Patenting and Research and Development: A Global View[*]

Mariano Bosch

Daniel Lederman

William F. Maloney

The World Bank

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Abstract: Using a new global data base on patents and innovation inputs, this paper employs several recently developed econometric techniques to examine the dynamic relationship between R&D and US patents granted. We confirm at the country level the recurrent micro-level finding of a strong relationship between the two and estimate the OECD elasticity to be effectively equal to one. This conflicts with the frequent micro-level finding of strongly diminishing returns in knowledge generation and suggests the importance of spillover effects measurable only at the aggregate level. Developing countries, however, do show diminishing returns. We then try to explain the variance in these elasticities by introducing proxies for the functioning of the national innovation system, the set of institutions and agents that create and disseminate knowledge. Across the entire sample education, security of intellectual property rights, and in some specifications, the quality of research institutions and their interaction with the private sector affect the transformation of R&D into patents.

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I. Introduction

The idea that technological progress is driven by research effort is the central insight of the endogenous growth literature.[1] In several of the canonical models (Romer 1990, Grossman and Helpman 1991 and Aghion and Howitt 1992), the assumption of constant returns to knowledge generation plus large spillovers to other researchers implies that more resources invested in R&D leads to increasing growth rates.[2]

However, there is disagreement over the technology generating new knowledge. Jones (1995) critiqued the relevance of such models, arguing that in the US, both growth and the intermediate measure of knowledge generation, patents, appear to be constant over time despite large increases in R&D employment, implying decreasing, rather than the increasing returns implicit in previous models.[3] In fact, a long and expanding literature offers support for this view. While it may well be the case that future researchers may "stand on the shoulders" of those past and find innovation easier (see, for instance, Romer 1990, Aghion and Howitt 1992), this may not be sufficient to offset increasing costs of generating knowledge as technological opportunity in a particular field diminishes (Evenson 1984, Evenson and Kislev 1976, Kortum 1997, Segerstrom 1998). Further, the fact that patenting gives monopoly rights over the rents from new ideas can give rise to increasing redundancy of R&D efforts when multiple firms pursue the same discovery (see Jones 1995, Kortum 1993, Reinganum 1984,1989). Not only can these factors enter directly as determinants of the rate of growth, but as Jones and Williams (2000) among others note, they dictate whether the market determined level of R&D is above or below socially optimal.[4]

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[1] See for example, Barro and Sala-I-Martin 1995; Romer 1987, 1990; Aghion and Howitt 1992; and Grossman and Helpman 1991.

[2] See, for example, Romer (1990), Segerstrom et al (1990).

[3] Aghion and Howitt (1998) counter, arguing that, measured as a share of GDP, R&D effort has been relatively constant, consistent with their extended model.

[4] As Jones and Williams note (2000) the "the standing on shoulders" effect implies socially sub-optimal levels of R&D investment while the is "step on toes effect" raise the private return above the social and imply above socially optimal levels of investment in R&D

An increasingly sophisticated empirical literature attempts to directly estimate the knowledge production function using patents as a proxy for new knowledge. Jaffe and Trajtenberg (2002) and Griliches (1990) offer as stylized facts that in cross section patents are probably roughly proportional to R&D, implying an elasticity of unity, while the "within" panel dimension suggests strongly decreasing returns to scale.[5] The few studies in the second category (Hausman, Hall and Griliches 1984,1986; Blundell, Griffith and Windmeijer 2002) along with Blundell, Griffith and Van Reenen (1995) which looks at the impact of market structure on innovation, have contributed important advances in the theory of count data estimators in a panel context. The latter two focus particularly on modeling dynamics and controlling for the unobserved heterogeneity that renders cross-sectional estimates suspect. In this sense, they parallel closely the recent literature on dynamic panel modeling with continuous dependent variables (Arellano and Bond 1991, Blundell and Bond 1998). Both issues are found to be of central importance in modeling the innovation process and generating consistent parameter estimates.

All the panel studies confirm the stylized fact of decreasing returns to scale. Hausman, Hall and Griliches's (1984) non-dynamic estimates of the elasticity of patents with respect to R&D are in the range of 0.3-0.6, depending on the technique employed. Hall, Griliches and Hausman's (1986) estimates hover around .35 and are similar to those estimated in a dynamic context by Blundell, Griffith and Windmeijer (2002) of around 0.5. Using industry level panel data Kortum and Lerner (2000) find an elasticity of .48-.52. There thus seems to be support in the micro level within estimates for the more pessimistic view of increasing difficulty and congestion.

Nevertheless, the firm level estimates, and to a lesser degree those at the industry level, may miss the spillover effects that one firm's R&D may contribute to another firm or industry's knowledge generation effort. The literature on estimating the returns to R&D, for example, finds differences of several multiples between the private returns to

[5] In cross section, Bound et. al (1984) introduce a wide variety of estimates, the most comparable being around .32-.38 and Pakes and Griliches (1980) offer an estimate of .61 although Griliches (1990) suggests that when accounting for reporting error, there is little evidence of diminishing return in cross section. See also Klette and Kortum (2002) for a discussion of the stylized facts around the patents and R&D.

R&D, estimated at the firm level, and those at the national level suggesting substantial spillovers.[6] Jaffe (1986) also finds that firms whose research is in areas where there is much research activity by other firms generate, on average, more patents per dollar of R&D and he finds the magnitudes of the spillovers to be substantial.

To date, there are very few investigations at the aggregate level that would more completely capture such spillovers and none are comparable to the micro studies. Bottazi and Peri (2003) have estimated the R&D/patent relationship at the aggregate level using a cross-section of European regions. As in the other cross-sectional firm literature, they find an elasticity close to 0.9 and in addition, significant, although small, regional spillover effects within 300 kilometers. Using an OECD panel on 17 countries, Furman, Porter and Stern (2002) more generally explore the relationship between a range of innovation inputs and institutions and patents but also do not offer parameter estimates comparable to the panel studies discussed above.

In this paper we construct a large panel of advanced and developing countries and generate estimates for the R&D-patent relationship at the global level that are comparable to those at the micro level discussed above. Including a large sample of emerging countries puts us somewhere between the count and continuous dependent variable literatures. Only 6.5% of the sample has observations of zero value, just under half the number found in Blundell, Griffith and Windmeijer (2002), so clearly the issue of integers and zero values is reduced, yet not so small as to be dismissed altogether. We, therefore employ the estimators recently developed in both literatures. This allows tests for robustness to the assumptions underlying the various estimators. We find that regardless of the technique employed, there is a strong relationship between R&D effort at the global level and innovation with a long- run elasticity surprisingly close to 1.

We contribute to the understanding of the dynamics of knowledge creation. Hall, Griliches and Hausman (1986) argue that, at the firm level, patenting occurs virtually

[6] One strand of the empirical literature working broadly in the growth tradition has measured the returns to R&D using both micro and cross-country data.

instantaneously, suggesting that much of R&D expenditures are dedicated to development as opposed to basic or applied research. Blundell, Griffith and Windmeijer (2002), however find the long-run elasticity substantially larger than the short run. Since spillovers may occur only with some lag from the initial discovery, we may expect larger lags at the aggregate level. In using both annual and quinquennial data, we find that in fact, the lags are quite long.

