Does research output cause economic growth or vice versa? Evidence from 34 OECD countries

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Abstract: The causal relation between research and economic growth is of particular importance for political support of science and technology as well as for academic purposes. This paper revisits the causal relationship between research papers published and economic growth in OECD countries for the period 1981-2011, using bootstrap panel causality analysis, which accounts for cross-section dependency and heterogeneity across countries. Our empirical results support unidirectional causality running from research output (in terms of total number of papers published) to economic growth for the US, Finland, Hungary, and Mexico; the opposite causality from economic growth to research papers published for Canada, France, Italy, New Zealand, UK, Austria, Israel, and Poland; and no causality for the rest of the countries. Our findings provide important policy implications for research policies and strategies for OECD countries.

Introduction

Past studies (King, 2004; Vinkler, 2008; Lee et al., 2011) examining the relationship between the growth of an economy measured by the country's gross domestic product (GDP) and the country's research output measured by scientometric indicators have concluded that there is some evidence for the existence between them. The scientometric indicators employed may refer to the quantity (number of journal papers) or specific quantity (number of papers per capita) or total impact (total number of citations) and specific impact (citations per paper) of the scientific information published. However, these studies do provide ambiguous conclusions as to the exact direction of causality, i.e. whether GDP promotes research output or vice versa. This difference in the existence and direction of the causality can be attributed to different time periods examined, dissimilar academic and research systems but also as Lee et al. (2011) mention, the different stages in a country's growth and development.

The aim of this paper is therefore to re-investigate the causal relationship between research output and economic growth in OECD countries over the period of 1981-2011 using the bootstrap panel Granger causality test. The paper differs from previous studies in three novel ways. Firstly, we focus solely on the OECD countries. The OECD group consists of quite homogenous economies with similar levels of growth and development – with a few exceptions – however with a variety of socioeconomic characteristics. Secondly unlike previous studies we take into account the possible existence of cross-sectional dependency and heterogeneity across these countries. Ignoring cross-section dependency may lead to serious bias and size distortions (Pesaran, 2006), implying that testing for the cross-section dependence is a necessary step in a panel data analysis. Lastly, by focusing on country-specific analysis, we apply panel causality approach which is able to examine cross-state interrelations and country-specific heterogeneity. With this approach, possible bias from converting non-stationary variables by differences are avoided since the testing procedure does not require stationary variables.

The rest of the paper is organized as follows. Section 2 briefly discusses local and international literature on the empirical evidence on the relationship between research and economic growth. In section 3 the methodology of the bootstrap panel Granger causality test proposed by Kónya (2006) is presented. Section 4 presents our empirical results and the policy implications of our empirical findings are discussed in the last section.

Literature review

The study of the impact of improved skilled human capital on the economic growth and development has not been recently examined in the literature. Romer (1986) found that higher levels of average knowledge stock end up in higher productivity levels. The topic has engaged many researchers conducting more theoretical approaches (Romer, 1986; Lucas, 1988 Tamura, 1991; Schumpeter, 2000) and applied approaches (Price, 1978; Kealey, 1996; De Moya-Anegon and Herrero Solana, 1999; King, 2004; Fedderke, 2005; Fedderke and Schirmer, 2006; Vinkler, 2008; Lee et al., 2011; Shelton and Leydersdorff, 2011; Inglesi-Lotz and Pouris, 2013; Inglesi-Lotz et al. 2013) to show that the accumulation of knowledge is a significant factor to improve the human capital. In a microeconomic sense, the economic productive capacity of a company gets improved by these positive knowledge externalities. On the other side, macroeconomically, an improvement in the quality of the labour through knowledge is advantageous to a country's innovation levels, economic growth and development.

Even though there is great interest in empirical analysis to identify possible consistent causal relationships between scientometric indicators and the GDP, the exact nature of the link has not been clarified so far. Price (1978) and Kealey (1996) in their own separate explorations both found a linear correlation between GDP and scientometric indicators of different countries. De Moya-Anegon and Herrero-Solana (1999) found significant correlation between the GDP of 19 Latin-American countries and the number of their articles in journals referenced by the Science Citation Index (SCI) of the Institute for Scientific Information (ISI) for the period 1991 to 1997. King (2004) examined historical data and found an exponential relationship between number of research articles published and the economic performance for OECD countries for the period 1993 to 2002.

