Patent Quality and R&D Productivity in Pharmaceuticals: The Role of Inflation and International Collaboration

Working Paper No. 27

George Messinis

Pharmaceutical Industry Project
Working Paper Series

August 2005

Centre for Strategic Economic Studies
Victoria University of Technology
PO Box 14428 Melbourne VIC 8001 AUSTRALIA
Telephone +613 9919 1340
Fax +613 9919 1350

Email: csesinfo@vu.edu.au
Website: http://www.cfses.com

Patent Quality and R&D Productivity in Pharmaceuticals: The Role of Inflation and International Collaboration*

George Messinis

1 August 2005

Abstract

Lanjouw and Schankerman (2004) proposed that patent quality is a key driver of R&D productivity but did not find supportive evidence for pharmaceuticals. This study revisits this hypothesis using OECD data for the period 1980-2000. It extends the literature in three ways: it develops new R&D price deflators to account for R&D price inflation; it employs two complementary indicators of patent quality, and applies dynamic panel data estimation techniques. When corrections are made for cross-sectional dependence, two major findings emerge: international inventor collaboration is an important indicator of patent quality, and there is strong support for the maintained hypothesis.

Keywords: R&D Price Inflation; Productivity; Patents; Collaboration; Panel Data; Spatial GMM.

J.E.L. Classification: L65; I11; O3.

---

* Work on this topic benefited from comments by Peter Sheehan, Naz Islam and seminar participants at Victoria University. I am grateful for research assistance by Steven Parker. The usual disclaimer applies to remaining errors and omissions. Correspondence: George Messinis, Centre for Strategic Economic Studies, Victoria University, Vic 8001 Australia. E-mail: george.messinis@vu.edu.au. Tel: + 613 9919-1339, Fax: + 613 9919-1350.

1 Introduction

New medicines make an important contribution to wellbeing since they improve health care and the quality of life (Lichtenberg 2002). On the other hand, new medicines absorb considerable resources for their development. We know that the pharmaceutical industry is one of the most R&D intensive sectors in the world (OECD 2003) and that R&D costs have surged over the last decade (DiMasi *et al.* 2003).

Cost-benefit analysis of business expenditure in R&D (BERD) in pharmaceuticals has taken centre stage in public policy.[1] The emerging question of whether R&D resources are efficiently utilised seems warranted on two grounds. One relates to the regulation of pharmaceuticals in the form of prices controls, R&D tax credits and health care subsidies (Productivity Commission 2001; Bloom *et al.* 2002). This state of affairs may give rise to prices that deviate from consumer value (Richardson 2001; Johnson 2001). Further, corporate governance issues and externalities may add to incentives for over-investment in R&D (Nam *et al.* 2003; Jones and Williams 2000).

Research productivity is a key indicator of the industry's innovation performance. The literature has reported an R&D productivity slowdown since the 1980's while BERD has grown rapidly.[2] A critical question is whether the decline in the patents to BERD ratio - the standard measure of R&D productivity – is attributable to a falling inventive output per unit of R&D investment (i.e., 'technological exhaustion') or simply due to an increase in the demand for BERD (Lanjouw and Schankerman 2004). An answer to this question can guide management towards optimal R&D investment (Lee and O'Neill 2003) but

[1] See, for example, Productivity Commission (2003) and PhRMA (2004).
[2] Lanjouw and Schankerman (2004) and Cockburn (2004) provide more details.

empirical analysis has grappled with two measurement problems. A major deficiency in the patents to BERD ratio is its neglect of changes in patent quality. One response to this problem is to utilise data on New Molecular Entities (NME's) approved by the US Food and Drug Administration and arrive at an adjusted measure of R&D productivity that captures original innovation in medicines (Cockburn 2004). Another approach is Lanjouw and Schankerman (2004) who go the extra mile to incorporate added USPTO patent information and construct an index of patent quality that is quite independent of the patents to BERD ratio. In their theoretical model, Lanjouw and Schankerman (2004) show that patent quality is an important driver of R&D productivity. Yet, their empirical results raise doubts about the validity of the model for pharmaceuticals.

The above literature, however, has largely focused on the output of innovation and little attention has been given to the measurement of *real* R&D investment. Empirical studies have relied on GDP price deflators to adjust for R&D price inflation. When combined with exchange rates data, these series yield the familiar GDP PPP's indexes[3] that accompany the OECD STAN database. The convention has prevailed mainly due to the absence of alternative R&D price deflators. Yet, it is now established that the use of GDP PPP's in structural analysis is highly problematic since they tend to miss sectoral variation in input prices and they ignore intermediate goods and services (Dougherty *et al.* 2003; Cameron 1996; Jankowski 1993).

This paper develops three new R&D price deflators for pharmaceuticals in the OECD. For consistency and parsimony, these new estimates derive from a methodology that relies on published data, economic theory and panel data econometric techniques. The paper utilises the new estimates to model research productivity and to re-examine

[3] For more detail on the measurement of PPPs, see Schreyer and Koechlin (2002).

the view that R&D productivity has declined and that patent quality is a key driver of productivity. It extends the literature with the construction of two complementary measures of patent quality by utilizing USPTO patents data. In contrast with Lanjouw and Schankerman (2004), this study finds little evidence of a persistent decline in R&D productivity but patent quality is a significant predictor of productivity. Furthermore, international inventor collaboration is a key indicator of patent quality.

This paper is organised in four sections. Section two outlines our methodology and presents the new R&D price deflators. The empirical assessment of the Lanjouw and Schankerman (2004) hypothesis follows in section three. The last section presents a summary and concludes.

2 New R&D Price Deflators: Pharmaceuticals

This section builds on Dougherty *et al.* (2003) to develop alternative R&D price deflators for the pharmaceuticals industry in the OECD. It extends the literature in three ways: (a) it derives new estimates of labour compensation in R&D; (b) it obtains industry-specific price indices for non-labour R&D costs, and (c) employs panel data econometrics to test whether the new R&D price deflators are consistent with economic theory. Overall, the approach facilitates a parsimonious construction of R&D price deflators, adopts an empirical methodology for the comparison of price deflators based on economic intuition and econometrics, and offers new insights on global trends in R&D price inflation and *real* R&D in pharmaceuticals.