We then divide the sample into OECD and developed countries and identify significant and important differences in scale economies and very large differences in implicit returns to R&D between the two samples. To examine the determinants of the differences in observed elasticities, we introduce interactively several variables likely to capture, especially, the degree of spillovers. In this sense we broadly parallel the literature on National Innovation Systems (NIS)[7] that focuses on how the deployment of human capital and financial resources in the various national institutions – universities, public think tanks, firms- and the interactions among these institutions affect the capacity of a country to generate knowledge. Furman, Porter and Stern's work on the OECD established that such factors often enter additively in determining the number of patents. Given the greater range of endowments, institutions, and institutional quality across our sample, we expect, and find, significant and important effects of these factors on the patenting elasticity.

The remainder of the paper is organized as follows. Section II describes the data, and outlines the econometric approach, and section III presents the main results regarding the relationship between patents and R&D expenditures. Section IV examines elements of the NIS that may influence the corresponding elasticity. Section V concludes.

[7] See Nelson 1993; OECD 1998, 2001; Lundvall et al. 2002, Furman et al 2002

II Estimating the Innovation Function

Data

Our dataset consists of a panel of 49 developed and developing countries from the 1960s to the present. We first review the measures of innovation output and input.[8]

Innovation Output: A large literature uses patents as an imperfect measure of innovation output although the limitations of the measure are well known (see for example, Griliches 1990, Trajtenberg 2001, Jaffe and Trajtenberg 2002). Of perhaps greater concern for the present work is that patents granted by national agencies are not comparable due to differences in national standards, costs of applying for patents, levels of intellectual property protection, pecuniary benefits from patenting, and other country-specific institutional features. To ensure comparability we follow Jaffe and Trajtenberg (2002), Branstetter (2001), Furman, Porter and Stern (2002) and use the number of patents granted by the United States Patent and Trademark Office (USPTO).[9] In the absence of a global patenting agency, the US remains the principal locus of patenting activity and the USPTO offers reliable panel data for the period 1963 to 2000 for a large number of countries. Granted patents are assigned by country of origin based on the country of residence of the first inventor.

That said, countries may differ systematically in their propensities to apply for patents in the US. Those with a large volume of exports to the US have a greater interest in patenting any invention that may be embodied in their exports.[10] Similarly, country endowments and economic structure may also impact the ratio of innovations to patents: manufacturing in general may generate higher patents per innovative dollar than natural resource based sectors. To control for these effects we include in our specifications the volume of merchandise exports to the US, drawn from the IMF Direction of Trade Statistics, and Leamer's (1984) index of natural resources endowments, net exports of

[8] See Lederman and Saenz (2003) for a complete discussion of the data.

[9] The U.S. PTO demands that the invention be "novel and nontrivial, and has to have commercial application" (Jaffe and Trajtenberg 2002, 3-4).

[10] See Trajtenberg (2001).

resource intensive products over labor force, constructed from the UN Statistics Department's Commodity Trade Statistics (COMTRADE).

Innovation Effort: Consistent with much of the microeconomic literature we employ real R&D expenditures as a measure of innovation effort. The data are derived ultimately from national surveys that use as a common definition of expenditures that include "fundamental and applied research as well as experimental development." [11] The data thus include not only the basic science expected in the more advanced countries, but also investments in the adoption and adaptation of existing technologies often thought more germane to developing countries. The series are constructed based on underlying data published by UNESCO, the OECD, the Ibero American Science and Technology Indicators Network (RICYT) and the Taiwan Statistical Data Book.

Though it would be desirable to study the evolution and efficiency of both private and public R&D, we work with aggregate R&D for several reasons. First, the data sources divide R&D not into private and public R&D, but into productive and non-productive sectors, the latter accounting for roughly 20% of the total. [12] The definition of "productive sector" includes both public and private for profit and not-for profit firms while "non-productive sector" includes R&D financed or undertaken by the executive branch of government.

Second, the productive/non productive split seems to occasionally lead to some critical issues in categorization. For instance, if a public company finances its R&D from retained earnings, this will count as productive sector R&D. If instead the same R&D is financed by a transfer from the treasury to the firm, it counts as "non-productive" R&D. For several countries in our sample, there were striking shifts in composition from one year to the next suggesting sensitivity to these accounting conventions. By contrast, the total R&D series were reasonably stable. The final consideration is more prosaic: many

[11] UNESCO Statistical Yearbook (1980) pg. 742. Definitions are common to the OECD, Ibero American Science and Technology Indicators Network (RICYT), World Bank ,and Taiwan Statistical Yearbook and all are based on the Frascatti manual definition.
[12] The median for countries with both series is 21%.

developing countries tabulate only the aggregate values and hence to maintain the largest sample we use the most common definition.

We describe the data in tables 1 and 2 and in figures 1, 2 and 3. Table 1 tabulates the basic descriptive statistics of all variables and table 2 the correlations among them[13]. Several facts merit attention. First, the patents variable ranges from 0 (Bolivia, Jamaica, Togo) to around 30,000 (Japan). [14] Similarly there are great differences in terms of R&D investment across countries. Figure 1 plots the overall relationship between patenting and R&D effort. Looking more closely, Figure 2 shows the same scatter for 2 groups of observations, those with less and more than 1,000 patents. Although some OECD countries have had bad years of patenting below 1,000, the graphs effectively capture the differences in the OECD/non-OECD samples. Both depict a clear relationship between patents and R&D expenditures. In addition to the strong relationship with log R&D, table 2 shows patents to be positively correlated with the log of US trade and negatively correlated with natural resource abundance.

Methodology

The estimation of the links between innovative capacity and its outputs, measured as the number of patents, is not straightforward for several reasons. First, the nature of the patent variable as discrete and non negative but with a non negligible probability of being zero has, in the firm level literature, dictated the use of count-data models with an exponential specification under the assumption of either Poisson or negative binomial distributions (see Hausman, Hall and Griliches's 1984 and Blundell, Griffith and Windmeijer 2002). However, the smaller number of zero-patent observations and generally greater patenting rates reduce somewhat the integer concerns underlying count models. Several recent studies at the country level treat the patent variable as continuous and estimate a standard dynamic log linear specification (see Botazzi and Peri 2003; Furman, Porter and Stern 2002). In our sample, roughly 6.5 % of the observations are zeros- not negligible particularly in the LDC sample where they are concentrated, but

[13] Appendix table A.1 tabulates in detail the means of the variables by country as well as the number of observations per country

[14] Note that the US has been left out of the sample due to the difficulty of controlling for trade with itself.

low enough to justify alternative approaches. Both approaches seem to fit the data reasonable well, although for low levels of patents there seems to be an increase in variance in the log linear specifications.[15] We explore both approaches here.

The second issue arises from the desirability of some dynamic structure in the estimation. There is likely to be lag between the commitment of the R&D expenditures and the actual output derived from them. For this reason, Hall, Griliches and Hausman, (1986) investigate the existence of a lag structure in the patents-R&D relationship. Although they argue that there is no evidence of a long lag between R&D and patenting, past R&D history seem to add to the current year's patent applications, although the effects are small. Additionally, Blundell Griffith and Windmeijer (2002) argue that there may be a feed-back effect between R&D expenditures and the patents generated by those expenditures. They develop an estimator which explicitly models the dynamics of the count process in the panel data taking into account that feed-back between patents and R&D.

Each of the techniques employed in the literature offers advantages and drawbacks. Our strategy is to explore the data with several of them to assess the robustness of our findings to their underlying assumptions.