Vinkler (2008) found significant discrepancies in the ratio and relative impact of the journal papers of several scientific fields of some Central and Eastern European countries compared to the European Union member states, the US and Japan. For European Community member states, the US and Japan countries correlation between the GDP and number of publications of a given year proved to be non-significant. Longitudinal studies conducted by Vinkler (2008) showed significant correlations between the yearly values of GDP and number of papers published. Studying data referring to consecutive time periods revealed that there is no direct relationship between the GDP and information production of countries. As Vinkler (2008) suggested it may be assumed that grants for Research & Development (R&D) do not actually depend on the needs of the market but they differ among countries due to the fact that high income countries can afford spending more rather than low-income countries. Sorenson and Fleming (2004) gave a comprehensive survey of the literature on relations of basic science and technological innovation. Their analysis of the patterns of citations from patents strongly implicates publication as an important mechanism for accelerating the rate of innovation.

Lee et al. (2011) in a recent study used quantitative time series analysis to determine the nature of causal relationships between research output and economic growth for the period 1981 to 2007. The results showed that there is mutual causality between research output and economic growth in developing Asian countries but causality in the developed Western countries was not clear. Lee et al. (2011) emphasized that the most important issues for any nation's science policy are research priorities and the efficiency of R&D investment and its relation to GDP. These empirical findings had policy significant implications for developing countries when deciding on how to direct their research investment: towards education, infrastructure and engineering, or more towards fundamental science. However, Lee et al. (2011) used single country analyses for 25 observations in a Vector Autoregressive (VAR) framework, and consequently, the results are likely to suffer from small-sample bias due to the small number of available degrees of freedom, unless some bootstrapping procedures were used to obtain critical values for the tests.

Inglesi-Lotz et al. (forthcoming) applied the bootstrap panel Granger causality approach to test the causal link between accumulated knowledge measured as the research performance of the country and proxied by the research papers of a country as a percentage share to the world and economic growth using data from the BRICS countries (i.e., Brazil, Russia, India, China, and South Africa) over the period of 1981-2011. Their results showed no causality for Brazil, Russia, China and South Africa and a positive feedback relationship for India.

Another part of the specific literature conducted single-country analysis. For example, Inglesi-Lotz and Pouris (2013) focused on the South African case for the period 1980 to 2008.

The authors examined the relationship between research output – measured by the comparative advantage of the country to the rest of the world – and economic growth (GDP) by making use of the ARDL method. The results showed that the comparative performance of the academic research output in South Africa could be considered as a factor affecting the economic growth of the country and the opposite didn't hold. After estimating several different linear regression models for 46 countries around the world, Jin and Jin (2013) found that research publications had positive and significant effects on economic growth for the period 1973 to 2003. However, it should be noted that the findings by Jin and Jin (2013) might overestimate the growth effect of research publications on economic growth due to the omitted variables and a reverse causality from GDP to research publications will be another problem. The endogeneity problem will be mitigated if the direction of causality was well defined.

Table 1 summarises the results of these studies.

Table 1: Results from selected studies

Study	Country	Methodology	Results
De Moya-Anegon and Herrero- Solana (1999)	Latin American countries	Indicators analysis	Research output is directly proportional to input indicators.
Vinkler (2008)	Central and Eastern European countries, EU, US and Japan.	Analysis of Mean Structural Difference	No causality/ correlation for EU, US and Japan.
Lee et al. (2011)	25 developed and developing countries	Granger causality single country analysis	No causality in the Western economies while bidirectional causality exists for the Asian countries.
Inglesi-Lotz et al. (forthcoming)	BRICS	Panel causality	No causality in any direction in Brazil, Russia, China and South Africa but positive bidirectional relationship in India for the years 1980-2011
Inglesi-Lotz and Pouris (2013)	South Africa	ARDL	Research output (%share to the world) Granger causes positively economic growth in 1980-2008; no opposite relationship

Contrary to these previous empirical papers that examine the relationship between research output and economic growth using data on individual country, we employ here panel Granger causality techniques for a panel of OECD countries. This approach is methodologically superior to single country analysis, particularly when considering the high degree of globalization, international trade and financial integration of the OECD countries. An economic shock in one country is likely to affect the other countries and hence, cross-sectional dependency may play important role in detecting causal linkages for OECD countries.

