Causal Connections between Scientometric Indicators: Which Ones Best Explain High-Technology Manufacturing Outputs?

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Abstract

Scientometric models can connect indicators via cross-country correlations, but these are not enough to assert causality. Sometimes a causal connection can be argued from the physical process. In other cases the causality or its direction is not clear, and the Granger test is often used to clarify the connection. Here it was shown that gross expenditures on R&D (GERD) Granger caused scientific papers in the U.S., EU, and some others, which has policy implications. Granger causality also reinforces earlier findings on why the EU passed the U.S. in papers in the mid-1990s. Downstream, it is difficult to prove the connection between research and gross domestic product (GDP), since the contributions of science are diluted by other factors. New data allows a focus on a sector that is more closely associated with science: high technology (HT) manufacturing outputs. This value-added data permits more accurate models for today's international supply chains. Correlations show that business expenditures on R&D (BERD) and scientific indicators like patents are closely connected with HT manufacturing outputs. However for BERD, either direction of causality is plausible, and enough countries had significant results to show that causality can indeed be in either direction. The connections between papers and patents with HT manufacturing were also investigated; in several countries patents could be said to have Granger caused HT manufacturing.

Conference Topic
Country-level studies

Introduction

Correlation does not imply causality, unless it can be augmented with other evidence. Many researchers have found strong cross-country correlations between national R&D funding and intermediate indicators like papers and patents. These findings bolster the policy argument that researchers deserve more funding, but may sound self-serving. Here however, there is a convincing physical argument that there is philosophical causality. Everyone knows that it take resources to do research. In some "big science" fields like ITER and CERN, it takes international consortia to provide the necessary big funding. Even the lonely bibliometrician needs a computer, data and Internet access, time to do the work, and travel funds to present the results in some pleasant clime.

Downstream in the innovation process, many researchers have also tried to connect those papers and patents to outputs like gross domestic product (GDP), with mixed success. Here the physical connection is not so clear, because science is only one of many factors that are involved. For example, several Asian nations became export powerhouses with skyrocketing GDPs, based initially on imported technologies, which were not reflected in their national papers and patents. Instead, the "New Economic Geography" developed by Paul Krugman (1991) identifies the most significant factors for location of manufacturing, and location of R&D is not high on the list. (He won the 2008 Nobel Prize for this work.) Once prosperous, these nations did invest in indigenous innovation.

In these more difficult cases, analysts rely on statistical tests to provide some evidence of causality. The most common test was devised by Clive Granger (1969). (He also won the Nobel Prize, in 2003.) It is applied to two time series, which the analyst suspects may be related. In simplified terms, a time series x can be said to "Granger cause" a second time series y if the additional knowledge of x allows a significantly better prediction of y than simply the past history of y. The Granger test function is available in several statistical programs; the open source R software was used here (R Core Team, 2014). In the R version, the model order k is the same for both x and y. The null hypothesis that x does not Granger-cause y is not rejected, if and only if no lagged values of x are retained in the regression.

Let y and x be stationary time series. To test the null hypothesis that x does not Granger-cause y, one first finds the proper lagged values of y to include in an autoregression of y:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_k y_{t-k} + residual_t$$

Next, the autoregression is augmented by adding lagged values of x:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_k y_{t-k} + b_1 x_{t-1} + \dots + b_k x_{t-k} + residual_t$$

One retains in this regression all lagged values of x that are individually significant according to their t-statistics, provided that they collectively add explanatory power to the regression according to an F-test; adapted from Seth (2007). Here the smallest model order that produces significant results is preferred.

Granger testing is not a panacea. It requires that both series be stationary, and scientometric series usually fail the standard Augmented Dickey Freeman (ADF) test. This is often because they have trends such as inflation, population growth, or just more journals in the Science Citation Index (SCI). One normally has to de-trend series, usually by differencing them one or more times. Even when both series are stationary, the Granger test often fails, or worse, shows bi-directional causality, raising more questions than it answers. Furthermore, Granger causality is based on a postulate that cause must precede effect, but is this always true? In the stock market, the prospect of future events, like increased earnings, can influence present stock prices. Thus, one cannot prove true philosophical causality with Granger tests, but may be able to show that one series is a leading indicator for another. True causality has perplexed philosophers for millennia, so we are will not settle the question here. Instead we will just present the most interesting results from many Granger tests for scientometric indicators.