2.1 Background

Every international comparative study of innovation faces the challenge of estimating R&D price inflation in order to arrive at constant-price R&D expenditures. Ideally, this estimation requires information on price and weights for each R&D input category. Such a database is not currently available but its development has become a key objective of official statistical agencies such as the OECD[4] and the National Science Foundation in the USA. However, the accomplishment of this objective would require substantial resources when considering the need for national industry-specific surveys.

In the absence of R&D input-specific data, research has mainly relied on GDP price deflators with little attention been given to structural differences in R&D input prices.[5] There are two difficulties with the GDP PPP approach. First, industry output prices diverge considerably from aggregate GDP price levels and, thus, GDP PPP's lead to misleading comparisons (Van Ark 1996). US data confirm this view for pharmaceuticals: the Biomedical R&D price index (BRDPI) indicates much stronger price growth than the implicit GDP deflator (Adams and Griliches 1996). O'Mahony and Van Ark. (2003) find that the labour cost structure varies considerably within the OECD. Second, output deflators exclude prices of intermediate goods and services that form a major part of R&D. Since these inputs are not traded internationally, standard GDP PPP's can be grossly misleading if substantial structural differences exist between OECD countries (OECD 1994). Therefore, the GDP PPP convention has the potential to contaminate comparative analysis with a significant bias given the dominant role of labour compensation in BERD.

[4] See, for example, Breitschopf and Grupp (2004).
[5] Freeman and Young (1965) is an early but rare inquiry.

We, thus, examine the possibility that an alternative to GDP PPP's exists that maintains parsimony and continuity in data utilisation, and consistency with economic intuition. There is a high priority for new R&D price deflators for pharmaceuticals in view of the rise of the industry as one of the most innovative in the OECD and the increasing focus of public policy on health. A greater understanding of R&D price inflation and real BERD can guide public policy towards a resolution to the dilemma of sustainable drug innovation and access to new medicines (Dickson *et al.* 2003).

Early attempts towards an alternative to the GDP deflator for the USA are Jaffe (1973) and Griliches (1984). They draw on the fact that labor costs represent the largest component of R&D expenditure to propose a weighted R&D price index that combines a labor costs index with a broader output deflator. The assumption here is that price changes of the output produced by the industry should reflect price movements of non-labor R&D inputs. Given the lack of industry-specific value added deflators, they employ the GDP deflator as a proxy for the non-labor cost index. Dougherty *et al.* (2003) compare the Griliches-Jaffe approach with a fully developed R&D deflator that incorporates industry specific information on non-labor costs. They are able to show that the Griliches-Jaffe R&D deflators perform as well as the fully developed R&D PPP's. The Dougherty *et al.* (2003) result suggests that detailed data on non-labor input prices may not be essential.

Recent US studies have employed the National Institutes of Health Biomedical R&D Price Deflator (BRDPI), developed by the Bureau of Economic Analysis, as an alternative measure of R&D price index. Cockburn (2004) uses the BRDPI to correct for R&D price inflation but his adjusted series does not alter the established view that B&R

productivity has declined in the USA. Compared to the GDP price deflator, the BRDPI series is certainly an improvement since it more directly relates to medical R&D. Unfortunately, however, there is no information on the suitability of BRDPI as a proxy of R&D price inflation in the *private* sector. The series is an input price index for the NIH budget that is dominated by labour compensation of academic and Federal employees. It is weighted according to the pattern of expenditures supported by NIH awards (mainly basic R&D)[6] and, thus, it would not necessarily track R&D price inflation in the private sector if we consider the Cockburn and Henderson (1997) finding that 'research conducted in the public sector is managed and rewarded quite differently from work conducted in the private sector' (p. 13). More importantly, an equivalent to BRDPI does not exist for other OECD countries.

2.2 Methodology

This section outlines the methodology we follow in developing three new R&D price deflators as Tornqvist (T) indices. We define an R&D price deflator j as follows:

$$RDP_{j,t} = \prod_i \left(\frac{P_{it}}{P_{i0}} \right)^{\frac{1}{2}(w_{i0} + w_{it})} = \exp\left[\frac{1}{2} \sum_{i=1}^{k} (w_{i0} + w_{it}) \ln\left(\frac{P_{it}}{P_{i0}} \right) \right] \quad (1)$$

where $P_{i,t}$ is the price level of R&D input *i* in the current period t, $P_{i,0}$ is the price level in the base year (1995 in this study), $w_{i,t}$ and $w_{i,0}$ are the expenditure weights of input *i* in the current and base year respectively and k is the number of R&D inputs considered.

[6] We are indebted to James Schuttinga at the NIH for information on the BRDPI series.

Due to data limitations, it is a literature convention to assume that k=1 and use the general price level to approximate *P*. This is the GDP Deflator approach. Following Dougherty *et al.* (2003), we extend the existing literature in four respects. First, we expand the range of R&D inputs to consider the case of k=4. Based on SIRF (2001), the R&D cost structure comprises of four main elements: (1) labour costs; (2) laboratory consumables; (3) laboratory and office equipment, and (4) occupancy & office expenses. Second, given the lack of data on R&D labour costs, we utilise two alternative estimates of R&D unit labour costs. One is the average labour cost in the industry; as the standard measure in the R&D literature (Frantzen 2000). This forms the basis for our first R&D price deflator, RDP^1. This crude measure is adjusted on the basis of relative value-added growth in pharmaceuticals to arrive at a second measure, RDP^2. For comparison with Jaffe (1973) and Griliches (1984), we also consider the case of k=2 using the adjusted unit labour cost index with the GDP deflator as a proxy for non-labour R&D inputs. This generates a third R&D price deflator, RDP^3.

Third, we draw on economic foundations to subject the above price deflators to econometric scrutiny. Economic theory offers useful insights on the empirical behaviour of real R&D investment that derive from an optimal theory of the firm. We focus on the core economic intuition of a direct link between real BERD and the cost of R&D. Bloom *et al.* (2002) directly relate real BERD to the cost of R&D and show that a CES production function leads to the following relation:

$$r_{it} = a_0 + a_1 r_{it-1} + a_2 y_{it} + a_3 p_{it} + e_{it} \qquad (2)$$

where r_{it}, y_{it}, p_{it} are the log of R&D expenditure, output and the user cost of R&D respectively and e_{it} is an error term. The model predicts that real R&D investment

expenditure ought to relate positively to output and inversely to price; that is, $\alpha_2>0$ and $\alpha_3<0$. The authors adopt the GDP Deflator approach and are able to confirm the prediction at the national level.

