Patent Applications and EPO Membership: How Big is the Drop?

By Robert Embree
Ph.D. Student, University of Toronto
robertembree@gmail.com

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Abstract

The number of domestic patent applications is dramatically affected by membership in the European Patent Organization (EPO). Other work in the field does not consider the effect of EPO membership, and does not use all available exogenous variables as regressors. Using three different methods - the Pooled Mean Group Estimator, fixed effects, and nearest-neighbour matching, this paper estimates the decline in national-office patent applications as the result of membership in the EPO. The predicted drop is found to be 78% using PMG, 59% using fixed effects, and 80% using nearest-neighbour matching. Effects on patenting from changes in R&D spending, real GDP, and manufacturing output are also estimated.

Contents

1 Introduction and Contribution

This research project considers the impact of membership in the European Patent Office on annual numbers of patent application filings at national patent offices. As well, I will examine the effects of changes in research and development (R&D) spending, real GDP, and manufacturing activity on patent counts.

The European Patent Office is an organization which allows for patents to be filed at the same time with the same effect in multiple jurisdictions. By filing with the EPO, patent holders have patent protection in all EPO member countries. Obviously, this has a significant disincentive effect on filing in national member country offices, as those patents only provide protection in one country. However, differing cost and fee structures, local incentives or rules, and differences in patent litigation may still induce some national level applications, along with simple ignorance or bureaucratic inertia by applicants. As well, there may be circumstances where national level patent projection provides righter intellectual property protection than EPO patent, or when patent protection at the national level interacts favourably with other forms of IP such as local copyrights or trademarks. National patents may be required by counterparties in R&D such as government or local universities. Thus, while EPO membership substantially reduces the number of patents filed locally, it doesn't eliminate them entirely.

The link between manufacturing and patenting activity was the subject of prior work that I did during my MA at Carleton, working in the Research Methods class of Dr. Lynda Khalaf and Dr. Marcus Voia.[1] That original work explored the impact of manufacturing using the Pooled Mean Group estimator. Manufacturing is significant because it may generate spillover economic activity that is disproportionately more important in generating patents than are other sectors of GDP. Furthermore, companies may sometimes pursue defensive patents in countries where local manufacturing capacity is high enough to lead to significant competition. In the prior work, I didn't consider EPO membership or use data from any EPO member states. I ignored all data from countries who were members of the European Patent Office.

Using a panel data set, the goal of this paper is to determine the effect of membership in the EPO on national level patent application filings. This requires the use of panel data to isolate the membership-specific effect as opposed to simply being an advanced economy. None of the past studies have considered the impact on national-level patent offices of EPO membership. They have either attempted to forecast patenting in a non-EPO member (the US), looked at filings to the EPO, or, as in Gabaly and Hidalgo's work, attempted to forecast national-level patents in a single office which was a long-

[1] I'd also like to thank the team in the Policy, International, and Research Office of the Canadian Intellectual Property Office, particularly Dr. Elias Collette, Anne-Marie Monteith, and Diego Santilli for their help and guidance.

term EPO member (Spain). The papers by Gabaly and Hidalgo simply take Spain's membership in the EPO as given, and don't consider the magnitude of its impact.

There are three main potential applications of this work. Firstly, we can better understand the determinants of these variables, and see the economic links between innovation, institutions, and patenting. This can inform future research on topics from economic growth to industrial organization.

Secondly, this work can improve forecasting models, so that policymakers in national patent offices can better predict what their future volumes of numbers of patent applications will be. Forecasting the number of patent applications in national patent offices is extremely helpful for those patent offices for several reasons. It allows for better forecasting of workflow and work volumes. It may have ramifications for hiring or for fee structure. From a policy perspective, the annual number of patent applications is often used as a proxy for innovation.

Thirdly, we can better understand the size of national level difference in patenting volumes, which could be used to shed light on the impact of different fee structures or patent regimes. We can use the findings in the model to make retrospective projections about national patenting levels. In other words, we can work backwards, taking a country's national GDP, R&D spending, EPO membership status, and manufacturing output, and ask what the patenting level "should" be. By examining country-level fixed effects and country-specific trends, we can use these findings to understand which countries are above or below what would be expected. For example, Canada is a country where many commentators (see Speer and Robichaud) believe that patenting levels are lower than they should be - Canadian patent application levels domestically have not grown in about 15 years. We could use this paper's results to examine these claims more closely, and to distinguish between short and long run effects.