Methodology and data

Preliminary analysis.

One important issue in a panel causality analysis is to take into account possible cross-section dependence across countries. This is because high degree of globalization, international trade and financial integration make a country to be sensitive to the economic shocks in other countries. Cross-sectional dependency may play important role in detecting causal linkages for OECD countries since these countries are highly integrated.

The second issue to decide before carrying out causality test is to find out whether the slope coefficients are treated as homogenous or heterogeneous to impose causality restrictions on the estimated parameters. As mentioned by Granger (2013), the strong null hypothesis is the causality from one variable to another variable by imposing the joint restriction for the panel. Furthermore, as Breitung (2005) contends the homogeneity assumption for the parameters is not able to capture heterogeneity due to country specific characteristics. In the research papers published and economic growth nexus – as in many economic relationships – while there may be a significant relationship in some countries, vice versa may also be true in some other countries.

Taking the above into consideration before we conduct tests for causality, we start with testing for cross-sectional dependency, followed by slope homogeneity across countries. Then, we decide to which panel causality method should be employed to appropriately determine the direction of causality between research papers published and economic growth in OECD countries. In what follows, we outline the essentials of econometric methods used in this study.

Testing cross-section dependence.

To test for cross-sectional dependency, the Lagrange multiplier (LM hereafter) test of Breusch and Pagan (1980) has been extensively used in empirical studies. The procedure to compute the LM test requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \text{ for } i = 1, 2, ..., N \text{ ; } t = 1, 2, ..., T \quad (1)$$

where i is the cross section dimension, t is the time dimension, x_{it} is $k \times 1$ vector of explanatory variables, α_i and β_i are respectively the individual intercepts and slope coefficients that are allowed to vary across states.

In the LM test, the null hypothesis of no-cross section dependence- $H_0 : Cov(u_{it}, u_{jt}) = 0$ for all t and $i \neq j$- is tested against the alternative hypothesis of cross-section dependence $H_1 : Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan (1980) developed the LM test as:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \quad (2)$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of equation (1) for each i.

Under the null hypothesis, the LM statistic has asymptotic chi-square with $N(N-1)/2$ degrees of freedom. It is important to note that the LM test is valid for N relatively small and T sufficiently large.

However, the CD test is subject to decreasing power in certain situations that the population average pair-wise correlations are zero, although the underlying individual population pair-wise correlations are non-zero (Pesaran et al., 2008, p.106). Furthermore, in stationary dynamic panel data models the CD test fails to reject the null hypothesis when the factor loadings have zero mean in the cross-sectional dimension. In order to deal with these problems, Pesaran et al. (2008) propose a bias-adjusted test which is a modified version of the LM test by using the exact mean and variance of the LM statistic. The bias-adjusted LM test is:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{\nu_{Tij}^2}} \tag{3}$$

where μ_{Tij} and ν_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, that are provided in Pesaran et al. (2008, p.108). Under the null hypothesis with first T→∞ and then N→∞, LM_{adj} test is asymptotically distributed as standard normal.

Testing for slope homogeneity.

Second issue in a panel data analysis is to decide whether or not the slope coefficients are homogenous. The causality from one variable to another variable by imposing the joint restriction for whole panel is the strong null hypothesis (Granger, 2013). Moreover, the homogeneity assumption for the parameters is not able to capture heterogeneity due to country specific characteristics (Breitung, 2005).

The most familiar way to test the null hypothesis of slope homogeneity- $H_0 : \beta_i = \beta$ for all i- against the hypothesis of heterogeneity- $H_1 : \beta_i \neq \beta_j$ for a non-zero fraction of pair-wise slopes for $i \neq j$ - is to apply the standard F test. The F test is valid for cases where the cross section dimension (N) is relatively small and the time dimension (T) of panel is large; the explanatory variables are strictly exogenous; and the error variances are homoscedastic. By relaxing homoscedasticity assumption in the F test, Swamy (1970) developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. However, both the F and Swamy's test require panel data models where N is small relative to T. Pesaran and Yamagata (2008) proposed a standardized version of Swamy's test (the so-called $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ test is valid as $(N,T) \to \infty$ without any restrictions on the relative expansion rates of N and T when the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, first step is to compute the following modified version of the Swamy's test:

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \tilde{\beta}_{WFE} \right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left(\hat{\beta}_i - \tilde{\beta}_{WFE} \right) \tag{4}$$

where $\hat{\beta}_i$ is the pooled OLS estimator, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, M_τ is an identity matrix, the $\tilde{\sigma}_i^2$ is the estimator of σ_i^2.* Then the standardized dispersion statistic is developed as:

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}} \right) \tag{5}$$

Under the null hypothesis with the condition of $(N,T) \to \infty$ so long as $\sqrt{N}/T \to \infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has asymptotic standard normal distribution. The small sample properties of $\tilde{\Delta}$ test can be improved under the normally distributed errors by using the following bias adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{\mathrm{var}(\tilde{z}_{it})}} \right) \tag{6}$$

where the mean $E(\tilde{z}_{it}) = k$ and the variance $\mathrm{var}(\tilde{z}_{it}) = 2k(T-k-1)/T+1$.

Panel Causality Test.

Once the existence of cross-section dependency and heterogeneity across OECD countries is ascertained, we apply a panel causality method that should account for these dynamics. The bootstrap panel causality approach proposed by Kónya (2006) is able to account for both cross-section dependence and country-specific heterogeneity. This approach is based on Seemingly Unrelated Regression (SUR) estimation of the set of equations and the Wald tests with

* In order to save space, we refer to Pesaran and Yamagata (2008) for the details of estimators and for Swamy's test.

individual specific country bootstrap critical values. Since country-specific bootstrap critical values are used, the variables in the system do not need to be stationary, implying that the variables are used in level form irrespectively of their unit root and cointegration properties. Thereby, the bootstrap panel causality approach does not require any pre-testing for panel unit root and cointegration analyses. Besides, by imposing country specific restrictions, we can also identify which and how many states exist in the Granger causal relationship.

The system to be estimated in the bootstrap panel causality approach can be written as:

$$\begin{aligned}
y_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1} \beta_{1,1,i} y_{1,t-i} + \sum_{i=1}^{lx_1} \delta_{1,1,i} x_{1,t-i} + \varepsilon_{1,1,t} \\
y_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1} \beta_{1,2,i} y_{2,t-i} + \sum_{i=1}^{lx_1} \delta_{1,2,i} x_{2,t-i} + \varepsilon_{1,2,t} \\
&\vdots \\
y_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{ly_1} \beta_{1,N,i} y_{N,t-i} + \sum_{i=1}^{lx_1} \delta_{1,N,i} x_{1,N,t-i} + \varepsilon_{1,N,t}
\end{aligned} \tag{7}$$

and

$$\begin{aligned}
x_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2} \beta_{2,1,i} y_{1,t-i} + \sum_{i=1}^{lx_2} \delta_{2,1,i} x_{1,t-i} + \varepsilon_{2,1,t} \\
x_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2} \beta_{2,2,i} y_{2,t-i} + \sum_{i=1}^{lx_2} \delta_{2,2,i} x_{2,t-i} + \varepsilon_{2,2,t} \\
&\vdots \\
x_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{ly_2} \beta_{2,N,i} y_{N,t-i} + \sum_{i=1}^{lx_2} \delta_{2,N,i} x_{N,t-i} + \varepsilon_{2,N,t}
\end{aligned} \tag{8}$$

Where y denotes real income, x refers to research papers published (in terms of total number of papers published), l is the lag length. Since each equation in this system has different predetermined variables while the error terms might be contemporaneously correlated (i.e. cross-sectional dependency), these sets of equations are the SUR system.

In the bootstrap panel causality approach, there are alternative causal linkages for each country in the system that (i) there is one-way Granger causality from x to y if not all $\delta_{1,i}$ are zero, but all

$\beta_{2,i}$ are zero, (ii) there is one-way Granger causality running from y to x if all $\delta_{1,i}$ are zero, but not all $\beta_{2,i}$ are zero, (iii) there is two-way Granger causality between x and y if neither $\delta_{1,i}$ nor $\beta_{2,i}$ are zero, and finally (iv) there is no Granger causality in any direction between x and y if all $\delta_{1,i}$ and $\beta_{2,i}$ are zero.