Background

Scientometric models are similar to econometric ones. A nation's innovation establishment can be considered to be an economic system that needs inputs of resources like labor and capital to produce outputs such as products and exports. System inputs and outputs can be measured using indicators. Figure 1 shows the relations between the system model and these indicators. This is a simplified linear model of a more complex situation. In reality there are feedback loops--e.g., an overall one that shows that sales of products can provide resources for investments in R&D.

Previous cross-country analysis showed that there is a strong correlation between inputs and intermediate indicators like papers. Leydesdorff (1990) regressed world share of publications in the SCI as output on GERD as an input. Shelton (2006) identified national inputs most important in encouraging papers. His model suggested that changes in the GERD share have been the driver of national changes in paper share, which can account for the rise of China since 2001 (Jin & Rousseau, 2005; Shelton & Foland, 2010). Later, the models were refined

using components of GERD as explanatory variables (Leydesdorff & Wagner, 2009). Similar models showed that government investments in R&D and higher education spending on R&D (HERD) were especially effective, helping to explain Europe's passing the U.S. in papers during the 1990s (Foland & Shelton, 2010). Conversely, the industrial component of GERD was shown to be more effective in encouraging patents (Shelton & Leydesdorff, 2012). Here these methods are applied to high-technology (HT) outputs as an overall measure of the success of a national innovation enterprise. The preliminary cross-country analysis (Shelton & Fadel, 2014) raised questions about the direction of causality, so a longitudinal approach for time series for individual countries has now been added, using the Granger test.

Such analysis is becoming more common in scientometrics, but sometimes with limited results. After considerable effort, Vinkler (2008) found no significant link between economic performance and research. Peng (2010) found some causality between R&D expenditure and GDP in China, but it is not clear that his series had the required stationarity. LC Lee, Lin & YW Lee (2011) used Granger testing of whether research papers can be said to cause GDP output—aggregated by regions. One result was that there is mutual causality between research and economic growth in Asia, but the results are not so clear in the West. Inglesi, Chang & Gupta (2013) tried Granger testing between research papers and economic growth in Brazil, Russia, India, China, and South Africa (the "BRICS"), which mostly failed to demonstrate causality, except for some positive results for India. Inglesi, Balcilar & Gupta (2014) got more positive results for the connections between U.S. paper output and GDP.
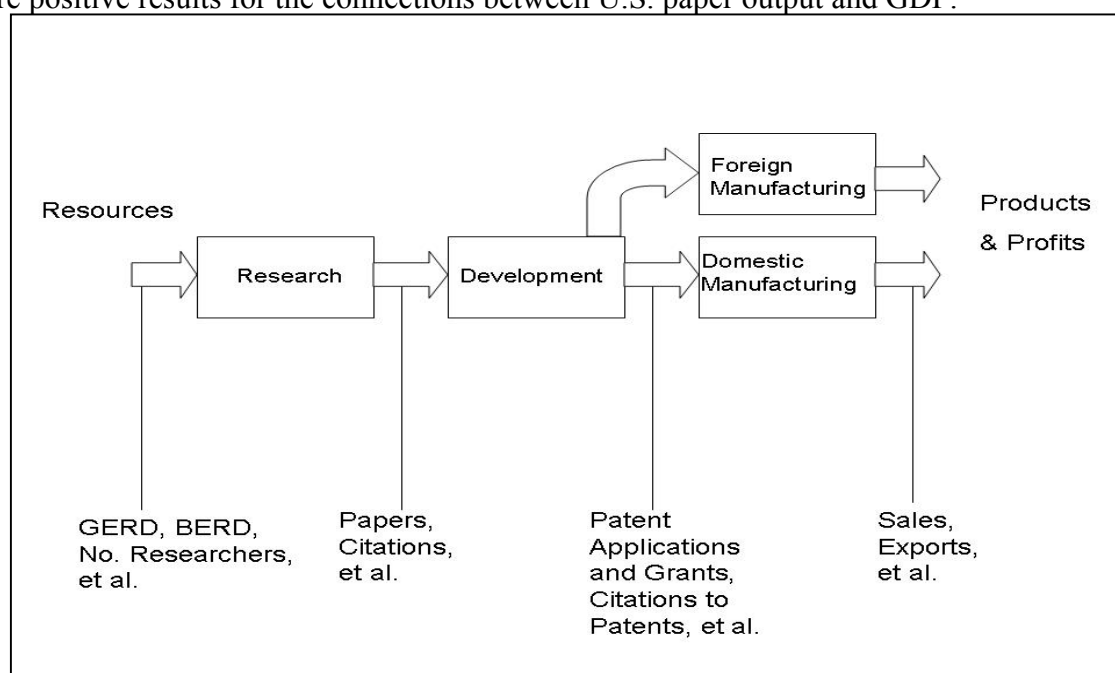

Figure 1. Linear model of an innovation enterprise with some indicators.