As Brexit (the UK's pending exit from the European Union, which is currently under negotiation) looms, the question of the membership effects in the EU is relevant. It remains unclear whether Britain will once again have a nationally independent patent process. This paper can only capture the effect of joining the EPO rather than leaving it, but this work can give us a starting point for understanding the policy consequences of such a move.

This paper will use three different techniques to examine the effect of the EPO: the Pooled Mean Group estimator, a simple regression using fixed effects, and nearest-neighbour matching.

2 Literature Review

The key references here deal with methods of patent forecasting, and some work on the connections between manufacturing and patent filings. I performed an extensive Google Scholar search to ensure that no contemporary work deals with the relevant issues considered here.

Griliches described the correlations between R&D spending and patent activity at the firm level and the national level (1990, 1986). Griliches argues that firm level data shows the connection between R&D and patents is causal and runs from in that direction (1989).

Accordingly, past work on forecasting primarily uses research and development spending as the main exogenous variable when predicting patent applications. The major use of exogenous regressors to understand patent counts was done by Adams et al (1997) at the US Patent and Trademark Office (USPTO). They use either R&D spending totals, or GDP. GDP was used only because R&D wasn't available on a quarterly basis. They find that using an exogenous regressor can improve on a simple ARIMA approach using only past patent levels to predict future ones. More recent work on Spanish patenting by Hidalgo and Gabaly (2012, 2013) builds on the USPTO methodology, using ARIMA smoothing with GDP as the only added regressor. Shares of GDP spent on R&D and manufacturing are not considered, nor are any other exogenous variables.

The literature on patent forecasting deals largely with general issues and does not consider the implication of EPO membership. The book edited by Hingley and Nicholas (2006) does deal with EPO forecasting, but it is examining patent applications to the EPO as a whole, the opposite of the question considered here. Some of the models in the book, for example Hingley and Park (in Hingley and Nicholas, 2006), add the number of researchers or scientists as an exogenous regressor, but manufacturing isn't considered. National-level offices are not considered.

These existing models considered either R&D activity itself or used GDP as a proxy. By separately considering R&D share and real GDP, we can explore the whether the effects are the same of or different.

The theoretical basis for including manufacturing in this work comes from several sources. Some of these suggest that the effect on patenting would be positive, but some suggest that it would be negative. Work by Ulku (2005) finds positive correlations and suggests that the causality may run from patenting to manufacturing. If so, manufacturing capacity is providing spillover innovation that shows up in patents statistics, which may not be captured of by the effect of R&D because the innovation is more informal.

Scherer (1983) suggests that useful inventions lead to both patenting and a surge in manufacturing activity. However, changes in global markets and the increase in globalization in the last 35 years may have led to structural changes in this link. Teece (1986) argues that patenting decisions are made by firms after considering several factors, including competition in both distribution and manufacturing. The capacity of firms to manufacture rival goods may thus affect the number of patent applications filed that are associated with a sector or product line. We should conclude that companies may take manufacturing capacity into account for strategic reasons, and that there may be uncaptured spillover effects distinct from R&D spending. Much innovation happens on the factory floor, with engineers and manufacturing personnel working together, and not necessarily in a formal laboratory. The differences between routine management and true innovation may be blurred in modern manufacturing processes. All of this would suggest a positive coefficient on manufacturing, which is what I found in my prior work that omitted the EPO countries.

However, the effect of manufacturing on patenting be negative. A focus on "old economy" industries that involve a large share of manufacturing GDP may hold back economic growth and development. Countries which disproportionately manufacture may not be doing much innovation. This effect is likely stronger today because of increases in globalization, as factories and R&D labs can now be geographically separate.

3 Models and Methodology

EPO membership is common in European countries. In this data set, we have economic data on 31 countries, obtained from the OECD. Several OECD member states are excluded due to an insufficient amount of data obtainable on their patent applications. Patent data was obtained from the World Intellectual Property Organization (WIPO). WIPO gathers and aggregates data from member national offices. Of these countries, 8 are never in the EPO in this data set, 13 are in the EPO for all years they are in the data set, and 10 are in the EPO for some years but not others. The countries in the data set fall into several types. Some are Latin American or Asian economies, but most are European. Several Eastern European countries are in the data, set, such as Hungary, Slovakia, and Slovenia. The panel data is unbalanced. Each observation is a year of country level data, for a total of 653 observations. Additional information on the data set is contained in the Appendix.

