Highlights

1. The paper examines the co-evolution of technological diversification and international collaboration.
2. The paper examines how co-evolution of technological diversification and international collaboration affect innovation.
3. A two-step approach using granger causality and vector autoregression is applied.
4. International collaboration is found to positively influence the intensity of innovation.
5. Technological diversification has a negative effect on innovation in a country.

On the drivers of innovation: Does the co-evolution of technological diversification and international collaboration matter?

Abstract

This paper examines the co-evolution of technological diversification and international collaboration, and how they affect the intensity of innovation in a country. A two-step analysis is applied on a global panel dataset consisting of patents and macroeconomic data for 54 countries, covering a period of 40 years. First, the co-evolution patterns and characteristics of diversification and collaboration are explored. Then, a series of econometric techniques are employed in an attempt to explain the observed patterns. This step involves conducting the Toda–Yamamoto and Dolado–Lutkepohl (TYDL) Granger causality test to analyze the directions of the causal effects of technological diversification and international collaboration on innovation. Such version of the Granger causality test is valid and consistent regardless of whether a series is stationary at level, first order or second order difference; and non-cointegrated or cointegrated of any arbitrary order. In addition, reduced form vector autoregression (VAR) models are estimated to determine the scale of the impacts of both diversification and collaboration on a country's innovation performance. Our empirical results show that there is a bidirectional causality between technological diversification and innovation. This result is robust across different time periods and groups of countries. Furthermore, international collaboration is found to positively influence the intensity of innovation in a country while technological diversification has a negative effect.

Keywords: Innovation, international collaboration, technological diversification, TYDL, VAR

1. Introduction

Global-economic forces and financial constraints have made innovation-driven growth more essential now than at any other time in history. A country's ability to develop and exploit its innovative potential is critical for its long run economic growth. This fact, acknowledged by well-known pioneering works such as the Schumpeterian growth theory (Schumpeter, 1934) and endogenous growth theory (Romer, 1994, 1990, 1986), has generated a lot of academic interests from various research disciplines. Countries' needs to stay ahead of changing global challenges continuously yield pressure for unprecedented developments in innovation. This, in turn, leads to fierce competition from firms that are aggressively pursuing their own innovation-driven future. Consequently, innovations accelerate and economies grow. The marked increases in number of patents accompanied by sustained and strong annual economic growth rates in East Asian countries over the past three decades, such as China (Huang, 2010), is a classic example of this.

Given the importance of innovation, scholars have long been pursuing the question of what drives innovation (Conceição et al., 2006; Horbach, 2016; Pacheco et al., 2017). Some of the most heavily researched areas in innovation literature include entrepreneurship (Schumpeter, 2013); absorptive capacity and knowledge recombination (Cohen and Levinthal, 1990; Jansen et al., 2005; Moaniba et al., 2018a; Zahra and George, 2002) government policies (Ghisetti and Pontoni, 2015); R&D expenditure (Ghisetti and Pontoni, 2015); trade and foreign direct investment (Wu et al., 2017); and environmental factors (Su and Moaniba, 2017a).

This study, built on the previous literature, aims to provide a more fine-grained view of the dynamics and characteristics of drivers of innovation – focusing on the co-evolution of technological diversification and cross-country technical collaboration (referred to as "international collaboration" in this paper). Specifically, to empirically examine the causal effects of two common business strategies, international collaboration and technological diversification, on a country's innovation performance. In doing so, it should help disentangle the puzzling and complex interdependency between the three. In addition, given the increasing popularity and adoption of the two business strategies over the past decades, we have reached a point at which the question arises regarding whether the increasing simultaneous adoptions of both strategies might not be a coincidence. Is it possible that technological diversification stimulates international collaboration, or vice versa? If either is true, then a special modeling case should be implemented when analyzing the impact of each of the two strategies on innovation performance. Such special modeling case has never been used before in related innovation studies. To do this, quantitative indicators of innovation performance, technological diversification, and the level of international collaboration are constructed and analyzed using an endogenous modeling approach. These indicational indices are computed based on patents data.

The complexity in the nature of the associations between the diversity of technologies and international collaboration, and their causal relationships with innovation is reflected by the limited number of previous studies investigating the triadic relationship between the three (i.e., innovation-diversity-collaboration). Furthermore, most studies related with technological diversification have been conducted at the firm level rather than country level. These include papers that explored the relationships between diversification and firm output such as financial performance (Chen et al., 2013; Chiu et al., 2008; Chun et al., 2014; Evangelista and Vezzani, 2010). In contrast, studies conducted on a country scale have tended to focus on technological specialization, instead of diversification (Archibugi and Pianta, 1992a, 1992b; Attaran, 1986; Cantwell and Vertova, 2004; Evangelista and Vezzani, 2010; Hasan and Tucci, 2010; Mancusi, 2001; Pianta and Meliciani, 1996). Studies related with technical collaboration, on the other hand, cover a broader range of issues. The majority of these concerns collaboration across industries as opposed to across countries (Chen et al., 2015; Mancusi, 2001; Pianta and Meliciani, 1996). Only a few studies have focused on the link between international collaboration and innovation (Archibugi and Pianta, 1992a, 1992b; Cantwell and Vertova, 2004).

This present study is designed to fill two important research gaps. First, although the effects of international collaboration and technological diversification on innovation performance have been investigated extensively at organizational level, the equivalent phenomenon at country level is rarely studied. It is important to understand the benefits and consequences of such business strategies not only on the businesses themselves but also on the country as a whole. At a microlevel, international collaboration has been found to exert a positive effect on the innovation performance of firms (Ebersberger and Herstad, 2013; Rodríguez et al., 2018), however it is not clear yet whether it has the same positive effect on a country's economic growth or not. On the other hand, a country's diverse technology base can be an hindrance to its economic growth (Moaniba et al., 2018b). Therefore, given a strong correlation between innovation and economic growth observed in the past, it is likely that technological diversification may also negatively affect a country's innovation performance. Consequently, with these opposing effects, it is difficult to foresee what will happen to a country's economy that engaged heavily in both technological diversification and international collaboration. Second, given that the majority of countries engaging in international collaborations have also shown a high diversity of technology bases, the question of whether or not the collective efforts of local firms to diversify their technologies stimulate more technological collaborations with outside countries quickly arises. Relatedly, a country could engage more in international collaborations as a result of more technological diversification strategies (or activities) implemented by firms in that country. To the best of our knowledge, this phenomenon has never been investigated before.

Understanding the roles of international collaboration and a diverse technology in innovation at a country level is imperative for policy-makers in formulating policies that can stimulate technological progress and economic growth. Moreover, it may help countries (through their Governments) with their decisions on whether to provide more financial subsidies to innovating firms and their R&D projects or regulate their technological diversification activities. Research-wise, recently developed features and functions of various popular statistical software packages facilitate conducting investigations from multiple perspectives. In the context of this study, the term "innovation" encompasses all forms of new inventions, products and processes.

This present paper contributes to literature on the analysis of the drivers of innovation by examining the complex interaction between the diversity of technologies and openness to international collaboration in a country, and how the two have co-evolved to influence innovation. International collaboration and technological diversification have been investigated quite extensively in the past but separately. We believe, to the best of our knowledge, this present paper is the first research attempt to empirically explore the sophisticated triple helix of technological diversity, international collaboration, and innovation. Further, our empirical results support past studies' findings and existing management and economic theories such as the theory of economics of scope and the resource based view (RBV) theory (Wernerfelt, 1984).

The remainder of this paper is organized as follows. Section 2 provides the theoretical background on the drivers of innovation, and the relationships between innovation, international collaboration, and technological diversification. Hypotheses are also presented in this section.

Section 3 describes the data and our method. Next, the empirical analysis results and a discussion on the key findings are presented in Section 4. Finally, Section 5 concludes the paper.

2. Theoretical background and hypotheses

2.1. Drivers of innovation

Innovation has long been widely recognized as one of the key drivers of economic growth. Some of the early prominent scholarly works explaining the strong linkage between innovation and growth include the Schumpeterian growth theory (Schumpeter, 1934), Solow–Swan growth model (Solow, 1956; Swan, 1956), and endogenous growth theory (Romer, 1994, 1990, 1986). These theories are amongst the first to emphasize the bidirectional relationship between innovation and economic growth – which form the basis of our argument that the two dimensions of technological progress, diversification and collaboration, are likely to have bidirectional links with innovation. Other contributing factors to economic growth identified by recent theoretical and empirical studies include government consumption, trade and trade terms, political stability, income distribution, inflation, the rule of law, and fertility (e.g. in Barro, 1996; Chen and Feng, 2000; Anaman, 2004; Cuaresma et al., 2014; Vedia-Jerez and Chasco, 2016; Barro, 1991; Qayum, 2005; Vedia-Jerez and Chasco, 2016; Persson and Tabellini, 1992). However, the degree to which how much each factor is contributing to growth varies considerably from one industry to another, and across countries.

