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R&D, Innovation and Growth: Evidence from Four Manufacturing Sectors in OECD Countries

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Abstract

This paper provides an empirical analysis of the relationship between R&D intensity, rate of innovation and the growth rate of output in four manufacturing sectors from 17 OECD countries. The findings suggest that the knowledge stock is the main determinant of innovation in all four manufacturing sectors and that R&D intensity increases innovation in the chemicals and the electrical and electronics sector. In addition, the rate of innovation has a positive effect on the growth rate of output in all sectors except for the drugs and medical sector. These results lend strong support for the non-scale endogenous growth models.

Keywords: non-scale endogenous growth; R&D; patent, innovation; output growth; system GMM
JEL classification: O14; O30; O31; O33; O41

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INTRODUCTION

This paper examines the relationship between R&D intensity, rate of innovation, and the growth rate of output in four manufacturing sectors of 17 OECD countries for 1981-1997. The empirical analysis is based on the non-scale endogenous growth models of Young (1998), Aghion and Howitt (1998) and Dinopoulos and Thompson (2000), (hereinafter called the Y/AH/DT model),[1] which state that technological innovation is driven by the knowledge stock and R&D intensity, and that the long-term growth rate of output is determined by the rate of innovation, physical and human capital saving rate, and population growth. The findings of the system GMM analysis show that there is a positive relationship between knowledge stock and innovation in all sectors, while the effect of R&D intensity on innovation is significant only in the chemicals and the electrical and electronics sectors. In addition, the rate of innovation and the degree of openness have a positive effect on the growth rate of output in the majority of the sectors. Overall, these results lend strong support for non-scale endogenous growth models.

The main advantage of sector level analysis over aggregate analysis is that it provides more reliable results as the sectoral data have less noise than aggregate data. However, if the analysis is restricted to one country, which is the case in many sector level studies, the results might be biased and cannot be generalized. To enhance the explanatory power of sector level analysis, some recent studies have used international sectoral data to examine endogenous growth models. For example, Frantzen (2003) employs R&D data from 22 manufacturing sectors in OECD countries and finds that R&D has a positive impact on TFP. Zachariadis (2004) shows that the effect of R&D intensity on productivity and output growth is positive both in the aggregate economy and manufacturing sector of 10 OECD countries. Similarly, Griffith, Redding and Reenen (2001) provide evidence that R&D intensity, human capital and trade have a positive impact on the TFP of the manufacturing sector of 14 OECD countries. Meliciani (2000) examines the relationship between patent and R&D using international sector level patent and R&D data and concludes that R&D is more effective in generating patents in science based industries, while physical investment is more important in production intensive industries.[2]

This study extends previous research in a few important ways. First, we estimate both the innovation function and the growth rate of output by utilizing sector level international patent and R&D data. To the best of our knowledge, there are no sector level studies that estimate both the innovation function and the growth rate of output using R&D and patent data. The main advantages of using patent data are that they allow us to estimate the innovation function of endogenous growth models, and they are better proxy for innovation than R&D intensity that is commonly used in the literature. Second, we conduct our empirical analysis for four main manufacturing sectors separately, which allows us to compare the results across sectors and check the robustness of our analysis. Also, by pooling similar industries in four manufacturing sectors we take into account the effect of knowledge spillovers across similar industries on innovation and the growth rate of output. Finally, we employ system GMM regression technique that has many advantages over difference GMM and fixed effects analysis. The findings of our analysis provide strong support for the non-scale endogenous growth models.

The remainder of the paper is organized as follows: section two presents the model briefly, section three describes data and documents the descriptive statistics of the variables, section four reports the stylized facts, section five presents the empirical analysis and the results, and section six concludes.

MODEL

The empirical analysis is based on the non-scale endogenous growth model of Y/AH/DT. The Y/AH/DT model eliminates the scale effect of the first generation endogenous growth models of Romer (1990), Grossman and Helpman (1992) and Aghion and Howitt (1992), (hereinafter called R/GH/AH), by using the R&D intensity rather than the level of R&D in the innovation function. The elimination of the scale effect from the endogenous growth models invalidates the implication of these models that the long-term growth rate of output is determined solely by the growth rate of population, which has been rejected by Jones (1995). The innovation function in Y/AH/DT takes the form

$$\dot{A}_{it} = A_{it}^{\phi} \gamma \delta n_{it}, \quad where \quad \phi = 1, \; n_{it} = \frac{R_{it}}{Qit}. \qquad (1)$$

$\dot{A}$, A, and n are innovation, knowledge stock, and R&D intensity, respectively; R is the total amount of output invested in R&D, and Q is the total output.[3] This specification of the innovation function leads to the balanced growth rate of per capita output that depends on the rate of technical progress, physical and human capital saving rate and population growth (Dinopoulos and Thompson, 2000). The short form of the function for the steady state growth rate of output can be written as

$$g = \beta s_h + \alpha s_k + \gamma g_L + \psi g_n \qquad (2)$$

where α,β,γ and ψ are the parameters of the model to be estimated, S_h, S_k are saving rate of physical and human capital, respectively, g_L *is* the growth rate of population, and g_n is the rate of innovation (technical progress)[4]. In our empirical analysis, we estimate equation (1) and (2) for four manufacturing sectors from 17 OECD countries. Different from the previous literature, we utilize international panel data of sectoral R&D intensity, patent and trade series from four main manufacturing sectors. Furthermore, we employ system GMM regression technique that allows us to obtain more reliable results.

DATA AND METHODOLOGY

Data are obtained from the following sources: patent applications made to U.S. Patent Office (NBER Patent Citation Database); sector level business enterprise R&D expenditure (BERD) (ANBERD-OECD, 2003); sector level output, investment, employment, import and export (STAN-OECD, 2003); GDP deflator and exchange rate (OECD, 2003); population (WDI, 2003); GDP in current $U.S. (WEO, 2003), imports and exports of U.S. from the partner countries (IMF-Direction of Trade, 2003). Each country's GDP share of the U.S. trade is calculated adding up the absolute value of total exports and imports of the U.S. to and from each partner country, and dividing this total by each country's GDP. To control for the openness of the sectors to international trade, a variable called "openness" is constructed by adding up the absolute values of sectoral exports and imports and dividing the total by sectoral output.

The construction of four manufacturing sectors, namely chemicals (excluding drugs and medicals), drugs and medical, electrical and electronics and machinery and transport for patents and the remaining variables are documented in appendix II, Table 4A. Construction of the series from OECD database was straightforward, as they all have unified SIC codes. The corresponding sectors for the patent data have been constructed using the technology codes reported in Hall, Jaffe and Trajtenberg (2001). When matching the technology classification for patents to industrial classification of the other variables from OECD we also made use of the information from more disaggregated classification. All series, except for the patents, are deflated using the GDP implicit price deflator with 1995 base year, and converted to US dollars using current exchange rate obtained from OECD database. Patent and capital stock is calculated using perpetual inventory method with 0.2 and 0.1 depreciation rates, respectively.[5]

The patent data include all utility patents from 1960-1997 in manufacturing sector issued to inventors residing in different countries.[6] Of the categories in the NBER database we use chemicals, drugs and medical, electrical, electronics and communication and machinery sectors. The main reasons for using international patent data from the U.S. is that: first, the data are readily available; they have both disaggregated and aggregated technology codes and a detailed information on data can easily be obtained from Hall, Jaffe, Trajtenberg (2001). Second, using patent applications made in one country ensures that the patent applications of all countries are subject to the same laws and regulations thus decreases the heterogeneity in the data. The potential disadvantages of using the U.S. patent applications such as the distance from the U.S., or the economic alliance with the U.S. have been taken into account throughout the analysis. In addition, we use successful patent applications instead of granted patents, as the time lag between the application and the grant year can be very long. Although some disadvantages of using patent data to measure innovation have been cited in the literature, such as the variation in the intrinsic value of patents and inability of patents to capture the whole range of innovation, these problems can be accounted for in the econometric models.[7]

We include all OECD countries in the analysis that have yearly data on the main variables of the model for more than or equal to 3 consecutive years. The only exception to this rule is the U.S., which is not included in the regression analysis as the patent applications are obtained from the U.S. Patent Office. The sample size and the number of countries change across sectors and the regression models depending on the variables included in the analysis (appendix II, Table 5A).

