# Manufacturing and Patent Applications: Empirical Evidence for Advanced and Middle-Income Economies

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**Abstract**

Past work on the number of domestic patent applications typically relies only on research and development spending and does not consider manufacturing capacity as an explanatory variable. This paper considers the impact of manufacturing on the number of domestic patent applications, utilizing the Pooled Mean Group estimator to isolate the long run effects. Using panel data from 9 advanced economies, I find a 0.17% increase in patent applications for a 1% increase in the share of GDP from manufacturing. Using panel data from 9 middle-income countries in the OECD, I find a much larger effect, a 1.14% increase in patenting for a 1% increase in the share of GDP from manufacturing. The effect sizes of changes in real GDP per capita and in the share of GDP spent on R&D are also considered.

# Contents

## 1 Introduction and Contribution

Models for explaining the annual number of domestic patent applications in a country typically rely on lagged patent applications and total expenditure on research and development. This paper includes manufacturing output in the model for determining domestic patent applications, and finds that manufacturing output has a positive effect that is statistically significant at the 1% level.

Domestic patent applications are all applications to a national patent office. This includes both applications from residents and those from non-residents. It excludes patent applications filed by residents at other offices.

Existing models of the number of domestic patent applications use numerous exogenous variables, notably expenditure on R&D, but do not use manufacturing output. Grilliches (1990) describes how economic variables are correlated with patenting activity. In particular, R&D is strongly correlated with patenting activity, with an R-squared from a simple regression on the order of 0.9 according to Grilliches et al. (1986). This is a classic result, and most economists have consequently used R&D expenditure as the main exogenous variable for forecasting patenting activity. Grilliches (1989 p. 311) summarizes this as follows by writing that, at the firm level, "so far as it is testable, causality runs from R&D

to patents." He also notes "the absence of a significant finding of direct effects of demand-side macroeconomic variables", and concludes that at the firm level, other variables act through R&D and not independently.

The gold standard of patent forecasting models is the 1997 paper by Adams et al., presenting the model used by the United States Patent and Trademark Office (USPTO). The USPTO considers several approaches, including a completely-trend based approach to forecasting patent applications, which works fairly well. Their more sophisticated model uses R&D variables to forecast patent applications. This is the typical approach when exogenous variables are used, as in the work on Spanish patents of Hidalgo & Gabaly (2013), or the European patent analysis of Hingley &Nicolas (2004). However, manufacturing output is not considered separately from the rest of GDP. Indeed, these models typically do not use GDP directly, but instead consider GDP as a proxy for R&D expenditures under some circumstances, such as quarterly forecasting models where R&D data is not available. As such, a statistically significant finding of an impact of any type of GDP, beyond the impact on R&D, would be an interesting contribution to the literature.

Hingley and Park (Chapter 4 of Hingley and Nicholas 2006) describe a standard theoretical model used to engage in patent application forecasting. Their model is based on a theoretical undestanding of firm-level behaviour. Firms will patent inventions if they believe the benefits of doing so exceed the costs. Thus, the number of inventions that are profitable to patent is the number to be estimated. Their variables of interest for national-level forecasting are R&D expenditure, the number of scientists working in R&D, potential firm profits from that country (for which GDP can be used as a proxy), patent strength, and patent cost. Patent cost would include not only fees, which make a relatively small part of the total cost of a patent, but also the costs of preparing the application, legal and agent fees, and translation costs. However, the Hingley and Nicholas-edited book Forecasting Innovation, which contains an extensive discussion of methods of patent forecasting, does not consider the separate effect of manufacturing capacity.

The original motivation for the inclusion of manufacturing capacity comes from a puzzle in the Canadian patent application data. There is a persistent view (expressed recently in the Financial Post by Speer and Robichaud) that Canadian levels of domestic patenting activity are inadequate, and that this reflects a problem in Canada's patent system. Canadian domestic patent applications (i.e. applications for patents in Canada, as opposed to applications by Canadians in other jurisdictions) have not increased since 2000. Despite substantial GDP growth, and growth in international patent applications by Canadians, there has not been corresponding growth in domestic patent applications. The period of stagnation in Canadian domestic patent applications begins at around the same time as a period of stagnation in Canadian manufacturing output. This suggests that manufacturing may be part of the explanation for the trend in domestic patent applications.