Data

The annual data used in this study covers the period from 1981 to 2011 for the 34 OECD countries. The variables include total real GDP (RGDP) and research papers published (in terms of total number of papers published). Research papers published is expressed in terms of total number of papers published and data is from National Science Indicators Database of the Institute for Scientific Information (ISI). Thomson Reuters currently indexes over 10,000 journals in the Sciences, Social Sciences, and Arts & Humanities. In the NSI database the ISI counts articles, notes, reviews and proceeding papers, but not other types of items and journal marginalia such as editorials, letters, corrections, and abstracts (Inglesi-Lotz and Pouris, 2011). Real GDP is measured in constant 2005 U.S. dollars and comes from the World Development Indicators (World Bank, 2012).

Empirical results

Before we test for causality we first test for both cross-sectional dependency and country-specific heterogeneity as we believe that OECD countries are highly integrated in their economic relations. To investigate the existence of cross-section dependence we carried out four different tests (*LM, CDlm,CD, LMadj*). Secondly, as indicated by Kónya (2006), the selection of optimal lag structure is of importance because the causality test results may depend critically on the lag structure. In determining lag structure we follow Kónya's approach that maximal lags are allowed to differ across variables, but to be same across equations. We estimate the system for each possible pair of ly1, lx1, ly2 and lx2 respectively by assuming from 1 to 4 lags and then choose the combinations which minimize the Schwarz Bayesian Criterion. Thirdly, because

Bootstrap panel causality test proposed by Kónya (2006) requires T>N, and we have 34 countries with 31 years for each country, therefore, we divide these 34 countries into two groups: A and B based on their GDP of the countries in 2010 (See Table 2).

Table 2. Country classification into two groups based on their GDP in 2010

GROUP A	GROUP B
Australia, Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, Netherlands, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, UK, US	Austria, Chile, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Iceland, Ireland, Israel, Mexico, Norway, Poland, Slovakia, Slovenia, South Korea

Our tests for cross-sectional dependency and heterogeneity are presented in Tables 3 and 4, respectively for group A and group A and group B.

Table 3. Cross-sectional Dependence and Homogeneous Tests (Group A)

CD_{BP}	1196.005***
CD_{LM}	64.272***
CD	30.905***
LM_{adj}	187.504***
$\tilde{\Delta}$	1043.695***
$\tilde{\Delta}_{adj}$	36.718***
Swamy Shat	6102.740***

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively

Table 4. Cross-sectional Dependence and Homogeneous Tests (Group B)

CD_{BP}	530.741***
CD_{LM}	23.935***
CD	17.146***
LM_{adj}	192.403***
$\tilde{\Delta}$	546.984***
$\tilde{\Delta}_{adj}$	90.891***
Swamy Shat	3.190***

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

The null hypothesis of no cross-sectional dependency and slope heterogeneity across the countries is strongly rejected at the conventional levels of significance. This finding implies that a shock that occurred in group A (and/or group B) OECD countries seems to be transmitted to other countries. Furthermore, the rejection of slope homogeneity implies that the panel causality analysis by imposing homogeneity restriction on the variable of interest results in misleading inferences. In this respect, the panel causality analysis based on estimating a panel vector autoregression and/or panel vector error correction model by means of generalized method of moments and of pooled ordinary least square estimator is not appropriate approach in detecting causal linkages between research papers published and economic growth in the groups A and B of the OECD countries.

The establishment of the existence of cross-sectional dependency and heterogeneity across group A suggests the suitability of the bootstrap panel causality approach. The results of the bootstrap causality tests are presented in Tables 5 and 6 for group A.

Table 5. Research Output does not Granger Cause GDP (Group A)

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
AUSTRALIA	0.033	1.809	9.657	13.343	22.306
BELGIUM	0.023	5.473	14.435	20.032	33.411
CANADA	-0.018	2.028	17.674	26.471	46.600
FRANCE	0.011	2.257	19.780	27.196	49.154
GERMANY	0.009	0.636	17.819	24.470	45.688
ITALY	-0.006	1.375	15.646	21.149	38.080
JAPAN	0.017	1.077	13.679	19.737	21.241
LUXEMBOURG	-0.004	3.680	9.762	14.573	31.155
NETHERLANDS	0.040	15.827	17.028	25.097	40.065
NEW ZEALAND	0.045	11.585	13.069	18.326	34.903
PORTUGAL	-0.002	0.235	13.692	18.975	33.815
SPAIN	0.011	4.728	20.006	29.024	48.187
SWEDEN	0.031	4.048	20.586	28.802	47.108
SWITZERLAND	0.013	1.505	14.084	20.359	37.622
TURKEY	0.033	4.637	10.985	17.450	31.430
UK	0.002	0.018	14.525	21.829	40.810
USA	0.053	**14.185***	13.506	19.556	36.905