We also check the statistical properties of the series and find that there is no heteroskedasticity and the unit root in the data for most of the countries and the variables, while there is first order autocorrelation (appendix II, Table 6A-8A)[8]. The first order autocorrelation is taken into account by employing system GMM and Prais-Winsten fixed effects regression analyses.[9] The diagnostic tests of the system GMM, namely sargan and second order autocorrelation tests, and the Prais-Winsten analyses have been reported at the end of each regression column. All regression analyses include year dummies, and the country fixed effects have been taken into account either by including country dummies (Prais-Winsten) or using differenced series and instruments (system GMM). The outliers in each regression model are eliminated using a standard procedure embodied in STATA.

STYLIZED FACTS

This section documents the average R&D and patent intensity and the growth rate of real output for four manufacturing sectors across 15 OECD countries (Figures 1-4). In each figure we rank the countries according to their average patent intensity. As the patent applications used in the analysis are from the U.S. Patent Office, the U.S. ranks the first in patent intensity in all sectors. Therefore, one should not compare the U.S. performance on patent intensity with the rest of the countries in the analysis. All countries that have data on patents, R&D and the growth rate of output for more than 5 years are included in the figures.

A common feature of the figures in all four sectors is that, Italy and Spain always have the lowest patent and R&D intensity (Figures 1 to 4). Moreover, Japan, Finland and Sweden always rank in the first four (the first being the U.S. in all sectors), except for the drugs and medical sector, in which Japan and Sweden are in the lower rank. Among these three countries, Sweden and Finland continue to be in the high rank in terms of the R&D intensity in all sectors, with the exception that Sweden's R&D intensity is lower in the chemicals, while Finland's R&D intensity is lower in the machinery and transport sector. Japan, on the other hand, in spite of its exceptional performance in the patent intensity in all but the drugs and medical sector, has lower R&D intensity in all but the chemicals sector.

Among the remaining countries that perform well in patent intensity, Germany is one of the leading countries in the chemicals sector and among the high-ranking countries in the machinery and transport, and the drugs and medical sectors. As for its R&D performance, it is still in the high rank in the chemicals, and the machinery and transport sector, while in the low rank in the drugs and medical sector. Furthermore, Denmark and UK are among the leading countries in the drugs and medical sector in both patent and R&D intensity. In the remaining sectors, UK is among the average performers in both patent and R&D intensity, while Denmark performs very poorly in the electrical and electronics sector in terms of both patents and R&D, and average in the other two sectors.

Canada is another country that performs well in terms of its patent intensity in two of the sectors for which it has data. It ranks the highest in the drugs and medical sector (after the U.S.), and among the high-ranking countries in the chemicals sector. However, a surprising observation is that, Canada is among the poorest performers in terms of R&D intensity in both sectors. This is unusual, as the countries in the analysis do not exhibit big discrepancy between their performances in the patent and R&D intensity. One explanation for Canada's exceptional performance in patents in spite of its low R&D intensity could be its geographic and economic proximity to the U.S., where the patent applications have been made.

The Figures 1 through 4 also document the growth rate of real output for each sector. A quick look at these figures reveals that there is a notable positive correlation between patent intensity and the growth rate of output in the machinery and transport, and the electrical and electronics sector, while a positive but modest correlation in the chemicals and the drugs and medical sector.

Overall, the simple statistics reported in figure 1 through 4 indicate a positive association between R&D and patent intensity and the growth rate of output across OECD countries in all main manufacturing sectors, as suggested by the non-scale endogenous growth models.

The next section carries out a more comprehensive analysis of the interrelationships between these variables.

Figure 1. Average R&D, Patents and Real Output Growth
in Chemicals Sector (Excludes Pharmaceuticals), 1987-1997

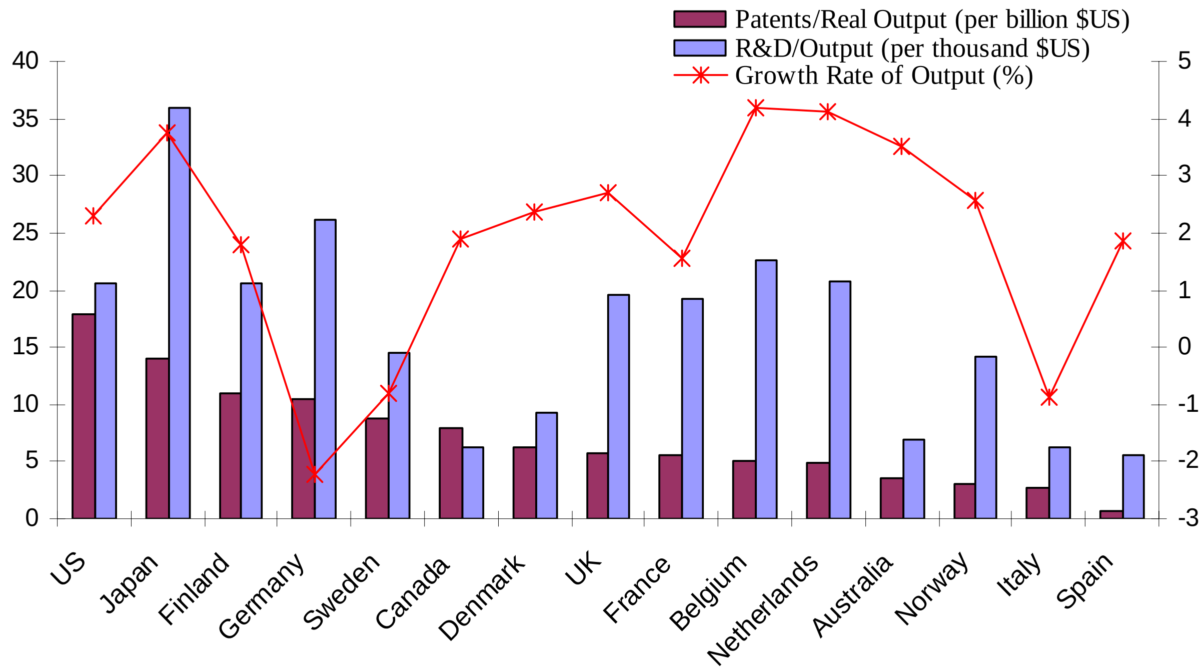


Figure 2. Average R&D, Patents and Real Output Growth
in Drugs & Medical, 1987-1997

