Centre on Regulation and Competition

WORKING PAPER SERIES

Paper No. 120

INNOVATION AND MARKET STRUCTURE IN THE MANUFACTURING SECTOR: AN APPLICATION OF LINEAR FEEDBACK MODELS

Yuichiro Uchida and Paul Cook

Centre on Regulation and Competition
University of Manchester

December, 2005

ISBN: 978-1-905381-19-0

Further details: Centre Secretary
Published by: Centre on Regulation and Competition,
Institute for Development Policy and Management, University of Manchester,
Harold Hankins Building, Precinct Centre, Oxford Road, Manchester M13 9QH, UK
Tel: +44-161 275 2798 Fax: +44-161 275 0808
Email: crc@manchester.ac.uk Web: www.competition-regulation.org.uk

INNOVATION AND MARKET STRUCTURE IN THE MANUFACTURING SECTOR: AN APPLICATION OF LINEAR FEEDBACK MODELS

Yuichiro Uchida and Paul Cook

1. INTRODUCTION

Technology has long been regarded as one of the pivotal factors in driving economic growth. Technological progress is inheritably a dynamic process. It is hardly a random process but is the result of the accumulation of inventive and innovative activities over time. The significance of such activities has been scrutinised in the industrial organisation literature. In recent years it has been increasingly recognised that the relationship between market structure and inventive and innovative activities is endogenous (Dasgupta and Stiglitz, 1980). In a dynamic setting, competition from new entrants in the market, that experiment with new technologies, has become the driving force for innovation, and in turn market incumbents are forced to innovate for their survival. As inefficient enterprises fail to survive, leaving the more successful innovators, a more concentrated market structure may be associated with a higher degree of competition. Inventive or innovative activities have usually been captured in economic studies through measures of research and development (R&D) expenditure (as an input to innovation) and counts of patents (as an output of innovation). Drawing on data from developed and developing countries the paper applies linear feedback models to assess the relationship between competition and technological innovation. Measures are used to reflect the influence of the levels of domestic and foreign competition. Following the introduction, section 2 provides a brief outline of the relevant literature. Section 3 describes the methods and data used in the analysis. Section 4 discusses the results of using a number of variants of the linear feedback model. The final section draws conclusions.

2. INNOVATION AND COMPETITION

The patent–R&D relationship has been examined empirically by applying various count models (Hausman, Hall and Griliches, 1984; Montalvo, 1993, 1997; Crépon and Duguet, 1993, 1997a, 1997b; Blundell, Griffith and Van Reenen, 1995; Blundell, Griffith and Windmeijer, 1995, 2002; Cincera, 1997). Two implications arise from the application of patent count data models. First, patent count data are discrete and non-negative in nature, so that non-linearity rules out the application of standard linear regression models. Second, in count panel data unobserved enterprise specific effects, or unobserved heterogeneity, arising from the difference in the propensity to innovate or engage in innovative activities across enterprises, are most likely to be present and correlated with explanatory variables. In order to deal with these issues, or specifically to let the unobserved heterogeneity correlate with explanatory variables, Hausman, Hall and Griliches (1984) initially developed a fixed effect model, the so-called Poisson conditional maximum likelihood estimator. However, it was evident that this estimator was problematic as far as the patent-R&D relationship was concerned, since it rested on the highly restrictive assumption relating to the strict exogeneity of regressors. An alternative non-linear quasi-differenced GMM estimator was proposed by Chamberlain (1992), and was applied by Montalvo (1993, 1997), Blundell, Griffith and Van Reenen (1995), Blundell, Griffith and Windmeijer (1995), Cincera (1997), and Crépon and Duguet (1997a, 1997b). This estimator relaxed the assumption of strict exogenity and instead assumed that the regressors were predetermined.

Subsequently, Blundell, Griffith and Van Reenen (1995) and Blundell, Griffith and Windmeijer (1995, 2002) have transformed the quasi-differenced GMM estimator into a dynamic linear feedback model (LFM), and have also proposed an alternative model, the pre-sample mean (PSM) estimator, in which the pre-sample mean of the dependent variable replaces the fixed effect. Blundell, Griffith and Windmeijer (2002) have shown that the PSM estimator performs better than the quasi-differenced GMM estimator, particularly in small samples, which is particularly useful when applying it to data incorporating developing countries.

Most of the studies on the patent-R&D relationship have incorporated present and/or lagged values of R&D expenditures, except for Crépon and Duguet (1993) and Cincera (1997). Blundell, Griffith and Windmeijer (1995, 2002), have explicitly included past patents in their dynamic panel models. While the results of these studies have shown a degree of sensitivity to the econometric models and their specifications, they have generally found a contemporaneous positive relationship between the two variables, suggesting that innovative activities have taken a relatively short time to generate tangible results (patents).

In recent years both the theoretical and empirical literature on competition has emphasised the productive and dynamic efficiency gains that accrue through the process of innovation (Bailey and Gersbach, 1995; Nickell, 1996, Audretsch, Baumol and Burke, 2001). It is argued that competition induces innovation and technological progress, through the incentives that are provided by the disciplining effect of the market, and through the process of selection. In the former, enterprises introduce cost reducing improvements in production and accelerate technological innovation in response to the incentives provided by market competition i.e. reduced information asymmetries and improved performance monitoring within enterprises (Aghion and Howitt, 1998). In the latter, competition enables weaker enterprises to give way or be replaced by more efficient ones. In this way innovating enterprises can enter a market and compete with incumbents with more conventional technologies (Ahn, 2002). This view of dynamic competition sees new entrants as the driving force of innovation, who either survive or fail, and whose fate is in part determined by the strength of the response of incumbents in the market (Dasgupta and Stiglitz, 1980). The literature also emphasises the positive effects that some form of market power can have on innovation (Cohen and Levin, 1989). This occurs through the incentive to innovate provided by either the expectation of some temporary ex-post market power or through ex-ante market power that favours innovation.

A number of studies have examined the relationship between innovative activities, usually measured by R&D expenditures or patent counts and competition (Symeonidis, 1996; Geroski, 1990). Competition has typically been measured by market concentration or the price-cost margin to gauge the degree of market power. The import penetration ratio has similarly been used as a measure of foreign competition. These measures, as representatives of the degree of competition, have their weaknesses. In particular, as Aghion et al (2001) point out, competition weeds out the least productive enterprises, leaving a higher market share for those remaining, but this could be indicative of a higher degree of competition, even though it is associated with greater concentration within the market. Similar arguments apply to the rise of import penetration ratios as measures intended to reflect the extent of foreign competition.