There is a theoretical link between manufacturing and R&D activity, with causation running in both directions. However, there may be an additional effect of manufacturing, beyond the spillover effects to R&D. Economists recognize that the decision to patent or not to patent is driven, in part, by a firm's strategic analysis about the likelihood of competition, and what the scale of production of that competition or replication will be (Teece 1986). The absence of sufficient manufacturing capacity may cause fewer patents to be filed, as firms don't need to file "defensive" patents if they are less worried about competition in low-manufacturing countries. The motivation of a firm to seek IP protection is related to its concern about competitors existing in that market. This theory would suggest that manufacturing capacity, not simply R&D and inventions that may spill over from manufacturing, affects patenting behaviour. If manufacturing capacity affects the strategic decision of firms to patent, manufacturing output would have an additional positive effect on patenting.

Ulku (2005) examines the links between R&D and manufacturing output, taking a sector-specific view. He finds that knowledge levels determine innovation in manufacturing sectors, and that the rate of innovation boosts the growth rate of manufacturing output levels. This suggests that the causality may be running in the other direction, with patenting and innovation boosting manufacturing output rather than the other way around. The idea that useful inventions are driving both patent counts and increased manufacturing output was also considered by Scherer (1983). In either case, there should be a positive correlation between manufacturing and patent applications.

Thus, manufacturing may affect patenting in several distinct ways. At the firm level, there may be spillover innovations that occur because manufacturing is being done by the firm, leading to additional patenting activity. Firms may be filing more patent applications strategically, if they are concerned about either having capacity to produce themselves or if they are concerned about the capacity of competitors. And at the macroeconomic level, an economy more oriented towards manufacturing may have structural effects on research and education they lead to higher levels of patenting. However, this paper is an empirical study, and cannot differentiate between these theoretical possibilities.

This paper's contribution to the literature is to include the share of GDP from manufacturing as a separate explanatory variable. To understand the effects of GDP growth and increased spending on R&D separately, we also consider real GDP and the share of GDP spent on R&D as two distinct variables rather than looking only at total R&D spending. A panel data approach is taken, with time-series data from two different groups of OECD countries. Because the relationships among these variables may be affected by the stage of economic development, advanced and middle-income economies are considered separately.

There are three primary reasons for undertaking this research. The first would be to assist with the construction of predictive models and systems that are used to forecast the demand for patents in coming years. This is the original impetus for most of the work in the literature, particularly the landmark USPTO paper from 1997, as well as more recent European work. If manufacturing GDP does have a distinct impact, then existing models could be refined. All of these current models use either a simple time-trend, excluding exogenous variables from the model entirely, or they simply use GDP and/or R&D expenditure, without breaking GDP down into components.

The second reason for this study would be to better understand the economic links between manufacturing, GDP, R&D, and domestic patent applications. Economic models can help economists understand what determines the number of patent applications and the relationship between patent applications, innovation, and other economic processes. As economists, we are interested in impacts of different variables on patents, and understanding what the sizes and directions of those effects are.

Thirdly, we can use the coefficients estimated here to compare what a country's patenting "should be", based on macroeconomic fundamentals, to what it actually is. This helps us understand country-specific effects.

Overall, this study contributes to the literature on patents and patent forecasting by better understanding the sources of patent activity.

## 2 Models and Methodology

Data on GDP, manufacturing, and R&D expenditure was obtained from the OECD. Data on domestic applications was obtained from the World Intellectual Property Office. A complete discussion of the data is included in the Appendix below.

Some of the countries in the OECD are members of the European Patent Office (EPO) during part or all of the time period. Member states of the EPO participate in a Europe-wide patent system, with central applications made to the EPO office, rather than to individual member state patent offices. This is efficient for the filer, but it reduces the number of patents filed domestically in those countries. Thus, this study excludes any observations for years in which the country was a member of the EPO. Some countries which later joined the EPO have pre-accession data included here.