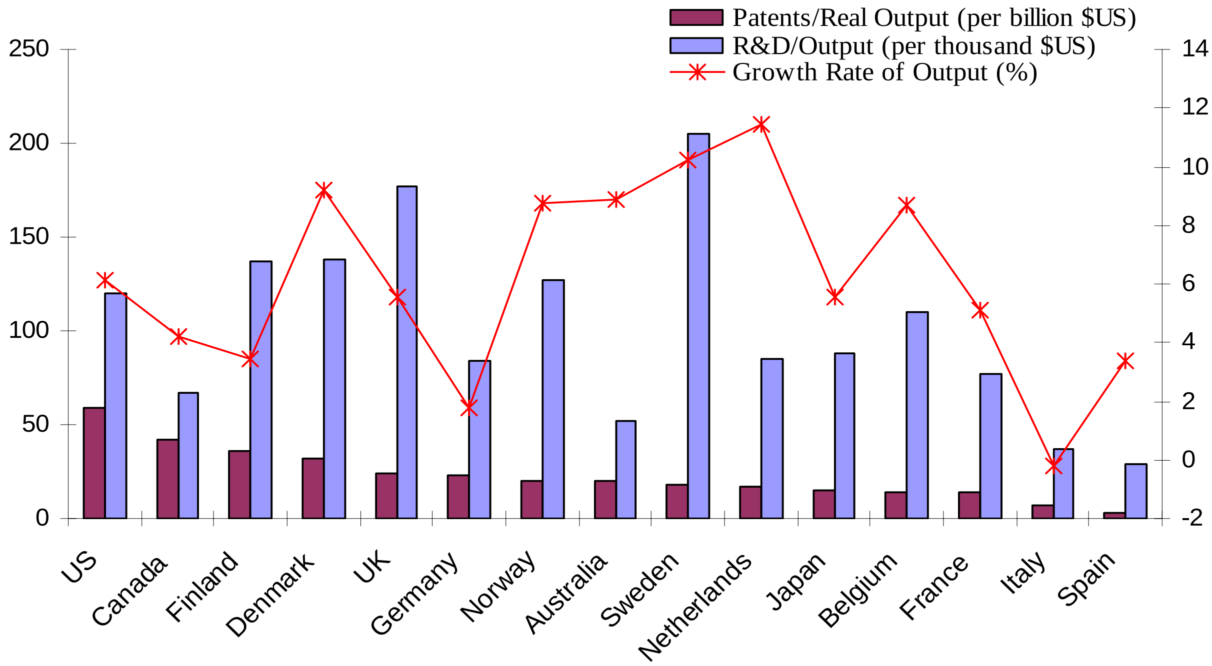


Figure 3. Average R&D, Patents and Real Output Growth
in Machinery & Transport Sector, 1987-1997

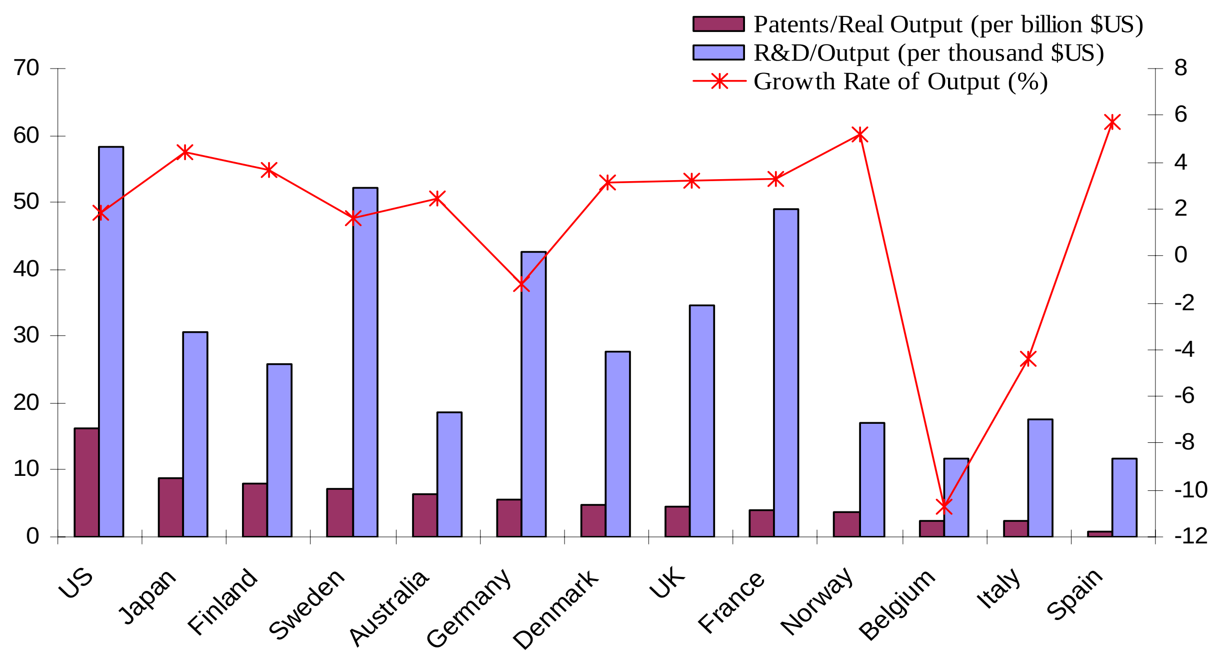
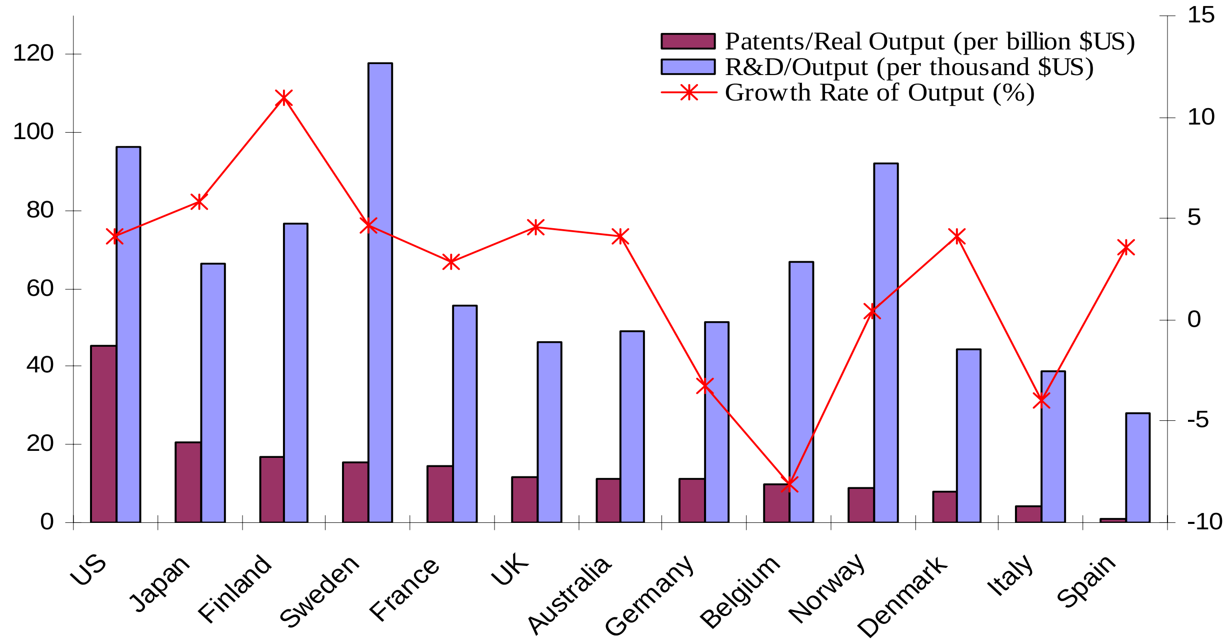


Figure 4. Average R&D, Patents and Real Output Growth
in Electricals & Electronics Sector, 1987-1997



EMPIRICAL ANALYSIS

The estimations of the innovation function and the growth rate of output for four manufacturing sectors are carried out using system GMM regression technique proposed by Arellano and Bover (1995). The main difference between system GMM and difference GMM is that the former estimates the system of the level and difference equations using the lagged levels of the series as instruments for the first-difference series, and lagged first-differences of the series as instruments for the level series, while the latter estimates only the first-difference equation using the lagged levels as instruments. We choose system GMM over difference GMM, as the latter has finite sample bias and poor precision when the series are persistent. As shown in Monte Carlo simulations in Blundell and Bond (1998), when the number of time series observations is small, as it is in our case, there are dramatic efficiency gains in using a system rather than difference GMM.[10]

In addition, unlike the difference GMM, the system GMM estimators are consistent even in the presence of unit root, Binder, Hsiao and Pesaran (2003). Furthermore, since the system GMM utilizes the lags of both the difference and level series of all variables in the model, it reduces the potential endogeneity problem. To avoid making discretionary choices in choosing the set of instruments, we include in the matrix of instruments the whole set of the lags of the regressors and we treat them as predetermined variables.[11] To further increase the precision of our results, we remove the outliers from the model by using a standard procedure embodied in STATA.[12] We include year dummies in all regressions to eliminate the unobserved time fixed effects. As a robustness check, we also report the results of the Prais-Winsten fixed effects analysis in the appendix.