3. METHODOLOGY AND DATA

Dynamic Panel Count Models: Linear Feedback Models (LFM)

A conventional count model takes the following exponential form:

$$y_{it} = exp(x'_{it}\, \beta) + u_{it}\,, \qquad (1)$$

where y_{it} is the discrete count variable for observation unit i, $i = 1,\ldots, N$ at time t, $t = 1,\ldots, T$ and x_{it} denotes a vector of explanatory variables. In a panel data count model, unobserved individual fixed effects are commonly modelled multiplicatively (for more details, see Hausman, Hall and Griliches (1984), Gourieroux, Monfort, and Trognon (1984), Winkelmann (2000), Windmeijer (2002)):

$$y_{it} = exp(x'_{it}\,\beta + \eta_i) + u_{it}, \qquad (2)$$

where $exp(\eta_i)$ is permanent differences in the level of innovative activities across enterprises or countries, and η_i is an unobservable individual enterprise or country specific effect. Let $exp(x'_{it}\,\beta)$ and $exp(\eta_i)$ denote μ_{it} and v_i, respectively. The corresponding regression model is expressed as:

$$y_{it} = \mu_{it}\, v_i + u_{it}, \qquad (3)$$

However, η_i is likely to be correlated with x_{it}. Thus, conventional random effect estimators are inconsistent and unable to estimate equations (3), owing to the assumption of stochastic independence between regressors and errors. In order to resolve this problem, suppose x_{it} are strictly exogenous, and the following conditional mean of y_{it} is satisfied:

$$E(y_{it}|\ v_i, x_{it}) = E(y_{it}|\ v_i, x_{i1},\ldots, x_{iT}). \qquad (4)$$

On the basis of this proposition, Hausman, Hall, and Giliches (1984) have applied the Poisson conditional maximum likelihood estimator (CMLE) by conditioning on the $\sum^{T}_{t=1} y_{it}$ to estimate model (3). In addition, Blundell, Griffith and Windmeijer (1995) have shown that the Poisson maximum likelihood estimator (MLE) for β is also consistent, and the same as the Poisson CMLE, in a model that includes separate individual specific constants. Further, Blundell, Griffith and Windmeijer (2002) have shown that the model (2) can be transformed into a dynamic count panel data model by introducing dynamics based on the integer-valued autoregressive (INAR) process (for INAR models, see Al-Osh and Alzaid (1987), Alzaid and Al-Osh (1990), and Jin-Guan and Yuan (1991)). The dynamic count panel data model they have proposed is in the form of a linear feedback model (LFM) and is defined as (of order p):

$$y_{it} = \sum_{j=1}^{p} \gamma_j\, y_{i-j} + exp(x'_{it}\beta + \eta_i) + u_{it} \qquad (5)$$

Consequently, the corresponding regression model is:

$$y_{it} = \sum_{j=1}^{p} \gamma_j \, y_{it-j} + \mu_{it} \, v_i + u_{it}, \qquad (6)$$

The LFM can be estimated by level, within-group mean scaling, and a generalized method of moments (GMM) estimators by solving respective moment conditions (see Appendix 1). These estimators, however, may not be efficient if the time-series data are highly persistent over time, so that the instruments of these estimators will only provide weak predictions of future changes. This problem is well recognised in the case of the GMM estimator, particularly when the number of observations is small and the explanatory variables themselves are used as instruments (Blundell and Bond, 1998; Blundell, Griffith and Windmeijer, 2002). Similarly, the LFM in the within-group estimator gives results which are highly biased and inconsistent when the number of observations is small (Windmeijer, 2002).

As a result, Blundell, Griffith and Windmeijer (2002) have proposed a pre-sample mean (PSM) estimator, in which pre-sample information on a dependent variable is used in the estimator. The PSM estimator takes the following form:

$$y_{it} = exp(\beta_0 + x'_{it} \, \beta + \theta \ln \overline{y}_{ip}) + u_{it}, \qquad (7)$$

where $\overline{y}_{ip}$ is the pre-sample mean of y, and $\overline{y}_{ip}$ = (1/TP) $\sum_{r=0}^{tp-1} y_{i,0-r}$, TP = the number of pre-sample observations (see Appendix for the moment conditions to be solved to estimate the PSM).

Blundell, Griffith and Windmeijer (2002) have conducted Monte Carlo experiments to examine the performance of these estimators. It appears that the PSM outperforms other estimators, particularly when the number of observations is small. Specifically, the level estimator generates upwardly biased estimates, and in contrast, the estimates by the within-group estimator are biased downwards. The quasi-differenced GMM estimator also generates downwardly biased estimates when the number of observation is small. As a result, the PSM estimator outperforms these estimators in almost all settings in the experiments.

Data

This study primarily examines the relationship between patent application counts as proxies for innovative activities and the effects of market share, competition, and research and development. The patent application counts were obtained from the National Bureau of Economic Research (NBER) United States Patent Citations (USPC) (Hall, Jaffe, and Tratjenberg, 2001). Griliches (1990) comprehensively reviews the advantages and disadvantages of using patent application counts. A number of the previous studies, Blundell, Griffith and van Reenen (1999) and Blundell, Griffith and Windmeijer (2002) have used patents based on the year they were granted. However, Hall, Jaffe, and Tratjenberg (2001) point out that counts ought to be based on the year of application since there is a considerable time lag between the granting of a patent and its application owing to bureaucratic delays. This study, therefore, has collected patent counts on the basis of the year of application.

The measures of competition include the presence of foreign competition in domestic markets (hereafter IM) and the degree of domestic competition among domestic firms (DC). IM was measured as import penetration in the manufacturing sector in a given country (manufactured imports/(GDP - manufacturing exports + manufacturing imports). Primary data on import penetration was obtained from the World Bank World Development Indicators (WDI). DC was measured as the Herfindahl–Hirschman Index (HHI) and was calculated as $\sum^{p}_{i=1} s_i^2$, where p is the number of enterprises in a given market, i is a i-th enterprise, and s is the market share of i-th enterprise. The primary enterprise-level data for DC were obtained from Thomson One Banker database. In addition to these, the market share of each sample country in international markets (MS) and the magnitude of R&D activities (RD) were also included. MS was measured as the manufacturing export share of a country in the world, and the primary data were taken from WDI. RD was calculated as total R&D expenditure of domestic manufacturing enterprises divided by total sales of domestic manufacturing enterprises.