For decades, numerous scholars from different disciplines have dedicated their works to investigating the links between innovation and other factors, both at country and firm level (Conceição et al., 2006; Horbach, 2016; Pacheco et al., 2017; Su and Moaniba, 2017a). Among the most mentioned factors in literature are entrepreneurship (Schumpeter, 2013), government policies (Ghisetti and Pontoni, 2015), R&D expenditure (Ghisetti and Pontoni, 2015), trade and foreign direct investment (Wu et al., 2017), open innovation and knowledge management (Cammarano et al., 2017; Michelino et al., 2016; Natalicchio et al., 2017), and environmental factors (Su and Moaniba, 2017a). Yet, to date broad generalizations on what drives innovation and whether innovation has reverse effects on them seem impossible. This present paper is probably one of the rare works designed towards achieving the overarching goal of such generalization taking into account the reverse effects and the bidirectional relationships. Establishing a concrete framework for understanding the general motives and incentives for innovation, and the links between involved factors is not an easy task. However, most of the aforementioned factors often fall into three main groups – the supply side of technical change, intellectual property (IP), and the financing of innovation (Nicholas, 2011).

The supply side of technical change refers mainly to the inventions and thus depends heavily on entrepreneurs and firms. Organizational strategies and computerization changes affect a firm's innovative capacity far more than its size (François et al., 2002) – underlining the importance of the level of self-sufficiency and the recognition of a researcher's status.

Diversification and collaboration are amongst the most commonly business innovation strategies adopted by organizations. Further, IP plays a vital role in innovation. IP and other intangible assets such as knowledge are indispensable. The wider scope of knowledge transformed and utilized by a firm, the higher value of the invention produced (Ibrahim and Fallah, 2005; Su and Moaniba, 2017b). However, the protection of IP can cripple a firm's effort to collaborate or engage in open innovation with others if not carefully designed (Alexy et al., 2009). Science alters inventors' search processes (Fleming and Sorenson, 2004) therefore firms should also implement strategies to look for not only technical knowledge but also scientific knowledge. Financial commitments to innovative activities also foster technological change.

Innovation has also been found to respond strongly to the changes in environmental factors such as climate (Su and Moaniba, 2017a). With the increasing impacts of climate change, the number of climate friendly inventions has risen exponentially over the last few decades. In addition, numerous organizational factors and firm characteristics have also been known to influence innovation activities. For instance, researchers have argued that the level of innovation in an organization is not only substantially influenced by the organization size (Schumpeter, 1934), but also by its networking capability (Dahlander and Gann, 2010).

2.2. The relationship between international collaboration and innovation performance

The sophisticated interactions between economic variables have been a major hindrance to understanding the links between innovation and other factors. This complexity often gives rise to the important question in an empirical study of whether each pair of investigated variables has a bidirectional cause-and-effect relationship or not. A significant body of both theoretical and empirical studies have explored the bidirectional relationships between innovation and other important factors. For instance, between innovation and economic variables such as transportation-related technologies and economic growth (Duffy-Deno and Eberts, 1991; Eisner, 1991; Garcia-Milà and McGuire, 1992; Moomaw et al., 1995), and carbon dioxide emissions technologies and energy consumption (Dritsaki and Dritsaki, 2014). The bidirectional causal effects of technological diversity and international collaboration on innovation intensity are yet to be empirically tested. However, a reverse causal effect from economic growth on innovation has been observed in previous studies (Murmann, 2003; Nelson, 1994). This reverse effect creates a bidirectional relationship between innovation and economic growth which in turn often cause an endogeneity problem (Cainelli et al., 2006; Coad and Rao, 2010). This endogeneity issue is often neglected in many innovation-related studies. The bidirectional relationships reflect the interactive nature of innovation processes and how such processes rely on wealth and income, and vice versa. To ensure that we take into account in this study the bidirectional relationship and the endogeneity created by such relationship, we need to carefully examine the directions of the effects between innovation and the two dimensions – technological innovation and innovation performance.

More engagement in international collaborations can have either a positive or a negative effect on a country's innovation output. As a matter of fact, the impact of technological collaboration on the innovative performance of countries involved is rarely investigated. By comparison, the impact of collaboration on firms' innovative output has been studied quite extensively. Despite this, there is still no consensus about how the collaboration between countries impact the quality of inventions at firm level (Alnuaimi et al., 2012; Furman et al., 2005; Penner-Hahn and Shaver, 2005; Singh, 2008). Some of the past studies have argued that cross-country collaborations lead to better inventions because they allow the combination of diverse knowledge and competences (Levinthal and March, 1993; March, 1991). Yet, the opposing studies pointed to the high coordination costs and problems associated with integrating diverse knowledge (Furman et al., 2005; Grant, 1996; Singh, 2008). In addition, relying on collaborations involves tremendous effort to search for partners, and in doing so, may force firms to incur more costs related with administration – not just in terms of financing but also time and resources (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Prashant and Harbir, 2009; Wassmer, 2008). Premature endings to collaborations are also quite common due to problems caused by the lack of sustained mutual understandings and interests between partners such as free riding, opportunistic behavior, and value misappropriation (White and Siu-Yun Lui, 2005). Based on these, we formulate our first hypothesis as follows.

Hypothesis 1a: The more firms in a country engaging in technological collaborations with firms from other countries will lead to a lower innovative performance of such country.

Previous studies have also highlighted the possibility of the opposite phenomenon i.e., the reverse effect of innovation on the level of international collaborations in a country. Although, such studies suggest a positive effect of a firm's investments in R&D and other innovative activities on the extent of its collaborative partnerships (Dahlander and Gann, 2010; Lin et al., 2012; Lokshin et al., 2008), the costs involved can be quite unbearable for firms. For instance, firms in a country will need to establish their knowledge base by searching, acquiring, and exploiting external knowledge effectively (Todorova and Durisin, 2007; Zahra and George, 2002). Such innovation process may require expensive R&D outsourcing activities from firms (Weigelt, 2009). With constrained cognitive abilities, the complex innovation process involved in combing internal and external knowledge can increase coordination and managerial costs to firms (Nooteboom et al., 2007). Moreover, knowledge is context specific which makes it costlier to transfer and apply in different technological innovation processes (Szulanski, 1996). However, recent studies seem to emphasize on the positive link between innovation performance and collaboration across countries (Giuliani et al., 2016). Furthermore, from the perspective of knowledge management, the positive relation between a firm's internal knowledge and its absorptive capacity i.e., its ability to search, absorb, and utilize external knowledge (Cohen and Levinthal, 1989) , requires some level of commonality between partners (Lane and Lubatkin, 1998; Mowery et al., 1996). These observations lead us to our second hypothesis.

Hypothesis 1b: The more innovative activities or efforts of firms in a country will lead to more collaborations with firms from other countries.

2.3. Possible bidirectional relationship between innovation and technological diversification

Diversification is not a new research topic in the fields of innovation management and innovation economics. Some of the past studies on technological diversification include Breschi et al. (2003), Cantwell and Piscitello (2000), and Penrose (1995); Piscitello (2000).

Technological diversification has been investigated quite extensively in the past. Silverman (1999) reported that in manufacturing industries, firms are more likely to diversify by engaging in other industries only if their available resources are applicable in other industries. Another study analyzed firm data from 1978–1993 from the European Patent Office and observed that firms are more likely to diversify into knowledge-based fields (Breschi et al., 2003). However, although the importance of diversification for firm survival is widely acknowledged, the equivalent phenomenon at the macro (or country) level has seldom been explicitly explored. Greater technological diversification in a country engenders a shift in that country's technological development, which in turn relies upon social learning processes (Dalum et al., 1992). Relatedly, technological specialization is another very popular research topic investigated over the past decades such as in technological specialization and trade (Dosi et al., 1990; Greaney and Karacaovali, 2017; Manwa and Wijeweera, 2016; Mustafa et al., 2017; Silberberger and Königer, 2016; Soete, 1987; Sokolov-Mladenović et al., 2017), technological specialization and economic growth (Meelen et al., 2017; Murshed and Serino, 2011; Rehner et al., 2014, 2014; Šipilova, 2015), and heterogenous technological diversification patterns (Kodama, 1986; Mowery and Nelson, 1999; Pavitt et al., 1989). The bulk of these studies have provided evidence pointing to the positive impacts of technological specialization in a country as opposed to diversification. Based on these observations, we develop our next hypothesis as below.

Hypothesis 2a: The collective efforts of firms in a country to diversify their technological outputs negatively influence the overall innovation performance of such country.

A significant body of prior studies have also investigated the opposite effect of innovation on technological diversification. This causal impact of innovation on technological diversification, has also been explored in the fields of innovation and strategic management (Rodríguez-Duarte et al., 2007; Sugheir et al., 2012). Technological diversification may be the result of an innovation process, especially in new ventures, as part of their efforts to explore new business opportunities (Rosa, 1998). In their pursuit for understanding the relationship between innovation and diversification, past studies have provided evidence indicating unidirectional link between the two. However, a few recent studies have shown that the relationship between the diversification and economic growth is bidirectional at country level (Moaniba et al., 2018b). Given a strong positive correlation between innovation and economic growth, the same bidirectional relationship between diversification and innovation is anticipated. This relationship is probably due to the fact that firms constantly engage in a virtuous circle of growth (Teece, 1980) in which they have to switch between technological specialization and diversifying innovation outputs to exploit the economies of scope of their resources. This innovation cycle may involve increased managerial challenges that requires more organizational coordination efforts and forcing companies to tighten up their controls on their financial resources when shifting between strategic and financial strategies (Baysinger and Hoskisson, 1989). Based on this logic, an innovation process clearly affects firms' decision to whether engage in technological diversification or not and therefore we suggest the following hypothesis.