Estimation of Innovation Function

We estimate the innovation function presented in equation (1) in section 2

$$\dot{A}_{it} = A_{it}^{\phi} \gamma (R_{it} / Q_{it}) \tag{3}$$

where, $\dot{A}$ is innovation, A is knowledge stock, R is R&D expenditure and Q is output. The regression model is constructed by taking the natural log of equation (3) and including control variables and time fixed effects into the model

$$Log(\dot{A})_{i,t} = \phi A(t) + \psi \, Log(R_{it} / Q_{it}) + Log\,(x_{i,t}) + \mu_t + \varepsilon_{i,t}, \tag{4}$$

where i and t are country and time subscripts, respectively; x is a matrix of control variables, μ is time fixed effects and ε is regression residuals. We measure $\dot{A}$, A, R and Q for each sector using patent flows, patent stock, business R&D expenditure, and output, respectively. The control variables include the trade share of output in each sector, referred to as openness, and the U.S. trade share of GDP. The openness is assumed to capture the international knowledge spillovers between relevant sectors, and the U.S. trade share of GDP is included to control for the effect of the economic alliance with the U.S. on the patent applications made in the U.S. Patent Office.

We first estimate the innovation function in equation (4) without knowledge stock variable. The results of the system GMM analysis for each sector are reported in Table 1.[13] As the table shows, the elasticity of R&D intensity is positive and significant in all four sectors with an elasticity of over one in the chemicals and the machinery and transport sectors, close to one in the drugs and medical sector and 0.5 in the electrical and electronics sector. Surprisingly, the degree of the openness of the sectors to international trade is negatively related to patent flows in all sectors. This implies that the negative effect of the openness on innovation resulting from increased competition overcomes its positive effect resulting from increased knowledge spillovers. It might also be capturing the fact that the more open the sectors to international trade, the more likely they will have patents in countries other than the U.S. The U.S. trade share of output has a positive effect on the patents in all sectors, which implies that the economic alliance with the U.S. is an important determinant of the patent applications in this country. It might also mean that the knowledge spillovers from the U.S. have a positive impact on countries' sectoral innovation.

The next regression model includes knowledge stock variable measured by patent stock of each sector. The results are reported in Table 3. As expected, the coefficient of patent stock is positive and significant in all sectors with the magnitude of around 0.95. However, after we control for the effect of knowledge stock on innovation flows, the elasticity of R&D intensity becomes insignificant in the drugs and medical sector and the machinery and transport sector.[14] This might imply that in these sectors, increases in R&D intensity promotes innovation through its contribution to knowledge stock rather than its direct impact on innovation. It also suggests that the time lag between increases in R&D intensity and innovation might be longer in the drugs and medical and the machinery and transport sectors.

Table 1. System GMM Estimation of the Sectoral Patent Flows, 1987-1997

Sectors	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
R&D/output	1.381 (13.91)***	0.905 (7.34)***	1.104 (10.91)***	0.523 (2.31)**
Openness	-1.517 (13.95)***	-1.454 (15.08)***	-2.443 (22.61)***	-2.720 (16.18)***
U.S. trade/GDP	0.633 (8.21)***	0.379 (4.65)***	0.796 (5.96)***	1.809 (6.98)***
Constant	1.524 (4.26)***	-0.194 (0.42)	1.075 (2.26)**	-2.332 (2.61)**
Sargan-p values[a]	0.58	0.58	0.64	0.64
AR(2)-p values[b]	0.90	0.97	0.58	0.78

Observations	142	142	112	112
Number of country1	14	14	12	12

Absolute value of t statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1% Note: All series are in natural logs. All series are sector level, except for the U.S. trade share of GDP. All regressions include year dummies.
b/ H_0: regressors are not correlated with the residuals.
c/ H_0: errors in first difference regression exhibit no second order serial correlation.

Table 2. System GMM Estimation of the Sectoral Patent Flows, 1987-1997

Sectors	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
Patent stock	0.954	0.952	0.945	0.950
	(62.76)***	(57.20)***	(43.77)***	(52.88)***
R&D/output	0.055	-0.004	-0.039	0.092
	(1.94)*	(0.14)	(1.11)	(2.04)**
Openness	-0.077	-0.013	-0.190	-0.221
	(2.53)**	(0.40)	(3.31)***	(3.84)***
U.S. trade/GDP	0.017	0.031	0.024	0.052
	(1.00)	(1.76)*	(0.67)	(0.86)
Constant	-1.257	-1.475	-1.172	-1.471
	(15.66)***	(14.45)***	(9.36)***	(8.57)***
Sargan-p values[a]	0.78	0.78	0.84	0.84
AR(2)-p values[b]	0.77	0.73	0.07	0.31
Observations	142	142	112	112
Number of countries	14	14	12	12

Absolute value of t statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1% Note: All series are in natural logs. All series are sector level, except for the U.S. trade share of GDP. All regressions include year dummies.
Note: The regression model for machinery sector has second order autocorrelation. However, the coefficients of the variables do not change much even after correcting for AR (2).
b/ H_0: regressors are not correlated with the residuals.
c/ H_0: errors in first difference regression exhibit no second order serial correlation.

In the chemicals and the electrical and electronics sector the elasticity of R&D intensity with respect to patent flows is around 0.06 and 0.10, respectively. This means that in these two sectors innovation has constant or increasing returns to scale with respect to knowledge stock and R&D intensity, as suggested by non-scale endogenous growth models. The inclusion of patent stock variable in the regression does not change the coefficient of the openness variable in any of the sectors, except for the drugs and medical sector in which it becomes insignificant. In addition, the coefficient of the U.S. trade share of output becomes insignificant in all sectors except for the drugs and medical sector, which shows that the countries' previous years' patents in the U.S. is more important determinant of their current patents than their economic relationship with the U.S.

To sum up, these results are in line with the first postulation of the R&D based growth models that the knowledge stock is the engine of innovation flows. The results also provide strong evidence for the non-scale endogenous growth models in the chemicals and the electrical and electronics sector, in that both knowledge stock and R&D intensity have positive effect on innovation and their combined elasticity is over one.