Thus, I have data available on real GDP, EPO membership status, number of patents filed, R&D spending, and manufacturing output. From this, all needed regressors, such as the share of GDP produced by manufacturing, can be computed. These variables are all correlated with each other. As economies grow, the extend to have a lower share of spending on R&D, a lower share of economic activity stemming from manufacturing, and higher numbers of patenting applications. As well, all of the variables tend to have an upward trend over time. De-trending is described in the Appendix.

I use logs of variables in the regression. This gives a log-log interpretation of some of the coefficients, with percentage changes. Membership in the EPO is included with dummy variables. GDP and R&D spending are in real terms.

I consider the impact of EPO membership using three different methodologies, all of which give broadly similar results. They are: the Pooled Mean Group Estimator, fixed effects, and treatment effect calculations using nearest neighbour matching.

The Pooled Mean Group (PMG) estimator allows for divergent short run effects but common long run effects. Developed by Pesaro, Shin, and Smith (1997), this estimator is a compromise between the mean group estimator, which calculates coefficients for each country separately and averages them, and fixed effects. The PMG estimator uses an error-correction specification of the model. The long-run coefficients are treated as constant across countries, but the short-run coefficients are allowed to vary. The long-run coefficients are those of primary interest. Stata implements the PMG estimator through the xtpmg command package written by Blackburne et al (2007).

Unfortunately, there are limits are the number of regressors we can add and still computationally estimate the model given the size of the data set. Therefore, for the PMG model, I only consider total R&D spending, the method used by the USPTO (Adams 1997), and manufacturing is exlcuded entirely. Then, we use the PMG specification. Formally, the lags of the variables are first added as regressors:

$$\begin{aligned} lnPA_{i,t} = \theta_0 + \theta_1 lnRD_{i,t} + \theta_2 lnRD_{i,t-1} + \\ \theta_3 EPODummy_{i,t} + \theta_4 EPODummy_{i,t-1} + \lambda_1 lnPA_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad (1)$$

This is then rearranged into an error correction form:

$$\begin{aligned} \Delta lnPA_{i,t} = \phi_i(lnPA_{i,t-1} - \beta_1 - \beta_2 lnRD_{i,t} - \beta_3 EPODummy_{i,t}) \\ - \beta_4 \Delta lnRD_{i,t} - \beta_5 EPODummy_{i,t} + \epsilon_{i,t} \end{aligned} \quad (2)$$

Some of the desired regressions become unwieldy or impossible to run with the PMG hesitator because of an insufficient number of observations. Australia has the fewest number of complete observations in this data set with just 10. When doing the PMG estimator, Australia had to be dropped from the data set.

The use of fixed effects provides an alternative method. While it doesn't differentiate between the short- and long-run effects, it still provides a useful point of comparison for the coefficients. I can now consider GDP and R&D separately, as well as adding manufacturing. The fixed effects model estimates the model below, with different EPO dummy packages as specified in the results. The EPO variable may be the EPO membership dummy variable, or two different dummies separating out those countries in their first year of EPO membership. To determine how much of the change is in the first year of EPO membership, as opposed to later years, we use the two-dummy-variable combination.

$$lnPA_{i,t} = \beta_0 + \beta_1 RDShare_{i,t} + \beta_2 MShare_{i,t} + \beta_3 lnRGDP_{i,t} + \beta_4 EPODummy_{i,t} + \epsilon_{i,t} \quad (3)$$

Finally, I use nearest neighbour matching to determine the treatment effect of EPO membership. Nearest neighbour matching provides a way of estimating the average treatment effect on countries that joined the EPO. Average Treatment Effect on the Treated, sometimes also called Conditional Average Treatment Effect, is the effect on average on an country that received the treatment, i.e. on those countries who did join the EPO. Each observation is marched with a nearest neighbour, calculated on the regressors using minimum Mahlanobis distance.

There is the question of unit roots. Error correction models do not necessarily fail because of the presence of unit roots. For the fixed effects specification, we can deal with the issue of trends in two diverse ways. We can simply include a time trend, represented here by the year, or we can detrend each variable separately. This detrending was performed by regression each variable on time and then capturing the residuals. The detrending of each variable gives comparable results. There is a discussion of Dickey-Fuller tests in the Appendix. Dickey-Fuller tests were run for all countries separately on the patent applications per capita time series and the real GDP per capita time series, and we cannot reject the null of the unit root. The panel data Fisher test gave a similar result.