We depart from Bloom *et al.* (2002) in our approach to estimation. We choose to work with the model in first differences and focus on short-term dynamics for three reasons. First, it is unlikely that the three alternative price deflators are independent when considering, for example, that the labour costs index is by construction a major component of RDP^1 RDP^2 and RDP^3. Hence, the three series could share a common trend that would make it difficult to distinguish between the three. Second, literature concerns about spurious regression cannot easily subside with the use of panel unit root and residual-based cointegration tests given the deficiencies in existing tests.[7] Third, there is evidence that first-difference estimators are less likely to suffer from spatial correlation bias (Haris *et al.* 2000). Hence, all panel series in this study are in first differences.

Finally, we apply a variety of econometric techniques to examine whether the three new R&D price deflators, as well as the GDP deflator, are consistent with the Bloom *et al.* (2002) model. One option is the feasible GLS estimator. Another is the dynamic panel data estimator of Arellano and Bover (1995). Third, given that the standard assumption of cross-sectional independence is often rejected, we employ spatial econometrics to obtain consistent estimates of standard errors. We employ the Conley (1999) and Driscoll and Kraay (1998) GMM estimators that nonparametrically correct for cross-sectional

[7] There are two major issues with standard panel unit root tests. First, they assume cross-sectional independence; this seems implausible as countries often share common shocks (Moon and Perron 2004). Second, they impose homogeneity since the null hypothesis is that, on average, *all* cross-section units contain a unit root (Strauss and Yigit 2003 and Taylor and Sarno 1998).

correlation. The former uses a weighting matrix based on economic distance while the latter is robust to general forms of cross-sectional dependence.[8]

2.3 Data

This study utilises OECD data for fifteen OECD countries[9] over the period 1980-2000. Towards an index of R&D unit labour costs, we utilise two alternative measures. The OECD *STAN* estimates of total labour compensation and total employment in the industry as a whole provide the basis for the first measure, LCP^1. As an alternative, we exploit value added data to adjust LCP^1 and arrive at a second estimate of R&D unit labour costs, LCP^2. We conjecture that the average salary of R&D personnel has a premium component that moves with above average growth in value added.[10]

For the non-labour R&D price indices of laboratory consumables, laboratory and office equipment, and occupancy & office expenses, we again utilise OECD *STAN* estimates of implicit value added deflators for the following industries respectively: 'chemicals and chemical products' (code 2400); 'electrical & optical equipment' (code 30-33), and 'business sector services' (code 50-74).[11] The OECD *ANBERD* database is also

[8] In STATA, the XTABOND2 procedure was used for System GMM, written by Roodman (2005). Professor Conley provided spatial OLS and GMM code (gsbwww.uchicago.edu/fac/timothy.conley). RATS was used to compute Driscoll and Kraay (1998) GMM estimates using code written by Steve Green (www.estima.com).

[9] These are Australia, Canada, Belgium, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, the UK and the USA. The Appendix provides a detailed account of data sources and variable definitions.

[10] That is, $LCP^2 = LCP^1 * (1+g)$ where g is the value added growth differential of growth in a particular country and the mean growth rate in the five largest OECD players: France, Germany, Japan, the UK and the USA.

[11] While the BERD share of labour costs varies across countries and over time, we fix the non-labour share of specific non-labour R&D inputs on the basis of SIRF (2001). Due to lack of data, we take the mean of France, Germany and the UK for Belgium, the mean of Germany and Sweden for Denmark, Sweden's share for Finland and Norway, and the mean of France and Germany for Italy, Netherlands and Spain.

used to obtain estimates of BERD. Note that we use *per capita* values for expenditures and output data.

2.4 Results

We proceed to test whether the above four price deflators and their corresponding measures of real BERD conform to the predictions of (2). We begin with feasible generalized least squares (FGLS) estimation to correct for AR (1) autocorrelation within panels, and contemporaneous cross-sectional correlation and heteroscedasticity across panels. Part (A) of table 1 reports the results for each of the four R&D price deflators when the autoregressive component is ignored. The first column of the table indicates that the GDP Deflator is not a good proxy as an R&D price deflator for pharmaceuticals since it has the wrong sign. Surprisingly, the industry-wide unit labour cost index also results in a coefficient estimate for price that has the wrong sign. The adjusted labour cost index, on the other hand, leads to a negative and statistically significant coefficient as expected. Further, a similar result is obtained when the Jaffe-Griliches approach is employed. Consistent with evidence in Dougherty *et al.* (2003), it indicates the critical role of R&D labour costs.[12]

- Table 1 about here -

At this stage, it seems prudent to treat the above results as tentative and examine the view that these may be due to spurious regression or to lack of dynamic estimation. On the first issue, it is important to test for the empirical validity of the cross-sectional independence assumption, given the growing literature emphasis on the geography of

[12] Of course, mismeasurement of the non-labor price deflators cannot be excluded as a source of this.

innovation; i.e., clusters and R&D spillovers.[13] Table 1 reports the Breusch-Pagan LM test statistic of cross-sectional independence (BP) using the FGLS residuals (Greene 2000). The null hypothesis is rejected in the last two regressions. This is in line with Moon and Perron (2004) who question the realism of the cross-sectional independence assumption. Thus, the results in table 1 are suspect, for standard errors are inconsistent in the presence of spatial correlation (Driscoll and Kraay 1998).

In order to correct for spatial correlation, we first employ the Conley (1999) OLS estimator. This approach relies on prior knowledge of the structure of temporal dependence but applies a nonparametric correction that accounts for economic distance when measured with error. We exploit the CEPII measure of distance between major cities[14] to obtain projected coordinates as in Conley (1999). The spatial OLS estimation results are summarised in part (B) of table 1 and are similar to those obtained in part (A), though the standard errors are now larger than the standard OLS estimates.