While there are some economic papers on factors that best explain *overall* international trade, there are relatively few that focus on the high-technology sector. One economic analysis of whether a country's high-tech exports (as a share of its overall exports) could be explained by R&D investment and country size was done by Braunerhjelm and Thulin (2008). They used the OECD data for 19 countries during 1981-1999. From their economic model, they concluded that overall R&D investment was significant.

Tebaldi (2011) used panel data to analyze factors that are most explanatory of high-technology trade. This approach adds data from more than one year to the usual cross-country analysis. Human capital, inflows of foreign direct investment, and openness to international trade were found to be the most significant of the factors he analyzed.

Data

Indicators like counts of papers and patents come from familiar sources like the SCI (Thomson Reuters 2015), (NSB 2014), and (OECD 2015). They provide insight into the success of national innovation enterprises. However, they are distant proxies for some of the quantities that the public cares most about: jobs, strength of their national economy, and survival of national industries. One scientometric measure of innovation that comes closer to these concerns is the performance of high-technology (HT) industries. Data on HT exports have been complied on a cash basis for decades by the OECD (2015) in its Main Science and Technology Indicators series. However, this measure of industrial output does not capture the nuances of where manufacturing really takes place. For example, the Apple iPad is assembled in China, but most of its components come from Japan, the U.S. and elsewhere (Xing, 2012). Recently a new dataset has been jointly developed by the OECD and the World Trade Organization for manufacturing output on a value-added basis, which avoids double-counting of imported components. This more accurate data, as summarized in (NSB, 2014), allows development of much-improved models that tie these key outputs to inputs like R&D investment. Figure 2 shows some national time series for this measure of HT manufacturing output. Forecasts show that China will soon take the world lead as the U.S. and Japan move final assembly of HT products to China. (Similar graphs for HT exports on a cash basis showed China taking the world lead in 2005.) The Europeans, especially the Germans, seem to have done less of this "off-shoring." There have obviously been big changes in the last decade, and scientometric models might provide insight on why, and what governments might do to respond.
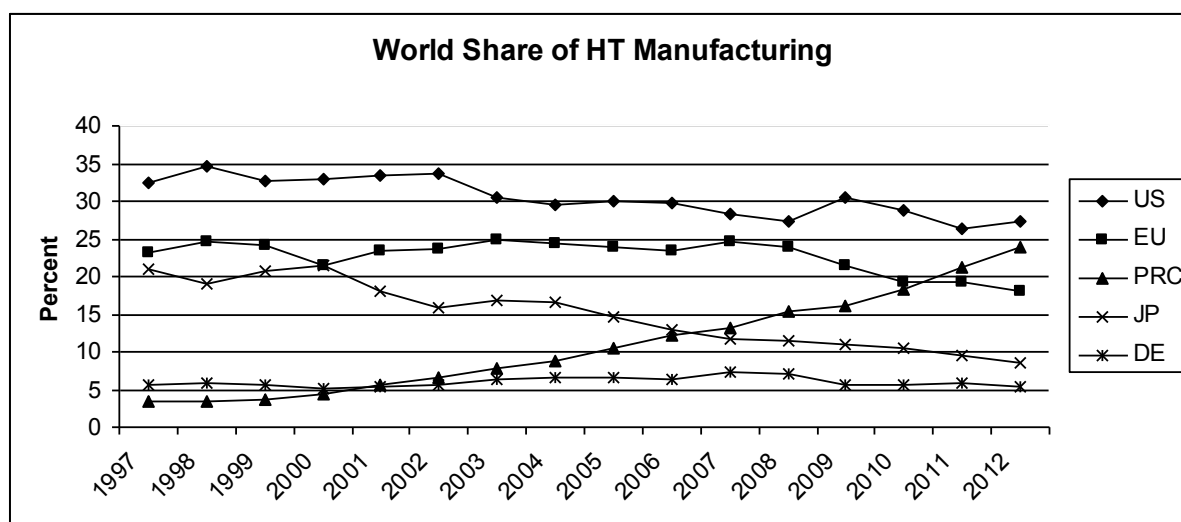

Figure 2. World share of manufacturing of high-technology products, on a value-added basis, for the United States, European Union (28), People's Republic of China, Japan, and Germany.