Static Modeling

Within the context of static models we estimate variants of the standard specification used in the R&D-Patents literature (see Hausman, Hall, and Griliches 1984). As Blundell, Griffith and Van Reenen (1995) note, convenient specifications can be derived from a Cobb-Douglas technology production function such as

$$P_{it} = R\&D_{it}^{b} a_{i}$$

[15] Countries with 0 patents were assigned ln Patents=0. Regressions using the linear approach in following sections include a dummy variable for these observations.

where P_{it} is the number of patents of country i in period t, $R\&D_{it}$ is the total expenditure in *R&D* of country i at time t, *ß* is the elasticity relating the two, and a_i is a fixed individual effect for country *i*. In the count-data context where zero values are of central concern we estimate

$$P_{it}^{US} = \exp(b \ln R\&D_{it} + \partial_1 \ln US_{it} + \partial_2 \ln LI_{it}) a_i + e_{it} \qquad \text{(1a)}$$

In the context where zeros are less problematic, we estimate a log linear specification:

$$\ln P_{it}^{US} = b \ln R\&D_{it} + \partial_1 \ln US_{it} + \partial_2 \ln LI_{it} + a_i + e_{it} \qquad \text{(1b)}$$

In both cases, P_{it}^{US} is the patents count of country i at time t, R&D is the innovation input, US, the value of real merchandise exports towards the United States, LI is the Leamer index of natural resource abundance, and a_i captures country specific fixed effects.

Dynamic modeling

The introduction of dynamics and more generally of pre-determined regressors in both 1a and 1b adds complications. First, the inclusion of a lag dependent variable in equations 1a and 1b yields the usual inconsistent estimates using within group estimators (Nickel 1981).[16] In the context of count data models, Chamberlain (1992) and Wooldridge (1997) develop a GMM estimator to deal with individual fixed effects when the regressors are pre-determined. However, as Blundell, Griffith and Windmeijer (2002) argue, the GMM estimators show small sample bias when the time series show a high degree of persistence as is the case with expenditures with R&D. In order to jointly deal with the existence of country fixed effects and predetermined regressors more generally, they suggest an estimator that measures the fixed effect component a_i directly. In the context of innovation functions at the firm level, the key unobserved individual

[16] Fixed effects estimators create a correlation between the de-meaned variables and the regression error implying a bias of order $1/t$.

heterogeneity comes from the large differences in the stock of knowledge among firms so the capacity to innovate should be captured by the past history of innovations defined as the pre-sample mean of the dependent variable, $P_{ip}^{US} = \frac{1}{TP}\sum_{r=0}^{TP-1} P_{i0-r}^{US}$ where TP is the number of pre-sample observations. The approach is also valid at the country level and has the additional advantage that, since normally the patents series are more complete than the R&D series, a substantial number of observations can be dedicated to calculating the pre-sample mean without restricting the effective sample size used for estimation.

An additional complication specific to count-data models is the way the lagged dependent variable enters the specification. Blundell, Griffith and Windmeijer (2002) argue that including the LDV as a logged term within the exponential leads to problems transforming observations with value zero, and can also lead to greater than unity coefficients on the lagged dependent variable that imply an explosive time path for patents. They therefore propose introducing the lag of the dependent variable linearly, hence giving the name "linear feedback model," which corresponds to the following specification:

$$P_{it}^{US} = rP_{it-1}^{US} + \exp(b \ln R\&D_{it} + \partial_1 \ln US_{it} + \partial_2 \ln LI_{it} + f \ln P_{ip}^{US})a_i + e_{it} \quad (2a)$$

Estimating 1b in a dynamic linear dynamic panel context has been extensively treated elsewhere (see Arellano 2003). From the empirical point of view the recent growth literature provides numerous examples of dynamic panels in the presence of very persistent regressors in order to estimate an specification such as

$$\ln P_{it}^{US} = a_i + r \ln P_{it-1}^{US} + b \ln R\&D_{it} + \partial_1 \ln US_{it} + \partial_2 \ln LI_{it} + e_{it} \quad (2b)$$

Very briefly and closely following Anderson and Hsiao (1982), Arellano and Bond (1991) and Caselli et. al. (1996) in the growth literature, we difference the data to eliminate unobserved fixed effects a_i yielding

$$\Delta \ln P_{it}^{US} = b\Delta \ln R\,\&\,D_{it} + \partial_1 \Delta \ln US_{it} + \partial_2 \Delta \ln LI_{it} + \Delta e_{it}, \qquad (3)$$

However, unless the idiosyncratic error follows a random walk, this differencing necessarily gives the transformed error a moving-average, MA, structure that is correlated with the differenced lagged dependent variable. This can be overcome by using instruments dated t-n and earlier. Arellano and Bond (1991) employ lagged levels as a proxy for differences in a Generalized Method of Moments (GMM) context. However, in the context where explanatory variables show little variation over time, as is the case with R&D here and with schooling or natural resource endowments in growth regressions, levels are often poor instruments. Bond, Hoeffler and Temple (2001) show that this "weak instruments" problem can be severe in cross-country growth regressions with panel data. For this reason, we follow Blundell and Bond (1998), Arellano and Bover (1995), and Levine, Loayza and Beck (2000) in employing a system estimator that combines (3) with equation (2b) in levels, using lagged differences of the endogenous variables as instruments. Finally we make use of the procedure proposed by Windmeijer (2000) to minimize the small sample bias in the standard errors from the efficient two step estimation.

Each estimating technique implies a different approach to the data. The static estimates of equations 1a and 1b allow us to maximize the number of observations used; however they neglect the possible dynamics of the patents-R&D process and the endogeneity of the R&D variable. Estimation of dynamic equation 2a is also undertaken using the same data periodicity although the sample is restricted somewhat since we now require that each country have at least two consecutive observations. Finally the GMM estimations require additional lags for use as instruments which, for most of our sample, are not available due to gaps in the data. For this reason we use quinquennial averages since 1975.

A priori, our preferred estimates are the exponential linear feedback model and the log linear GMM estimation on the grounds that they control for individual heterogeneity and possible endogeneity of the explanatory variables. However, whenever appropriate we present alternative techniques using the same time span and sample for the sake of comparability.

III. Results

Static Estimates

We begin following the existing firm level literature by estimating static specifications. Because we want to be broadly comparable with the dynamic estimates that follow, we introduce a static version of the PSM estimator as well.

Table 3 presents estimates of equations 1a and 1b using yearly data from 1976-2000 under both the Negative Binomial and Poisson distributions, using the naïve levels, the Within Group (WG), and the Pre Sample Mean (PSM) specifications.[17] For comparison, we begin in the first panel with a linear estimator under the assumption that the aggregate data do not suffer "too much" from zeros and integer issues: the dependent variable is log of patents and a dummy variable is included for those observations with 0 patents.

The first point to highlight is that regardless of technique, strong evidence emerges for an aggregate innovation production function mapping the inputs to outputs of innovation. Further, the controls for US exports are generally of expected (positive) sign but the control for natural resources is highly unstable in sign and intermittently significant.

The test for over dispersion- that the conditional variance of patent counts in fact exceeds the mean- is significant in all of the Negbin regressions suggesting that of the two distributions, it is preferred over the Poisson model. Nonetheless, with a few notable exceptions, the results tell a broadly consistent story. The levels specification yields estimates of the elasticity of patents with respect to R&D ranging from 1.00 to 1.14 across distributional assumptions. Controlling for heterogeneity through either the WG

[17] We use data on patents between 1963 and 1975 to construct the pre sample mean.

or PSM lowers the coefficient, with the exception of the WG Poisson which, at 1.65, jumps to 50% above the highest of the levels coefficients. With this exception, the pattern of estimates-Negbin falling in between the levels and Poisson- corresponds closely to that predicted by Blundell, Griffith, and Windmeijer (2002) in the context of endogenous regressors: the levels estimator is biased upwards and the WG estimator is biased downwards and the superior PSM lying in between. In this scenario, the true value is likely to be bracketed on the high end by the similar Negbin and Poisson estimates (.78 and .86. respectively) and the linear PSM of .44 is at the low end. The substantially lower linear estimates under the WG and PSM estimators cast doubt on the idea that aggregate data obviates the issues of integers and zeros. The instability of the WG estimates, and the fact the WG Negbin is the only specification to yield a counterintuitive sign on US exports call the robustness of the estimator somewhat into question in this context.