4 Results

We would expect not only a large negative effect of EPO membership on applications, but also that this impact would grow over time as applicants become more comfortable and aware of the advantages of the EPO process. We would expect positive coefficients on both R&D share and manufacturing share of GDP.

In the PMG results in Table 1, we see a large negative effect of EPO membership. This is translated into a percentage in Table 4.

With fixed effects, we can now consider the impact of manufacturing. I run three

Table 1: Results of PMG Estimation

	Coefficient	Std. Err.	P-Value	[95% Conf.	Interval]
Long-Run Effects					
R & D Spending	0.358	0.064	0.000	0.233	0.483
EPO Membership	-1.529	0.046	0.000	-1.619	-1.440
Short-Run Effects					
R & D Spending	0.512	0.166	0.002	0.187	0.836
EPO Membership	0.150	0.060	0.012	0.033	0.266
Constant	0.256	0.999	0.798	-1.701	2.213

Table 2: Results of Fixed Effects Estimation

	Coefficient	Std. Err.	P-Value	[95% Conf.	Interval]
Version 1					
R & D Spending	0.657	0.080	0.000	0.500	0.814
EPO Membership	-0.898	0.066	0.000	-1.027	-0.770
Version 2					
R & D Share	0.803	0.093	0.000	0.620	0.987
Real GDP	0.733	0.178	0.000	0.383	1.084
Manufacturing	-1.043	0.174	0.000	-1.384	-0.702
EPO Membership	-0.894	0.067	0.000	-1.025	-0.763
Version 3					
R & D Share	0.909	0.088	0.000	0.736	1.082
Real GDP	0.945	0.169	0.000	0.613	1.276
Manufacturing	-1.050	0.163	0.000	-1.369	-0.730
EPO Membership	-1.042	0.065	0.000	-1.169	-0.915
Just Joined Dummy	1.182	0.128	0.000	0.930	1.435

Table 3: Results of Nearest Neighbour Matching

	Coefficient	Std. Err.	P-Value	[95% Conf.	Interval]
Average Effect	-1.504	0.052	0.000	-1.607	-1.402
Average Effect on the Treated	-1.625	0.054	0.000	-1.731	-1.519

different versions (see Table 2): the first, a simple re-creation of the variables used in the PMG estimator; the second, the preferred model; and the third, including a dummy for the year a country joined the EPO, to allow for initial transitions. In all three regressions, I also use detrended series for all variables except the dummies, to remove any time trend. This is particularly important with the real GDP time series which has a strong time trend. With versions 2 and 3, I can disentangle the R&D and GDP effects by using R&D shares as separate regressors. Note that the coefficients for real GDP and R&D share are very close. This suggests that GDP growth translates into higher patenting activity through the mechanism of higher R&D. A Wald test shows that we can't reject the null that the two coefficients are the same.

The third version, which includes a separate dummy for countries which have just joined the EPO, has a large positive coefficient in the third regression, such that the net effect when combined with the EPO membership dummy is a net positive. This odd results suggests that the dummy variable is simply capturing selection bias in the types of economies who joined part of the way through the time series, rather than a real economic effect. Thus, version 2 is the preferred specification.

Nearest neighbour matching was used to estimate the treatment effect of EPO membership (see Table 3). Using detrended variables, the matching variables were R&D share, real GDP per capita, and manufacturing share.

The percentage drops in Table 4 are calculated from the coefficients using the formula

$$\%\Delta y = 100(e^{\beta_i} - 1) \tag{4}$$

The PMG and NNM methods give broadly similar results, finding a drop of around 80%. The fixed effects methods suggest a somewhat smaller effect of around 60%. In my past work, I considered advanced and middle-income economies separately, finding that

Table 4: Estimated Effect of EPO Membership, by Method

	Coefficient	[95% Conf.	Interval]	% Change	[95% Conf.	Interval]
PMG	-1.529	-1.619	-1.440	-78.3	-80.2	-76.3
FE 1	-0.898	-1.027	-0.770	-59.3	-64.2	-53.7
FE 2	-0.894	-1.025	-0.763	-59.1	-64.1	-53.4
FE 3	-1.042	-1.169	-0.915	-64.7	-68.9	-60.0
NNM ATE	-1.504	-1.607	-1.402	-77.8	-79.9	-75.4
NNM ATET	-1.625	-1.731	-1.519	-80.3	-82.3	-78.1

a 1% increase in manufacturing output led to a 0.17% increase in patent applications at a national office in an advanced economy, and a much larger 1.14% increase in a middle-income economy. The work here suggests that the impact of manufacturing may actually be negative.