Hypothesis 2b: The more innovative a country is, indicated by the collective activities of firms in such a country, may result in a higher technological diverse base in that country.

In summary, Fig. 1 illustrates the technological dimensions of innovation we examine in this study, how they are possibly linked with one another based on what we found in the literature review, and our theoretical hypotheses. Specifically, the figure represents our theoretical framework that focuses on the dynamics of technological diversity and the co-inventions between countries, and their impacts on innovation performance. These two key dimensions of innovation are selected to capture two important technological characteristics of a business strategy known to be conducive to innovation. The two characteristics (or elements of a successful business strategy) are technological breadth and the scope of technical collaboration. As shown in the framework, to measure the technological breadth of a firm's effort and the level of engagement in international collaboration, we construct quantitative indicators built on the diversity index and the number of countries involved per patented invention, respectively. A country's innovation performance is measured using the number of patents. Full details of these indicators are provided in the next section.

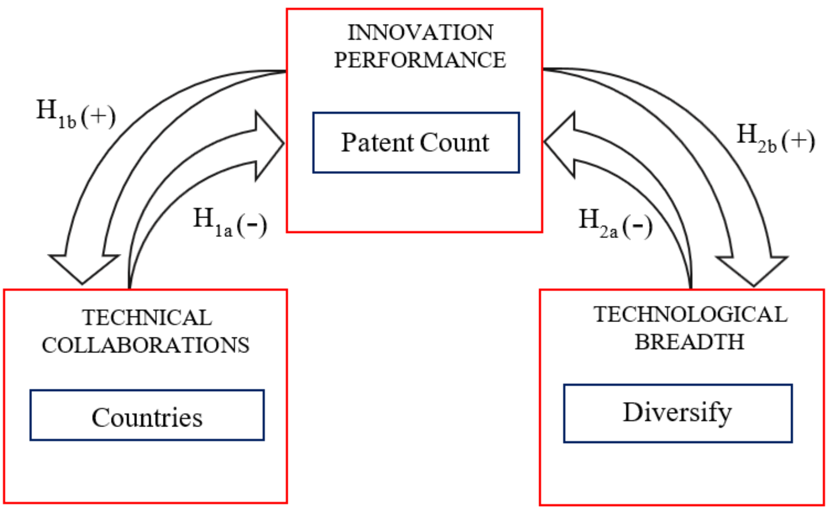


Fig. 1. The technological drivers of innovation theoretical framework

Note: All arrows indicate the possible directions of the causal effects

3. Data and methodology

3.1. Dataset description

The empirical analysis in this present study uses a dataset consisting of patent data and countries macro data. Patent data from 1976 to 2015 are obtained from the United States Patent and Trademark Office (USPTO) database. A total of 4,644,755 patents 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' country classification of income levels. Countries with very few patents are discarded to avoid truncation bias and estimation inefficiencies. The final sample consists of 54 countries. 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. In order to maintain consistency, this study covers only the years 1976 to 2015.

3.2. Dependent variable: Innovation index

Previous studies have proposed that patent data can be used as an indicator of innovation (Hasan and Tucci, 2010; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999). In this study, we devise our dependent variable, innovation index, as a way to measure and indicate the intensity of innovation in a country, by operationalizing the (log) number of patents granted to such country by USPTO. Thus, we can express the index as:

$$Innovation\ index = \begin{cases} \ln\left(\dfrac{1}{N}\displaystyle\sum_{i=1}^{N} K_i\right),\ x > 0 \\ 0,\ x = 0 \end{cases}$$

where K_i represents the number of patents owned by firm i and N is the total number of firms in a country. x is the total count of firms in the country that have more than 1 patent granted in a given year. The higher value of the index implies the higher innovation intensity. To prevent selection bias, countries with zero innovation values in most years are not included in the final 54 countries sample.

3.3. Independent variables

Our key independent variables in this study are the constructed measures of a country's technical international collaboration and technological diversity. Such indicators are computed and cross-examined against the country's innovation index. The two variables are described below.

3.3.1. Collaboration index

We construct a measure for the degree of technical collaboration between a country and other countries based on the number of co-inventing countries per patent. We propose that greater collaboration between countries should have a more positive impact on a country's innovation intensity performance. Our formula for the collaboration index is as follows:

$$Collaboration\ index = \begin{cases} \frac{1}{X}\sum_{j=1}^{X} V_j, & X > 0 \\ 0, & X = 0 \end{cases}$$

where X refers to the total number of patents in a country and V_j denotes the number of countries collaborating in patent j. The minimum value of this measure is 1 for $X > 0$, where 1 indicates that the country in question does not collaborate technically with other countries. A value of zero, on the other hand, indicates that the country has no patented invention as shown by $X = 0$. The higher value of the index means the more open a country to international collaboration. We use the index as our proxy for the degree of international technical collaboration and it is, basically, the average number of co-inventing countries per patent.

3.3.1. Diversity index

Our main indicator of technological diversification is the diversity index, which is adapted from a popular measure of technological diversification used in previous studies (Wang et al., 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 Van Looy et al. (2006). The diversity index is calculated as follows:

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

where P_i represents the share of a country's patents accounted for by the ith field. 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.

3.4. Control variables

To ensure we control for influences of other major drivers of innovation, the following variables are added to our specification models. These variables are selected based on literature review.

3.4.1. *Flow of technical knowledge*

A commonly employed indicator of knowledge flow is patent citation. Under specific circumstances, patent citation can be interpreted as knowledge flow from one invention to another (Duguet and MacGarvie, 2005; Jaffe et al., 1993) and used to identify innovations with breakthrough impacts. Following previous studies (e.g. Nemet and Johnson, 2012; Su and Moaniba, 2017b), we propose that cross-citation (i.e. a form of patent citation that occurs when a patent backward cites patents from other technological domains) has a significant influence on innovation levels and therefore should be controlled. In this study, we compute the cross-citation data for a country by counting the number of patents in such country that used cross-citation.

3.4.2. *Legal protection of technologies and inventions*

Because of the need to protect intellectual property, economic agents often file patents and claim property rights to their inventions. In this context, the number of claims in a patent is considered a good indicator of the level or degree of IP protection in a country. In this study, we use the average number of claims per patent in a country as a proxy for the extent to which a country protects its technologies.

3.4.3. *The size of the economy*

Another important control used 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 a country's economic size. GDP is a well-accepted proxy for economic growth and has been used in many previous studies (Crosby, 2000; Hasan and Tucci, 2010; Su and Moaniba, 2017a).

Apart from all the above reported variables, we also employ a number of dummy and categorical variables to control for country differences such as geographical location (using geographical regions), income class, and the dummy for years after 2011. The statistical details of all our variables are reported in Table 1.

Table 1. Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Max
Country	2,160	27.5	15.58939	1	54
Year	2,160	1995.5	11.54607	1976	2015
Innovation index	2,160	3.860867	2.889115	0	11.51007
Collaboration index	2,160	1.208467	0.586595	0	5
Diversity index	2,160	1.943733	1.21179	0	3.3969
Patent claim	2,160	12.25572	6.72962	0	63
Cross-citation (ln)	2,160	3.645004	3.182303	0	13.23924
GPD per capita (ln)	2,134	9.558416	1.208037	5.573032	11.65271

Region	2,160	3.111111	1.048463	1	5
Income class	2,160	1.333333	0.471514	1	2
Dummy (for year>2011)	2,160	0.1	0.30007	0	1

3.5. 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. To avoid these problems, 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.

Pairwise correlation tests are also carried out. The results in Table 2 indicate some major collinearity issues between collaboration index and patent claim, and diversity index and cross-citation. Other critical tests are performed during and after the estimations. All variables are stationary at first difference with no cointegration found at levels. In summary, heteroskedasticity, autocorrelation, cross-residual dependence, endogeneity, and unit roots are all present in our data. Our solutions to such data issues, including the correlation between collaboration index and patent claim, and diversity index and cross-citation, are discussed in Section 4.2.2.

Table 2. Pairwise correlations

	Variable	1	2	3	4	5	6	7	8	9
1	Innovation index	1								
2	Collaboration index	0.439*	1							
3	Diversity index	0.877*	0.503*	1						
4	Patent Claim	0.436*	0.680*	0.486*	1					
5	Cross-citation	0.930*	0.420*	0.791*	0.461*	1				
6	GDP per capita	0.566*	0.280*	0.569*	0.347*	0.574*	1			
7	Dummy (10year)	0.272*	0.389*	0.254*	0.519*	0.420*	0.189*	1		
8	Dummy (yr>2011)	0.044*	0.117*	0.031	0.148*	0.199*	0.097*	0.447*	1	
9	Country income class	-0.465*	-0.173*	-0.420*	-0.235*	-0.443*	-0.778*	0	0	1

* indicates significance at 95%. GDP per capita is in natural log

4. Empirical analysis and results

The analytical approach we undertake in this study is twofold. First, we use graphs and plots to analyze the trends and current levels of our main variables of interest – innovation index, collaboration index, and diversity index. And second, we employ a number of econometric techniques to explain the trends and current levels found in the first step. To do these, we exploit the integrated patent–macroeconomic country dataset described in Section 3.