Next, we consider the complete model in (2) but ignore, for the time being, spatial dependence. We adopt the dynamic panel data estimation (DPD) approach pioneered by Arellano and Bond (1991) and fully developed by Arellano and Bover (1995). The procedure, known as the *System GMM* panel estimator, exploits information on all series to obtain separate instruments for each lag and each time period, and then uses GMM to weight them. Here, we allow for the lagged dependent variable to appear as an explanatory factor and treat both Δy and Δp as exogenous. Table 2 reports robust two-step system GMM estimates of (2). Although asymptotically more efficient, the two-step GMM estimator tends to produce standard error estimates that are severely downward

[13] On the geography of R&D, see Kyle (2004) for pharmaceuticals, and Simmie *et al.* (2002) and Conley and Ligon (2002) for other industries.
[14] This is variable 'distwces' available at http://www.cepii.fr/anglaisgraph/bdd/distances.htm

biased (Arellano and Bond 1991). We account for this with a finite-sample correction as in Windmeijer (2005) who shows that the correction makes the twostep robust GMM estimator more efficient than the onestep estimator. Table 2 also reports the Hansen J test of over-identifying restrictions[15] and the Arellano-Bond tests (AB) for AR(1) and AR(2) applied to the first-difference equation residuals.

- Table 2 about here -

The results show that the Δr_{t-1} coefficient is significant which is consistent with previous evidence of persistence in R&D.[16] Note, however, the coefficients of both Δy and Δp are no longer statistically significant, although the latter now exhibits the right sign. Also, the AB test results do not question the validity of the model specification.[17]

In the context of dynamic panel estimation, we wish to know whether the results in table 2 are spurious. Given the assumption of cross-sectional dependence is violated in table 1, we press on with GMM estimation that is robust to spatial correlation. We employ two spatial GMM estimators: Conley (1999) and Driscoll and Kraay (1998). The results in table 3 again indicate that both the GDP deflator and the industry-wide unit labour cost index are not appropriate as an R&D price index. Conversely, the R&D–specific unit labour cost index yields an R&D price deflator (i.e., RDP^2) that is consistent with the predictions of model (2). Further, the results provide support for the Jaffe-

[15] We use the 'collapse' sub-option in 'xtabond2' that creates one instrument per variable and lag distance and excludes instruments for each time period. This is in order to avoid a bias that arises when the number of instruments approaches the number of observations (Bond 2002).

[16] See Achilladelis and Antonakis (2001). Helfat (1994) discuss the sources of persistence.

[17] For robustness, we also obtained system GMM estimates using a sub-sample that excludes the USA to test for sensitivity to a major player. The results are almost identical to those in tables 1-3 and are available upon request.

Griliches approach of using the GDP deflator as a proxy for non-labour R&D costs, as in Dougherty *et al.* (2003).[18]

- Table 3 about here -

The analysis of R&D price inflation concludes with an illustration that compares the GDP deflator and RDP^2. Figure 1 shows that the two deflators have followed different paths in the USA. In fact, the USA is the only OECD country where the R&D price deflator has grown faster than the GDP deflator. Figure 1 also depicts the evolution of the two series in other OECD countries relative to those in the USA respectively. It is discernable that the USA has experienced lower general price inflation than other OECD counties, except Japan and Germany. On the other hand, most OECD countries exhibit substantially lower R&D price inflation in pharmaceuticals than in the USA, especially Japan, Australia and Germany. Most surprising, however, is the case of the UK with the highest average R&D price inflation in the OECD.

- Figure 1 about here –

3 Patent Quality and R&D Productivity

Numerous empirical studies have observed an alarming trend in the productivity of business research in pharmaceuticals. Lanjouw *et al.* (1998) cite evidence of a persistent decline in R&D productivity in several OECD countries. Lanjouw and Schankerman

[18] Another potential source of spurious regression may be that real BERD, columns 3-4 in tables 1-3, inversely relates to the R&D price deflator by construction. We re-estimate (2) with *nominal* BERD (US$) as the dependent variable and test whether the Δp_t coefficient is <1. The Conley (1999) GMM estimates (s.e.) for Δp_t are 1.47 (0.12), 1.29 (0.08), 0.75 (0.05) and 0.01 (0.03) when the GDP deflator, RDP^1, RDP^2 and RDP^3 are used respectively.

(2004) utilise patents data at the firm level over the period 1980-1993 and report a 'sharp decline in the patents to R&D ratio' for the USA. Using US data on new molecular entities, Cockburn (2004) also observes a 'shrinking' R&D productivity over the period 1996-2002. This trend has been attributed to a surge in R&D costs (DiMasi *et al.* 2003) associated with a technological change in the conduct of R&D (Cockburn 2004). It is, however, puzzling that R&D investment expenditures have grown rapidly despite the apparent decline in R&D productivity.

As a first step to understanding this productivity puzzle, figure 2 offers a visual inspection of the patents to BERD ratio using both the GDP deflator and RDP^2. In the USA, the decline in R&D productivity reported by Lanjouw and Schankerman (2004) is evident but this trend has been reversed in the late 1990s. Also, when the RDP^2 price deflator is used to adjust for inflation, the decline looks less alarming and R&D productivity in the late 1990s seems to have reached record high levels. The pattern is similar in France and Germany but the recovery of the ratio is less pronounced. Japan and the UK, however, have not recovered from the secular decline in R&D productivity. Further, there is no visible trend in Australia and Sweden but both, Canada included, have seen a sharp rise in R&D productivity. Last, a more careful inspection reveals that the R&D productivity growth rate has declined in the late 1990s in Australia, Canada, Denmark, Finland, Spain, Japan and the USA but has increased sharply in Germany.

- Figure 2 about here –

3.1 An Empirical Model

For greater intuition, we again draw on economic theory. Lanjouw and Schankerman (2004) have provided a formal empirical model of R&D productivity. It accounts for change in the quality of patents, q, and market power as key determinants of R&D productivity. It also allows for 'technological exhaustion'. The authors show that the theoretical model gives rise to the following empirical specification:

$$pr_{it} = \alpha e(t) + \beta q_{it} + \gamma s_{it} + v_{it} \quad (3)$$

where pr_{it} is the log of R&D productivity, $e(t)$ is the log of R&D elasticity, q_{it} is the log of expected quality of inventions, s_{it} is the log of sales as a proxy for market power and v_{it} is normal, independently and identically distributed error. Technological exhaustion is captured by the $\alpha e(t)$ term. The model predicts that α, β, $\gamma < 0$. That is, an increase in patent quality or market power would provide a motivation for a reduction in the *number* of patents per R&D dollar spent. As an example of the role patent quality plays in the model, consider the case of greater R&D emphasis on blockbuster drugs (Grabowski 2002). According to (3), patent quality would increase and productivity would fall.