The sample countries and period chosen have been based on the availability of data and their consistency. For the following empirical analysis, two basic datasets were compiled. The first dataset has included all explanatory variables, and consists of 33 developed and developing countries that have more than 5 time-series data. As a result, an unbalanced panel dataset consisting of a total of 373 observations was compiled. The second dataset was developed to examine the effects of competition. The RD variable, as well as the MS variable have been excluded but the dataset has been extended to include countries that have more than 10 time-series data. Consequently, an unbalanced panel dataset of 391 observations, including 25 developed and developing countries has been used. The sample countries, periods selected and descriptive statistics for the base data have been provided in Appendix 2. Finally, patent counts for the 10 year period prior to each country's sample period were collected to calculate the pre-sample mean for the PSM estimator in equation (7).

4. RESULTS

In order to examine the effects of market share, competition, and research and development on innovative activities or the number of patents, the dynamic panel count LFM models in level, within-group mean scaling, quasi-differenced GMM, and pre-sample mean estimators were calculated using two specifications. All variables, except for patent counts, were entered in log form in these estimators. Time dummies were included in the instrument sets. Since the number of observations are quite small, the results ought to be interpreted with a fair degree of caution. In this respect, instead of deriving specific effects from the explanatory variables on innovative activities, interpretation is confined to the analysis of the signs (positive or negative) of the estimated coefficients. In theory, it is expected that the level estimator generates upwardly biased estimates, and the within-group estimator results in downwardly biased estimates. While the other estimators' results may fall in between these two upper and lower estimates, the quasi-differenced GMM estimator may also generate downwardly biased estimates, owing to the small number of observations.

Basic Analysis

The results obtained by including all the explanatory variables are shown in Table 1. The results in the first column were obtained by including a lagged dependent variable (patent counts) at time, t-1, or P_{t-1}, and four explanatory variables at time, t, MS_t (market share of a country's manufacturing sector world-wide), IM_t (import penetration or the presence of foreign products or competition in a given country's domestic manufacturing markets), DC_t (domestic competition among domestic manufacturing enterprises), and RD_t (magnitude of research and development in the domestic manufacturing sector).

The interpretation of the results in the first column is complex. The Sargan tests of over-identifying restrictions for GMM-A and GMM-B are statistically significant at 0.10 level, and, therefore, these results are discounted. Note that if these GMM models are appropriately specified, the Sargan test and the second-order autocorrelation (2^{nd} AR) are expected to be statistically insignificant, and the first-order autocorrelation statistically significant. As for the rest of the models, the results are highly mixed, except for DC_t, in which case, all results are negative and statistically significant. As for the lagged dependent variable, P_{t-1}, only the result obtained by the within-group estimator is statistically significant. However, little in the way of a conclusion can be drawn from only one estimate, particularly from the within-group estimator which may be downwardly biased.

With respect to the other explanatory variables, MS_t is statistically significant and positive in the cases of the PSM and the level estimators. In contrast, the result by the within-group estimator is negative and statistically significant and is substantially biased, suggesting that the within-group estimator is indeed highly biased and inconsistent. The results for IM_t obtained by the level and the within-group estimators are negative and statistically significant, and the result by the latter appears to be highly biased. The result obtained by the PSM is, however, positive and statistically significant, again compounding the difficulty of drawing a firm conclusion. On the other hand, all the results for DC_t are negative and statistically significant, suggesting that lower market concentration (or higher levels of domestic competition) lead to greater innovative activities. The results for RD_t obtained by the PSM and the level estimators are positive and statistically significant, while the result for the within-group is statistically insignificant. Given that the results by the within-group estimator are highly biased, then, judging from the results obtained by the PSM and the level estimators, it appears that a higher market share, the level of domestic competition and research and development expenditure have a positive impact on innovative activity. The effect of foreign competition is unclear at this stage.

The results in the second column in Table 1 were obtained by including an additional lag, P_{t-2}, and the specification of the other variables are the same as those in the first column. Note that other combinations of lags were also tested, but the inclusion of further lags for the dependent and explanatory variables makes the calculations highly problematic and possibly invalid owing to the small number of observations.

As for the two lags of the dependent variables, P_{t-1} and P_{t-2}, P_{t-1} is positive and statistically significant in all the estimators, while P_{t-2} is negative and statistically significant, suggesting that at a sectoral level, the effects of innovative activities in the past may have been relatively short. This is expected since the patent application counts data were collected on a country rather than on an enterprise basis and, therefore do not convey information on the continuity of innovative activities at the enterprise level. In addition, as far as these variables are concerned, the result obtained by the level estimator appears to be upwardly biased. In contrast, the within-group estimator is downwardly biased, and that for the PSM estimator falls in between. Thus, it appears that the inclusion of the additional lag for the dependent variable reduced the bias in the within group estimator. The estimate by the GMM-A appears to be further downwardly biased, whereas the Sargan test of over-identifying restrictions for GMM-B is statistically significant. On the whole these results confirm our expectations for the range of coefficient values among these estimators.

In terms of MS_t, the results are all positive and statistically significant. The estimates by the level and the within-group estimators are upwardly and downwardly biased respectively, and those by the PSM and the GMM estimators fall in between. The results for IM_t, are also highly mixed. The result obtained by the PSM estimator is statistically insignificant. The result by the within-group estimator is positive and statistically significant, whereas those by the level and the GMM-A are negative and statistically significant. As a result, we are unable to draw any firm conclusions regarding the effects of this variable on innovative activities.

The results for DC_t are all negative and statistically significant, reaffirming the previous results in the first column. Interestingly, in this case, the results by the PSM and the GMM are lower than those by the level and the within-group estimators. In relation to RD_t, the results are all positive and statistically significant. Similar to the results for DC_t, the PSM and the GMM estimators, in particular the former, are lower than that provided by the level estimator. In contrast, the estimate for the variable by the within-group estimator has the highest value, exhibiting a bias and inconsistency. It appears that the inclusion of an additional lag for the dependent variables has considerably improved the efficiency of the estimators, and as a result, it could be concluded that higher market share, lower market concentration and research and development expenditure have positive effects on innovative activities. The specific impact of foreign competition through imports remains unclear.