Dynamic Estimates

Table 4 presents the dynamic estimates of the innovation function. In the first two panels, we present the linear and exponential models, analogous to the previous exercise although, to recall, the linear feedback model has only been developed in the exponential case for the Poisson distribution. It is important to note that in the linear models the ln R&D coefficient retrieves the short-run elasticity which needs to be transformed in standard fashion to a long-run elasticity whereas in the exponential models the coefficient already gives the long-run elasticity. This implies a lack of direct comparability of the ln R&D coefficients across specifications and hence we focus on the short and long-run elasticities. Since including lagged variables implies a loss of a quarter of the observations, the actual numerical results between the dynamic long-run coefficients and the ln R&D coefficients in the static case are not strictly comparable. Nonetheless, it is striking is that the same patterns of relative magnitudes of the long run coefficients emerge again with the ordering of levels, PSM and WG holding in the linear case and the pattern not holding in the Poisson case due to, again, an unusually high coefficient on the WG estimator. With the exception of this estimate, the long-run elasticities are broadly similar in magnitude to those of the static case.

Of more interest are the comparisons within the dynamic specifications. In particular, the second two panels work with five-year averages necessary to generate the instruments for the system GMM estimator. The specification is clear of second-order serial correlation and passes the Sargan test for over identifying restrictions. We also replicate the exponential exercises at quinquennial frequency, for comparability with the linear specifications and with the estimates at annual frequency.

Though the long-run elasticity differs across models, there are also impressive commonalities. The linear and exponential estimates at 5-year frequency are strikingly similar to the OLS, GMM, levels Poisson and PSM ranging between .86 and 1. The exponential levels and PSM estimates at annual frequency also track closely their quinquennial analogues. The annual levels and PSM linear specifications are substantially lower at .71 and .54 and the WG specifications are especially low, with the exception of the 2.64 on the annual exponential estimator, showing the same highly erratic behavior across estimation technique seen in the static regressions. Again, in the annual exponential and quinquennial linear cases, they generate a counterintuitive negative sign on US trade which also casts some doubt on their reliability. If, for these reasons and for the usual bias reasons associated with fixed effects in a dynamic context, we discount the WG estimator, and hold aside the linear PSM at annual frequency, all estimates are found between .71 and 1.06 with the bulk clustered around .88-1.06.

These results strongly support a relationship between R&D and patents at the economy-wide level. Further, they suggest elasticities that are substantially higher than those at the firm level and overall, consistent with constant returns to scale in the production of patents.

Advanced vs. developing countries

Tables 5 and 6 present the summary statistics for the variables that may influence the magnitudes of the patenting elasticities in the high-income and low-income samples.

As mentioned earlier, the vast majority of emerging countries have far below 1000 patents and the mean is a mere fraction of that found in the advanced countries which never shows any zeros.

Table 7 breaks the sample into OECD and developing countries.[18] We again report the results for our two preferred estimators although we now have clearer reasons to choose one over the other. Of the 6.5 % of zero patent values in the sample, all are found among the developing countries. Hence, in theory, the LFM estimator should be preferable for this sample and the GMM for the advanced countries. In practice, there is little difference in the estimates for the OECD-.95 for the LFM and 1.04 for the GMM-offering somewhat stronger evidence for constant returns in the advanced countries.

The suspicion that, for some reason, the higher returns to scale arise from using aggregate as opposed to private sector R&D spending turns out not to be justified. Using a reduced sample for the OECD of countries with complete data on R&D done by the productive sector versus the non productive sector (including government) still generates an elasticity very close to unity for both aggregate and productive-sector investment.

Since our aggregate sample spans a wide variety of sectors and countries which cannot be seen as the aggregate counterpart to the US manufacturing firm level data, asserting that the gap between this finding and the bulk of the micro findings captures spillovers is probably too heroic. Nor does a finding of constant returns to scale in the production of patents necessarily imply the same is true of knowledge generally. Still, the robustness to technique, sample and proxy for variable of the CRS finding for the OECD sample is suggestive that we cannot rule out scale economies emerging at the aggregate level that may offset the increasing difficulty and/or patent race effects that might be found at the level of the firm.

The results from the developing countries are strikingly different, however, with the LFM for the developing countries yielding a coefficient of .7 and the probably

[18] OECD includes Korea but excludes Mexico which looks far more like the poor country sample.

inappropriate GMM, .9. Given the relatively small standard errors, the former estimate suggests substantial decreasing returns to scale.

The final row of table 8 provides some "back of the envelope" calculations of the "return to R&D measured in patents" by multiplying the elasticities by the ratio of the average levels of patents to average level of R&D. If we crudely assume that patents have equal average value across samples, then we can calculate the relative rate of return to R&D. For the OECD sample, we find only a slight increase above those emerging from either the Hall et al. or Griffith et al. estimates at the micro level. This strongly contrasts with direct estimates of high social rates of return not appropriated privately summarized by Jones and Williams (1998) which could well reflect the lack of comparability among data sets. Staying within our sample, however, it can be said that the OECD countries show a rate of return that, in the more reliable LFM estimates, is higher by a factor of 5. If we assume that interest rates are probably higher in the developing world than in the OECD and hence the private rate of return should also be higher, developing countries exhibit decreasing returns to scale and substantially fewer spillovers than those enjoyed in the advanced countries.

IV. Assessing and Explaining the Efficiency of Innovation

The striking differential in elasticities and implicit rates of return raises the question as to what elements of LDC national innovation systems are giving rise to this result. The greater variance in the nature and quality of the institutions comprising the NIS across poor and rich countries offers the possibility of estimating their impact on how an economy uses R&D to produce knowledge.

Data

We experiment with four variables, interacting them with R&D to see which may raise or lower the elasticity. Again, we describe the data in tables 1and 2 and figure 3. As tables 5 and 6 show, the means of all of the variables are also substantially lower for the non-OECD than is the case with the OECD although the amount of overlap is quite large.

Years of Education: Recent literature stresses the complementarities between technological progress and education. In Lucas (1988), for instance, knowledge spillovers involve interactions among well educated people (see also more recently Acemoglu and Zilibotti 2001). We employ the standard measure of the quality of human capital, from the Barro and Lee (2000) data base, namely the average years of schooling at the beginning of each five year period.

Perceived Quality of Academic Institutions: Low quality researchers, or even good quality researchers housed in institutions with poor incentive systems, are less likely to produce patentable innovations for a given allocation of resources and would be less likely to detect possibilities for building on other individuals' discoveries. The World Economic Forum's World Competitiveness Report (2000) provides the average of the subjective rating by entrepreneurs on a 7-point scale of the perceived quality of their research institutions.

Level of Collaboration between the Research Institutions and the Private Sector: The literature increasingly stresses the importance of networks and collaboration across the various elements of the NIS as essential to the efficiency of generating new ideas, and to building on existing ones. Again, the World Competitiveness Report asks entrepreneurs to rank on a seven-point scale the level of collaboration among the private sector and research institutions.