I estimate the models on two different sets of countries: 9 advanced countries not in the EPO (Canada, New Zealand, the United States, Australia, Japan, Denmark, Iceland, Norway, and Finland) and 9 middle-income economies not in the EPO (Chile, Mexico, South Korea, Israel, the Czech Republic, Hungary, Poland, Slovakia, and Slovenia). These countries are separated because of a concern that the assumption of a homogeneous slopes across both data sets would not hold. This assumption of homogeneous slopes is required for the PMG method described below to be reasonable. Middle-income countries, which are undergoing catch-up growth, may have a different relationship between innovation and GDP.

The panel data is highly unbalanced, with some data points either unavailable due to a lack of R&D data, or excluded because of EPO accession. Almost all of the data is for the years 1994-2014, but both Denmark and Norway have data starting in 1981.

The share of manufacturing from GDP and the share of GDP spent on R&D both have a persisitent time trend, particularly for advanced countries. As such, those series were de-trended, as described in the Appendix, so that only changes relative to the trend would be considered.

I consider real GDP per capita, the share of GDP from manufacturing, and the share of GDP spent on R&D as explanatory variables. The latter two variables are expressed as shares to reduce any possible multicollinearity issues, as GDP, manufacturing output, and total R&D spending are three time series that move closely together. While data on the number of research scientists, patent fees and costs, and an index of patent strength would all be valuable additions to this model, the data on those factors is difficult to obtain for all countries in the data set.

I use the method of Pesaran, Shin, and Smith for constructing the Pooled Mean Group (PMG) estimator. The PMG estimator is a compromise between the two extremes commonly used with dynamic panel data, the Mean Group estimator and dynamic fixed effects. The Mean Group (MG) estimator allows all coefficients to vary among panels, and simply averages them. It is less effective in cases where some slopes are homogeneous across panels. The dynamic fixed effects method (DFE) assumes that all slopes are the same across panels, and has panel-specific dummy variables measuring the fixed effect. If slopes are heterogeneous, it will be inconsistent.

The PMG estimator is both consistent and efficient across countries as long as slopes are homeogeneous. (Blackburn III and Frank 2007). The separation of countries into advanced and middle-income is done to make this a reasonable assumption. PMG is robust to the possibility of heterogeous slopes among the different countries for the short-run effects. This estimator is designed for cases where T, the number of years, is larger than N, the number of panels. In this paper, the data set of the advanced countries has 162 observations, where N=9 and T = an average of 17.0. For the middle-income countries, there are 101 total observations, with N=9 and T= an average of 10.2. The panel data is unbalanced. The estimator is very flexible and will work with both stationary and non-stationary regressors

(Pesaran et al. 1997 page 6). A discussion of the non-stationarity of the regressors, tests run on the data, and other methodological details is found in the Appendix.

The model that is estimated is an error-correction parameterization, following the outline that is presented in Pesaran et al. (1997). Below is the general model of the determinants of the number of domestic patent applications: research and development spending and manufacturing output as shares of GDP, and real GDP. I take logs of the number of patent applications, real GDP, and the manufacturing and R&D shares of GDP (those last two series are de-trended after logs are taken). Note that the delta coefficients may vary between countries. It is this variation that is specified with the PMG estimator.

$$lnPA_{i,t} = \delta_0 + \delta_1 RDShare_{i,t} + \delta_2 MShare_{i,t} + \delta_3 lnRGDP_{i,t} + \epsilon_{i,t} \tag{1}$$

I then consider an autoregressive distributed lag process, ARDL(1,1,1). The theta or beta coeficients here are different than the coefficients above.

$$\begin{aligned} lnPA_{i,t} = \theta_0 + \theta_1 RDShare_{i,t} + \theta_2 RDShare_{i,t-1} + \theta_3 MShare_{i,t} \\ + \theta_4 MShare_{i,t-1} + \theta_5 lnRGDP_{i,t} + \theta_6 lnRGDP_{i,t-1} + \lambda_1 lnPA_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{2}$$