Estimation of the Growth Rate of Output

The growth rate of output is estimated for each sector using the model from Dinopoulos and Thompson (2000) presented in section 3

$$g = \beta s_h + \alpha s_k + \gamma g_L + \psi g_n \tag{5}$$

where g is the steady state growth rate of output, S_h, S_k are saving rate of physical and human capital, respectively, g_L *is* the growth rate of population, and g_n is the rate of innovation (technical progress). The panel data regression equation of the above model is

$$g_{i,t} = \beta s_h + \alpha s_k + \gamma g_l + \psi \, Log(\dot{A}_{i,t} / A_{it}) + Log\,(x_{i,t}) + \mu_t + \phi_i + \varepsilon_{i,t} \tag{6}$$

where *i, t* are country and time subscripts, $\dot{A}/A$ is the innovation rate measured by the ratio of patent flows to patent stocks; *x* is a matrix of control variables, μ is time fixed effects, ϕ is country fixed effects, and ε is regression residuals. In the estimation of equation (6), we employ sector level data for all variables except for the population growth. The saving rate of physical capital and human capital are measured as the ratio of capital stock to output and ratio of employment to population, respectively; the rate of innovation is measured as the log of the ratio of the patents to patent stock, and the growth rate of output is measured as the log differenced real output in each sector. The degree of the openness of the sectors to international trade, the control variable for international knowledge spillovers, is measured as the sum of the sectoral imports and exports divided by sectoral output.

We first estimate equation (6) with respect to the rate of innovation and the degree of openness only, and then with respect to all variables of the model. The results of the first estimation using system GMM are reported in Table 3. As seen from the table, the innovation rate is positive and significant in all sectors. The highest return to the rate of innovation in terms of the growth rate output is in the machinery and transport sector (0.13%), which is followed by the electrical and electronics sector (around 0.9%), the chemicals sector (0.08%) and the drugs and medical sector (0.06%). The degree of openness of the sectors is not significant in any sectors, except for the drugs and medical sector.

Table 3: System GMM Estimation of the Growth Rate of Sectoral Real Output, 1981-1997

Sectors	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
Patent rate	0.084	0.057	0.162	0.088
	(2.48)**	(1.98)**	(3.71)***	(2.56)**
Openness	-0.003	0.015	0.008	-0.005
	(0.37)	(2.05)**	(0.60)	(0.35)
Constant	-0.007	0.212	0.112	-0.011
	(0.11)	(5.59)***	(1.42)	(0.18)
Sargan-p values[a]	0.72	0.43	0.45	0.78
AR(2)-p values[b]	0.28	0.96	0.31	0.45
Number of Observations	233	257	187	183
Number of countries	15	17	13	12

Absolute value of t statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%

Note: All series are in natural logs and sector level.

b/ H_0: regressors are not correlated with the residuals.

c/ H_0: errors in first difference regression exhibit no second order serial correlation.

Table 5 reports the results of the system GMM regression analysis that includes all the variables in equation (6).[15] The first observation from the table is that the inclusion of the other variables does not affect the coefficient of the rate of innovation in any sectors, except for the drugs and medical sector. With the inclusion of other variables in the model, the degree of openness becomes positive and significant in all sectors except for the chemicals sector, implying that the international knowledge spillovers have a positive effect on the growth rate of output in the three main manufacturing sectors. In addition, the saving rate of physical capital is positive and significant only in the chemicals sector, while the saving rate of human capital is insignificant in all sectors except for the electrical and electronics sector in which it has a positive coefficient with the elasticity of 0.19. Finally, the population growth is insignificant in all sectors.

Overall, these results indicate that the innovation rate is an important determinant of the steady state growth rate of output in all sectors except for the drugs and medical sector. The insignificant coefficient on the rate of innovation in the drugs and medical sector might be due to the fact that the time lag between the patent applications and the realization of the output in this sector might be longer compared to the other sectors, as they need to be approved by Drug Administration Office. The reason for insignificant or negative coefficient on the saving rate of physical capital stock might be due to the fact that these sectors are knowledge intensive. However, that the saving rate of human capital does not have a significant effect on the long-term growth rate of output in any of the sectors, except for the electrical and electronics, is surprising. This could be closely related with the fact that here human capital is measured using sectoral employment data rather than the number of researchers and scientists, as the sectoral data on later is not available.

These results are similar to the findings of Dinopoulos and Thompson (2000), which estimate the same model using aggregate cross-sectional data. In particular, both analyses find that the innovation rate and the knowledge spillovers are important determinants of the growth rate output. However, different from Dinopoulos and Thompson (2000), our results do not indicate a significant relationship between the saving rate of the physical capital and the growth rate of output. In summary, the estimation results provide strong evidence that the rate of innovation and the degree of the openness of the sectors to trade are two important determinants of the growth rate of output in the majority of the sectors. these findings are inline with the implication of the non-scale growth models that the long-term growth rate of output is driven by the rate of innovation.

Table 4: System GMM Estimation of the Growth Rate of Sectoral Real Output, 1981-1997

Sectors	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
Patent rate	0.072	0.014	0.134	0.065
	(1.82)*	(0.39)	(2.37)**	(1.86)*
Openness	0.009	0.063	0.065	0.090
	(0.51)	(4.25)***	(2.68)***	(3.74)***
Capital stock/output	0.035	-0.035	-0.032	-0.203
	(1.60)	(2.26)**	(1.06)	(5.70)***
Employment/population	-0.017	0.028	0.046	0.191
	(0.64)	(1.07)	(1.08)	(6.27)***
Population growth	1.288	2.268	2.206	-2.368
	(0.86)	(1.07)	(0.71)	(0.79)
Constant	-0.220	0.441	0.794	3.013
	(0.58)	(1.13)	(1.48)	(6.42)***
Sargan-p values[a]	0.99	0.99	0.99	0.99
AR(2)-p values[b]	0.82	0.81	0.28	0.59
Observations	139	143	86	86
Number of country1	10	11	7	7

Absolute value of t statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%

Note: All series are in natural logs. All series are sector level except for the population growth. All regressions include year dummies.

b/ H_0: regressors are not correlated with the residuals.

c/ H_0: errors in first difference regression exhibit no second order serial correlation.

CONCLUSION

The objective of this paper was to utilize international sector level patent and R&D data to examine the main implications of the R&D based non-scale endogenous growth models that the long-term growth rate of output is driven by the rate of innovation, which is in turn determined by the knowledge stock and R&D intensity. Though several empirical studies that use aggregate cross-country or micro level country specific data lend support for non-scale endogenous growth models, there has not been a study that utilizes international sector level patent and R&D data to estimate both the innovation function and the growth rate of output in these models.

The findings of our empirical analysis provide strong support for non-scale endogenous growth models. In particular, the results show that the knowledge stock is the most important determinant of innovation in all four sectors, and that R&D intensity has a positive impact on innovation in the chemicals and the electrical and electronics sector. In addition, the innovation rate appears to be the main determinant of the growth rate of output in all sectors except for the drugs and medical sector. Although the degree of openness of the sectors to international trade has a negative effect on innovation in all sectors, apart from the drugs and medical sector, it has a positive effect on the growth rate of output in all sectors except for the chemicals sector. However, some limitations of our analysis should also be noted. First, we employ only the patent applications from the U.S. Patent Office, which might not represent the true patenting propensity of the sectors and countries. Second, the R&D data covers only the business enterprise R&D leaving out higher education and the government R&D that might play an important role especially in the drugs and medical and the chemicals sectors.

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Appendix I. Regression Tables

Table 1A. Prais-Winsten Fixed Effects Estimation of the Patent Flows, 1987-1997

	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
R&D/output	0.388	0.208	0.232	0.199
	(3.01)***	(2.65)***	(2.80)***	(1.51)
Openness	-0.072	-0.287	-0.717	-0.819
	(0.45)	(1.17)	(4.83)***	(3.48)***
U.S. trade/GDP	-0.041	0.339	-0.177	0.574
	(0.43)	(2.50)**	(2.21)**	(4.71)***
R-squared	0.99	0.99	0.99	0.99
Observations	142	142	112	112
Number of countries	14	14	12	12

z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logs. All regressions include year and country dummies.