Intellectual Property Rights (IPRs): IPRs, in theory, can reduce the flow of spillovers by making it more costly to create new inventions building on others' discoveries. On the other hand, weak intellectual property protection within a country may lead firms to simply hide their discoveries preventing spillovers all together. Thus, the protection and revelation aspects of IPRs have countervailing effects with unclear ex ante impact. The measure is taken from Park (2001) who combines indexes on patents, copyrights and trademarks into one IPR measure. These sub-indices in turn are ranked on coverage of protection, duration of protection, restrictions on exclusiveness of property rights, membership in international treaties, and enforcement of rights on a scale from zero to one, and then aggregated to form an index from 1 to 5. The variable is available only at quinquennial frequency, but among proxies available, it is the only one with temporal variation.

As is clear, the quality of these proxies is mixed, ranging from standard measures to very subjective evaluations of difficult to measure phenomena. Further, the subjective measures of quality of institutions and collaboration between the research institutions and the private sector lack a time dimension and hence offer limited variation. Both the years of education and the intellectual property indexes are reported every five years. Since all of these variables appear correlated with level of development, we add to our core control variables and interactive term with GDP per capita. Thus, the interpretation of the interactions of our proxies is net of any effect due to the level of development.

Results

Given the lack of temporal variation and the potential difficulty of introducing several interactive variables simultaneously, we begin with the non-dynamic version of our preferred PSM specification. We then add back the dynamics and, despite the few degrees of freedom, we run the exercise again with the GMM for completeness.

The results with the static specification suggest that our variables do have the power to explain substantial differences in the elasticity. In the first column of table 9 the significance of the interactive with log GDP and its positive sign confirm the results of the previous section that the elasticity is higher for OECD countries than for developing countries.

Columns 2-5 add the four NIS variables sequentially. All enter strongly significantly with level of education and the quality of research institutions emerging as the most important. In all cases, the coefficient on the log GDP interactive variable drops by at least a third. Since, as table 2 suggests, there is a high degree of correlation even within the NIS variables, Column 6 includes them all simultaneously. All preserve their significance although the quality of academic institutions and the level of education emerge as the most quantitatively important. The negative sign and marginal significance of the collaboration variable may arise because of the high correlation of the two subjective variables and their lack of variance over time. In the next two columns, we introduce them separately and confirm their significance and positive influence individually.

In the full LFM specification (table 10), all variables retain their signs and overall level of magnitude although the two subjective variables lose substantial significance. In the specifications with all NIS variables included, only education emerges as significant with IPRs retaining its sign but being significant only at the 15% level. The subjective interactive dummies maintain sign but not significance. Dropping them, the IPR variable appears again significant. Together, IPRs and education levels reduce the coefficient on the GDP/capita interactive term by over half from .029 to .013 suggesting that they account for much of the difference in elastic observed across income groups. The results for the GMM dynamic specification (table 11) are strikingly similar with, again, education and IPR entering significantly separately but only education maintaining its level of significance when combined. Again, given the few degrees of freedom, this is perhaps not surprising. Though admittedly imperfect, the proxies for elements of the NIS appear to be significant determinants of the rate at which R&D is converted into patents.

V. Conclusions

Using a new global data base on patents and innovation inputs and drawing on recent advances in dynamic estimation techniques, this paper confirms at the country level the recurrent micro-level finding of a strong relationship between expenditures in R&D and innovation output measured by US patents granted. The results are broadly robust to estimation technique and imply a unitary elasticity for OECD countries or constant returns to scale. This contrasts with firm level estimates using the same techniques that imply decreasing returns to scale. One interpretation is that the increasing difficulty of invention and redundant innovation efforts brought on by patent races observed at the micro level are offset by spillover effects only observable at higher levels of aggregation. The lack of comparability of the aggregate and micro samples leaves this as a conjecture only.

What is very striking is both the lower elasticity found among developing countries (suggesting strong decreasing returns to scale) and implicit rates of return that are perhaps 20% of those found in the OECD. We find that several elements of the national innovation system contribute to the differing elasticities observed. Education and the security of intellectual property rights emerge robustly as important factors, and in non-dynamic specifications the quality of research institutions and their interaction with the private sector enter as well.

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Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	% of zeros
Patents	1132	3509	0	31104	6.45
ln R&D	20.90	2.33	11.25	25.82	
ln US trade	15.20	1.68	7.82	19.05	
Natural Resources	0.21	1.66	-4.74	14.88	
Quality of Academic Institutions	4.93	0.97	2.80	6.30	
Collaboration with the Private Sector	3.97	0.95	2.54	5.78	
Education	7.05	2.23	2.21	11.84	
IPR	2.93	0.94	0.33	4.57	
ln (Mean Patents)	3.48	2.70	-2.56	8.39	

Table 2: Correlations

	Patents	ln R&D	UStrade	Natural Res.	ln (Mean Patents)	Quality Acad. Inst.	Coll. Private Sector	Educ.	IPR
Patents	1.00								
ln R&D	0.51	1.00							
ln US trade	0.47	0.69	1.00						
Natural Resources	-0.27	-0.16	-0.07	1.00					
ln (Mean Patents)	0.27	0.66	0.35	0.01	1.00				
Quality of Academic Institutions	0.32	0.59	0.34	0.08	0.90	1.00			
Collaboration with the Private Sector	0.27	0.51	0.34	0.27	0.64	0.71	1.00		
Education	0.30	0.63	0.30	-0.07	0.64	0.64	0.70	1.00	
IPR	0.47	0.84	0.61	-0.07	0.69	0.61	0.60	0.64	1.00

<u>Table 3: Static Estimates Patents on R&D</u>

Observations 636
Countries 49
Period 1976-99

	Linear			Exponential					
				Negbin			Poisson		
	Levels	**WG**	**PSM**	**Levels**	**WG**	**PSM**	**Levels**	**WG**	**PSM**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln R&D	1.01 ***	0.36 ***	0.44 ***	1.14 ***	0.56 ***	0.78 ***	1.00 ***	1.65 ***	0.86 ***
	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.06)	(0.03)	(0.01)	(0.04)
ln US trade	0.17 ***	0.25 ***	0.14 ***	0.11 ***	-0.29 ***	0.14 ***	0.19 ***	0.04 ***	0.22 ***
	(0.05)	(0.07)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.01)	(0.02)
Natural Resou	0.05 ***	-0.10 ***	-0.02	0.06 ***	0.00	0.00	0.05 ***	-0.01 ***	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
ln (Mean Patents)			0.61 ***			0.33 ***			0.11 ***
			(0.04)			(0.04)			(0.04)
Over-Dispersion				0.65 ***	0.28 ***	0.50 ***			
				(0.04)	(0.01)	(0.06)			(0.04)

Note: The dependent variable in the linear specifications is log Patents. We also include an dummy for those countries with no Patents. The dependent variable in the exponential specification is the count of Patents. Robust standard errors were estimated in all the specifications. All specifications include time dummies. WG and PMS refer to the within-group and the pre-sample mean estimations respectively.