5 Conclusion

The contributions of this paper are to include the effect of EPO membership in patent estimation models, and to estimate the effect of EPO membership in three ways. These three measures give broadly consistent results, suggesting a large, rapid, and sustained drop in national patent levels after EPO accession.

However, I acknowledge some potential issues with this work. National offices may seek to encourage or retain their business, operating as a self-interested bureaucracy, by changing fees or operating procedures to encourage filing despite the advantages of seeking an EPO patent. However, to the extent that this effect occurs, it would likely underestimate the effect of EPO membership on patents. We should also recognize that EPO membership is not simply a random decision, but that it is a benefit conferred on countries that are in Europe, which are more likely to be advanced economies. EPO eligibility is likely associated with meeting conditions simultaneous for accession to other EU institutions. Nonetheless, this paper represents a useful and rigorous evaluation of the effects of EPO membership.

Future work could include filling out the data set to include more observations, introducing the number of scientific researchers as a separate explanatory variable, or using national-level filings to the EPO as an explanatory variable or an instrument. As well, additional data on patent strength or fee levels, if available, would be useful to include.

A Appendix: Details on Data and Methodology

Note: Some parts of this appendix are re-used from my MA paper, as they were simply describing the same data sources and methods.

There were 31 countries used. Eight were never in the EPO: Australia, Canada, Israel, Japan, Mexico, New Zealand, South Korea, and the United States. Thirteen were in the EPO for each observation: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. Ten were in the EPO for some observations but not others: the Czech Republic, Denmark, Estonia, Finland, Iceland, Hungary, Norway, Poland, Slovenia, and Slovakia. There are a total of 653 observations.

Australia had to be excluded for some of the PMG estimations due to insufficiently many observations. The OECD countries without sufficient patent or other data, which are excluded entirely, are Turkey, Switzerland, and Chile.

The data was gathered from two primary sources. All OECD countries have data available through that organization. Data on GDP, gross R&D expenditure, population, and the share of value added from manufacturing was obtained from the OECD data center on their website. This manufacturing share was given as percentage of GDP. The OECD converts data to US dollars with the purchasing power parity method. The US GDP deflator series was used to convert the US dollar data into constant dollars. When relevant, variables are adjusted to be on a per-capita basis, and then logs are taken of the total variables and the share variables.

This panel data was unbalanced, as some GDP and R&D series go as far back as 1981, but others begin in later years. Almost all of the countries have data up to 2014, except those which accede to the EPO before then. Several series had gaps. In particular, for some years in the data set, Australia, New Zealand, and Norway reported their total expenditure on R&D biannually instead of annually. To fill these gaps, I interpolated the missing years between the logs of the inflation- and currency-adjusted R&D expenditure totals. This affected 27 observations in total.

From the European Patent Office, I obtained the list of all members and their years of accession. From the World Intellectual Property Organization, I obtained the total number of domestic patent applications in each year for each national office. Note that the number of applications is not the same as the number of patent grants. Applications represent only the beginning of the patenting process. These domestic applications may or may not have been filed by domestic residents. These data sets were merged together using Microsoft Query, and regressions were performed in Stata.

A Dickey-Fuller test was run separately on each panel's data for the patent applications and real GDP per capita. The null of a unit root cannot be rejected, with a small number of exceptions, such as Israel's patent applications time series and the real GDP per capita series for Australia and Japan. They are non-stationary, so the use of a method like the PMG estimator is suggested, because of the possibility of cointegration.

The share of manufacturing from GDP and the share of GDP spent on R&D both have a persistent time trend, particularly for advanced countries. To ensure that the regression did not capture spurious correlation, these variables were de-trended (after taking logs) by regressing them on the year and then retaining the residuals. These residuals are used in the fixed effects regressions and nearest-neighbour matching.

The PMG estimator is a maximum likelihood estimator. I use a quasi-Newton optimization method, the Davidon-Fletcher-Powell method.

