita	0.602	3	0.896
		ALL	0.602	3	0.896
	Originality index				
		Lags of GDP per capita	0.368	3	0.947
		ALL	0.368	3	0.947
Non-high income countries	GDP per capita				
		Lags of Originality	3.212	3	0.360
		ALL	3.212	3	0.360
	Originality index				
		Lags of Originality	6.685	3	0.083
		ALL	6.685	3	0.083

Table C.3. Granger causality test results for GDP per capita and generality index

Sample	Dependent	Independent	Chi2	df	Prob
High income countries	GDP per capita				
		Lags of GDP per capita	1.383	3	0.709
		ALL	1.383	3	0.709
	Generality index				
		Lags of GDP per capita	0. 782	3	0.854
		ALL	0.782	3	0.854
Non-high income countries	GDP per capita				
		Lags of Generality index	3.006	3	0.391
		ALL	3.006	3	0.391
	Generality index				
		Lags of Generality index	14.115	3	0.003
		ALL	14.115	3	0.003