Causality Methods

Cross-country correlations over the countries in the OECD database are well known. Granger testing can be illustrated by revisiting the key results from Foland & Shelton (2010). That paper provided evidence that the EU passed the U.S. in papers in the mid-1990s because of a U.S. shift in research funding from government to industry, which was less effective in producing papers. At the time, this argument was based on cross-country correlations, and visual inspection of the U.S. and EU15 paper curves, which were very similar to their government GERD (GG) curves, just lagged by a couple of years. Granger testing can now add some quantitative evidence to this conclusion. First the series passed the ADF tests on the

data from 1988 to 2002, once second differences were calculated. The resulting Granger significance probabilities are in Table 1; bold entries are significant ($p < 0.1$).

Table 1. Significance probabilities for Granger tests of Government GERD component (USGGFF) causing papers (USPFF) on the NSI CD--or the reverse. FF means second difference. The "→" symbol means "Granger causes."

Model Order (k)	USGGFF →USPFF	USPFF →USGGFF
1	**p = 0.095**	p = 0.52
2	**p = 0.041**	p = 0.19
3	**p = 0.092**	p = 0.73

Thus the government GERD indicator can be said to "Granger cause" papers in the U.S. in this time interval. The most significant result was for a model order of two years, and there was no significant reverse causality. This provides additional evidence that relative changes in the Government GERD component led to the EU becoming much more efficient than the U.S. in producing papers, and led to its passing the U.S. in the mid-1990s to become the world leader in this indicator.

The Granger test has low power, that is, it often does not find significant results, particularly when the sample size is small. The sample size for Table 1 is only $N = 15$, preventing the use of higher model orders, so it is fortunate that some definitive results were obtained. To seek more definitive results, longer series were extracted for US, EU15, Japan, Netherlands, and Turkey from the Web of Science and the OECD for 1980 – 2012 where possible. After the second differences necessary for stationarity, this resulted in $N = 30$ samples for 1982-2012.

One experiment investigated whether total GERD (using constant $ and PPP weights) could be said to cause papers in the WoS (articles, letters, and reviews), with whole counts from the SCI-E and SSCI indexes. The results showed that U.S., EU15, and Japanese papers were indeed Granger caused by their national GERD with the significance probabilities in Table 2. None showed reverse causality. It did take a much higher model order to demonstrate Japanese causality. It was not possible to demonstrate significant results for the Netherlands or Turkey.

With these longer series, there is also the possibility that structural changes may take place over years. Sometimes a sliding window is used to examine shorter intervals within a longer one (Inglesi, Balcilar & Gupta, 2014). Here an auxiliary analysis simply examined the most recent years 2000 – 2012 ($N = 13$). The U.S. still exhibited Granger causality with the best result of $p = 0.012$ for a model order of $k = 2$. However, the other four country results for this shorter interval were not significant.

Table 2. Significance probabilities for Granger tests of GERD (G) causing papers (P) in the WoS (or the reverse) for 1983-2012. All used second differences.

Order (k)	USG→USP	USP →USG	EUG →EUP	EUP→EUG	JPG→JPP	JPP→JPG
1	**0.0067**	0.53	0.41	0.67	0.30	0.65
2	**0.0024**	0.89	0.53	0.94	0.53	0.53
3	**0.013**	0.90	0.76	0.82	0.54	0.54
4	**0.034**	0.91	**0.085**	0.92	0.54	0.79
5	0.10	0.86	0.14	0.96	**0.064**	0.80
6					**0.0029**	
7					**0.0090**	
8					**0.011**	

A similar test for Patent Cooperation Treaty (PCT) applications (OECD, 2014) in the U.S. was not so conclusive. Only for a model order of k = 6, could it be said that GERD Granger caused PCT patents, with p = 0.09. There was no reverse causality, however.

Another experiment tried to confirm a finding from Foland & Shelton (2010), that higher education spending on R&D (HERD) was closely associated with more papers. The dataset again included the U.S., EU15, the Netherlands, Japan, and Turkey, for the data range 1988-2002. Significant results were obtained only for the last two countries (Table 3). It was necessary to use fairly large model orders for Japan. The series passed the ADF tests with second differences, and there was no reverse causality for these model orders. Thus it can be said that, in Japan and Turkey at least, HERD Granger caused papers in these years. This might be useful for professors in those countries to mention in their battles for more funding.