Table 1 Results of LFM Models
(all sample countries included)

	PSM	Level	Within	GMM-A	GMM-B
P_{t-1}	0.003 (0.07)	-2.09 (1.26)	0.76 (0.02)***	0.50 (0.07)***	0.76 (0.03)***
MS_t	0.30 (0.07)***	0.83 (0.07)***	-2.43 (0.21)***	0.47 (0.22)**	0.46 (0.14)***
IM_t	0.14 (0.06)**	-0.61 (0.12)***	-2.00 (0.20)***	-0.42 (0.30)	-0.21 (0.16)
DC_t	-0.47 (0.05)***	-0.55 (0.07)***	-0.88 (0.05)***	-0.71 (0.13)***	-0.77 (0.10)***
RD_t	0.17 (0.04)***	0.43 (0.04)***	-0.04 (0.05)	0.34 (0.09)***	0.34 (0.06)***
1st AR				-0.51 (0.61)	-2.09 (0.04)
2nd AR				-1.34 (0.18)	-0.91 (0.36)
Sargan				23.32 (0.04)	25.14 (0.01)

Note: PSM = pre-sample mean estimator, solving the moment conditions (A5); Level = level estimator estimated by solving (A.1);
Within = within-group mean scaling estimator solving (A.2); GMM-A = quasi-differenced GMM estimator solving the Wooldridge moment conditions (A.3), and the instruments are (1, P_{it-1}, MS_t, IM_t, DC_t, RD_t);
GMM-B is the same as GMM-A except the instruments (time dummies, ΔP_{it-1}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).
Robust standard errors are in the parenthesis.
For the diagnostic tests for the GMM, 1st AR = first-order autocorrelation, 2nd AR = second-order autocorrelation, Sargan = Sargan test for over-identifying restrictions, and p-values are in the parenthesis.
*, **, *** = statistically significant at 0.10, 0.05, and 0.01 level, respectively.

	PSM	Level	Within	GMM-A	GMM-B
P_{t-1}	1.14 (0.18)***	2.30 (0.36)***	1.11 (0.01)***	0.77 (0.09)***	0.68 (0.07)***
P_{t-2}	-1.39 (0.29)***	-2.61 (0.70)***	-0.90 (0.01)***	-0.82 (0.14)***	0.06 (0.08)
MS_t	0.28 (0.06)***	1.01 (0.09)***	0.15 (0.03)***	0.65 (0.22)***	0.53 (0.15)***
IM_t	0.09 (0.06)	-0.85 (0.16)***	0.08 (0.03)**	-0.50 (0.23)**	-0.20 (0.23)
DC_t	-0.44 (0.05)***	-0.35 (0.11)***	-0.35 (0.01)***	-0.55 (0.08)***	-0.77 (0.12)***
RD_t	0.11 (0.05)**	0.41 (0.08)***	0.95 (0.03)***	0.31 (0.08)***	0.34 (0.06)***
1st AR				-2.36 (0.02)	-1.49 (0.13)
2nd AR				1.20 (0.23)	-1.21 (0.23)
Sargan				17.59 (0.13)	22.67 (0.02)

Note: GMM-A's instruments are (1, P_{it-1}, P_{it-2}, MS_t, IM_t, DC_t, RD_t) and GMM-B's are (time dummies, ΔP_{it-1}, ΔP_{it-2}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).

In a further step, countries that have less than 100 patent counts each year were excluded from the analysis in order to investigate the sensitivity to the inclusion of countries with fewer patent counts. Table 2 shows the results. Despite the reduction in the number of observations (from 373 to 270), the results have generally remained the same, except for IM. The results for the Sargan tests of over-identifying restrictions are also statistically insignificant for the GMM-A in both specifications. In the first column, the specifications are the same as the first column in Table 1. As for P_{t-1}, the within-group and the GMM-A generated statistically significant positive results. All the results for MS_t, except for the within-group, are positive and statistically significant. This time, the result for IM_t obtained by the PSM has changed and is negative and statistically significant. Consequently, all the statistically significant results for this variable are negative. The results for DC_t continue to show statistically significant negative estimates. In terms of RD_t, the result by the within-group is negative and statistically significant this time, while the other results are positive and statistically significant. However, the coefficients estimated by the within-group are significantly biased, particularly for MS_t and IM_t. This confirms that the within-group estimator generates highly biased and inconsistent results when the number of observations is small. In essence, a higher market share, increased domestic competition, and research and development expenditure have positive effects on innovative activities as previously. However, it is suggested that foreign competition has a negative effect on innovative activities.

The specification in the second column in Table 2 is the same as the second in Table 1. The signs for P_{t-1} and P_{t-2} are the same, positive and negative respectively. The coefficient value for the PSM estimator has substantially increased, while the opposite is the case for the level estimator. Interestingly, the PSM estimator appears to generate an upward estimate for this variable compared with other estimators. The estimates for MS_t are all positive and statistically significant, and those for the PSM and the GMM-A fall in between those for the level and within estimators. The interesting result relates to IM_t, here the signs of the statistically significant results are negative, which suggests that foreign competition may have a negative effect on innovative activities. With respect to DC_t, the results continue to indicate that higher domestic competition leads to innovative activities. As for RD_t, all the results are positive and statistically significant, indicating that research and development has a positive impact on innovation.

Table 2 Results of LFM Models

	PSM	**Level**	**Within**	**GMM-A**	**GMM-B**
$\mathbf{P_{t-1}}$	-0.26 (0.16)	-0.06 (0.14)	0.75 (0.01)***	0.67 (0.05)***	0.86 (0.02)***
$\mathbf{MS_t}$	0.47 (0.05)***	0.72 (0.09)***	-3.01 (0.21)***	0.44 (0.23)*	0.31 (0.16)**
$\mathbf{IM_t}$	-0.25 (0.08)***	-0.73 (0.07)***	-2.68 (0.21)***	-0.19 (0.24)	0.05 (0.21)
$\mathbf{DC_t}$	-0.66 (0.07)***	-0.67 (0.08)***	-1.11 (0.05)***	-1.08 (0.14)***	-1.12 (0.08)***
$\mathbf{RD_t}$	0.16 (0.04)***	0.34 (0.03)***	-0.21 (0.05)***	0.30 (0.10)***	0.23 (0.06)***
1st AR				-1.76 (0.08)	-1.97 (0.05)
2ndAR				-0.69 (0.49)	-0.28 (0.79)
Sargan				18.35 (0.14)	19.09 (0.09)

Note: PSM = pre-sample mean estimator, solving (A5); Level = level estimator estimated by solving (A.1);

Within = within-group mean scaling estimator solving (A.2); GMM-A = quasi-differenced GMM estimator solving the Wooldridge moment conditions (A.3), and the instruments are (1, P_{it-1}, MS_t, IM_t, DC_t, RD_t);
GMM-B is the same as GMM-A except the instruments (time dummies, ΔP_{it-1}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).
Robust standard errors are in the parenthesis.
For the diagnostic tests for the GMM, 1st AR = first-order autocorrelation, 2nd AR = second-order autocorrelation, Sargan = Sargan test for over-identifying restrictions, and p-values are in the parenthesis.
*, **, *** = statistically significant at 0.10, 0.05, and 0.01 level, respectively.