3.2 Data

The empirical estimation of (3) faces a major hurdle: the measurement of patent quality and R&D productivity. Various measures of patent quality have been proposed including citations, claims and renewals. Yet, there are drawbacks with these measures. For example, patent citations and claims may actually be associated with increased competition and litigation and, thus, imply reduced market value (Bosworth *et al.* 2003). Alternatively, they may simply relate to growth in the practice of patent citation (Hall *et al.* 2001).

In order to overcome some of these limitations, Lanjouw and Schankerman (2004) utilise several indicators to arrive at a single patent quality index. However, the multi-dimensional index of Lanjouw and Schankerman (2004) remains a single all-encompassing index. In this study, we utilise USPTO data on applications and patents granted to arrive at two distinct but complementary indicators of patent quality.

The first measure, q^1, builds on the concept of patent grant intensity (i.e., the ratio of patents granted in the current year and patent applications in the last four years). Given that the patent grant lag is about 2 years (Hall *et al.* 2001), this definition is not likely to suffer from the 'truncation problem'.[19] The concept is a baseline indicator of patent quality, provided that the US Patents Office preserves its patent assessment standards over time. However, this assumption has been severely criticised in recent literature. Sanyal (2002) and Jaffe and Lerner (2004) have argued that the US Patent Office has founded increasingly difficult to distinguish between genuine innovation and imitation. In order to account for this possibility, we adapt the approach taken by Hall *et al.* (2001): we scale the grant intensity and express it as a ratio to the mean grant intensity of all OECD patents in the same year. On the assumption that the processing of patent applications by the USPTO is free of a country bias, the above criticism does not affect our first measure of patent quality.

The second, q^2, is the number of patents granted to inventors residing in different OECD countries as a share of total patents granted to a specific country. This measure is based on the literature of innovation that suggests that research collaboration and formal

[19] Visual inspection of the q^1 series supports this view since there is no apparent downward trend in the grant intensity ratio at the end of the sample period.

knowledge networks yield considerable value (Sheehan and Messinis 2003). Adams and Marcu (2004) explore in some detail the role of Research Joint Ventures (RJVs) in the USA and find that RJVs make an important contribution to innovation.[20]

In measuring R&D productivity, the challenge has often involved the choice between patent applications and patents granted. Although the latter better relates to the concept of innovation output, it suffers from the 'truncation problem': counts of patents granted become available some years after patent applications data. On the other hand, the use of patent applications towards a measure of R&D productivity may lead to a loss of valuable information if the disparity between patents granted and patent applications contains information on patent quality. In this study, we minimize the truncation problem with a four-year lag between USPTO data collection and our last observation.

Finally, empirical research on R&D productivity has paid little attention to the measurement of R&D price inflation and, by extension, to *real* R&D expenditure.[21] Next, we utilise the new R&D price deflators to test the validity of the Lanjouw and Schankerman (2004) hypothesis.

3.3 Results

We begin with part (A) of table 4 that presents the system GMM estimation results. Note, the Davidson and MacKinnon (1993) exogeneity test statistic (DM) advises against

[20] Perhaps, it may not be apparent how the benefits of collaboration reflect patent quality. This can be accommodated with a broad definition of patent quality that incorporates both technical innovation and market value, as in Lanjouw and Schankerman (2004).

[21] Most of the evidence on RD productivity is based on the practice of using GDP PPP's to account for inflation; Cockburn (2004) is an exception. This debate seems like a repeat of the early 1980s, until Hutt (1982) was able to show that the rapid growth in BERD was mainly due to R&D price inflation and real BERD had actually declined.

the use of Δq^1_t as an exogenous variable, precisely the approach taken by Lanjouw and Schankerman (2004). The dynamic panel data coefficient estimates are of the right sign for both Δq^1_t and Δs_t but the former is not statistically significant.

This finding is consistent with the evidence in Lanjouw and Schankerman (2004). We proceed to investigate whether this is due to spatial correlation since the BP statistic clearly rejects the assumption of cross-sectional independence. This is confirmed when we account for spatial dependence in part (B) of table 4. Here the Δq^1_t coefficient is statistically significant and negative as expected. In fact, both patent quality and sales seem to be important predictors of R&D productivity as Lanjouw and Schankerman (2004) envisaged. We obtain similar results when both measures of patent quality are utilised in table 5. Again, *system GMM* estimation suggests that none of the two measures are important predictors of R&D productivity.[22] When, however, we employ spatial GMM methods, the importance of both patent quality and market power is confirmed. Particularly interesting is the fact that international inventor collaboration seems to be a crucial indicator of patent quality that has an independent effect on R&D productivity.

Finally, we extend the empirical analysis to examine the hypothesis of 'technological exhaustion'. That is, we wish to test whether $\alpha < 0$ in (3). When the model is expressed in first differences, the test translates into the null of the constant being greater or equal to zero. Due to space limitations, the estimation results are not reported here but they are available upon request. They show that the null hypothesis cannot be rejected.

[22] Note that the Δq^1_t coefficient becomes significant when we allow the lagged dependent variable to be a predictor but the Δq^2_t coefficient remains insignificant. The results are available upon request.

4 Summary and Conclusions

Innovation is fundamental in health care. By investing heavily on R&D, the pharmaceutical industry plays a leading role in the discovery of new medicines. Given the critical role of health care in welfare and public finance, cost-benefit analysis of the industry's innovation performance can advance understanding of the value of medical innovation and can lead to a better public health policy. This is particularly important in the light of a growing literature questioning the efficacy of R&D in pharmaceuticals.

This paper is an OECD comparative study of the patents to BERD ratio as a key indicator of R&D productivity in pharmaceuticals. The paper has drawn on economic intuition and employed dynamic panel data estimation techniques to develop new R&D price deflators to account for price inflation and estimate real R&D business expenditure. Further, it has utilised US patents data to measure R&D productivity and develop two complementary indicators of patent quality. In the process, this study has dealt with key measurement issues such as the 'truncation problem' and the possibility of an institutional shift towards lower assessment standards by the US Patent Office.

The evidence presented in this study of pharmaceuticals is as follows. First, the GDP deflator was found to be inconsistent with the theory of R&D investment. Industry-wide data on labor compensation also resulted in R&D price deflators that did not conform to economic intuition. Second, both the UK and the USA have witnessed record high R&D price inflation when compared to other OECD nations. Third, international inventor collaboration is an important element of patent quality. Fourth, there is little evidence of a long-term decline in R&D productivity. Fifth, patent quality and market power are key drivers of productivity and, thus, the Lanjouw and Schankerman (2004) hypothesis is

consistent with the data. Finally, cross-sectional dependence is pervasive and the employment of spatial GMM estimators is critical in the modeling of R&D productivity.