Endogeneity is always a possible concern. The error terms may be correlated with research and development spending because of the omission of data on the number of research scientists. This headcount could not be obtained for all countries in the data set. A second possible source of endogeneity is the direction of causation between the variables. New patents may be encouraging increases in future R&D spending. However, as mentioned above, most work on firm-level data suggests that it is R&D that drives patenting more than the other way around. Similarly, there may be a concern that manufacturing activity is driven by patents rather than the reverse. The separation of short-run and long-run effects reduces this problem. Endogeneity can also arise due to measurement error. In particular, patent fees and local patent application rules vary significantly, and may change over time. However, patent fees themselves make up a relatively small amount of the cost of a panted application, which is much more related to approval time and requirements. Nevertheless, the non-inclusion of these variables may be introducing error. As well, R&D measurement error may be high.

References

[1] Adams, Kay & Kim, Douglas & Joutz, Frederick L. & Trost, Robert P. & Mastrogianis, Gus, 1997. "Modeling and forecasting U.S. Patent application filings," Journal of Policy Modeling, Elsevier, vol. 19(5), pages 491-535, October.

[2] Blackburne III, Edward F. & Mark W. Frank, 2007. "Estimation of nonstationary heterogeneous panels," Stata Journal, StataCorp LP, vol. 7(2), pages 197-208, June.

[3] Embree, Robert, 2017. "Manufacturing and Patent Applications: Empirical Evidence for Advanced and Middle-Income Economies". Not published. Submitted to Dr. Lynda Khalaf and Dr. Marcel Voia as part of MA work at Carleton University.

[4] Griliches, Zvi, 1990. "Patent Statistics as Economic Indicators: A Survey," Journal of Economic Literature, American Economic Association, vol. 28(4), pages 1661-1707, December.

[5] Griliches, Zvi, 1989. "Patents: Recent Trends and Puzzles," Brookings Papers on Economic Activity, Brookings Institution.

[6] Griliches, Zvi & Pakes, Ariel & Hall, Bronwyn H., 1986. "The Value of Patents as Indicators of Inventive Activity," NBER Working Papers 2083, National Bureau of Economic Research, Inc.

[7] Hidalgo, A. & Gabaly, S., 2012. "Use of prediction methods for patent and trademark applications in Spain," World Patent Information 34(1), pp. 19-29.

[8] Hidalgo, A. & Gabaly, S., 2013. "Optimization of prediction methods for patents and trademarks in Spain through the use of exogenous variables," World Patent Information 35(1), pp. 130-140.

[9] Hingley, Peter & Nicolas, Marc, 2004. "Methods for forecasting numbers of patent applications at the European Patent Office," World Patent Information, Elsevier, vol. 26(3), pages 191-204, September.

[10] Hingley, Peter & Nicolas, Marc (Editors), 2006. "Forecasting Innovations: Methods for Predicting Numbers of Patent Filings," Springer, Berlin, Germany.

[11] OECD (2017), Value added by activity (indicator). doi: 10.1787/a8b2bd2b-en (Accessed on 06 February 2017)

[12] Persyn, D. & J. Westerlund, 2008. "Error Correction Based Cointegration Tests for Panel Data," Stata Journal 8 (2), 232-241.

[13] Pesaran, M. H. & Shin, Y. & Smith, R. P., 1997. "Pooled Estimation of Long-run Relationships in Dynamic Heterogeneous Panels," Cambridge Working Papers in Economics 9721, Faculty of Economics, University of Cambridge.

[14] Pesaran, M. Hashem & Smith, Ron, 1995. "Estimating long-run relationships from dynamic heterogeneous panels," Journal of Econometrics, Elsevier, vol. 68(1), pages 79-113, July.

[15] Scherer, F.M., 1983. "The Propensity to Patent," International Journal of Industrial Organization pp. 107-128.

[16] Speer, Sean & Robichaud, Michael. "Fixing Canada's weak patent regime is better than handouts for spurring innovation," The Financial Post, July 5, 2016.

[17] Teece, David J., 1986. "Profiting from technologicial innovations: Implications for integration, collaboration, licensing and public policy", Research Policy, Elsevier, Vol. 15, pp. 285-305.

[18] Ulku, Hulya, 2005. "R&D, Innovation and Growth: Evidence from Four Manufacturing Sectors in OECD Countries," Development Economics and Public Policy Working Papers 30542, University of Manchester, Institute for Development Policy and Management (IDPM).

[19] Westerlund, J. 2007. "Testing for Error Correction in Panel Data," Oxford Bulletin of Economics and Statistics 69(6): 709-748.