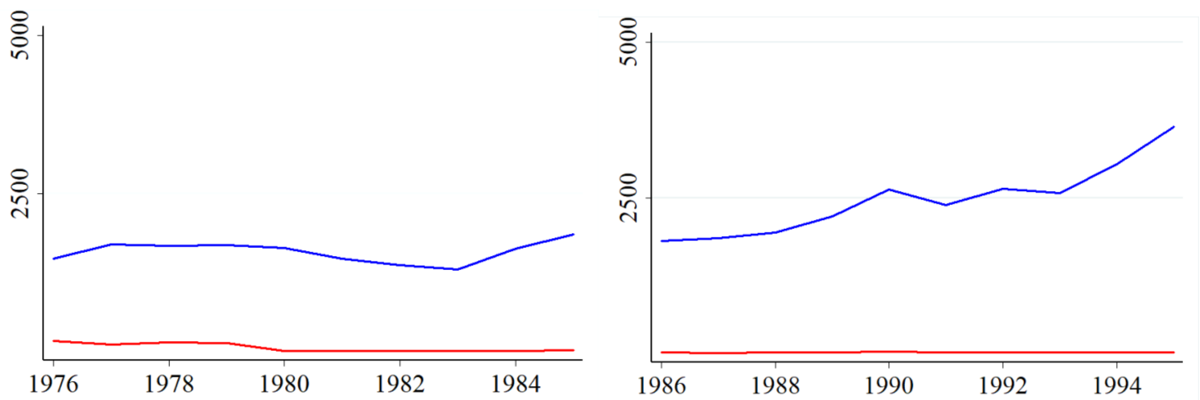
4.1. Trend analysis

Before trying to understand how technological diversity and cross-country technical collaboration are influencing the intensity of innovation in a country, it is crucial to understand first what is going on in that country – in terms of the trends and levels of technological diversity, technical collaboration, and innovation intensity. It is therefore essential to visualize, explore, and analyze the levels of innovation, technological diversity and international collaboration in high-income countries, and compare them with those in non high-income countries. Our perception is that levels of technological diversity, international collaboration, and innovation intensity are significantly different in high-income countries and non high-income countries. In order to do this comparison, we divide up the dataset into two samples: (1) high-income countries data sample, and (2) non high-income countries data sample. Note, the second group combines data for countries that are categorized as low income, lower-middle income, and upper-middle income countries in the 2015 UN's income-class country classification.

There are two important reasons to divide the samples into high-income and non high-hincome countries. First, it will allow us to investigate and confirm our assumption that the levels of international collaboration, technological diversification, and innovation are significantly different across the 54 countries in our sample. Hence, by dividing the sample, we are controlling for these country differences. Second and most importantly, this approach will help us provide broader policy implications to countries from a diverse range of economic backgrounds – i.e., not only highly developed countries but also smaller developing countries.

4.1.1. Innovation levels – 1976 to 2015

Fig. 2 reports the levels of innovation index for the entire 40-year period (i.e. 1976 to 2015). Each plot represents a 10-year period, the blue lines indicate the (average) innovation index level for a high-income country, and the red lines represent (average) level for a non high-income country.



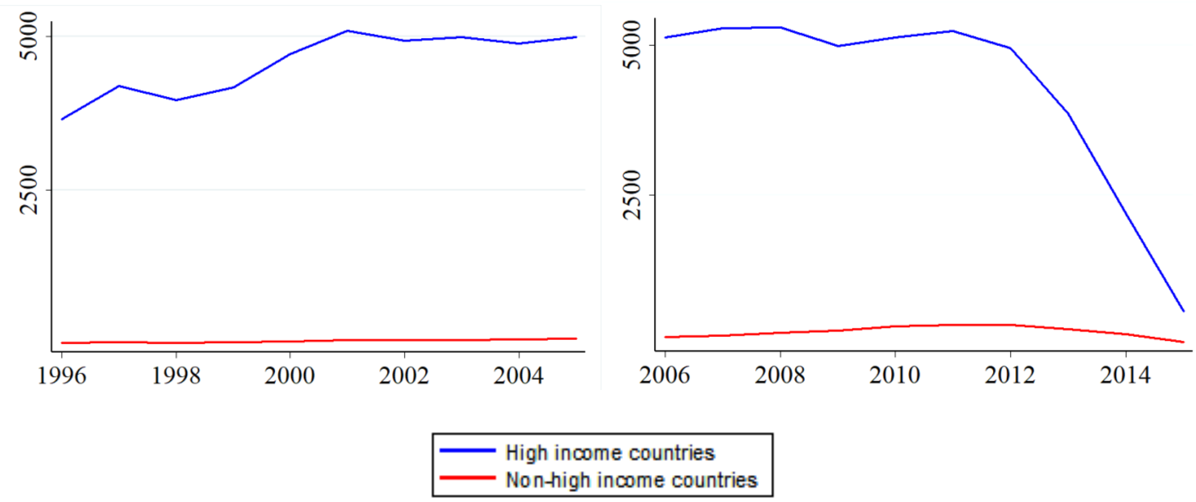
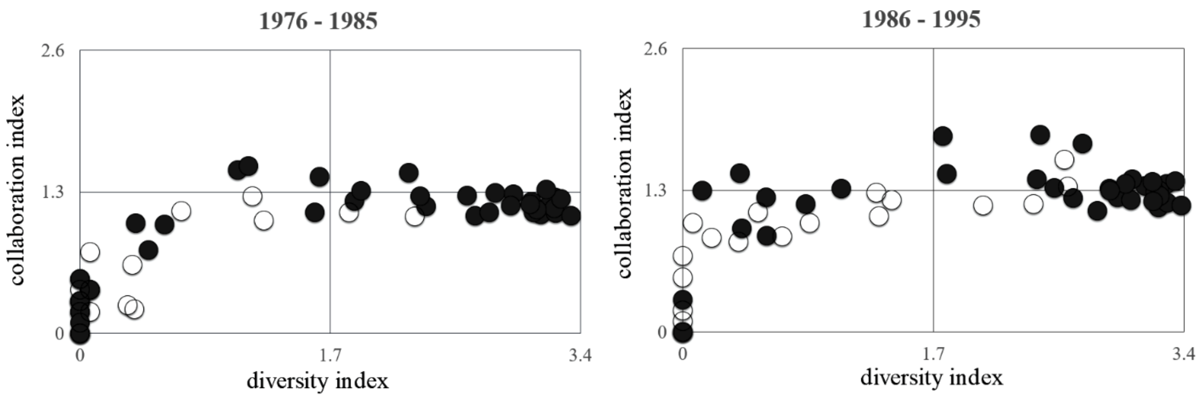


Fig. 2. The innovation indices from 1976 to 2015

As depicted in the graphs, the innovation index in high-income countries is substantially larger than the innovation index in non high-income countries. In addition, both indices for high and non high-income countries are generally increasing over time, except after 2011. This decline is normal reflecting the fact that it often takes a few years before applied patents are accepted by USPTO. The important finding from these graphs is that although levels of innovation index increase, with some fluctuations, the indices for higher-income countries tend to accelerate at a much faster rate compared to those for non high-income countries, especially during the first three decades investigated.

4.1.2. The co-evolution of technological diversification and cross-country collaboration

Fig. 3 presents both the diversity index and collaboration index for the 54 countries from 1976 to 2015. In each graph, the vertical axis labels the collaboration index while the horizontal axis labels the diversity index.



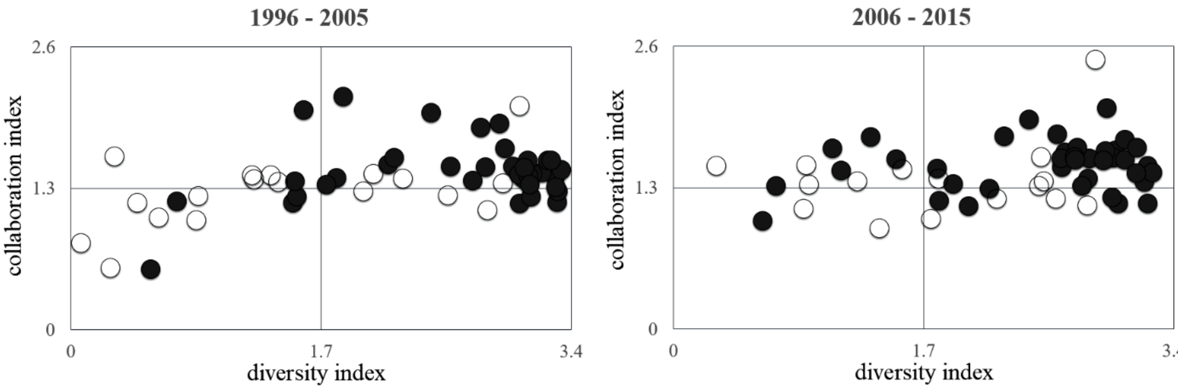


Fig. 3. Diversity and collaboration indices

Solid dots represent high-income countries and white dots represent non high-income countries. Despite the different levels of technological diversity and technical collaboration in countries, the important finding from these plots is that both groups of countries tend to become more open to international technical collaboration and technologically diversified at the same time over the 40-year period. This finding clearly highlights the increasing importance of having diverse technologies in a country and being more technically collaborative.