	PSM	**Level**	**Within**	**GMM-A**	**GMM-B**
$\mathbf{P_{t-1}}$	2.72 (0.27)***	1.80 (0.13)***	1.07 (0.01)***	1.01 (0.08)***	0.69 (0.05)***
$\mathbf{P_{t-2}}$	-2.71 (0.39)***	-1.55 (0.14)***	-0.97 (0.01)***	-0.79 (0.09)***	0.26 (0.07)***
$\mathbf{MS_t}$	0.34 (0.04)***	0.75 (0.06)***	0.14 (0.03)***	0.46 (0.23)**	0.25 (0.27)
$\mathbf{IM_t}$	-0.28 (0.07)***	-0.82 (0.12)***	0.05 (0.03)	-0.63 (0.32)**	0.08 (0.35)
$\mathbf{DC_t}$	-0.49 (0.09)***	-0.61 (0.11)***	-0.37 (0.01)***	-0.70 (0.14)***	-1.34 (0.11)***
$\mathbf{RD_t}$	0.13 (0.03)***	0.37 (0.03)***	0.92 (0.03)***	0.29 (0.09)***	0.24 (0.06)***
1st AR				-2.73 (0.01)	-0.28 (0.78)
2nd AR				1.32 (0.19)	-1.82 (0.07)
Sargan				15.78 (0.20)	18.46 (0.07)

Note: GMM-A's instruments are (1, P_{it-1}, P_{it-2}, MS_t, IM_t, DC_t, RD_t) and GMM-B's are (time dummies, ΔP_{it-1}, ΔP_{it-2}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).

The results presented in Tables 1 and 2 could be biased owing to the relatively small number of observations and the inclusion of countries which only have a small number of time series data. Specifically, the dataset used in the previous estimates included countries that have minimum of five years data. To examine the sensitivity of estimators to the time dimension of the data, only countries with more than 10 years data are left in the dataset. This reduced the number of observations to 303.

Table 3 shows the results using this modified dataset. The specifications in the first and second columns are the same as in previous tables. In the first, the Sargan tests of over-identifying restrictions for GMM-A and GMM-B are statistically significant at the 0.10 level, and the results for the within-group estimator are highly biased and inconsistent. Apart from these, the results obtained from the PSM and the level estimators are identical in terms of the signs of the coefficients to those obtained earlier. P_{t-1} is positive and statistically significant in these estimators. MS_t and RD_t are positive and statistically significant, whereas IM_t and DC_t are negative and statistically significant. As far as these results are concerned, it appears that market share, higher domestic competition and research and development have positive effects on innovative activities. While foreign competition has a negative impact.

In the second column, the inclusion of the further lag, P_{t-2}, appears to have reduced the higher bias in the within-group estimator although a degree of bias continues to exist, and the Sargan test of over-identifying restrictions for GMM-A is statistically insignificant. With respect to the signs of the coefficients, all the statistically significant results are identical, and the implications of these results are the same as those derived from the first column. As for IM, it becomes increasingly plausible to assume that IM has a negative effect on innovation. It is also the case that, despite the reduction in the number of observations, the estimations of these models using a longer time-series improves the efficiency of the estimators.

Table 3 Results of LFM Models

	PSM	**Level**	**Within**	**GMM-A**	**GMM-B**
$\mathbf{P_{t-1}}$	0.24 (0.04)***	0.12 (0.07)*	0.73 (0.01)***	0.46 (0.06)***	0.72 (0.03)***
$\mathbf{MS_t}$	0.53 (0.09)***	0.84 (0.07)***	-2.88 (0.18)***	0.68 (0.22)***	0.51 (0.14)***
$\mathbf{IM_t}$	-0.41 (0.08)***	-0.90 (0.13)***	-2.61 (0.20)***	-0.38 (0.27)	-0.33 (0.10)***
$\mathbf{DC_t}$	-0.44 (0.07)***	-0.48 (0.09)***	-1.10 (0.05)***	-0.81 (0.13)***	-0.83 (0.09)***
$\mathbf{RD_t}$	0.18 (0.03)***	0.38 (0.02)***	-0.08 (0.03)**	0.31 (0.07)***	0.27 (0.07)***
1st AR				-2.33 (0.02)	-2.75 (0.006)
2ndAR				-1.15 (0.25)	-0.88 (0.38)
Sargan				20.53 (0.08)	20.01 (0.07)

Note: PSM = pre-sample mean estimator, solving (A5); Level = level estimator estimated by solving (A.1);
Within = within-group mean scaling estimator solving (A.2); GMM-A = quasi-differenced GMM estimator solving the Wooldridge moment conditions (A.3), and the instruments are (1, P_{it-1}, MS_t, IM_t, DC_t, RD_t);
GMM-B is the same as GMM-A except the instruments (time dummies, ΔP_{it-1}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).
Robust standard errors are in the parenthesis.
For the diagnostic tests for the GMM, 1st AR = first-order autocorrelation, 2nd AR = second-order autocorrelation, Sargan = Sargan test for over-identifying restrictions, and p-values are in the parenthesis.
*, **, *** = statistically significant at 0.10, 0.05, and 0.01 level, respectively.

	PSM	**Level**	**Within**	**GMM-A**	**GMM-B**
$\mathbf{P_{t-1}}$	1.28 (0.13)***	1.15 (0.15)***	1.07 (0.006)***	0.95 (0.08)***	0.69 (0.12)***
$\mathbf{P_{t-2}}$	-1.13 (0.12)***	-0.96 (0.12)***	-0.97 (0.01)***	-0.79 (0.05)***	-0.09 (0.13)
$\mathbf{MS_t}$	0.43 (0.07)***	0.88 (0.08)***	0.10 (0.02)***	0.74 (0.21)***	0.58 (0.16)***
$\mathbf{IM_t}$	-0.33 (0.08)***	-1.03 (0.14)***	0.02 (0.03)	-0.57 (0.19)***	-0.37 (0.14)***
$\mathbf{DC_t}$	-0.40 (0.07)***	-0.38 (0.11)***	-0.38 (0.008)***	-0.71 (0.11)***	-0.77 (0.11)***
$\mathbf{RD_t}$	0.13 (0.04)***	0.41 (0.02)***	0.94 (0.03)***	0.26 (0.08)***	0.25 (0.07)***
1st AR				-3.01 (0.002)	-1.82 (0.07)
2ndAR				1.67 (0.11)	-0.15 (0.88)
Sargan				16.83 (0.16)	19.76 (0.05)

Note: GMM-A's instruments are (1, P_{it-1}, P_{it-2}, MS_t, IM_t, DC_t, RD_t) and GMM-B's are (time dummies, ΔP_{it-1}, ΔP_{it-2}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).