This is then rearranged into an error correction model, which is estimated.

$$\begin{aligned} \Delta lnPA_{i,t} = \phi_i(lnPA_{i,t-1} - \beta_1 - \beta_2 RDShare_{i,t} - \beta_3 MShare_{i,t} - \beta_4 lnRGDP_{i,t}) \\ - \beta_5 \Delta lnRD_{i,t} - \beta_6 \Delta MShare_{i,t} - \beta_7 \Delta lnRGDP_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

As in Pesaran et al. (1997), the error correction model is parameterized with the current rather than lagged values because it allows for the special case of ARDL(1,0,0). The variables that measure the long-run relationships of interest, $\beta_2, \beta_3$, and $\beta_4$, are fixed by the PMG estimator and the others are allowed to vary. Adjusting the data to per capita statistics makes international data more comparable across differently sized countries. Accordingly, both real GDP and patents are adjusted to be on a per capita basis, before logs are taken.

A Hausman test showed that the PMG estimator is preferred to the MG estimator for the advanced economies, because the null of non-systematic differences in estimated coefficients cannot be rejected at even the 10% level. However, the MG estimator cannot be estimated on the full middle-income data set because of insufficient observations for several countries, so a Hausman test could not be performed for that data set.

I perform the Westerlund tests to check if co-integration exists among these variables (Westerlund 2007). Three of the advanced economies had an insufficient number of observations for the Westerlund test and had to be dropped for this calculation. We can reject the null of no co-integration in any panel at the 1% level (p-value of Gt test is 0.006), but cannot conclude that co-integration exists for the panel as a whole. For the middle-income economies, a smaller average number of observations per panel means that seven of the nine economies contain too few observations to be used in the Westerlund tests. The result of the tests on the middle-income economies in inconclusive.

## 3 Results

The estimation of this model answers the research question about the impact of manufacturing output on patenting.

I present only the long-run relationships from the PMG estimator in Table 1. The PMG estimator also produces short-run estimates for each country, but most of these variables are not statistically significant at even the 10% level. Because all variables are log variables, we can understand the coefficients as elasticities.

For the advanced economies, I find a 0.17% increase in patent applications for a 1% increase in the share of GDP from manufacturing. Note that this is not a 1 percentage point increase, but a 1% change in the share - for example, a 1% increase in a 15% share of GDP would mean 15.15% of GDP. For the middle-income economies, I find a 1.14% increase in patenting for a 1% increase in the share of GDP from manufacturing. This much larger effect likely reflects the greater importance of manufacturing-related innovation in driving patent activity in middle-income economies.

A 1% increase in real GDP per capita boosts patents per capita by 0.48% in advanced economies and 0.54% in middle-income economies in the long term.

Table 1: Effects on Patents per Capita in Advanced Economies

| | Coef. | Std. Err. | P-value | [95% Conf. | Interval] |
|---|---|---|---|---|---|
| Long-Run Effects | | | | | |
| R & D Share | 0.4493397 | 0.0057298 | 0 | 0.4381094 | 0.46057 |
| Real GDP Per Capita | 0.4841708 | 0.0086761 | 0 | 0.4671659 | 0.5011757 |
| Manufacturing Share | 0.1711186 | 0.0083672 | 0 | 0.1547191 | 0.187518 |
| Short-Run Effects | | | | | |
| Speed of Convergence | -0.5854316 | 0.2594589 | 0.024 | -1.093962 | -0.0769014 |
| R & D Share | 0.1641489 | 0.489915 | 0.738 | -0.7960669 | 1.124365 |
| Real GDP Per Capita | -0.0487467 | 1.28882 | 0.97 | -2.574787 | 2.477293 |
| Manufacturing Share | 0.1448491 | 0.3752074 | 0.699 | -0.5905439 | 0.8802421 |
| Constant | 1.528454 | 0.6758735 | 0.024 | 0.2037664 | 2.853142 |