4.1.3. Correlation patterns between diversity and collaboration

Further to understanding the characteristics of the co-evolution of technological diversity and international collaboration, it would be helpful to explore the statistical correlations between the two throughout the 40-year period. Fig 4 displays plots of the correlation coefficients between collaboration index and innovation index (red line), and diversity index and innovation index (blue line). As depicted in the graphs, the correlations for non high-income countries are relatively higher compared with high-income countries, especially for collaboration index. It is also important to note that the indices are declining over the 40-year period as shown by the negative slopes of the line plots. Furthermore, the correlation between collaboration and innovation declines much faster than the correlation between diversity and innovation, especially for high-income countries. One possible explanation for these patterns relates with the difference in the economic sizes between the two groups of countries and the interactions among their economic variables. With the sophisticated networks and interdependencies between a vast number of economic processes in high income countries, the relationship between diversity and collaboration is probably influenced by many other factors. This could translate into a lower correlation between the two. On the other hand, with less economic activities in non-high income countries, the interaction between diversity and collaboration is much higher.

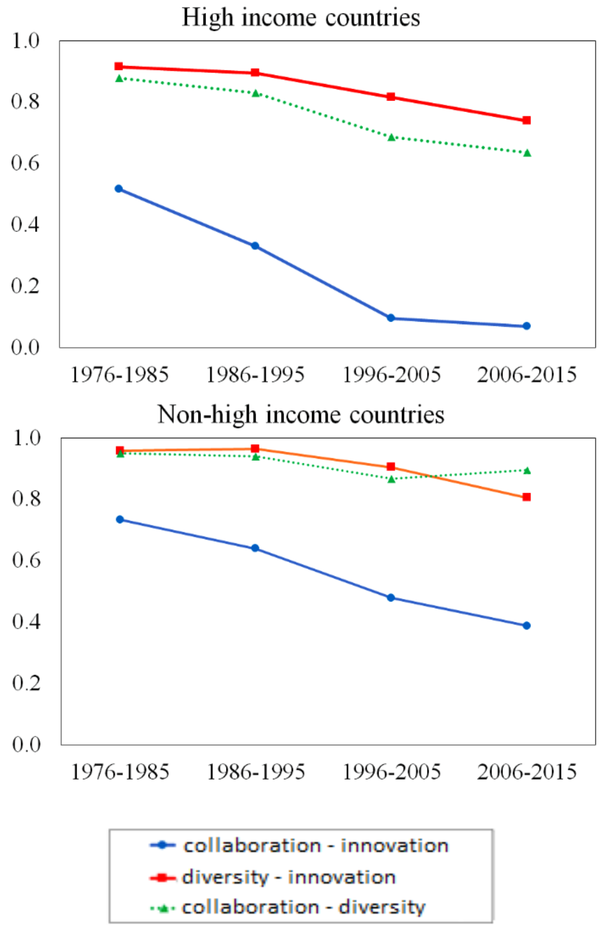


Fig 4. Correlations with innovation index across 10-year periods

4.2. Econometric analysis

Next, in an effort to understand the reasons why countries choose to become technological diversified and internationally collaborative (as found in Section 5.1), we examine the roles technological diversity and international collaboration play in innovation. We theorize that since countries opt to maximize their economic growth through innovation, technological diversity and international collaboration must be strongly associated with higher innovation and economic growth. To test this theory, we carry out a statistical inference analysis by employing several econometric techniques. Our goal is to understand the causal effects of diversity and collaboration on innovation.

Our econometric approach involves two parts discussed in the next subsections. In the first part, we test our hypotheses (in Section 2) by analyzing the *presence* and *directions* of the cause-effects between (1) innovation index and collaboration index, (2) innovation index and diversity index, and (3) collaboration index and diversity index. In the second part, we estimate the magnitudes of the effects of both collaboration index and diversity index on innovation index, taking into consideration the presence and directions of the cause-effects found in the first part.

4.2.1. The Toda–Yamamoto and Dolado and Lutkepohl (TYDL) granger causality test

The most common statistical test for cause-effect is the Granger causality test proposed by Granger (1969). In Granger testing two variables, the first variable is said to granger causes the second variable if its past values contain useful information that help to predict future values of this second variable. However, if the second variable is also found to granger causes the first variable (i.e., has a reverse effect), both variables are endogenous to one another and thus a VAR model is needed to analyze their relationship. On the other hand, if none of the variables granger-causes another, both variables are exogenous to the other and therefore should not be related to one another in the same VAR model. In such case, it may be appropriate to put them in separate models.

Unfortunately, the Granger causality test has a major weakness that can lead to specification bias and spurious regression. Granger causality test is invalid if the variables investigated are non-stationary at levels, regardless of whether they are cointegrated[1] or not (Toda and Yamamoto, 1995). Since our variables are non-stationary at levels, the standard Granger causality test is therefore not applicable.

Our solution is to adopt the Toda and Yamamoto (1995), and Dolado and Lutkepohl (1996) (TYDL) version of the Granger test which calculates a modified Wald test statistic (MWALD) based on augmented VAR modeling. This procedure has been found to be consistent and valid when variables are non-stationary. Furthermore, the TYDL does not require pre-testing for the cointegrating properties of the model and thus can be applied regardless of whether a series is I(0), I(1) or I(2), and whether cointegrated at any arbitrary order. Our baseline specification model for this test is written as follows:

$$Y_{i,t} = \alpha_t + \sum_{\Upsilon=1}^{m=p+d} \beta_{\Upsilon} X_{i,t} + \eta X_{i,t-m} + \gamma Z_{i,t} + \epsilon_{i,t} \tag{1}$$

where the two, $X_{i,\mathrm{t}}$ and $Y_{i,t}$, represent every pair from our three variables of interest – innovation index, collaboration index, and diversity index. $p + d$ indicates the augmented number of lags to use in the test where p is the optimal lag integration order of $X_{i,\mathrm{t}}$ and $Y_{i,t}$ in this VAR model, and d is the highest order of integration in each series, $X_{i,\mathrm{t}}$ and $Y_{i,t}$. $Z_{i,\mathrm{t}}$ denotes exogenous variables

[1] Engel and Granger (1987) defined two or more non-stationary variables as being cointegrated if their linear combination is stationary.

added as controls, α_t is the constant term and $\epsilon_{i,\gamma}$ is the error term. i stands for a country and t for year.

The main difference between the standard Granger causality test and the TYDL are the extra lags used (d in Eq. 1) and the exogenous m^{th} lagged value of $X_{i,t}$ added as a control. This trick is used to fix the test statistic's asymptotic distribution. The optimal lag order of integration p is determined by a selection criteria such as the Akaike information criteria (AIC) (Akaike, 1969), the Bayesian information criteria (BIC) (Rissanen, 1978; Schwarz, 1978), and the Hannan-Quinn information criteria (HQIC) (Hannan and Quinn, 1979).

In order to test the causality of technological diversity and international collaboration on innovation intensity, we conduct three TYDL Granger tests by estimating three pairs of reduced-form VAR models. The first tests causality between collaboration and innovation; the second, between diversity and innovation; and the third, between collaboration and diversity. For details of our model specifications used in these tests, please refer to Appendix B.

Table 3 presents the results of our TYDL Granger tests. Note, the arrows in column two indicates the presence of a cause-effect (or causality) found and the direction of the arrows represents the direction of the causality.

Table 3. TY Granger test results

Variable 1	TYDL G. Causality	Variable 2	N	Chi²	Prob.	Implication
collaboration		innovation	1885	3.151	0.369	
collaboration	←	innovation	1885	10.874	0.012	
diversity	→	innovation	1885	6.956	0.073	both are endogenous
diversity	←	innovation	1885	29.449	0.000	
collaboration	←	diversity	1885	6.618	0.085	
collaboration		diversity	1885	3.383	0.336	

Our results infer that international collaboration does not granger cause innovation and diversity. However, both innovation and diversity granger cause international collaboration. These results imply that causalities between collaboration and innovation, and diversity and collaboration are unidirectional. By comparison, diversity and innovation seem to granger cause one another as shown by their significant Chi^2 values. This bidirectional causal relationship suggests that the two variables are endogenous to each another.

4.2.2. Reduced form VAR model

Up until this stage, we have only revealed patterns and directions of the causal effects of technological diversity, international collaboration, and innovation intensity in our sample countries but has yet to explain the reasons behind them. This final step of our econometric analysis aims to explore these reasons. We propose that one of the main reasons why countries are shifting to a more diversified and collaborative setting is because technological diversification and collaboration lead to a higher intensity of innovation. To test this theory, we estimate the effects of diversity index and collaboration index on our proxy for innovation intensity, innovation index.