References

Achilladelis, B. and Antonakis, N. (2001) 'The Dynamics of Technological Innovation: The Case of the Pharmaceutical Industry', *Research Policy*, 30, 535-88.

Adams, J.D. and Griliches, Z. (1996) 'Measuring Science: An Exploration', National Bureau of Economic Research (NBER) Working Paper No. 5478.

Adams, J.D. and Marcu, M. (2004) 'R&D Sourcing, Joint Ventures and Innovation: A Multiple Indicators Approach', NBER Working Paper No. 10474.

Arellano, M. and Bover, O. (1995) 'Another Look at the Instrumental Variable Estimation of Error-Components Models', *Journal of Econometrics* 68: 29-51.

Arellano, M. and Bond, O. (1991) 'Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations' *The Review of Economic Studies* 58: 277-97.

Bloom, N., Griffith, R. and Van Reenen, J. (2002). 'Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979-1997', *Journal of Public Economics*, 85, July, 1-31.

Bond, O. (2002) 'Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice' Working Paper 09/02. Institute for Fiscal Studies, Nuffield College, London.

Bosworth D., Filiou, D. and Longland M., (2003) *Measuring the 'Quality' of Patents*, Report, UK Patent Office, UMIST and OIPRC, http://www.patent.gov.uk/about/ippd/ipresearch.

Breitschopf, B. and Grupp, H. (2004) 'Innovation Dynamics in OECD Countries: Challenges for German Enterprises,' *International Economics and Economic Policy* 1(2-3), 135-55

Cameron, G. (1996) 'On the Measurement of Real R&D - Divisia Price Indices for UK Business Enterpise R&D' *Research Evaluation*, 6(3), December, 215-19.

Cockburn, I.M. (2004). 'The Changing Structure of the Pharmaceutical Industry' *Health Affairs* 23(1), 10-22.

Cockburn, I.M. and Henderson, R. (1997). 'Public-Private Interaction and the Productivity of Pharmaceutical Research', NBER Working Paper No. 6018.

Conley, T.G. (1999) 'GMM Estimation with Cross-Sectional Dependence' *Journal of Econometrics*, 92(1), 1-45.

Conley, T.G. and Ligon, E. (2002) 'Economic Distance and Cross-Country Spillovers' *Journal of Economic Growth*, 7(2), 157-87.

Davidson, R. and MacKinnon, J. (1993). *Estimation and Inference in Econometrics*, New York: Oxford University Press.

Dickson, M., Hurst, J. and Jacobzone, S. (2003). 'Survey of Pharmacoeconomic Assessment Activity in Eleven Countries', OECD Health Working Papers No. 4, Paris: OECD.

DiMasi, J.A., Hansen, R.W. and Grabowski, H.G. (2003). 'The Price of Innovation: New Estimates of Drug Development Costs', *Journal of Health Economics,* 22(2), 151-85.

Dougherty, S.M., Inklaar, R., McGuckin, R.H. and Van Ark, B. (2003). 'International Comparisons of R&D Expenditure: Does an R&D PPP Make a Difference?' The Conference Board and Growth and Development Center, University of Groningen, Working Paper 03-03.

Driscoll, J.C. and Kraay, A.C. (1998) 'Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data', *Review of Economics and Statistics*, *80 (4)*, 549-60.

Frantzen, D. (2000) 'R&D, Human Capital and International Technology Spillovers: A Cross-country Analysis', *Scandinavian Journal of Economics* 102 (1): 57-75.

Freeman, C. and Young, A. (1965). *The Research and Development Effort in Western Europe, North America and the Soviet Union: An Experimental International Comparison of Research Expenditures and Manpower in 1962*, Paris: OECD.

Grabowski, H. (2002) 'Patents and New Product Development in the Pharmaceutical and Biotechnology Industries', Duke University, working paper 02-25.

Greene, W. (2000). *Econometric Analysis*. 4th Edition, Upper Saddle River, NJ: Prentice-Hall.

Griliches, Z. (1984). 'R&D, Patents, and Productivity', National Bureau of Economic Research, Cambridge, MA: University of Chicago Press.

Hall, B, Jaffe, A and Trajtenberg, M (2001) 'The NBER Patent Citations File: Lessons, Insights and Methodological Tools' NBER Working Paper 8498.

Harris, M.N., and Matyas, L. (2000) 'The Robustness of Estimators for Dynamic Panel Data Models to Misspecification', Economic Department, Central European University, working paper 16.

Helfat, C.E. (1994). 'Firm-specificity in Corporate Applied R&D' in *Organization Science*, 5(2), May, 173-84.

Hutt, P.B., (1982). 'The Importance of Patent Term Restoration to Pharmaceutical Innovation', *Health Affairs*, Spring 1(2), 6-24.

Jaffe, A.B. and Lerner, J. (2004) *Innovation and Its Discontents: How Our Broken Patent System is Endangering Innovation and Progress and What to Do About it*, Princeton University Press.

Jaffe, S. (1973). *A Price Index for Deflation of Academic R&D Expenditure*, National Science Foundation, NSF 72-310.

Jankowski, J.E. (1993). 'Do we need a price index for industrial R&D?', *Research Policy* 22(3), June, 195-205.

Johnson, D. (2001). 'Economic Issues in Health Policy', *The Australian Economic Review,* 34(3), 295-311.

Jones, C.I. and Williams, J.C. (2000). 'Too Much of a Good Thing? The Economics of Investment in R&D' *Journal of Economic Growth*, 5, March, 65-85.

Kyle, M. (2004) 'Does Locale Affect R&D Productivity? The Case of Pharmaceuticals' *FRBSF Economic Letter*, 2004-32, November.

Lanjouw, J.O., Pakes, A. and Putnam, J. (1998). 'How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data', *The Journal of Industrial Economics* 46 (4), 405-32.

Lanjouw, J.O. and Schankerman, M. (2004). 'Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators', *Economic J.ournal*, 441-465.

Lee, P.M. and O'Neill, H.M. (2003) 'Ownership Structures and R&D Investments of U.S. and Japanese Firms: Agency and Stewardship Perspectives', *Academy of Management Journal*, 46(2), 212-25.