Table 3. Does higher education spending Granger cause scientific papers?

Model Order (k)	Japan HERD →Japan Papers	Turkey HERD →Turkey Papers
1	p = 0.56	p = 0.24
2	p = 0.82	**p = 0.049**
3	p = 0.37	p = 0.12
4	**p = 0.090**	p = 0.21
5	**p = 0.016**	p = 0.30

Correlations for the Value-Added HT Manufacturing Indicator

Simple correlation over the 40 or so countries in the database of input resources in (OECD, 2014) can provide insight into which investments might be most productive in encouraging HT exports and manufacture. However, since many indicators simply increase with the size of the country, it is necessary to find explanatory variables whose correlations are much greater than those for measures like population or GDP. Furthermore, the U.S. and China are outliers; it is necessary to either omit them, or use log measures, if the contributions of smaller countries are to affect the results.

Table 4 from Shelton & Fadel (2014) shows the coefficients of determination (R^2) for two measures of performance of national HT industries with a number of explanatory or independent variables. For both measures, business expenditure on R&D (BERD) is best, with gross expenditure on R&D (GERD) not far behind. The correlations are far better for the new value-added data for HT manufacturing in the last column, than for the earlier exports on a cash basis. Indeed a quite accurate regression model can be constructed for this case (Equation 1), where NM9 is HT manufactures and BN9 is BERD, both in current dollars in 2009. Figure 3 shows the scattergram for this model.

$$\log NM9 = 0.385 + 0.944 \log BN9 \quad (R^2 = 84.1\%) \tag{1}$$

One would expect that there would be a delay between R&D investments and downstream benefits. For some indicators like patent grants, models that incorporate these delays can be more accurate (Shelton & Monbo, 2012). Here, correlations do not change much with lags, thus they did not improve the models enough to warrant the increased complexity. To see if a multiple linear regression would improve the model, a step-wise regression on HT manufacturing in 2009 was performed using the nine independent variables in Table 4. None of the other variables was significant in a multiple regression, once BERD was included as an explanatory variable, making a simple univariate regression without lags reasonable.

Table 4. Coefficients of determination (R^2 in %) of HT exports and overall HT manufacturing with explanatory variables in 2009. Uses log scales. More recent data downloads produce somewhat different correlations, and the values are sensitive to missing data points.

	Exports (Cash Basis)	Overall Output (Value-Added)
Papers SCI	41.7	71.0
Patents Triadic	48.8	69.9
Patent PCT Apps	34.3	61.5
GERD	44.8	79.8
BERD	49.0	84.5
Researchers	26.2	61.4
Business Researchers	29.3	71.6
Size GDP	27.3	56.9
Size Population	13.1	34.3

Despite the precision of the regression model in Equation (1), however, there is an alternate explanation for the trends of HT manufactures in the last decade. Could it be that HT manufacturing causes R&D investment, instead of the reverse? Indeed, it is the income from these sales that does provide some of those resources. OECD states that it picked the sectors for inclusion in the HT set precisely because these industries invest an extraordinary fraction of their income in R&D. And these correlations are too good to be true for BERD solely causing HT manufacturing--there are simply too many other factors that must also contribute. There have been frequent news accounts of Western and Japanese firms moving manufacturing to China and other low wage countries to increase their profits. China was also favored because its vast market offered potential for huge growth in HT sales.