***Significant at 10%, ** Significant at 5%, *** Significant at 1%**

Table 4: Dynamic Estimates: Patents on R&D

	Annual	Five Years
Observations	482	105
Countries	46	43
Period	1978-99	1985-99

	Annual						**Five Years**					
	Linear			**Exponential**			**Linear**			**Exponential**		
	Levels	**WG**	**PSM**	**Levels**	**WG**	**PSM**	**OLS**	**WG**	**GMM**	**Levels**	**WG**	**PSM**
Patents(-1)	0.95 ***	0.62 ***	0.91 ***	0.32 ***	0.41 ***	0.45 ***	0.82 ***	0.26 ***	0.62 ***	0.46 ***	0.47	0.54 ***
	(0.02)	(0.03)	(0.24)	(0.09)	(0.08)	(0.06)	(0.13)	(0.05)	(0.12)	(0.09)	(0.30)	(0.11)
ln R&D	0.03	0.12 ***	0.03	1.06 ***	2.64 ***	0.91 ***	0.18 ***	0.23 ***	0.37 **	0.91 ***	0.16	0.88 ***
	(0.02)	(0.03)	(0.02)	(0.04)	(0.37)	(0.07)	(0.07)	(0.06)	(0.15)	(0.16)	(0.10)	(0.12)
ln US trade	0.02	0.13 **	0.03 *	0.19 **	-0.24	0.22 **	0.11 ***	-0.06 ***	0.14 **	0.29 ***	1.38 ***	0.28 ***
	(0.01)	(0.06)	(0.02)	(0.10)	(0.19)	(0.12)	(0.02)	(0.02)	(0.05)	(0.06)	(0.25)	(0.08)
Natural Resources	0.00	-0.04 *	-0.01	0.09 ***	0.03 *	0.07 **	0.15	-0.19	0.01	0.01	-0.28 ***	0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.11)	(0.13)	(0.01)	(0.01)	(0.06)	(0.01)
ln (Mean Patents)			0.04 ***			0.10						0.06
			(0.02)			(0.07)						(0.05)
Long-Run Elast. of R&D	0.71	0.33	**0.37**	1.06	2.64	**0.91**	1.00	0.31	**0.96**	0.91	0.16	**0.88**
Short-Run Elast. of R&D	0.03	0.12	0.03	0.71	1.56	0.50	0.18	0.23	0.21	0.50	0.09	0.40
Sargan Test (p-value)									0.63			
First Order (p-value)									0.24			
Second Order (p-value)									0.23			

Note: The dependent variable in the linear specifications is log Patents. We also include an dummy for those countries with no Patents. Robust standard errors were estimated in all the specifications. The dependent variable in the exponential specification is the count of Patents. The exponential models were computed using EXPEND (see Windmeijer 2000), whereas the linear models were estimated in Stata. For the PSM models we include two lags of the dependent variable in set of instruments. The GMM system estimator used two lags of the variables and first differences to instrument. All the specifications include time dummies.

***Significant at 10%, ** Significant at 5%, *** Significant at 1%**

Table 5: OECD Statistics

Observations=346	**Mean**	**Std. Dev.**	**Min**	**Max**	**% of zeros**
Patents	1975	4560	1	31104	0
ln R&D	22.3	1.58	18.88	25.8	
ln US trade	15.7	1.53	12.73	19.0	
Natural Resources	0.28	2.08	-3.69	14.9	
Quality of Academic Institutions	5.53	0.62	4.10	6.3	
Collaboration with the Private Sector	4.53	0.75	2.92	5.8	
Education	8.32	1.71	3.27	11.8	
IPR	3.53	0.56	1.98	4.6	
ln (Mean Patents)	5.21	2.15	1.26	8.4	

Table 6: non-OECD

Observations=290	**Mean**	**Std. Dev.**	**Min**	**Max**	**% of zeros**
Patents	34	91	0	754	14.40%
ln R&D	19.23	1.95	11.25	22.80	
ln US trade	14.64	1.67	7.82	18.46	
Natural Resources	0.13	0.91	-4.74	5.07	
Quality of Academic Institutions	4.23	0.82	2.80	6.20	
Collaboration with the Private Sector	3.30	0.71	2.54	5.30	
Education	5.53	1.79	2.21	9.82	
IPR	2.22	0.80	0.33	3.90	
ln (Mean Patents)	1.41	1.60	-2.56	4.13	

Table 7: Elasticities: OECD vs. non-OECD

	Model	Periodicity	Total	OECD	Non-OECD
Static					
Linear	PSM	Annual	0.44 ***	0.82 ***	0.14 ***
			(0.05)	(0.05)	(0.02)
Exponential	PSM	Annual	0.78 ***	0.83 ***	0.22 ***
			(0.06)	(0.04)	(0.03)
Dynamic					
Linear	GMM	Quiquenial	0.96 ***	1.04 ***	0.89 ***
			(0.09)	(0.06)	(0.11)
Exponential	PSM	Annual	0.91 ***	0.95 ***	0.70 ***
			(0.06)	(0.04)	(0.12)

Table 8: Returns to R&D

	Hall et al (1986)	**Griffit et al (2002)**	**LFM**			**GMM**		
			Total	OECD	NON-OECD	Total	OECD	NON-OECD
Firms	642	407						
Patents	*35*	35	1132	1975	34	1097	1831	119
R&D Millions of Dollars of 1976	21.48	35.00						
R&D $M of 1995	49.91	*81.30*	9010	12050	722	8320	13700	1110
R&D/Patents	1.43	2.32	7.96	6.10	21.24	7.58	7.48	9.33
Correction Applied/Granted	0.65	0.65						
R&D/Patents (Corrected)	2.19	3.57						
Elasticity	0.3	0.506	0.91	0.95	0.7	0.98	1.04	0.9
Implied Returns to R&D	13.68%	14.16%	11.43%	15.57%	3.30%	12.92%	13.90%	9.54%

Table 9: NIS Efficiency Static Negative Binomial with Pre-sample mean

	Annual
Observations	636
Countries	49
Period	1976-99

ln R&D	0.366 ***	0.155 ***	0.314 ***	0.372 ***	0.301 ***	0.135 ***	0.188 ***	0.300 ***
	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)	(0.01)	(0.04)	(0.05)
ln US trade	0.262 ***	0.324 ***	0.280 ***	0.231 ***	0.316 ***	0.331 **	0.320 ***	0.288 ***
	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)
Natural Resources	-0.033 **	-0.061 **	-0.056 *	-0.075 ***	-0.004 *	-0.060 **	-0.060 **	-0.055 **
	(0.02)	(0.03)	(0.03)	(0.02)	(0.00)	(0.03)	(0.03)	(0.03)
ln GDPcap	0.028 ***	0.024 ***	0.021 ***	0.013 **	0.018 **	0.011 **	0.008 **	0.006 **
	(0.01)	(0.01)	(0.05)	(0.01)	(0.09)	(0.01)	(0.00)	(0.00)
ln (Mean Patents)	0.210 ***	0.174 ***	0.216 ***	0.229 ***	0.225 **	0.184 ***	0.207 ***	0.233 ***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Quality		0.097 ***				0.115 ***	0.065 ***	
		(0.03)				(0.03)	(0.01)	
Colaboration			0.054 ***			-0.049 *		0.025 ***
			(0.02)			(0.03)		(0.00)
Education				0.068 ***		0.053 ***	0.045 ***	0.050 ***
				(0.02)		(0.02)	(0.01)	(0.00)
IPR					0.021 ***	0.014 **	0.015 ***	0.016 ***
					(0.01)	(0.01)	(0.01)	(0.00)

Note: The dependent variable is the count of Patents. Robust standard errors were estimated in all the specifications. All specifications include time dummies.