Due to endogeneity found in Section 5.2.1 (TYDL tests) and some problems with our data reported in Section 4.2, it is vital to devise an estimation model that can handle such issues. First, because of the bidirectional causality between technological diversity and innovation, problems related with endogeneity may arise. In such case, the most commonly used ordinary linear regression (OLS) is no longer applicable as it will result in biased and inefficient estimates. Second, with heteroskedasticity, autocorrelation, cross-equation dependency, and unit roots found in our data, estimating the relationships using OLS may lead to further bias. To address these problems, we employ a reduced form VAR model with the following baseline specification:

$$\Delta inn_{i,t} = \sum_{l=1}^{L=3} \lambda_l \, \Delta inn_{i,t-l} + \sum_{l=1}^{L=3} \delta_l \, \Delta div_{i,t-l} + \eta \, \Delta coll_{i,t} + \beta \Delta X_{i,t} + \alpha_t + \epsilon_{i,t} \qquad (2)$$

where inn_{it} stands for the innovation index of country i in year t, $div_{i,t}$ for the diversity index of country i in year, and $coll_{i,t}$ for the collaboration index of country i in year t. Following the fact that past values of innovation index are affecting its current values as shown in our results in the previous section, $inn_{i,t-1}$, which represent lagged values of inn_{it} are added to the right-hand side of Eq. 2. This allows us to estimate the effects of innovations in the past on current innovations. $X_{i,t}$ is a vector for our control variables, α_t is the constant term, and $\epsilon_{i,t}$ is the error term. To address problems related with unit roots (i.e. non-stationarity), all variables are in their first order differences – instead of levels.

The above VAR is estimated with the Generalized method of moments (GMM)[2] which is a powerful estimator commonly used with dynamic panel data models where endogeneity is the issue (e.g. in (Su and Moaniba, 2017a); Bertoni et al., 2011; García-Manjón and Romero-Merino, 2012; Yang et al., 2012; Onishi, 2013; Colombo et al., 2013; Dosi et al., 2015). Endogeneity occurs not only when the lagged values of the dependent variable are correlated with the random

[2] Other popular estimators that also use GMM are the "difference GMM" and "system GMM" introduced by Arellano and Bond (1991), and Arellano and Bover (1995) and Blundell and Bond (1998). These estimators are developed for linear estimations. GMM estimators for non-linear relationships are rare and quite difficult to implement. One of these is the quasi-differenced GMM estimator developed by Chamberlain (1992, 1993) and Wooldridge (1997) and often used for panel count data models.

disturbances but also when there is bidirectional causality between the dependent variable and the independent variables. Since the causal relationship between technological diversity and innovation is bidirectional (i.e. they are endogenous to one another), as found in our TYDL Granger tests in the previous subsection, endogeneity may cause bias in our estimation.

Using a reduced form VAR solves the endogeneity problem by simultaneously estimating each of the two endogenous variables on the other (Sims, 1980). Technically, this involves two equations. The first equation, Eq. 2, is the one we are interested in since it relates diversity (as well as collaboration and other factors) to innovation. The second is the opposite. It models innovation (among other variables) to diversity and thus takes this form:

$$\Delta div_{i,t} = \sum_{l=1}^{L=3} \lambda_l \, \Delta div_{i,t-l} + \sum_{l=1}^{L=3} \delta_l \, \Delta inn_{i,t-l} + \eta \, \Delta coll_{i,t} + \beta \Delta X_{i,t} + \alpha_t + \epsilon_{i,t} \tag{3}$$

where all variables are the same as in Eq. 2. Both equations use the lagged values of the endogenous variables as instruments.

Our results for Eq. 2 are reported in Table 4. Due to some data collinearity issues discussed in Section 3.5, estimating all our variables in a single model may lead to biased results. To prevent this, highly correlated variables are estimated in separate models – A, B, C, and D.

Table 4. Vector Autoregression Results

	Dependent variable: innovation index			
	(A)	(B)	(C)	(D)
Innovation index (t-1)	-0.1787***	-0.1862***	-0.0678	-0.1834***
	(-3.9170)	(-4.2333)	(-1.0633)	(-4.0524)
Innovation index (t-2)	0.0880+	0.0772	0.1808*	0.0748
	(1.7001)	(1.5488)	(2.3846)	(1.4399)
Innovation index (t-3)	0.0547	-0.0000	0.1205+	0.0426
	(1.1407)	(-0.0005)	(1.7744)	(0.8879)
Diversity index (t-1)	-0.1370*	-0.0971+	-0.1455+	-0.1408**
	(-2.5141)	(-1.8428)	(-1.8979)	(-2.6246)
Diversity index (t-2)	-0.1697**	-0.1048+	-0.1642+	-0.1863**
	(-2.7982)	(-1.8108)	(-1.9147)	(-3.1117)
Diversity index (t-3)	-0.0458	-0.0160	-0.0555	-0.0402
	(-0.8264)	(-0.3063)	(-0.6778)	(-0.7285)
Collaboration index	0.3231***		0.3342***	0.3131***
	(10.0744)		(8.0287)	(9.9079)
Patent claim		0.0309***		
		(9.4945)		
GDP per capita (ln)			-0.0994	
			(-0.0927)	

Cross-citation (ln)				0.0688***
				(3.3885)
10year period	0.0565***	0.0615***	0.0511+	0.0592***
	(3.5842)	(3.8911)	(1.8532)	(3.7571)
Dummy (year>2011)	-0.8587***	-0.8556***	-0.8120***	-0.8573***
	(-19.0856)	(-19.8129)	(-10.0065)	(-19.0352)
N	1836	1836	1831	1836

t statistics in parentheses. Year dummies included in all regressions. All variables, except dummy and categorical variables, are in their first differences.
+ $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

As reported in the results, the coefficients of innovation are mostly significant but surprisingly negative in t-1 implying that innovations from the year before are hindering innovations in the current year. However, the coefficient signs change to positive in t-2 and t-3 suggesting that innovations from two and three years back are positively influencing the intensity of innovation in the current year. Of our two main variables of interest, diversity also shows unexpected negative results across all four models for the first two year lags, A to D. This could imply that the more diverse technologies in the past the harder it would be for countries to innovate. By contrast, coefficients for collaboration index are all positive and highly significant suggesting that a country's openness to technical international collaboration will boost up its domestic production of new inventions.

Similarly, two of our main control variables also have positive and significant results. The first one states that the number of invention claims protected by a patent positively influence future innovations. This result is quite reasonable given most inventors' needs to protect their inventions and hence often relocate to countries where protection is guaranteed. Cross-citation, on the other hand, also has a positive coefficient indicating that the flow of technical knowledge across different technology domains plays a vital role in innovation. This result supports previous studies such as (Su and Moaniba, 2017b). Surprisingly, contemporaneous changes in GDP per capita and innovation index, as indicated by the non-significant coefficient, do not seem to influence each other. Our perception is that production is expensive and often takes years before it can generate returns. To reaffirm this finding, we remove the GDP per capita variable from all four models (A, B, C, and D) and re-estimate them. The results, provided in Table C.1 in Appendix C, are not different from those in Table 4.

Note, since the focus of this paper is on the effects of technological diversity (and collaboration) on innovation (Eq. 2), the reverse, represented by Eq. 3 is irrelevant. For this reason, all results for Eq. 3 are not provided however are available upon request.

4.2.3. Robustness – Different time periods and income groups

To ensure our results and key findings in the previous sub-section are robust under different scenarios, we conduct two additional estimation analyses. The goal is to test the effects of collaboration and technological diversity on innovation while controlling for two important factors – 1) the difference in income levels across countries in our sample, and 2) the differences in technological and economic advancements across different time periods.

So far, we have been analyzing the effects of technological diversity and international collaboration on innovation for the entire 40-year period, 1976-2015. To isolate the effects countries have gone through and explain their behaviors in each era (discussed in Section 5.1), we conduct an extended cause-and-effect analysis by comparing the two groups of income class countries (i.e., high-income countries versus non high-income countries) for each 10-year period or decade. In doing so, we are controlling for the differences in economic sizes across countries in our sample. Furthermore, grouping the samples into 10-year periods also allow us to control for any economic shock such as the great recession in the late 2000(s) and the series of major technological advancements in each 10-year period. To do this, we repeat our simultaneous VAR estimations of Eq.2 and Eq.3 but this time imposing restrictions on the income group of countries and the ten-year periods. Similarly, since we are only interested in the effect of technological diversity (and international collaboration) on innovation, a relationship captured by Eq.2, all results for Eq.3 are not provided again. Note, the word "results" refers to the results of Eq.2 only hereafter.