Lichtenberg, F.R. (2002). 'The Effect of Changes in Drug Utilization on Labor Supply and Per Capita Output', NBER Working Paper No. 9139, NBER, Cambridge, Mass.

Moon, H.R. and Perron, B. (2004). ' Testing for a Unit Root in Panels with Dynamic Factors', *Journal of Econometrics*, 122, 81-126.

Nam, J., Ottoo, R.E. and Thornton, J.H. (2003) 'The Effect of Managerial Incentives to Bear Risk on Corporate Capital Structure and R&D Investment', *The Financial Review*, 38, 77-101.

OECD (2003). *Science, Technology and Industry Scoreboard 2001*, OECD: Paris.

OECD (1994). *Main Definitions and Conventions for the Measurement of R&D: A Summary of the Frascati Manual*, OECD: Paris. (http://www.oecd.org).

O'Mahony, M. and Van Ark, B. (2003). *EU Productivity and Competitiveness: An Industry Perspective. Can Europe Resume the Catching-up Process?*, Office for Official Publications of the European Communities, Luxembourg, November

PhRMA (2004). *Pharmaceutical Industry Profile 2004: Focus on Innovation*, Pharmaceutical Research and Manufacturers of America, Washington, DC.

PhRMA (2003). *Pharmaceutical Industry Profile 2003: New Medicines, New Hope*, Pharmaceutical Research and Manufacturers of America, downloaded from http://www.phrma.com.

Productivity Commission (2001). *International Pharmaceutical Price Differences*, Research Report, AusInfo, Canberra.

Rao, D.P. and Trimmer, M.P. (2003). 'Purchasing Power Parities for Industry Comparisons Using Weighted Elteto–Koves–Szulc (EKS) Methods', *Review of Income and Wealth*, Dec, 49 (4), 491-512.

Richardson, J. (2001). 'Supply and Demand for Medical Care: Or, Is the Health Care Market Perverse?', *The Australian Economic Review,* 34(3), 336-52.

Roodman D.M. (2005) Xtabond2: Stata Module to Extend Xtabond Dynamic Panel Data Estimator, Boston MA, Boston College Department of Economics, February, http://econpapers.repec.org/software/bocbocode/s435901.htm

Sanyal P. (2002) 'Understanding Patents: The Role of R&D Funding Sources and the Patent Office', *Economics of Innovation and New Technology, 12 (6),* pp. 507 – 529

Schreyer, P. and Koechlin, F. (2002). 'Purchasing Power Parities: Measurement and Uses', *OECD Statistics Briefs* No. 3, March.

Sheehan, P. and Messinis, G. (2003). 'Innovation in Australia', in I. McAllister, S. Dowrick and R. Hassan (eds.), *Cambridge Handbook of Social Sciences in Australia*, Cambridge: Cambridge University Press, 153-67.

Simmie, J., Sennett, J., Wood, P. and Hart,D. (2002). 'Innovation in Europe: A Tale of Networks, Knowledge and Trade in Five Cities' *Regional Studies*, 36(1), 47-64.

SIRF, Hay Group, Ernst &Young (2001). 'Benchmarking Study of R&D Costs in Selected Segments of Australian Biotechnology', Canberra: Invest Australia.

Strauss, J. and Yigit, T. (2003). 'Shortfalls of Panel Unit Root Testing', *Economics Letters*, 81(3), 309-13.

Taylor, M.P. and Sarno, L. (1998). "The Behaviour of Real Exchange Rates During the Post-Bretton Woods Period." *Journal of International Economics*, 46(2), 281-312.

Van Ark, B. (1996). 'Issues in Measurement and International Comparison Issues of Productivity: An Overview', in OECD *Industry Productivity, International Comparison and Measurement Issues*, Paris: OECD (http://www1.oecd.org/dsti/sti/stat-ana/prod/).

Windmeijer, F. (2005). 'A finite sample correction for the variance of linear efficient two-step GMM estimators'. *Journal of Econometrics* 126(1), 25-51.

Table 1. R&D Price Inflation and Real BERD: Feasible GLS and Spatial OLS

	GDP	RDP[1]	RDP[2]	RDP[3]
	(A) Feasible GLS			
Δy_t	**0.675**	**0.667**	**0.642**	**0.649**
	(0.022)**	(0.019)**	(0.028)**	(0.029)**
Δp_t	**0.235**	**0.093**	**-1.118**	**-1.127**
	(0.083)**	(0.055)	(0.054)**	(0.059)**
BP	130.1	100.7	138.4*	157.6**
	(B) Spatial OLS (Conley 1999)			
Δy_t	**0.681**	**0.681**	**0.826**	**0.811**
	(0.043)**	(0.056)**	(0.021)**	(0.031)**
Δp_t	**0.714**	**0.356**	**-1.031**	**-0.972**
	(0.203)**	(0.180)**	(0.075)**	(0.127)**

GDP is the GDP price deflator, RDP[1] is an R&D deflator based on total labor costs in the industry, RDP[2] is based on R&D labor costs and RDP[3] is based on RDP[2] with GDP as a proxy for the non-labor cost index. Standard errors are in parentheses. Respectively, ** and * denote significance at 1% and 5% level. BP is the Breusch-Pagan test of cross-sectional independence distributed $\chi^2(105)$.

Table 2. Real BERD: DPD System GMM (Arellano and Bover 1995)

	GDP	RDP[1]	RDP[2]	RDP[3]
r_{t-1}	**0.884**	**0.941**	**0.924**	**0.850**
	(0.086)**	(0.067)**	(0.103)**	(0.115)**
y_t	**0.174**	**0.098**	**0.126**	**0.217**
	(0.123)	(0.090)	(0.133)	(0.148)
p_t	**-0.090**	**-0.049**	**-0.066**	**-0.114**
	(0.072)	(0.051)	(0.071)	(0.078)
Hansen J	13.45	13.45	13.28	13.42
AB AR(1)	-2.83**	-2.95**	-2.77*	-2.65*
AB AR(2)	-1.46	-1.55	0.09	0.31

GDP is the GDP price deflator, RDP[1] is an R&D deflator based on total labor costs in the industry, RDP[2] is based on R&D labor costs and RDP[3] is based on RDP[2] with GDP as a proxy for the non-labor cost index. Standard errors are in parentheses. Respectively, ** and * denote significance at 1% and 5% level. The Hansen J test is distributed $\chi^2(k)$ where k is the over-identifying restrictions. Given our small sample, we used only 15 instruments. These are lags 2-13 of r_t , Δy_t and Δp_t in the first difference equation, and Δr_t in the levels equation.