Table 2A. Prais-Winsten Fixed Effects Estimation of the Patent Flows, 1987-1997

	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
Patent stock	1.067	1.206	1.277	1.327
	(4.77)***	(10.15)***	(6.53)***	(5.67)***
R&D/out	0.193	0.019	0.162	-0.204
	(1.96)*	(0.35)	(2.10)**	(2.61)***
Openness	0.268	0.152	-0.636	0.139
	(2.03)**	(1.08)	(7.18)***	(0.43)
U.S.trade/GDP	-0.170	0.061	-0.114	-0.223
	(2.19)**	(0.55)	(1.72)*	(1.32)
R-squared	0.99	0.99	0.99	0.99
Observations	142	142	112	112
Number of countries	14	14	12	12

z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logs. All regressions include year and country dummies.

Table 3A. Prais-Winsten Fixed Effects Estimation of the Patent Flows, 1981-1997

	Chemicals	Drugs and Medical	Machinery and Transport	Electrical and Electronics
Patent rate	0.135	0.038	0.089	-0.023
	(3.79)***	(1.18)	(1.36)	(0.54)
Openness	-0.105	-0.074	0.175	0.456
	(1.88)*	(1.03)	(1.46)	(5.52)***
Capital stock/output	-0.015	-0.028	-0.293	-0.402
	(0.41)	(1.16)	(2.71)***	(4.73)***
Employment/population	0.144	-0.120	0.283	0.222
	(1.39)	(0.81)	(2.00)**	(2.43)**
Population growth	-3.366	-3.110	-1.329	-1.588
	(1.48)	(0.88)	(0.34)	(0.76)

R-squared	0.99	0.99	0.99	0.99
Observations	139	143	86	86
Number of country1	10	11	7	7

z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logs. All regressions include year and country dummies.

Appendix II: Data, Statistical Analysis of the Series and Descriptive Statistics

Table 4A: Industry Classifications for Four Manufacturing Sectors

Sectors	Construction of Sectoral R&D, Output, Investment, Employment, Export and Import Data Using SIC codes [a]	Construction of Sectoral Patent Data[b] (Numbers indicate technology codes)
Chemicals Sector	24-Chemicals (Excludes 2423- Pharmaceuticals) 241-Basic chemicals 2411-Basic chemicals, except fertilizers 2412-Fertilizers and nitrogen compounds 2413-Platstics in primary forms; synthetic rubber 242-Other chemicals 2421-Pesticides and other agro-chemical products 2422-Paints, varnishes, printing ink and mastics 2424-Soap, cleaning and cosmetic preparations 2429-Other chemical products, n.e.c. 2430-Man-mad fibers 25- Rubber and Plastics Products 251- Rubber and Plastics Products 2511-Rubber tiers and tubes 2529-Other rubber products 2520-Plastic products	1-Chemicals 11-Agriculture, food, textiles 12-Coating 13-Gas 14-Organic compounds 15-Resins/organic rubbers 19-Misellanous-chemicals
Drugs & Medical Sector	2423-Pharmaceuticals, medicinal chemicals etc.	3. Drugs and Medical 31-Drugs 33-Biotechnology 39-Miscellaneous-drugs and medical
Electrical, Electronics &Communication Sector	30-Office, Accounting and Computing Machinery 3000-Office Accounting and Computing Machnery 31-Electrical Machinery and Apparatues 3110-Electric motors, generators and transformers 3120-Electricity distribution and control apparaturs 3130-Insulated wire and cable 3140-Accumulators, primary cells and batteries 3150-Lightning equipments and electric lamps 3190-Other electrical equipment, n.e.c 32-Radio Television and Communication Equipment 3210-Electronic valves, tubes, etc. 3220-TV/radio transmitters; line communications, apparat.	4. Electrical and Electronics 41-Electrical devices 42-Electrical lightning 43- Measuring and testing 44-Nuclear and x-rays 45-Power systems 46-Semi- conductor devices 49-Misellaneous-electrical 2. Computers and Communication 21-Communications[16] 23-Computer peripherals 24-Information storage

	3230-TV and radio receivers and associated goods	
Machinery & Transport Sector	29-Machinery and Equipment, n.e.c. 33-Medical, precision and optical instruments 34-35-Transport Equipment	5. Mechanical 51. Material processing and handling 52. Metal working 53. Motors, engines and parts 54. Optics 55. Transportation 32-Surgery and medical instruments 59. Miscellaneous-mechanical

a. Industry classification for output, investment and labour obtained from The OECD Stan database; and the industry classification for R&D is obtained from OECD-ANBERD database. These two databases have the same industry codes.
b. Industry classification for patent data is obtained from Hall, Jaffe and Trajtenberg (2001).

Table 5A. Data in the Regression of Innovation Function

	Data in the Regression of Patent Rate				Data in the Regression of Output Growth			
	Chemicals	Drugs & Medicine	Mach. & Transp.	Elect,& Electronic	Chemicals	Drugs & Medicine	Mach. & Transp.	Elect,& Electronic
Australia	11	11	11	11	17	17	17	17
Austria	..	..	..	..	17	17	17	17
Belgium	11	11	3	3	..	17	..	..
Canada	11	11	..	..	17	17	..	..
Denmark	11	11	11	11	17	17	17	17
Finland	11	11	11	11	17	17	17	17
France	11	11	11	11	17	17	17	17
Germany	3	3	3	3	6	6	6	6
Italy	7	7	7	7	17	17	7	7
Japan	11	11	11	11	17	17	17	17
Mexico	..	..	..	..	6	6	..	..
Netherlands	11	11	..	..	17	17	..	..
Norway	11	11	11	11	17	17	17	17
Portugal	..	..	..	..	..	8	4	
Spain	11	11	11	11	17	16	17	17
Sweden	11	11	11	11	17	17	17	17
UK	11	11	11	11	17	17	17	17
17 Countries	142	142	112	112	233	257	187	183

Table 6A. Levin-Lin-Chu Panel Data Unit Root Test
H_0: Series Are Nonstationary[17]

	Chemicals		Drugs & Medicine		Machinery & Transport		Electrical & Electronics	
	t-star	p	t-star	p	t-star	p	t-star	p
Output growth	-6.33	0.00	-6.41	0.00	-1.91	0.02	-3.07	0.00
Patent rate	-5.78	0.00	-3.51	0.00	-4.33	0.00	-6.73	0.00
Patent	-3.04	0.00	-3.34	0.00	-1.78	0.04	-3.48	0.00
Patent stock	-2.90	0.00	-4.46	0.00	-2.05	0.02	-1.74	0.04
Capital stock/output	-2.76	0.00	1.96	0.97	-1.22	0.11	-2.02	0.02
Openness	-3.57	0.00	-2.15	0.02	-2.30	0.01	-2.54	0.01
Employment/pop.	1.94	0.97	-2.44	0.01	-1.78	0.04	1.12	0.87
Population growth	-2.41	0.01	-2.89	0.00	-2.47	0.01	-3.23	0.00
U.S.trade/GDP	-2.85	0.00	-3.49	0.00	-2.58	0.00	-3.65	0.00

Note: All variables except for the U.S. trade/GDP and population growth are sector level. All variables are in natural logs. In the computation of the Levin-Lin panel data unit root test only one lag of the variables is included in the regression, except for the capital stock/output in the machinery sector and the employment/population in the electrical and electronics sector, which have 3 lags.