Analysis of the Effects of Competition

In the previous analysis, the inclusion of the research and development variable, RD, has reduced the number of observations owing to the lack of time-series data. In this section, the analysis concentrates on the effects of competition on innovative activities by dropping MS and RD and using the dataset that extends the time-series. The countries included in the dataset have more than 10 data with the result that the number of observations is raised to 391.

The results are presented in Table 4. The specification in the first column includes two lags of the dependent variable, P_{t-1} and P_{t-2}, and two competition related variables at time t, IM_t and DC_t. The Sargan test for GMM-B is significant, whereas that for GMM-A is insignificant. However, the test for the first-order autocorrelation is insignificant, indicating a mis-specification of the model. As a consequence the results obtained by these estimators are discounted. With respect to the results for the remaining estimators, the signs of the coefficients for P_{t-1}, P_{t-2}, and DC_t are the same as those in Table 3, reconfirming the previous findings. Again the results for IM_t, the results are mixed.

In order to scrutinise the ambiguous results for IM, another specification was tested, which is shown in the second column. The specification includes three lags of the dependent variable, P_{t-1} , P_{t-2}, and P_{t-3}, and the explanatory variables at time t and t-1, IM_t, IM_{t-1}, DC_t, and DC_{t-1}. After testing other specifications, this specification turned out to be the best in terms of the diagnostic test of the GMM estimators. The Sargan tests for these estimators are statistically insignificant, and the tests for the first-order autocorrelation are statistically significant. The results for the lags of dependent variables reaffirm that the effects of past innovative activities are relatively short lived.

Using this specification the results for IM reveal interesting implications about the effects of foreign competition over time. All the statistically significant results for IM_t are positive, while the results for IM_{t-1} are all negative and statistically significant. It appears, therefore, that foreign competition does have an initial positive effect on innovative activities. However, the positive effect is subsequently replaced by the negative effect. The results obtained by the level and the GMM estimators suggest that the overall effect of foreign competition is negative, whereas the PSM and the within-group imply it is positive. It should be emphasised that these results are inferred from the coefficient estimates for a relatively short time period, t and t-1, and thus, the effect of foreign competition in a longer time period is rather unclear. In addition, the opposite effect of foreign competition at time t and t-1 seems to be the source of the mixed results derived from the previous analysis, in which only IM_t was entered in the estimations.

Accordingly, it can be argued, even if tentatively, that the presence of foreign competition has an initial positive effect on innovative activities, although in the longer term the effect is uncertain. Over aggregation of the data for this variable may explain the ambiguous results. Intuitively, it can be argued, for instance, that the penetration of foreign products into finished product markets, and into intermediate and capital goods markets, ought to have a distinct impact on innovative activities. The former may discourage domestic innovative activities for the products in which imports are far superior in terms of quality and marketing. Penetration into domestic intermediate and capital goods markets may act to stimulate innovative activities since these feed into finished products, in which adaptation and learning by doing are essential. Whatever the inference, it is plausible to assume that the capabilities of countries to compete with foreign firms and products vary considerably.

Finally, in relation to DC_t and DC_{t-1}, the results by the PSM and the GMM-A are both negative and statistically significant. The level estimator generated a statistically significant negative result for DC_t and a statistically insignificant result for DC_{t-1}. The results obtained for the within-group and the GMM-B are statistically significant and negative for DC_t and statistically significant and positive for DC_{t-1}. The results for DC_{t-1} can, therefore, be considered as mixed. However, the GMM-B's estimates are clearly biased, and it is apparent from the previous analysis that the within-group estimator is inconsistent and unreliable for the small number of observations. These results and previous findings concur that higher market concentration has a negative effect on innovative activities.

Table 4 Results of LFM Models

	PSM	Level	Within	GMM-A	GMM-B
P_{t-1}	1.39 (0.15)***	1.27 (0.08)***	1.18 (0.001)***	0.59 (0.01)***	0.68 (0.03)***
P_{t-2}	-1.70 (0.20)***	-1.18 (0.07)***	-0.61 (0.001)***	0.39 (0.01)***	0.16 (0.03)***
IM_t	0.13 (0.03)***	-1.68 (0.09)***	0.27 (0.006)***	-0.33 (0.21)	-0.36 (0.20)*
DC_t	-0.60 (0.04)***	-0.86 (0.10)***	-0.35 (0.003)***	-1.50 (0.08)***	-1.26 (0.09)***
1st AR				-1.09 (0.28)	-1.27 (0.20)
2ndAR				-1.46 (0.14)	-1.12 (0.26)
Sargan				18.26 (0.25)	21.78 (0.08)

Note: PSM = pre-sample mean estimator, solving (A5); Level = level estimator estimated by solving (A.1);
Within = within-group mean scaling estimator solving (A.2); GMM-A = quasi-differenced GMM estimator solving the Wooldridge moment conditions (A.3), and the instruments are (1, P_{it-1}, P_{it-2}, MS_t, IM_t, DC_t, RD_t ;
GMM-B is the same as GMM-A except the instruments (time dummies, ΔP_{it-1}, ΔP_{it-2}, ΔMS_t, ΔIM_t, ΔDC_t, ΔRD_t).
Robust standard errors are in the parenthesis.
For the diagnostic tests for the GMM, 1st AR = first-order autocorrelation, 2nd AR = second-order autocorrelation, Sargan = Sargan test for over-identifying restrictions, and p-values are in the parenthesis.
*, **, *** = statistically significant at 0.10, 0.05, and 0.01 level, respectively.

	PSM	Level	Within	GMM-A	GMM-B
P_{t-1}	1.95 (0.19)***	1.32 (0.17)***	1.30 (0.003)***	1.09 (0.05)***	0.91 (0.03)***
P_{t-2}	-0.21 (0.12)*	-0.16 (0.16)	-1.00 (0.004)***	-0.17 (0.02)***	-0.10 (0.06)*
P_{t-3}	-2.60 (0.38)***	-1.56 (0.29)***	0.54 (0.003)***	-0.52 (0.03)***	0.18 (0.06)***
IM_t	0.54 (0.14)***	0.44 (0.33)	1.79 (0.05)***	0.71 (0.10)***	7.56 (1.16)***
IM_{t-1}	-0.46 (0.15)***	-2.28 (0.38)***	-1.51 (0.04)***	-1.90 (0.30)***	-7.81 (1.16)***
DC_t	-0.16 (0.06)***	-1.14 (0.27)***	-0.77 (0.02)***	-0.43 (0.04)***	-7.51 (1.21)***
DC_{t-1}	-0.28 (0.05)***	0.35 (0.30)	0.47 (0.03)***	-0.62 (0.08)***	5.92 (1.19)***
1st AR				-1.92 (0.05)	-2.49 (0.01)
2ndAR				-0.49 (0.62)	0.19 (0.85)
Sargan				13.92 (0.46)	18.24 (0.15)

Note: GMM-A's instruments are (1, P_{it-1}, P_{it-2}, P_{it-3}, MS_t, MS_{t-1}, IM_t, IM_{t-1}, DC_t, DC_{t-1}, RD_t, RD_{t-1}) and GMM-B's are (time dummies, ΔP_{it-1}, ΔP_{it-2}, ΔP_{it-3}, ΔMS_t, ΔMS_{t-1}, ΔIM_t, ΔIM_{t-1}, ΔDC_t, ΔDC_{t-1}, ΔRD_t, ΔRD_{t-1}).