This alternate explanation brings into question the efficacy of a nation increasing its HT manufacturing by encouraging greater business investment in R&D. It is possible that the results might be disappointing if the executives of the HT companies still prefer to locate the manufacturing abroad, the top path in Figure 1, so that some other nation reaps the benefits of the sales of HT goods. A policy remedy that addresses both explanations would be more likely to succeed. R&D investment policies could be coupled with trade policies that encourage location of manufacturing where the investments were made.
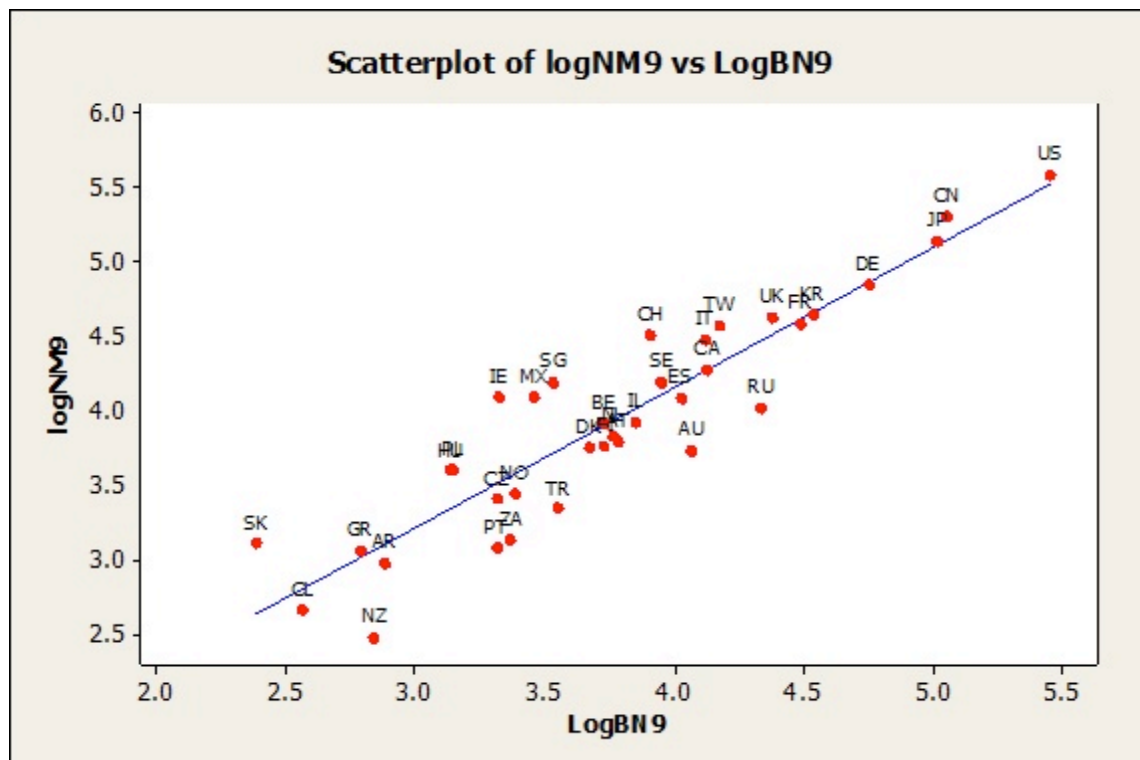
Figure 3. Scattergram of overall high-technology manufacturing vs. business expenditure on R&D in 2009. The cluster in the center contains BE, DK, IL, FI, and NL. HU and PL also overlap.

Further both manufacturing and BERD could be the results of an exogenous variable, some underlying third series. For example many of them seem to be closely tied to recent perturbations of the business cycle over the 1998 - 2011 data range available.

Causality Results for Value-Added HT Manufacturing

Table 1 shows that BERD has the highest correlation with HT manufacturing, so it will be analyzed first. Overall results for the sum of all countries in the OECD database were not significant. Findings for those individual countries with significant results are in Table 5. All are for model order k = 1, but orders up to k = 3 do not add countries to the list. Both series use current dollar values, and BERD used PPP weighting. The data ranges from 1999-2012.

Table 5. Does BERD Granger cause HT manufacturing (Mfg), or the reverse? Entries are significance probabilities; $p < 0.1$ is significant (bold type).

Country	Mfg →BERD	BERD→Mfg
Korea	0.21	**0.097**
Hungary	0.16	**0.0013**
Romania	0.57	**0.023**
PRC	**0.025**	0.32
Canada	**0.019**	0.43
Germany	**0.016**	0.19
Russia	**0.060**	0.54
Finland	**0.0014**	**0.010**

Of the some 24 countries with complete OECD data, 15 passed both ADF tests using second differences. The entries in bold type are the only ones that were significant from the Granger tests. While these results do not settle the question, they do show that (Granger) causality can indeed run in either direction for these indicators. Policymakers in Korea, Hungary, and Romania could benefit from knowing their country's business R&D investment did Granger cause its HT manufacturing output in these years, and may want to encourage more of this virtuous cycle. (Taiwan also showed this direction of causality for its available data from 2000-2012, using model order k = 2.) Chinese, Canadian, German, and Russian policymakers might be pleased to find that their country's HT manufacturing output Granger caused more BERD investment. Those in Finland would probably not find bi-directional causality very useful.