Table 7A. Durbin Watson and Heteroskedasticity Tests for Patent Regression[a,b]

	Chemicals		Drugs & Medical		Machinery & Transport		Electrical & Electronics	
Countries	Durbin-Watson[a]	Het. Test[b]	Durbin-Watson	Het. Test	Durbin-Watson	Het. Test	Durbin-Watson	Het. Test
Australia	0.99	1.00(0.32)	2.09	0.04(0.84)	2.17	0.52(0.47)	1.54	1.18(0.28)
Belgium	1.47	1.71(0.19)	1.85	1.13(0.29)	..	..	..	..
Canada	1.23	1.02(0.31)	1.00	6.4(0.01)	..	..	..	..
Denmark	2.01	1.20(0.27)	2.73	2.03(0.15)	1.81	0.04(0.85)	2.56	0.46(0.50)
Finland	1.71	0.03(0.86)	1.33	0.27(0.61)	2.01	0.01(0.92)	2.31	1.81(0.18)
France	1.98	2.51(0.11)	2.00	4.36(0.04)	1.70	0.35(0.55)	2.23	0.10(0.75)
Italy	..	..	1.69	0.01(0.90)	2.04	0.08(0.78)	1.64	0.71(0.40)
Japan	1.50	0.05(0.83)	2.74	3.49(0.06)	2.61	0.06(0.80)	1.58	1.85(0.17)
Netherlands	1.51	1.20(0.27)	2.22	0.23(0.27)	..	..	..	..
Norway	2.89	0.01(0.90)	1.63	0.11(0.74)	2.70	8.41(0.00)	1.80	0.38(0.54)
Spain	2.14	0.32(0.57)	2.56	0.23(0.63)	1.98	0.26(0.61)	2.05	1.42(0.23)
Sweden	..	..	1.37	0.56(0.45)	2.86	0.56(0.46)	2.07	0.10(0.76)
UK	..	..	1.33	3.10(0.08)	1.45	0.08(0.77)	1.90	0.10(0.75)

a. The values of d-statistics below or above 2 indicate the presence of first order autocorrelation.
b. Breusch-Pagan / Cook-Weisberg test for heteroskedasticity. Ho: Constant variance.
Note: The numbers of countries vary across sectors. DW test could not be computed for Germany and Sweden as they had only 3-year observations.

Table 8A. Durbin Watson and Heteroskedasticity Test for the Output Growth Regression

	Chemicals		Drugs & Medical		Machinery & Transport		Electrical & Electronics	
Country	Durbin-Watson[a]	Het. Test[b]	Durbin-Watson	Het Test	Durbin-Watson	Het Test	Durbin-Watson	Het Test
Australia	1.62	0.28(0.60)	2.03	0.00(0.99)	1.99	2.05(0.15)	2.11	1.24(0.26)
Austria	2.23	0.43(0.51)	2.12	2.10(0.15)	1.76	0.11(0.75)	1.41	1.72(0.19)
Belgium	2.45	2.40(0.12)	1.44	2.37(0.12)	..	..	..	..
Canada	1.96	2.22(0.14)	2.07	0.40(0.53)	..	..	..	
Denmark	1.47	0.23(0.63)	1.73	0.00(0.98)	1.53	0.00(0.99)	1.38	2.47(0.12)
Finland	2.27	0.20(0.65)	1.61	6.92(0.01)	1.56	0.11(0.74)	1.82	0.32(0.57)
France	2.47	3.17(0.08)	0.78	0.23(0.63)	2.26	0.96(0.33)	2.07	1.87(0.17)
Germany	..	0.04(0.84)	..	0.00(0.97)	..	0.64(0.42)	..	0.77(0.38)
Italy	2.17	0.25(0.62)	1.70	0.01(0.91)	2.43	0.22(0.64)	3.45	3.29(0.07)
Japan	2.12	1.13(0.29)	1.79	1.97(0.16)	1.95	0.90(0.34)	2.17	0.67(0.41)
Mexico	..	2.59(0.11)	..	1.06(0.30)	..	..	..	
Netherlands	1.67	1.47(0.23)	1.14	0.01(0.91)	..	..	..	
Norway	1.72	0.30(0.58)	1.50	1.53(0.22)	1.61	1.24(0.27)	2.01	2.23(0.14)
Portugal	2.39	..	1.54	0.01(0.91)	1.55	0.07(0.79)		..
Spain	1.64	0.20(0.16)	1.22	0.19(0.66)	1.27	0.67(0.41)	1.16	0.11(0.74)
Sweden	2.08	1.30(0.25)	1.23	0.24(0.62)	1.69	1.58(0.21)	1.41	1.55(0.21)
UK	..	1.84(0.17)	1.55	0.55(0.46)	2.32	0.02(0.88)	2.34	0.79(0.37)

a. The values of d-statistics below or above 2 indicate the presence of first order autocorrelation.
b. Breusch-Pagan / Cook-Weisberg test for heteroskedasticity. Ho: Constant variance.
Note: The numbers of countries vary across sectors. DW test could not be computed for Germany as it had only 3-year observations.

Table 9A. Summary Statistics of the Variables for Each Sector

	Chemicals Sector					Drugs and Medical Sector				
Variable	Obs	Mean	S.Dev	Min	Max	Obs	Mean	S.Dev.	Min	Max
Output Growth	299	-0.03	0.11	-0.47	0	318	0.02	0.13	-0.45	0
Patents	262	512	929	4	4493	288	133	196	1	1098
Patent Stock	262	2314	4055	29	19755	288	543	808	6	4126
Patent Rate	262	-1.54	0.16	-2.12	-1	288	-1.40	0.26	-2.31	-1
R&D/output	166	1.52	0.89	0.36	4	180	11	6	2	25
Openness	311	0.77	0.35	0.15	2	331	0.90	0.52	0.10	3
Capital stock/output	195	41	11	10	61	218	39	21	8	141
Employment/pop.	261	0.66	0.15	0.41	1	266	0.11	0.04	0.04	0
	Machinery and Transport Sector					Electrical and Electronics Sector				
	Obs	Mean	S.Dev	Min	Max	Obs	Mean	S.Dev.	Min	Max
Output Growth	231	0.00	0.14	-0.46	0.38	237	0.01	0.14	-0.30	0.47
Patents	271	639	1248	2	6515	270	709	1804	1	11238
Patent Stock	271	2845	5295	9	28103	270	2881	6984	14	45246
Patent Rate	271	-1.55	0.16	-2.41	-1.18	270	-1.49	0.23	-2.72	-0.89
R&D/output	138	2.95	1.35	0.86	6.21	138	6.00	2.70	2.06	16.35
Openness	244	1.03	0.41	0.26	2.21	250	1.18	0.50	0.26	2.48

Capital stock/output	137	35	14	12	79	138	35	12	14	69
Employment/pop.	200	1.82	0.57	0.67	4.02	206	0.75	0.38	0.30	1.96
Population growth	328	0.01	0.00	-0.00	0.03	--	--	--	--	--
U.S.trade/GDP	328	6.61	9.99	1.06	56	--	--	--	--	--

Notes: All variables except for the population and the U.S. trade share of GDP are sector specific. All ratios are in percentage.

Table 10A.Correlation Table of the Variables in the Chemicals Sector

	Output growth	Patent	Patent stock	Patent rate	R&D/ output	Open- ness	Cap.St. /output	Emp./ pop.	Pop. growth
Output growth	1.00								
Patent	0.21*	1.00							
Patent stock	0.16*	0.99*	1.00						
Patent rate	0.46*	0.14*	0.04	1.00					
R&D/output	0.01	0.56*	0.56*	-0.07	1.00				
Openness	0.06	-0.48*	-0.47*	-0.09	-0.14*	1.00			
Capital stock/output	0.13*	0.38*	0.37*	0.00	0.61*	0.51*	1		
Employment/pop	-0.04	0.20*	0.22*	-0.18*	0.13	0.17*	0.18*	1	
Population growth	-0.05	-0.23*	-0.23*	-0.02	-0.35*	-0.17*	-0.01	0.04	1
U.S.trade/GDP	0.01	0.00	0.00	-0.03	-0.36*	-0.03	-0.03	-0.03	0.51*

All variables are in natural logs.