Table 10: NIS Efficiency LFM Estimator

	Annual					
Observations	482					
Countries	46					
Period	1976-99					
Lagged Patents	0.419 ***	0.400 ***	0.440 ***	0.479 ***	0.409 ***	0.478 ***
	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	(0.08)
ln R&D	0.260 **	0.182 *	0.220 *	0.376 ***	0.260 **	0.350 ***
	(0.13)	(0.11)	(0.12)	(0.12)	(0.13)	(0.11)
ln US trade	0.290 ***	0.330 ***	0.300 ***	0.222 ***	0.315 ***	0.260 ***
	(0.08)	(0.08)	(0.11)	(0.07)	(0.11)	(0.08)
Natural Resources	-0.014	-0.037	-0.036	-0.046 *	-0.008	-0.044
	(0.02)	(0.04)	(0.03)	(0.03)	(0.01)	(0.05)
ln GDPcap	0.029 ***	0.029 ***	0.026 ***	0.018 ***	0.027 **	0.013 **
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
ln (Mean Patents)	0.154 **	0.120 **	0.162 ***	0.097 **	0.147 **	0.098 **
	(0.07)	(0.06)	(0.06)	(0.05)	(0.07)	(0.04)
Quality		0.034				
		(0.02)				
Colaboration			0.023			
			(0.02)			
Education				0.049 **		0.058 ***
				(0.02)		(0.02)
IPR					0.014 **	0.010 *
					(0.07)	(0.01)

Note: The dependent variable is the count of Patents. Robust standard errors were estimated in all the specifications. All specifications include time dummies.

Table 11: NIS Efficiency GMM Estimator

Observations	105					
Countries	43					
Period	1985-99					
Lagged Patents	0.580 ***	0.634 ***	0.583 ***	0.603 ***	0.586 ***	0.534 ***
	(0.14)	(0.17)	(0.18)	(0.14)	(0.12)	(0.16)
ln R&D	0.147 *	0.071	0.179	0.057	0.127	0.118
	(0.08)	(0.06)	(0.13)	(0.05)	(0.11)	(0.10)
ln US trade	0.229 ***	0.274 ***	0.204 ***	0.322 ***	0.201 ***	0.237 ***
	(0.06)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)
Natural Resources	-0.011	0.001	-0.012	-0.026	0.013	-0.020
	(0.03)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)
ln GDPcap	0.013 ***	0.012 *	0.009 *	0.007 **	0.010 ***	0.010
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Quality		0.018				
		(0.01)				
Colaboration			0.025			
			(0.02)			
Education				0.047 ***		0.037 ***
				(0.00)		(0.01)
IPR					0.010 ***	0.003
					(0.00)	(0.00)
Sargan Test (p)	0.88	0.85	0.86	0.90	0.99	1
First Order (p)	0.51	0.35	0.24	0.15	0.18	0.11
Second Order (p)	0.22	0.27	0.23	0.30	0.29	0.32

Note: The dependent variable is log Patents. Robust standard errors were estimated in all the specifications. All specifications include time dummies.The GMM system estimator used two lags of the variables and first differences to instrument.

Annex 1: Countries in the sample

Code	N	Patents	R&D	US trade	Natural Res.	Quality Acad. Inst.	Coll. Private sector	Edu.	IPR	Ln(Mean Patents 60-75)
ARG	14	26.36	20.58	14.43	0.64	3.40	2.71	7.64	2.59	3.09
AUS	11	420.73	22.11	15.26	2.26	5.90	4.84	10.14	3.37	5.04
AUT	20	336.45	21.72	14.14	-0.76	5.60	4.81	8.30	4.09	5.26
BOL	8	0.38	16.97	12.23	0.21	2.80	2.66	5.13	2.19	0.96
BRA	10	53.40	22.27	16.01	0.09	4.40	3.03	3.81	2.21	2.74
CAN	22	1723.91	22.67	18.44	2.29	5.70	4.81	10.51	2.95	6.95
CHE	10	1231.50	22.57	15.22	-1.70	6.30	5.15	9.32	3.55	6.98
CHL	16	5.50	19.26	14.31	1.10	4.30	3.77	6.79	2.57	1.31
CHN	5	66.40	22.45	17.95	-0.01	4.50	4.00	5.61	1.55	1.98
COL	7	5.71	18.88	15.07	0.25	3.70	2.98	4.59	2.25	1.59
CRI	10	1.70	16.88	14.08	0.54	4.80	3.66	5.44	1.61	-0.08
DEU	10	7508.50	24.78	17.43	-1.36	5.90	5.04	9.57	3.79	8.39
DNK	21	205.67	21.52	14.46	0.77	5.30	4.52	9.57	3.69	4.83
ECU	7	1.14	16.50	14.47	0.76	3.10	2.60	6.19	2.21	-0.62
EGY	10	1.80	20.84	13.36	-0.13	4.30	3.12	3.97	1.99	0.48
ESP	19	128.42	21.98	15.13	-0.77	4.80	3.24	5.91	3.57	4.06
FIN	20	292.55	21.54	14.21	1.85	6.30	5.78	8.83	3.18	3.92
FRA	22	2642.77	24.11	16.46	-0.73	6.20	4.59	7.32	3.88	7.47
GBR	18	2647.83	23.77	16.98	-0.63	6.10	4.73	8.68	3.54	7.93
GRC	14	9.43	19.53	13.09	-0.54	4.10	2.92	7.04	2.48	2.18
HUN	5	41.40	19.62	13.85	-0.10	5.20	3.59	8.67	3.37	3.50
IDN	12	2.08	19.17	15.74	0.22	3.70	3.14	3.35	0.41	1.55
IND	17	18.59	21.21	15.13	-0.01	5.20	2.76	3.31	1.56	2.53
IRL	21	45.52	19.98	14.50	0.92	5.60	4.77	8.10	3.07	2.55
ISR	16	346.25	21.43	15.24	-1.29	6.20	4.80	9.08	3.57	3.98
ITA	23	1053.87	23.00	16.38	-1.52	4.60	3.30	5.91	3.93	6.35
JAM	5	0.60	14.31	13.02	-0.09	4.50	3.10	3.81	2.86	-0.08
JOR	9	0.11	16.16	9.17	-1.23	4.50	3.12	3.49	1.86	-2.56
JPN	24	16017.38	25.41	18.28	-1.77	5.70	5.08	8.63	3.88	7.95
KOR	23	640.22	22.03	16.52	-0.92	4.90	4.07	8.13	3.62	1.26
LKA	4	0.25	16.48	13.16	0.00	4.00	3.00	5.36	2.95	-1.47
MEX	13	45.31	20.58	17.61	0.24	3.70	2.86	5.46	2.00	4.13
MYS	6	9.00	18.81	16.15	1.29	4.20	3.67	6.06	2.71	-0.26
NLD	22	821.00	22.66	15.52	1.21	6.20	5.14	8.44	4.20	6.31
NOR	17	107.12	21.22	14.75	5.66	5.40	4.62	9.14	3.31	4.20
NZL	7	51.71	20.12	14.23	3.65	5.60	4.47	11.28	3.48	2.85
PER	16	2.25	16.84	14.06	0.22	3.60	2.81	5.98	1.57	1.33
PHL	10	5.00	18.50	15.09	-0.02	4.00	3.00	6.35	2.67	1.67
POL	5	13.60	20.74	13.51	-0.15	4.50	3.13	9.82	2.90	3.01
PRT	10	3.90	19.85	13.62	-0.84	4.40	3.15	3.98	2.28	1.48
SGP	13	51.23	20.32	16.31	-1.96	5.60	5.30	6.10	3.08	0.69
SLV	9	0.33	17.95	13.42	-0.05	2.90	2.54	3.84	2.49	0.27
SWE	12	824.33	22.50	15.38	0.29	6.00	5.37	9.71	3.62	6.49
THA	14	3.21	19.03	15.17	0.04	4.20	3.52	4.77	1.91	-0.96
TTO	2	0.50	15.84	13.94	3.13	3.90	3.40	7.40	3.35	0.57
TUR	13	2.15	20.31	14.14	-0.14	3.50	3.11	4.01	1.80	0.65
URY	10	1.80	17.49	12.22	0.27	3.90	3.30	6.88	2.43	0.43
VEN	19	21.42	19.29	16.04	1.66	4.00	2.67	5.16	1.76	2.03
ZAF	5	99.80	20.75	14.58	0.32	5.10	4.42	5.11	3.57	4.06