The second highest correlation in Table 1 was with overall GERD. As expected, these results were not as conclusive as those for the BERD component. Of the some 40 countries in the OECD Group, 30 had complete data. Of these 13 passed the ADF test for stationarity for both time series, using second differences. Using k = 1, only Hungary and Korea showed positive results (p = 0.0029 and p = 0.069, respectively). In the reverse direction of Mfg causing GERD, only Canada and Germany showed significant results (p = 0.026 and p = 0.0075 respectively. The Slovak Republic showed bi-directional causality with p = 0.091 for GERD causing Mfg and p = 0.025 in the reverse direction. These results seem to show that the higher correlation of BERD with manufacturing is necessary to get more definitive results.

BERD and GERD are not always thought of as scientometric indicators, though. What can be said about causality of HT manufacturing for traditional intermediate scientometics indicators like papers and patents? Only a couple of countries had significant results for papers, but the PCT patent applications were more interesting (Table 6). Using second differences, the ADF tests showed that 29 countries of the 37 countries with data had both series stationary, and 10 countries, plus the EU as a whole, showed Granger causality. The results are for order k =1, except for Denmark and the Czech Republic where k = 2. Two countries had bidirectional causality: Germany and the Netherlands.

Table 6. Do PCT international patent applications Granger cause HT manufacturing, or the reverse? Entries are significance probabilities; p < 0.1 is significant (bold type).

Country	Patents→Mfg	Mfg→Patents
EU28	**0.060**	0.14
Austria	**0.036**	0.24
Belgium	**0.046**	0.24
Canada	**0.060**	0.15
Czech Republic	**0.055 (k = 2)**	0.54
Denmark	**0.012 (k = 2)**	0.78
Korea	**0.063**	0.92
New Zealand	**0.0064**	0.11
Switzerland	**0.014**	0.40
Germany	**0.0014**	**0.0047**
Netherlands	**0.050**	**0.055**

So, there are quite a few countries where it can be said that their patenting activity Granger causes HT manufacturing output. This connection was suggested by the correlation results in Table 1, of course. There are good physical reasons that make this causality plausible, but the results do *not* imply that a national initiative to file more PCT applications would necessarily

result in more manufacturing. The Granger tests do add quantitative evidence that investments in science and technology indeed bear fruit in outputs that the public cares about.

Conclusions

For further work, statistical testing for causality can enrich study of the connections between scientometric indicators, and there are many others. However, the Granger test often fails, even when strong cross-country correlations exist and there are good physical reasons to suspect causality. There are other tests, like Toda & Yamomoto (1995), which can be employed. And more sophisticated data analysis might also help: other methods of de-trending, sliding windows for long series, panel data, et al. As always, one needs to be cautious of spurious results from data mining; running many tests is likely to turn up some positive results by chance.

The results here show that GERD did Granger cause papers and patents for the U.S., which is probably true for some others as well. This quantitative evidence bolsters the case that R&D funding is important for the success of a nation's science. In particular, the U.S. has a goal of maintaining its science leadership, but is rapidly falling behind in the funding race with China. In a rare good year, the U.S. increases its GERD by a real 3%; Chinese GERD has been increasing by more than 15% annually for decades.

New data on value-added manufacturing outputs provides quantitative insight on which inputs can be most effective in encouraging high-technology industries. Not surprisingly, there is a strong connection between such success and investments in R&D, particularly by the business sector. In countries where this can be demonstrated to be a cause of these successes, governments might wish to adopt policies, such as tax incentives, which can encourage such investment. Intermediate indicators like patents can also be good explanatory variables, showing quantitatively that traditional scientometric measures indeed provide useful information about outputs that directly affect a nation's prosperity.

Of course there are many other benefits of science and technology beyond the manufacture and sale of the HT products considered here. Science can lead to better healthcare, cleaner air and water, solutions of problems like global warming, improved communications that allow more extensive cooperation and collaboration, and many others. Most of these benefits can accrue to everyone, regardless of their nationality. Even in the competitive analysis of national market share of HT manufactures considered here, one should not lose sight of the overall performance of the sector. Worldwide sales have almost doubled over the last decade with only a slight pause during the Great Recession, reaching over $1.5 trillion in 2012. This growth has created millions of new jobs and a cornucopia of wonderful new products most people can enjoy--the ubiquitous cell phone has provided the first rapid communications in some of the poorest countries.

Acknowledgments

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