Table 11A.Correlation Table of the Variables in the Drugs and Medical Sextor

	Output growth	Patent	Patent stock	Patent rate	R&D/ output	Open- ness	Cap.St. /out.	Emp./ pop.	Pop. growth
Output growth	1.00								
Patent	0.11*	1.00							
Patent stock	0.07	0.98*	1.00						
Patent rate	0.24*	0.24*	0.09	1.00					
R&D/output	0.09	0.04	0.05	-0.03	1.00				
Openness	0.04	-0.40*	-0.42*	0.06	0.38*	1			
Capital stock/output	0.00	0.01	-0.02	0.15*	0.48*	0.30*	1		
Employment/pop	0.06	0.36*	0.38*	-0.04	0.17*	-0.02	-0.04	1.00	
Population growth	-0.03	-0.17*	-0.17*	0.01	-0.27*	-0.20*	-0.05	-0.31*	1.00
U.S.trade/GDP	-0.01	0.02	0.02	0.01	-0.0471	-0.08	-0.1339*	-0.26*	0.49*

All variables are in natural logs.

Table 12A.Correlation Table of the Variables in the Machinery and Transport Sector

	Output growth	Patent	Patent stock	Patent rate	R&D/ output	Open- ness	Cap.St. /out.	Emp./ pop.	Pop. growth
Output growth	1.00								
Patent	0.01	1.00							
Patent stock	-0.03	0.99*	1.00						
Patent rate	0.38*	0.19*	0.10	1.00					
R&D/output	-0.08	0.55*	0.57*	-0.31*	1				

Openness	0.00	-0.71*	-0.69*	-0.23*	-0.19*	1			
Capital stock/output	-0.13	0.73*	0.75*	-0.36*	0.78*	0.01	1		
Employment/pop	0.05	0.57*	0.58*	0.00	0.62*	-0.31*	0.74*	1.00	
Population growth	-0.05	-0.29*	-0.28*	-0.10*	-0.21*	-0.21*	-0.10	0.08	1.00
U.S.trade/GDP	-0.15*	-0.07	-0.07	-0.03	0.36*	-0.39*	0.06	0.20*	0.54*

All variables are in natural logs.

Table 13A.Correlation Table of the Variables in the Electrical and Electronics Sector

	Output growth	Patent	Patent stock	Patent rate	R&D/ output	Open-ness	Cap.St. /out.	Emp./ pop.	Pop. growth
Output growth	1.00								
Patent	0.13*	1.00							
Patent stock	0.11	0.99*	1.00						
Patent rate	0.27*	0.27*	0.16*	1.00					
R&D/output	0.05	0.14	0.14	0.07	1				
Openness	0.04	-0.59*	-0.58*	-0.17*	-0.01	1			
Capital stock/output	-0.13	0.44*	0.45*	-0.10	0.27*	0.01	1		
Employment/pop	0.21*	0.71*	0.71*	0.11	0.39*	-0.51*	0.64*	1.00	
Population growth	-0.06	-0.35*	-0.34*	-0.12*	0.09	-0.04	0.03	0.00	1.00
U.S.trade/GDP	-0.04	-0.09	-0.09	-0.06	0.22*	-0.22*	-0.19*	0.39*	0.54*

All variables are in natural logs.

Notes

[1] The main difference between the first generation growth models, Romer (1986, 1990), Grossman and Helpman (1991) and Aghion and Howitt (1992), and Y/AH/DT is that the latter eliminates the scale effect prediction of the first generation models that the long term growth rate of output is determined solely by the growth rate of population, which has been rejected by Jones (1995).

[2] The aggregate level cross country studies, such as Dinopoulos and Thompson (2000), Frantzen (2000), Guellec and Potterie (2001), Gong, Greiner, Semmler (2004), and the micro level studies covering one country, such as Griliches (1986, 1990), Jaffe (1986, 1988), Aghion and Howitt (1998), and Zachariadis (2003) also provide strong support for non-scale endogenous growth models.

[3] Dinopoulos and Thompson (2000) model is the same as Y/AH model in spirit. The only difference in DT model is that instead of R&D intensity they use the share of human capital in the R&D sector in total population.

[4] See Dinopoulos and Thompson (2000) for more details on the derivation of the PEG model.

[5] The initial level of patent stock is calculated using $P^{s}{}_{t-1} = P_t /(r+\delta)$ formula, where $P^{s}{}_{t-1}$ is the initial patent stock, r is the average growth rate of patent flows and δ is the depreciation rate. Patent stock for the following years are calculated using perpetual inventory method: $P^{s}{}_{t} = P_t + (1-\delta)P^{s}{}_{t-1}$. Capital stock has been computed using the same method.

[6] In the NBER database, the total number of utility patents for the period 1961-1999 is 2,699,606. The last two years are not included in the analysis as the patent data in those years were not complete.

[7] See Comanor and Scherer (1969), Griliches (1990, 1994) for in depth analysis of the statistical properties of patent and R&D data and their applications in endogenous growth models.

[8] We test the stationarity of the panel series using Levin-Lin-Chu unit root test developed by Levin, Lin and Chu (2002).

[9] The main regression technique of the empirical analysis is system GMM. The Prais-Winsten fixed effects results are reported in the appendix as benchmark results.

[10] In the Monte Carlo simulation Blundel and Bond (1998) compares the difference and system GMM results using samples with 100 and 500 observations. Their results show dramatic efficiency gains in the system GMM analysis compared to the difference GMM in both samples. See also Blundell, Bond and Windmeijer (2000) for more details on the efficiency comparisons of the system GMM and difference GMM analyses. See Levine and Beck (2000) and Hansen and Tarp (2001) for the applications of system GMM in the growth regressions.

[11] Two assumptions are necessary for GMM estimators to be consistent. The original errors should not be serially correlated with the regressors and the series should not have second order autocorrelation. To address these issues, sargan test and second order autocorrelation test are reported in the regression tables. First order autocorrelation in the level series does not present a problem for the GMM analysis as it uses the first difference series.

[12] This procedure, referred to as "hadimvo" in STATA, is developed by Hadi (1992).

[13] See appendix I, Tables 1A-2A for the results of Prais-Winsten fixed effects regression. Prais-Winsten analysis corrects for AR (1) by transforming the series using AR(1) coefficient (Prais and Winsten, 1954). Though the estimators of fixed effects analysis are more likely to be biased due to endogeneity problem, they are only reported as benchmark results.

[14] The correlation between patent stock and R&D intensity is not high in any of the sectors. Thus the fact that the R&D intensity becomes insignificant in the drugs and medical and the machinery and transport sector after the inclusion of the patent stock is not related to the multicollinearity problem (see appendix II Tables 10A-13A for the correlation coefficients of the variables).

[15] See appendix I, Table 3A for the results of the Prais-Winsten fixed effects analysis.

[16] The subcategory 'communications' includes the following subcategories: Telegraphy, wave transmission lines and networks, electrical communications, radar and radio navigation, radio wave antennas, facsimile or television recording, electrical communications include acoustic wave systems and devices, dynamic information storage or retrieval, multiplex communications, error detection/correction and fault

detection/recovery, pulse or digital communications, telephonic communications and telecommunications.

[17] The test can be viewed as an Augmented Dickey-Fuller (ADF) test, with the null hypothesis that of nonstationarity (I(1) behavior). After transformation, the t-star statistic is distributed standard normal under the null hypothesis of nonstationarity, Levin, Lin and Chu (2002).