Figure 1: Patents vs. R&D Expenditures

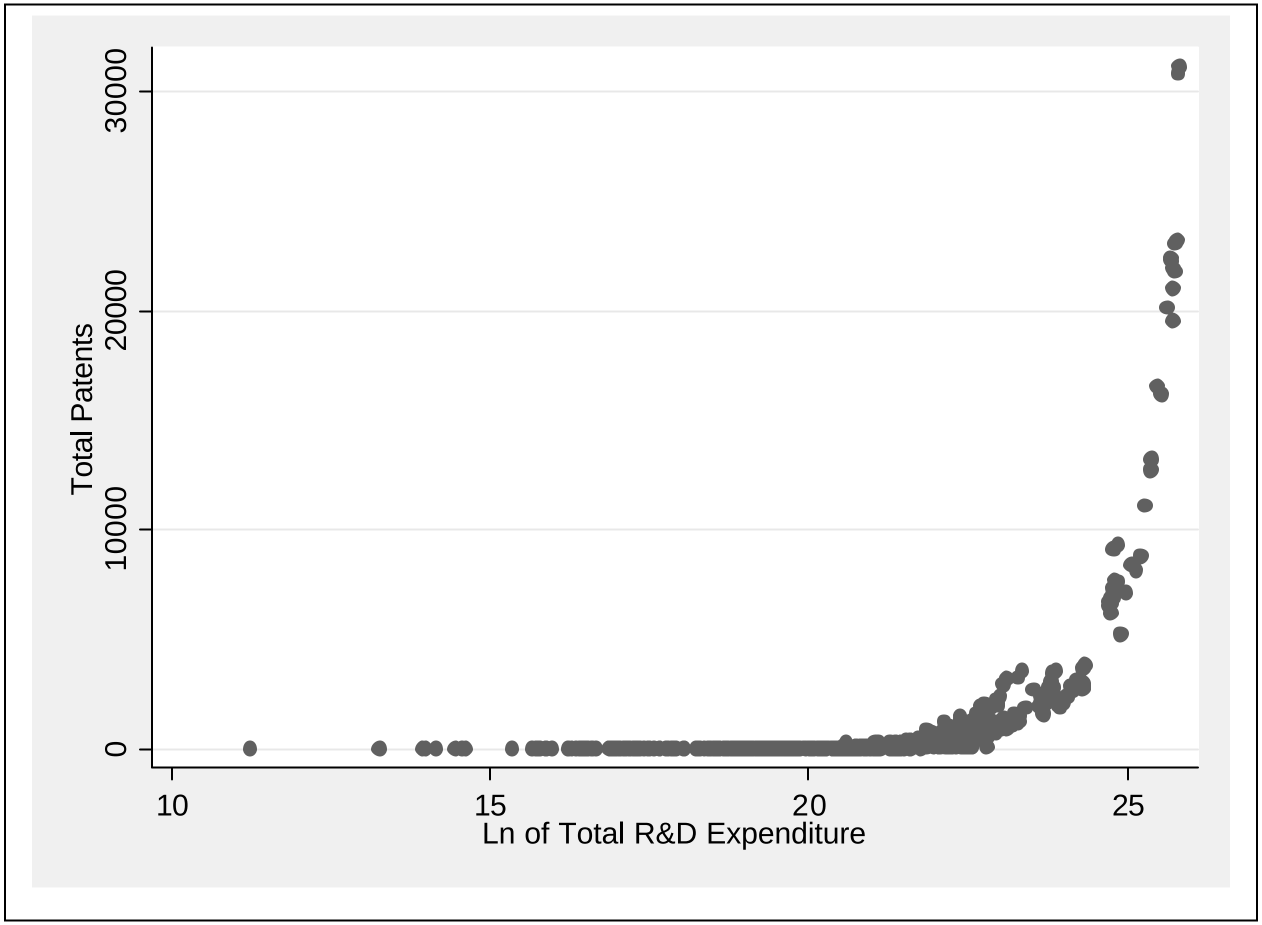

Figure 2: Patents vs. R&D Expenditures

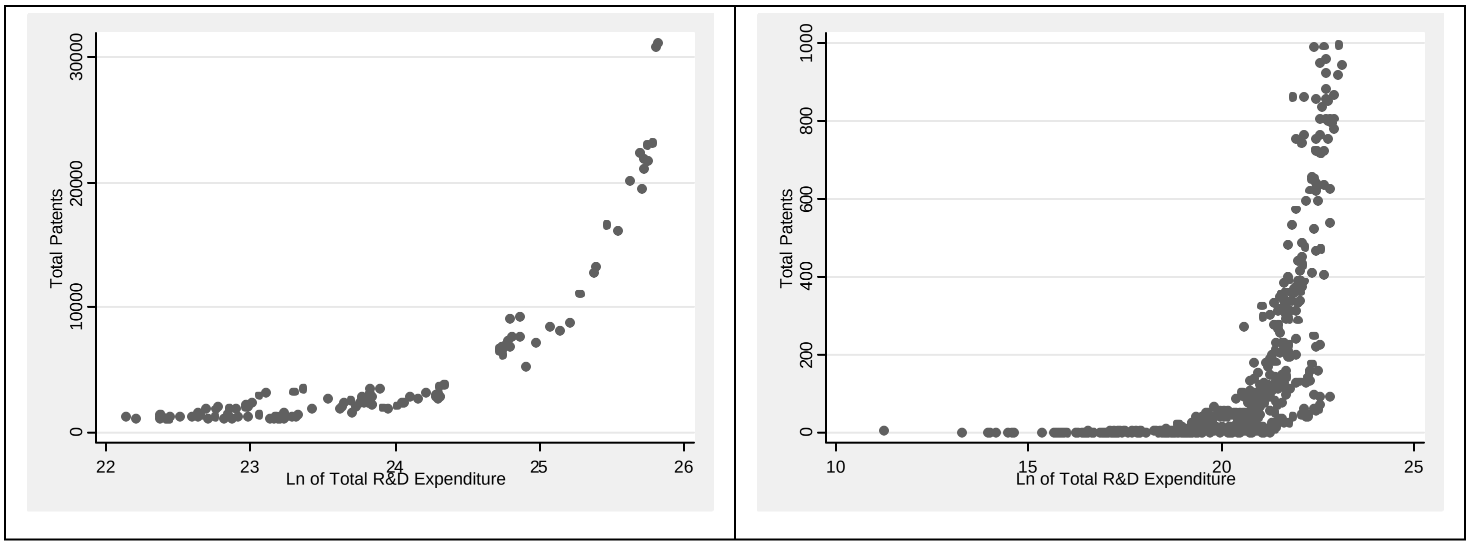

Figure 3: ln Patents vs NIS variables