Table 5. VAR results by 10-year periods for high-income

	Dependent variable: innovation index				
	1976-1985	1986-1995	1996-2005	2006-2015	All 40 years
Innovation index (t-1)	-0.2512*	-0.1533*	-0.1247	1.1948***	0.8033***
	(-2.5056)	(-2.0360)	(-1.4435)	(6.9550)	(6.7514)
Innovation index (t-2)	-0.2113*	0.1153	0.0989	0.8312***	0.9792***
	(-2.0142)	(1.3552)	(1.3214)	(4.0181)	(6.6734)
Innovation index (t-3)	-0.0720	0.0434	-0.0963	0.9468***	0.5764***
	(-0.7073)	(0.4420)	(-1.1391)	(4.8467)	(4.5888)
Diversity index (t-1)	0.0239	-0.1662+	-0.1811*	-0.4298	-0.8378***
	(0.2106)	(-1.7604)	(-2.0050)	(-1.3505)	(-5.8444)
Diversity index (t-2)	-0.0030	-0.3520***	-0.0432	-0.1739	-0.8274***
	(-0.0242)	(-3.5066)	(-0.4860)	(-0.5947)	(-5.1093)
Diversity index (t-3)	0.2282+	-0.1098	0.0095	-0.5899*	-0.5307***
	(1.6466)	(-0.8592)	(0.1029)	(-2.4349)	(-3.8649)
Collaboration index	0.1735**	0.1041+	0.2700**	0.5004*	0.4463***
	(3.2598)	(1.7606)	(3.0713)	(2.3737)	(5.8451)
Patent claim	0.0190**	0.0362***	0.0086	0.0291*	0.0125+
	(3.1474)	(8.0152)	(1.1951)	(2.4727)	(1.8907)
Cross-citation (ln)	0.1062*	0.0428	-0.0551	0.1221*	0.0629
	(2.0568)	(1.0887)	(-1.2197)	(2.1879)	(1.6198)

10year period	-0.0121	-0.1039***	-0.3607***	0.0000	-0.0990***
	(-1.0643)	(-8.6407)	(-11.7505)	(.)	(-5.1196)
Dummy (year>2011)				-0.1680*	
				(-2.1192)	
N	180	360	360	324	1224

t statistics in parentheses. Year dummies included in all regressions. All variables, except dummy and categorical variables, are in their first differences.
+ $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

The results for high-income countries and non high-income countries are presented in Table 5 and Table 6, respectively. Overall, these results are consistent with those reported in Table 4. The only, and interesting exception is the change in signs of the coefficients of innovation index from mostly negative (in Table 4) to all positive (in both Table 5 and 6). This result suggests that past innovations help initiate and advance current innovation activities: another empirical evidence supporting the economics of scope theory and resource based view (RBV) theory (Wernerfelt, 1984). Such theories emphasize the role of cost minimization through capitalizing on the same existing resources (in this case, past inventions) to produce a variety of different products (such as new inventions or innovations).

Table 6. VAR results by 10-year periods for non high-income countries

	Dependent variable: innovation index				
	1976-1985	1986-1995	1996-2005	2006-2015	All 40 years
Innovation index (t-1)	-0.4020**	-0.2523*	-0.2693**	-0.1034	0.1278
	(-3.2874)	(-2.1776)	(-2.9720)	(-0.8162)	(0.9355)
Innovation index (t-2)	0.0272	-0.1310	-0.0147	0.1419	0.4157**
	(0.1777)	(-0.8971)	(-0.1604)	(0.8591)	(2.6636)
Innovation index (t-3)	0.0859	-0.1126	0.1027	-0.2518+	0.1810
	(0.6598)	(-1.0110)	(1.1375)	(-1.8308)	(1.6090)
Diversity index (t-1)	-0.0123	-0.1051	-0.1947*	0.1056	-0.3308*
	(-0.0562)	(-0.6355)	(-2.0281)	(0.6790)	(-2.0273)
Diversity index (t-2)	-0.3867*	0.1889	-0.2102*	0.0549	-0.3285+
	(-2.0022)	(1.1821)	(-2.0358)	(0.3306)	(-1.9584)
Diversity index (t-3)	-0.1845	0.1419	-0.1720	0.4268**	-0.1258
	(-0.9378)	(1.0587)	(-1.5908)	(2.7535)	(-0.9562)
Collaboration index	0.3001***	0.2585***	0.2787***	0.0977	0.2723***
	(3.4894)	(3.5483)	(4.2138)	(0.9186)	(4.5978)
Patent claim	0.0108	0.0218**	0.0219***	0.0216*	0.0293***
	(1.4874)	(2.7266)	(4.3157)	(2.3657)	(5.6529)
Cross-citation (ln)	-0.0182	0.1208*	0.0542+	0.0763	0.1121**
	(-0.2255)	(2.2489)	(1.6772)	(1.5682)	(2.9575)
10year period	0.0287	-0.0494+	-0.3243***	0.0000	-0.1350***

	(1.4005)	(-1.9566)	(-8.1531)	(.)	(-4.0824)
Dummy (year>2011)				-0.5821***	
				(-5.6049)	
N	90	180	180	162	612

t statistics in parentheses. Year dummies included in all regressions. All variables, except dummy and categorical variables, are in their first differences.
+ $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

4.3. Further discussions and implications of the results

In summary, our study finds that although there seems to be no significant long-term effect of international collaboration on innovation as indicated by the results in Table 3 (i.e., the granger effects of international collaboration from the lag years 1-3), its short-term effect (i.e., the effect of the current year) is generally significant and positive. This short-term effect is indicated by the positive and mostly significant coefficients for international collaboration in Tables 4, 5, and 6. These results provide us with empirical evidence that international collaboration is contributing positively to a country's innovation performance, in the short term. However, this finding on the short-term effect does not support our first hypothesis H1a.This finding possibly relates to the fact that the more people involved in a collaborated invention, the more knowledge and skills integrated that could help produce inventions of higher quality. By comparison, our results shown in Table 3 also show that innovation granger-causes international collaboration. Not reported in the table is the coefficient for the innovation index when regressed on collaboration index is 0.2669762. This result, which supports our second hypothesis H1b, suggests that a country's innovation outputs from the past three years positively influence its level of engagement in international collaborations in the present year. This is not surprising given that higher innovation performance often leads to higher income and returns that in turn could be spend on more collaboration activities.

Furthermore, although the coefficients for technological diversification collaboration is not always significant, the majority of them are significant and negative as can be seen in Table 4, 5, and 6. Theoretically, this means that our third hypothesis H2a is supported confirming our theoretical expectation that there is a negative causal effect, both short term and long term, of technological diversification on a country's level of innovation output. In contrast, there is also a statistically significant but positive reverse-effect from innovation to diversification as reported in Table 3 and Table 4-6. This finding supports our fourth and last hypothesis H2b which states that a country's innovative capability stimulates its technological diversification efforts.

The above findings imply that our theory in which we claim that both diversification and collaboration are important drivers of innovation might not be true. International collaboration seems to be the only one that contributes positively to a country's innovation performance. One possible explanation for this is the lack of control from governments on firms' technological diversification activities. Previous studies have shown that diversification is vital for a firm's survival and competitive advantage, which is why firms have chosen to diversify their products and services over the 40-year period. Collectively, it has resulted in diverse technology bases for countries as observed in Fig 3. A mass scale of firms engaging in technological diversification in a country could lead to a decline in economic growth or a country's gross domestic product, i.e., GDP (Moaniba et al., 2018b). This is possible related with the excess supplies in certain markets and industries caused by a huge proportion of firms in a country diversifying their technological outputs. In such case, certain markets are likely to fail or become inefficient. With market failures, firms' revenues will go down which later could affect their innovative capabilities. Thus, for a country as a whole, the more of its firms affected by over-diversification, the lower its innovation performance. One important policy implication from this is for governments to take responsibility in controlling firm-level diversification activities.

Finally, to ensure our results are robust, all regressions are repeated multiple times. First, with diversity and collaboration variables regressed in separate models. This is done to control for the lagged effects of diversification on international collaboration as indicated by our TY-Granger causality test results in Table 3. The results (not shown here but available upon request) are consistent with those reported in Table 3, 4, 5, and 6 – even though the number of significant coefficients are much less especially for diversity index while the number of coefficients for collaboration index that are significant increases. Second, all regressions are again repeated with a smaller sample. This sample consists of 49 countries and covers a span of only 20 years (from 1994 to 2013). The goal in reducing the sample size is to completely remove any country with zero innovation index in any given year. In this way, we eliminate any possibility of a selection bias or truncation bias. Despite not getting an endogenous relationship between innovation and diversification when using this smaller sample, the results still support our key findings that diversification has a negative effect on innovation whereas collaboration has a positive effect.

5. Conclusion

This paper brings fresh insights to the existing innovation management-economics literature on drivers of innovation by exploring the relationship between the co-evolutionary dynamics of technological diversity and international collaboration on innovation. Although literature has converged on the positive link between international collaboration and innovation performance (Giuliani et al., 2016), the role of technological diversification in innovation is still unclear. If fact, existing evidence for both the impact of innovation on technological diversification (Baysinger and Hoskisson, 1989; J. Miller, 2004; Silverman, 1999), and the impact of diversification on innovation (Rogers, 2002) has raised concerns on the possibility of a simultaneity and endogeneity between the two, which has been neglected by the majority of previous related studies. The importance of taking this possibility into account is vital to eliminate estimation bias (J. Miller, 2004; Shaver, 1998). This paper aims to address this concern by providing one of the first empirical evidence on the causal effects of international collaboration and technological diversification on innovation, taking into consideration the endogeneity issue. The empirical objectives of this paper are: (1) to assess the direction of the causal effects of technological diversification and international collaboration on innovation, and (2) to analyze the size of such effects of technological diversity and international collaboration on innovation.