Table 2: Effects on Patents per Capita in Middle-Income Economies

| | Coef. | Std. Err. | P-value | [95% Conf. | Interval] |
|---|---|---|---|---|---|
| Long-Run Effects | | | | | |
| R & D Share | 0.5249091 | 0.1247906 | 0 | 0.280324 | 0.7694941 |
| Real GDP Per Capita | 0.5403968 | 0.1916676 | 0.005 | 0.1647351 | 0.9160585 |
| Manufacturing Share | 1.446626 | 0.2036144 | 0 | 1.047549 | 1.845703 |
| Short-Run Effects | | | | | |
| Speed of Convergence | -0.4110778 | 0.2315178 | 0.076 | -0.8648444 | 0.0426888 |
| R & D Share | 0.5677372 | 0.5829885 | 0.33 | -0.5748993 | 1.710374 |
| Real GDP Per Capita | -0.6722646 | 0.9526328 | 0.48 | -2.539391 | 1.194861 |
| Manufacturing Share | -1.224403 | 1.410243 | 0.385 | -3.988429 | 1.539623 |
| Constant | 0.5398534 | 0.2909892 | 0.064 | -0.0304748 | 1.110182 |

A 1% increase in the share of GDP spent on R&D (which, again, is not a 1 percentage point increase), is found to increase patents per capita by 0.45% in advanced economies and 0.52% in middle-income economies.

The similarity between the R&D share coefficients and the GDP coefficients suggest that both may be acting through a similar mechanism - in other words, that the increase in GDP translates to patents by boosting R&D, and thus has the same effect as simply boosting the share of the economy spent on R&D. A Wald test could not reject the hypothesis that the coefficients are equal for middle-income economies, but did reject the hypothesis of equality for advanced economies, significant at the 5% level. Nonetheless, the effect sizes are very close.

Additionally, all of the GDP and R&D share long-run elasticities are found to be less than 1. The reported speed of convergence is an average across panels because the PMG estimator allows that coefficient to vary. It is negative, as expected, in all regressions.

# 4 Conclusion

I conclude that manufacturing does have an impact on domestic patent applications. Admittedly, one possible explanation for this data is reverse causality, with patenting driving GDP and manufacturing output. However, the negative value of the speed of convergence coefficients suggests that the model is correctly specified.

Manufacturing output having a significant impact on the number of patent applications may suggest that we should be modifying our forecasting systems. Given the estimated coefficients, we can build better models of expected numbers of domestic patent applications.

Furthermore, my finding deepens our understanding of the complex links between patenting, innovation, and manufacturing. If manufacturing capacity has an additional impact beyond the spillover effects on increased research and development, the view that manufacturing is part of the "old economy" and not important to a modern, innovation-focused, knowledge economy, may be weakened. The rise of 3-D printing, additive manufacturing, and other advanced manufacturing techniques may have a significant effect on manufacturing output, and thus, on patenting activity.

These types of conclusions have substantial policy implications. If manufacturing capacity has an additional spillover effect on patenting, this may strengthen the case for some type of industrial policy to promote manufacturing specifically. Furthermore, it reduces the pressure for substantial reforms of the Canadian patent system, and contrasts directly with the view that Canada "isn't patenting enough".

Future extension of this work would include adding fees or other data on patent cost, an index of patent strength, and information on the number of researchers in each country.

# A Appendix: Details on Data and Methodology

The advanced economies used are: Austrla, New Zealand, Canada, the United States, Japan, Denmark, Norway, Iceland, and Finland, for a total of 162 observations. The middle-income economies used are: Chile, Mexico, South Korea, Israel, the Czech Republic/Czechia, Hungary, Poland, Slovenia, and Slovakia, for a total of 101 observations.

The data was gathered from two primary sources. All 34 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 (but not 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 persisitent 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 (separately for each data set to capture different time effects) and then retaining the residuals. These residuals are used in all regressions.

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 manufacturning 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. The non-inclusion of these variables may be introducing error. As well, R&D measurement error may be high.

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