5. CONCLUSION

The relationship between market structure and technological innovation has been examined using Linear Feedback Models. This approach is more amenable when the number of observations is restricted. The inclusion of further time-lags for the dependent variable and the use of a longer time-series has offset some of the limitations associated with the small numbers of observations. With the exception of the within-group estimator, the application of LFM, with a careful choice of specification and time-series data, has worked reasonably well.

The results have indicated that success in international markets, measured by the share in world-wide manufacturing exports, higher domestic competition among domestic firms, and research and development efforts, have had positive effects on innovative activities. Although structural measures have been used to measure competition, the results confirm the importance of promoting and preserving the competitive process in developing countries as an element in stimulating technological progress and contributing to economic development.

On the other hand, import penetration as a proxy for the presence of foreign competition in a given domestic market generated highly mixed results. By including additional lags of the dependent variable and extending the time-dimension of the data, thereby possibly improving the effectiveness of the instrument sets, the results show that foreign competition does have an initial positive impact on innovative activities. Such an impact, however, is short-lived and soon turns negative. While further investigation into the effects of foreign competition is necessary, it appears that foreign competition has a distinctively different effect on innovative activities compared with the effect of competition among domestic enterprises.

REFERENCES

Aghion, P. & Howitt, P. (1998) *Endogenous Growth Theory*, Cambridge, MIT Press.

Ahn, S. (2002) 'Competition, innovation and productivity growth: a review of theory and evidence', Economics Department Working Papers No. 317, Paris, OECD.

Al-Osh, M. & Alzaid, A. (1987) 'First-order integer valued autoregressive (INAR(!)) process,' *Journal of Time Series Analysis*, Vol.8, 261-275.

Alzaid, A. & Al-Osh. M. (1990) 'Integer-valued *p*th order autoregressive structure (INAR(*p*)) process,' *Journal of Applied Probability*, Vol.27, 314-324.

Audretsch, D., Baumol, W. & Burke, A. (2001) 'Competition policy in dynamic markets', *International Journal of Industrial Organisation*, Vol.19, 613-634.

Bailey, M. & Gersbach, H. (1995) 'Efficiency in manufacturing and the need for global competition', Brookings Paper on Economic Activity, 307-358.

Blundell, R. & Bond, S. (1998) 'Initial Conditions and Moment Restrictions in Dynamic Panel Data Models,' *Journal of Econometrics*, Vol.87, 115-149.

Blundell, R., Griffith, R. & van Reenen, J. (1995) 'Dynamic count data models of technological innovation,' *Economic Journal*, Vol.105, p.333-344.

Blundell, R., Griffith, R. & van Reenen, J. (1999) 'Market Share, Market Value andInnovation in a Panel of British Manufacturing Firms', *Review of Economic Studies*, Vol.66, 529-554.

Blundell, R., Griffith, R. & Windmeijer, F. (1995) 'Individual Effects and Dynamic Feedback in Count Data Models', *Institute of Fiscal Studies (IFS) Working Paper 99/9*.

Blundell, R., Griffith, R. & Windmeijer, F. (2002) 'Individual effects and dynamics in count data models', *Journal of Econometrics*, Vol.108, 113-131.

Chamberlain, G. (1992) 'Comment: sequential moment restrictions in panel data', *Journal of Business and Economic Statistics*, Vol.10, 20-26.

Cincera, M. (1997) 'Patents, R&D, and Technological spillovers at the firm level: some evidence from econometric count models for panel data,' *Journal of Applied Econometrics*, Vol.12, p.265-280.

Cohen, W. & Levin, R. (1989) 'Empirical studies of innovation and market structure', in Schumalensee, R. and Willig, R. (eds) Handbook of Industrial Organisation, Vol. 11, Amsterdam, North Holland.

Crépon, B. & Duguet, E. (1993) 'Research and development, competition and innovation:what patent data show,' *Working Paper No. 9314*, Institut National de la Statistique et des Etudes Economiques, Paris.

Crépon, B. & Duguet, E. (1997a) 'Research and development, competition and innovation Pseudo-maximum likelihood and simulated maximum likelihood methods applied to count data models with heterogeneity,' *Journal of Econometrics*, Vol.79, p.355-378.

Crépon, B. & Duguet, E. (1997b) 'Estimating the innovation function from patent numbers: GMM on count panel data, *Journal of Applied Econometrics*, Vol.12, p.243-263.

Dasgupta, P. & Stiglitz, J. (1980) 'Industrial Structure and the Nature of Innovative Activity,' *Economic Journal*, Vol.90, June, 266-293.

Geroski, P. (1990) 'Innovation, technological opportunity and market structure', Oxford Economic Papers, Vol.42, 586-602.

Gourieroux, C., Monfort, A. & Trognon, A. (1984) 'Pseudo maximum likelihood methods: applications to poisson models,' *Econometrica*, Vol.52, 701-720.

Griliches, Z. (1990) 'Patent statistics as economic indicators: a survey,' *Journal of Economic Literature*, Vol.28, p.1661-1701.

Hall, B. H., Jaffe, A. B. & Tratjenberg, M. (2001) 'The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools,' *NBER Working Paper 8498*.

Hausman, J., Hall, B. & Griliches, G. (1984) 'Econometric models for count data and an application to the patents-R&D relationship,' *Econometrica*, Vol.52, 909-938.

Jin-Guan, D. & Yuan, L. (1991) 'The integer-valued autoregressive (INAR(p)) model,' *Journal of Time Series Analysis*, Vol.12, 129-142.

Montalvo, J.G. (1993) 'Patents and R&D at the firm level: a new look,' *Rivista Espanola de Economia*, Vol.67, p.67-81.

Montalvo, J.G. (1997) 'GMM estimation of count-panel-data models with Fixed Effects and Predetermined Instruments,' *Journal of Business and Economic Statistics*, Vol. 15, p.259-382.