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

2. Bootstrap critical values are obtained from 10,000 replications.

Table 6. GDP does not Granger Cause Research Output (Group A)

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
AUSTRALIA	0.188	4.555	26.523	38.374	70.274
BELGIUM	0.460	11.756	25.014	33.768	61.806
CANADA	0.283	**19.646****	11.335	17.684	33.058
FRANCE	0.409	**22.741***	22.279	33.087	56.139
GERMANY	0.235	4.854	22.212	32.863	53.321
ITALY	0.606	**25.337***	20.009	26.999	48.558
JAPAN	0.296	5.350	22.412	35.836	67.152
LUXEMBOURG	2.809	22.117	23.291	33.427	62.953
NETHERLANDS	0.286	14.025	14.498	23.375	37.731
NEW ZEALAND	1.158	**21.368****	10.678	16.273	31.738
PORTUGAL	0.717	6.113	14.077	20.087	32.454
SPAIN	0.319	8.746	12.674	18.624	29.676
SWEDEN	0.077	1.556	12.558	18.541	34.643
SWITZERLAND	0.520	12.154	17.339	24.615	41.059
TURKEY	0.151	4.482	15.936	23.129	46.595
UK	0.224	**27.023****	13.918	19.407	34.395
USA	0.107	0.129	19.566	29.162	65.022

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

2. Bootstrap critical values are obtained from 10,000 replications.

Empirical results support unidirectional causality running from research papers (in terms of total number of papers published) to economic growth for the US only; the opposite causality from economic growth to research papers published for Canada, France, Italy, New Zealand, and the UK; and no causality in any direction between research papers published and economic growth for the rest of 11 countries. In the case of Canada, France, Italy, New Zealand, and the UK; the results show a unidirectional causality running from economic growth to total number of papers published. This indicates that economic growth stimulates research papers published which in their turn, boost economic growth even further in these countries. In contrast, in the US, there was an opposite causality running from research papers published to economic growth meaning that research papers have a certain impact on economic growth, supporting the research-growth hypothesis in the US. Tables 7 and 8 report the results of the bootstrap causality tests across group B.

Table 7. Research Output does not Granger Cause GDP (Group B)

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
AUSTRIA	0.001	0.574	12.782	20.146	41.636
CHILE	0.001	0.173	11.208	17.057	26.992
CZECH REPUBLIC	0.000	0.337	18.641	28.193	58.933
DENMARK	0.004	7.914	9.981	13.441	19.364
ESTONIA	0.006	7.843	14.165	20.528	32.921
FINLAND	0.007	**30.248****	21.131	29.034	47.475
GREECE	0.003	2.656	14.165	20.343	41.783
HUNGARY	0.010	**14.701***	12.523	17.595	33.338
ICELAND	0.001	0.542	18.228	26.538	48.071
IRELAND	-0.006	5.300	10.633	15.834	27.806
ISRAEL	0.009	3.434	15.404	22.955	40.924
MEXICO	0.011	**27.238****	11.255	18.181	30.380
NORWAY	0.000	0.058	10.199	14.959	22.983
POLAND	0.009	15.258	20.325	28.103	53.378
SLOVAKIA	0.000	0.702	13.712	19.815	36.005
SLOVENIA	0.000	0.093	19.557	28.024	66.197
SOUTH KOREA	0.003	2.419	10.805	14.791	27.266

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

2. Bootstrap critical values are obtained from 10,000 replications.

Table 8. GDP does not Granger Cause Research Output (Group B)