In a nutshell, we find evidence that over the course of the 40 years, both high income and non-high income countries have tended to shift into a more diversified and collaborative technological setting. Our TYDL tests show that while international collaboration and innovation intensity have a unidirectional causal relationship, the intensity of innovation in a country and technological diversity are endogenous to one another. This bidirectional cause-and-effect relationship exemplifies the complicated nature of most economic variables and thus requires extra care when analyzing them. Consequently, we estimate the causal effects of collaboration and diversity on innovation using a simultaneous VAR. Our findings support the broad conjecture stemming from the existing theories of economics and innovation management literature, to which some of the primary drivers of innovation are reversely affected by innovation creating sophisticated economic relationships.

5.1. Contribution to theory and policy implication

The paper contributes to the analysis of the drivers of innovation and the ensuing dynamics of technological diversity and international collaboration by investigating the developments of the innovative behaviors of countries, and the complexities in the triple helix nature of innovation-diversity-collaboration. Specifically, by analyzing the relationships between the diversity of technologies in a country and its openness to international collaboration, and how they have co-evolved and influenced innovation. International collaboration and technological diversification have been investigated quite extensively in the past, but separately. We believe this present study is one of the first attempts to explore the possibility of a special link between technological diversity and international collaboration. For instance, for one, we have provided the answer to the mystery of why countries that engage heavily in international collaborations tend to also diversify their technologies, especially high income countries. As discussed in our results section, there seems to be a granger-causality effect of diversification on collaboration. In other words, as more firms in a country engage in diversification, they are likely to end up collaborating with firms from other countries in subsequent years (indicated by the lagged causal effects). As a result, the levels of diversification and international collaboration in a country always seem to go hand in hand. However, it is important to note that international collaboration on the other hand does not have a granger causal effect on diversification. Second, our empirical results vindicate past studies' findings and existing well-known management and economics theories. For instance, the positive impacts of past innovations on present and future innovation activities found in this study provide new empirical evidence supporting the theory of economics of scope and resource base view theory (Wernerfelt, 1984). These theories relate how cost minimization through capitalizing on the same existing resources (in this case, past inventions) is imperative for a firm's survival. As evidenced in this present study, the impacts of innovations from past years on innovation in the current years tend to grow from negative to positive over the last 40 years. This is an interesting phenomenon that has never been observed or made known before. This finding is another important contribution of our study to the current scholarly understanding on the drivers and dynamics of innovation by highlighting the possibility that technology nowadays is getting more effective and last longer than those in the previous decades.

The essential policy implication that can be drawn based on these findings is the need for technological specialization by countries. Even though technological diversification may be essential for firms in expanding their products range and markets penetration, a mass scale of firms engaging in technological diversification in a country may lead to the country's decline in innovation performance, and therefore to economic inefficiency. The negative causal impacts of diversification on innovation for countries found in this study indicates the need for countries to concentrate their innovations within a smaller range of technology domains. Based on our findings, we argue that countries, through their governments, should regulate the diversification activities of firms by making sure that only a certain proportion of them should be allowed to do so – i.e., to ensure that the majority of firms do not diversify their technologies. This can be done through subsidies by which governments should prioritize allocating their subsidies to firms that engage more in technological specialization. Moreover, findings from our trend analysis show diversification is common with non-high income countries. As countries become richer, they tend to focus more on specialized areas of technology.

5.2. Limitations and future research directions

Our study has some limitations. First, due to data unavailability, we cannot control for nor investigate some major drivers of innovation such as the size of the market demand for new innovations in a country. Second, despite the use of patent count as a proxy for innovation in many innovation management and economics studies, it represents only a fraction of the intensity of innovation in a country. Hence, our general results might underestimate the extent of the phenomenon. Second, while cross-border co-invention is commonly used as a quantitative measure for international technical cooperation, it is occasionally criticized for its inability to fully reflect cross-border knowledge-intensive collaboration. Moreover, such co-inventions are mainly the outcome of labor mobility or consultancy work only (Bergek and Bruzelius, 2010). Therefore, by using the number of inventors per patent in the construction of our collaboration index, we might underestimate the actual effect of international technological collaboration on innovation. Third, we cannot adequately validate the accuracy of how USPTO categorizes its patents.

Based on some of the crucial findings of this study, there are several potential research topics that could be explored either as extensions to this study or as diverted research streams. These include the following: 1) examining how other social and technological drivers of innovation (that are not included in Fig 1) influence innovation intensity; 2) extending the study to examine how the sophisticated and co-evolutionary dynamics of diversity and cross-country technical collaboration affect economic growth; and 3) narrowing down the scope to selected technological industries, countries or geographical regions

Appendix A. Countries investigated in this study

Table A.1. The 54 countries covered in this study

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

Appendix B. TYDL Granger test models

To apply the Toda–Yamamoto and Dolado–Lutkepohl (TYDL) version of the Granger non-causality test, we devise and estimate the following three pairs of simultaneous VAR models. The first test the causality effect between innovation and international collaboration and is expressed as follows:

$$Inn_{i,t} = \sum_{j=1}^{k+s} \gamma_j Inn_{i,t-1} + \beta Inn_{i,t-k+s} + \sum_{j=1}^{k+s} \omega_j Coll_{i,t-1} + \lambda Coll_{i,t-k+s} + \alpha_t + \epsilon_{i,t} \qquad (1a)$$

$$Coll_{i,t} = \sum_{j=1}^{k+s} \eta_j Coll_{i,t-1} + \Omega Coll_{i,t-k+s} + \sum_{j=1}^{k+s} \delta_j Inn_{i,t-1} + \varphi Inn_{i,t-k+s} + \alpha_t + \epsilon_{i,t} \qquad (1b)$$

where $Inn_{i,t}$ denotes our innovation index for country i in year t and $Coll_{i,t}$ denotes collaboration index for country i in year t.

Our second model tests the causality between innovation and technological diversity and is written as follows:

$$Inn_{i,t} = \sum_{j=1}^{k+s} \gamma_j Inn_{i,t-1} + \beta Inn_{i,t-k+s} + \sum_{j=1}^{k+s} \omega_j Div_{i,t-1} + \lambda Div_{i,t-k+s} + \alpha_t + \epsilon_{i,t} \qquad (2a)$$

$$Div_{i,t} = \sum_{j=1}^{k+s} \eta_j Div_{i,t-1} + \Omega Div_{i,t-k+s} + \sum_{j=1}^{k+s} \delta_j Inn_{i,t-1} + \varphi Inn_{i,t-k+s} + \alpha_t + \epsilon_{i,t} \qquad (2b)$$

where $Inn_{i,t}$ denotes our innovation index for country *i* in year *t* and $Div_{i,t}$ denotes diversity index for country *i* in year *t*.

The third and last TYDL VAR model that we estimate to test the causal relationship between technological diversity and international collaboration is specified as follows:

$$Div_{i,t} = \sum_{j=1}^{k+s} \gamma_j Div_{i,t-1} + \beta Div_{i,t-k+s} + \sum_{j=1}^{k+s} \omega_j Coll_{i,t-1} + \lambda Coll_{i,t-k+s} + \alpha_t + \epsilon_{i,t} \qquad (3a)$$

$$Coll_{i,t} = \sum_{j=1}^{k+s} \eta_j Coll_{i,t-1} + \Omega Coll_{i,t-k+s} + \sum_{j=1}^{k+s} \delta_j Div_{i,t-1} + \varphi Div_{i,t-k+s} + \alpha_t + \epsilon_{i,t} \qquad (3b)$$

where $Div_{i,t}$ represents diversity index for country *i* in year *t* and $Coll_{i,t}$ represents collaboration index for country *i* in year *t*.

Appendix C. More results reduced-form VAR estimation results

Table C.1. Results of Vector Autoregression (without GDP)

	Dependent variable: innovation index		
	(1)	(2)	(3)
Innovation (t-1)	-0.1787***	-0.1862***	-0.1834***
	(-3.9170)	(-4.2333)	(-4.0524)
Innovation (t-2)	0.0880+	0.0772	0.0748
	(1.7001)	(1.5488)	(1.4399)
Innovation (t-3)	0.0547	-0.0000	0.0426
	(1.1407)	(-0.0005)	(0.8879)
Diversity (t-1)	-0.1370*	-0.0971+	-0.1408**
	(-2.5141)	(-1.8428)	(-2.6246)
Diversity (t-2)	-0.1697**	-0.1048+	-0.1863**
	(-2.7982)	(-1.8108)	(-3.1117)
Diversity (t-3)	-0.0458	-0.0160	-0.0402
	(-0.8264)	(-0.3063)	(-0.7285)
Collaboration	0.3231***		0.3131***
	(10.0744)		(9.9079)
Patent claim		0.0309***	
		(9.4945)	

Cross-citation (ln)			0.0688***
			(3.3885)
10year period	0.0565***	0.0615***	0.0592***
	(3.5842)	(3.8911)	(3.7571)
Dummy (year >2011)	-0.8587***	-0.8556***	-0.8573***
	(-19.0856)	(-19.8129)	(-19.0352)
N	1836	1836	1836

t statistics in parentheses. All variables, except dummy variables, are in their first differences
+ $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

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