Schumpeter, J. (1947) *Capitalism, Socialism and Democracy*, Second Edition, London: Allen and Unwin.

Symeonidis, G. (1996) 'Innovation, firm size, and market structure: Schumpeterian Hypotheses and some new themes', OECD Economic Studies, No. 27, 35-70.

Windmeijer, F. (2002) 'ExpEnd, A Gauss Programme for Non-Linear GMM Estimation of Exponential Models with Endogenous Regressors for Cross Section and Panel Data,' *Working Paper CWP14/02*, Centre for Micro Data Methods and Practice (CEMMAP), London.

Winkelmann, R. (2000) *Econometric Analysis of count data*, Third Edition, Berlin: Springer.

Wooldridge, J. (1997) 'Multiplicative panel data models without the strict exogeneity assumption,' *Econometric Theory*, Vol.13, 667-678.

APPENDIX 1:

Moment conditions for the LFM in levels, within-group, GMM and pre-sample mean estimators (for more details, see Blundell, Griffith and Windmeijer (2002) and Windmeijer (2002))

In order to calculate the LFM in levels, the following moment conditions are solved:

$$\sum_{i=1}^{N}\sum_{t=2}^{T} z_{it}\,(\,y_{it} - \gamma\, y_{it\text{-}1} + exp(\beta_0 + x_{it}\,\beta)) = 0, \qquad \text{(A1)}$$

where z_{it} = (1, $y_{it\text{-}1}$, x_{it}).

The following moment conditions are solved to estimate the LFM in within-group mean scaling:

$$\sum_{i=1}^{N}\sum_{t=2}^{T} z_{it}\,(\,y_{it} - \gamma\, y_{it\text{-}1} - \mu_{it}\,\frac{\overline{y}_{i} - \gamma\,\overline{y}_{i,-1}}{\overline{\mu}_{i}})) = 0, \qquad \text{(A2)}$$

where z_{it} = (1, $y_{it\text{-}1}$, x_{it}), $\overline{y}_{i}$ = 1/(T-1)$\sum_{t=2}^{T} y_{it}$, $\overline{y}_{i\text{-}1}$ = 1/(T-1)$\sum_{t=2}^{T} y_{it\text{-}1}$,

and $\overline{\mu}_{i}$ = 1/(T-1)$\sum_{t=2}^{T} exp(x_{it}\,\beta)$.

To estimate the LFM in quasi-differenced GMM, it can be achieved by applying the Wooldridge quasi-differencing transformation (Wooldridge, 1997):

$$\sum_{i=1}^{N}\sum_{t=2}^{T} x_{it\text{-}1}\, q_{it}, \qquad \text{(A3)}$$

where $q_{it} = \dfrac{y_{it} - \sum_{j=1}^{p}\gamma_j y_{it-j}}{\mu_{it}} - \dfrac{y_{it-1} - \sum_{j=1}^{p}\gamma_j y_{it-1-j}}{\mu_{it-1}}$.

When x_{it} is endogenous, the following moment conditions hold:

$E(q_{it} \mid y_i^{t\text{-}2}, x_i^{t\text{-}2}) = 0$.

Alternatively, the LFM in quasi-differenced GMM can be estimated by applying the Chamberlain quasi-differencing transformation (Chamberlain, 1992):

$$\sum_{i=1}^{N}\sum_{t=2}^{T} x_{it\text{-}1}\, s_{it},$$

where $s_{it} = (y_{it} - \sum_{j=1}^{p} \gamma_j\, y_{i\text{-}j})\,\dfrac{\mu_{it-1}}{\mu_{it}} - (y_{i\text{-}1} - \sum_{j=1}^{p} \gamma_j\, y_{it\text{-}1\text{-}j}),$ (A4)

When x_{it} is predetermined, the following moment conditions are satisfied:
$E(s_{it} \mid y_i^{t-2}, x_i^{t-1}) = 0$.

Finally, the LFM estimation by the pre-sample mean estimator solves the following:

$$\sum_{i=1}^{N} \sum_{t=2}^{T} z_{it} \left(y_{it} - \gamma\, y_{it-1} - exp(\beta_0^{*} + x_{it}\,\beta + \theta \ln \overline{y}_{ip}) \right) = 0, \qquad \text{(A5)}$$

where $z_{it} = (1, y_{it-1}, x_{it}, \ln \overline{y}_{ip})$.

APPENDIX 2: DESCRIPTIVE STATISTICS FOR THE BASE DATA

Dataset 1

	MS	IM	DC	RD	Patent
Max	0.15	1.17	0.29	0.05	77687
Min	0.00	0.02	0.01	0.00	0
Mean	0.03	0.21	0.07	0.01	3856.25
Median	0.02	0.17	0.05	0.01	433.0
Standard Deviation	0.04	0.18	0.05	0.01	11136.62

The sample countries and periods chosen for this dataset are: Chile (1993-1997), New Zealand (1993-1997), the Philippines (1993-1997), India (1992-1997), Israel (1992-1997), Pakistan (1992-1997), Indonesia (1991-1997), Mexico (1991-1997), Taiwan (1991-1997), Brazil (1990-1997), Turkey (1990-1997), South Korea (1988-1997), South Africa (1988-1997), Singapore (1988-1997), Austria (1987-1997), Spain (1987-1997), Ireland (1987-1997), Australia (1983-1997), Belgium (1983-1997), Canada (1983-1997), Germany (1983-1997), Denmark (1983-1997), Finland (1983-1997), France (1983-1997), Italy (1983-1997), Japan (1983-1997), Malaysia (1983-1997), Netherlands (1983-1987), Norway (1983-1997), Sweden (1983-1997), Switzerland (1983-1997), United Kingdom (1983-1997), and United States (1983-1997). As a result, a total of 373 observations were obtained.

Dataset 2

	IM	DC	Patent
Max	1.17	0.38	77687
Min	0.02	0.01	0
Mean	0.21	0.08	4107.87
Median	0.16	0.05	459.0
Standard Deviation	0.18	0.06	11291.64

The sample countries and periods are: South Korea (1988-97), South Africa (1988-97), Singapore (1988-97), Austria (1987-97), Brazil (1987-97), Mexico (1987-97), Spain (1986-97), Ireland (1985-97), United Kingdom (1983-97), Australia (1980-97), Belgium (1980-97), Canada (1980-97), Germany (1980-97), Denmark (1980-97), Finland (1980-97), France (1980-97), Italy (1980-97), Japan (1980-97), Malaysia (1980-97), Netherlands (1980-97), Norway (1980-97), New Zealand (1980-97), Sweden (1980-97), Switzerland (1980-97), and United States (1980-97). A total of 391 observations were obtained.