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
AUSTRIA	8.260	**26.750***	26.628	39.041	74.661
CHILE	1.196	2.026	28.205	37.668	64.112
CZECH REPUBLIC	12.105	2.102	23.298	31.570	61.442
DENMARK	0.751	0.321	23.360	33.328	59.527
ESTONIA	-0.086	0.058	13.480	20.321	36.367
FINLAND	-0.463	0.819	13.873	18.797	38.333
GREECE	2.992	4.917	13.876	21.885	43.158
HUNGARY	1.688	3.259	13.340	20.555	36.384
ICELAND	5.290	10.656	20.090	30.047	51.822
IRELAND	1.194	4.435	22.172	34.819	58.271
ISRAEL	4.609	**40.154*****	12.656	19.301	38.457
MEXICO	-0.353	0.193	19.001	28.824	47.725
NORWAY	2.860	12.482	32.746	43.837	78.319
POLAND	9.515	**56.493*****	11.696	17.264	33.623

SLOVAKIA	1.150	0.071	24.750	32.377	61.432
SLOVENIA	-5.233	0.262	15.201	22.861	49.009
SOUTH KOREA	5.254	31.318	34.198	47.162	82.235

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

2. Bootstrap critical values are obtained from 10,000 replications.

Empirical results support unidirectional causality running from research output (in terms of total number of papers published) to economic growth for Finland, Hungary, and Mexico; the opposite causality from economic growth to research papers published for Austria, Israel, and Poland; and no causality in any direction between research papers published and economic growth for the rest.

Concluding remarks

This study applied the bootstrap panel Granger causality approach to examine the causal link between research papers published and economic growth using data from 34 OECD countries over the period of 1981-2011. Our empirical results support unidirectional causality running from research papers (in terms of total number of papers published) to economic growth for the US, Finland, Hungary, and Mexico; the opposite causality from economic growth to research papers published for Canada, France, Italy, New Zealand, UK, Austria, Israel, and Poland; and no causality in any direction between research papers published and economic growth for the rest. The results are summarized in Table 9 below.

Table 9. Summary of results

DIRECTION OF CAUSALITY	COUNTRIES
Research output Granger causes GDP	US, Finland, Hungary, Mexico
GDP Granger causes Research Output	Canada, France, Italy, New Zealand, UK, Austria, Israel, Poland
No causality in any direction	Australia, Belgium, Germany, Japan, Luxembourg, Netherlands, New Zealand, Portugal, Spain, Sweden, Turkey, Switzerland, Austria, Chile, Czech Republic, Denmark, Estonia, Greece, Norway, Slovakia, Slovenia

Similar to other previous studies, what emerges from our empirical findings is that it is difficult to derive any consistent set of results concerning the nexus between research papers published and economic growth in OECD countries with the current available methodologies. As pointed out by Lee et al (2011), OECD countries are highly developed countries and can afford to fund the cost of research. Their research mainly includes fundamental research which is not based on addressing their immediate needs, but that maybe of high value in the future. For these economically advanced nations, innovation becomes a necessity to constantly maintain innovation momentum to sustain competitive advantage (Rai and Lal, 2000). Basic research leads to the development of new methods and instruments that will be useful in future research and development work in both the universities and the companies (Chuang et al, 2010). Newly discovered instruments methods will make considerable contributions to the economy, such as profit, productivity, employment, prosperity, market, and competitiveness. The link between research and economic performance is therefore broken for the majority of these developed nations. Nelson in Pavitt (1991) explains this by the fact that stabilized economies start investing less than the optimum in basic research because the benefits from other expenditures become obvious quicker. As Bornmann (2013) notes: “although the evaluation of research is important when it comes to making investment decisions in research and ensuring the effectiveness of the national innovation system, note that research is, by its very nature, dealing with what we do not know”.

On the other side, a number of countries experience economic growth as a factor to higher research outputs. In these cases, the levels of economic growth and development enable the policy makers to invest more on R&D and hence, improve the output of the research community.

As a whole, this paper has emphasized the complex relationship between research output and economic growth. Research output presents only one facet of the complex concept of technological progress or innovation that as a whole affects the economies in different ways (Luo et al, In press) but it represents the stock of knowledge in a country. Although investment in fundamental research is at the base of innovation and has a positive impact on economic growth, the decision on whether to invest more on fundamental research or more on applied research rests on the country's development level. Less developed OECD countries should direct their research investment towards applied research to address their immediate needs, whereas higher growth countries should focus on basic research to achieve more innovativeness and to sustain competitive advantage.

Future research in the topic should examine how additional regressors can provide a holistic picture of the research market and its impact to the countries' economies. In addition, research should be conducted on the possible changes of the direction of causality through the years.

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