Table 3. R&D Price Inflation and Real BERD: Spatial GMM

	(A) Conley (1999)				(B) Driscoll and Kraay (1998)			
	GDP	RDP[1]	RDP[2]	RDP[3]	GDP	RDP[1]	RDP[2]	RDP[3]
Δr_{t-1}	**0.109**	**0.062**	**0.179**	**0.135**	**0.147**	**0.164**	**0.251**	**0.247**
	(0.025)**	(0.018)**	(0.011)**	(0.015)**	(0.071)*	(0.068)*	(0.064)**	(0.062)**
Δy_t	**0.672**	**0.667**	**0.769**	**0.717**	**0.644**	**0.639**	**0.762**	**0.757**
	(0.012)**	(0.016)**	(0.008)**	(0.009)**	(0.037)**	(0.031)**	(0.064)**	(0.072)**
Δp_t	**0.465**	**0.424**	**-0.833**	**-0.564**	**0.521**	**0.225**	**-1.155**	**-1.108**
	(0.092)**	(0.064)**	(0.024)**	(0.028)**	(0.118)**	(0.171)	(0.115)**	(0.134)**
Hansen J	2.43	2.35	2.23	2.21	5.34	7.72	8.03	8.31

GDP is the GDP price deflator, RDP[1] is an R&D deflator based on total labor costs in the industry, RDP[2] is based on R&D labor costs and RDP[3] is based on RDP[2] with GDP as a proxy for the non-labor cost index. Standard errors are in parentheses while ** and * denote significance at 1% and 5% level respectively. The Hansen J test is distributed $\chi^2(k)$ where k is the number of over-identifying restrictions. Here, k =5 since eight instruments were used: lags 2-3 of Δr_t and growth in gross profit (i.e., profit is defined as value added minus labour compensation), Δy_t, Δp_t as well as two lags of growth in sales, Δs_t.

Table 4. Patent Quality and Real R&D Productivity: System GMM and Spatial GMM

	(A) System GMM		(B) Spatial GMM			
	Arellano and Bover (1995)		Conley (1999)		Driscoll and Kraay (1998)	
	RDP^1	RDP^2	RDP^1	RDP^2	RDP^1	RDP^2
Δq^1_t	**-0.159**	**-0.174**	**-0.259**	**-0.301**	**-0.262**	**-0.311**
	(0.116)	(0.118)	(0.016)**	(0.021)**	(0.063)**	(0.062)**
Δs_t	**-2.912**	**-2.908**	**-0.428**	**-0.416**	**-0.505**	**-0.478**
	(0.059)**	(0.059)**	(0.052)**	(0.055)**	(0.054)**	(0.058)**
S	0.09	0.17				
DM (Δq_t)	34.70**	29.95**				
BP	295.7**	283.9**				
Hansen J	12.26	12.13	3.07	3.07	7.07	5.76
AB AR(1)	-1.02	-1.08				
AB AR(2)	1.46	1.57				

GDP is the GDP price deflator, RDP^1 is an R&D deflator based on total labor costs in the industry, RDP^2 is based on R&D labor costs and RDP^3 is based on RDP^2 with GDP as a proxy for the non-labor cost index. Standard errors are in parentheses. ** and * denote significance at 1% and 5% level respectively. In (A), the DM test of exogeneity is distributed $\chi^2(1)$ in an IV regression with lags 1-2 of Δq^1_t and Δs_t used as instruments. S is the Sargan test of over-identifying restrictions. The Breusch-Pagan (BP) test of cross-sectional independence is $\chi^2(105)$. In the system GMM, 15 instruments were used: lags 1-13 of pq^1_t and Δs_t in the first difference equation, and $\Delta pq1_t$ in the levels equation. In (B) eight instruments were used: lags 1-3 of Δq^1_t , lags 2-3 of growth in value added, Δy_t, and growth in gross profit, and Δs_t. Hence, the Hansen J test is distributed $\chi^2(13)$ in part (A) and $\chi^2(6)$ in part (B).

Table 5. Patent Quality, Collaboration and Real R&D Productivity: System GMM and Spatial GMM

	(A) System GMM		(B) Spatial GMM			
	Arellano and Bover (1995)		Conley (1999)		Driscoll and Kraay (1998)	
	RDP^1	RDP^2	RDP^1	RDP^2	RDP^1	RDP^2
Δq^1_t	**-0.143**	**-0.161**	**-0.308**	**-0.346**	**-0.296**	**-0.342**
	(0.131)	(0.135)	(0.016)**	(0.017)**	(0.053)**	(0.053)**
Δq^2_t	**-0.271**	**-0.269**	-0.182	-0.196	**-0.188**	**-0.177**
	(0.188)	(0.186)	(0.016)**	(0.021)**	(0.040)**	(0.042)**
Δs_t	**-3.013**	**-3.010**	**-0.398**	**-0.386**	**-0.478**	**-0.453**
	(0.076)**	(0.072)**	(0.047)**	(0.049)**	(0.052)**	(0.060)**
S	0.11	0.03				
DM ($\Delta q1_t$)	23.59**	20.12**				
DM ($\Delta q2_t$)	0.85	0.85				
BP	237.7**	230.2**				
Hansen J	12.77	12.45	2.97	2.98	7.99	6.27
AB AR(1)	-0.68	-0.76				
AB AR(2)	1.77	1.80				

GDP is the GDP price deflator, RDP^1 is an R&D deflator based on total labor costs in the industry, RDP^2 is based on R&D labor costs and RDP^3 is based on RDP^2 with GDP as a proxy for the non-labor cost index. Standard errors are in parentheses. ** and * denote significance at 1% and 5% level respectively. In (A), the DM test of exogeneity is distributed $\chi^2(1)$ in an IV regression with lags 1-2 of Δq^1_t, Δq^2_t and Δs_t used as instruments. S is the Sargan test of over-identifying restrictions. The Breusch-Pagan (BP) test of cross-sectional independence is $\chi^2(105)$. In the system GMM, 15 instruments were used: lags 1-12 of pq^1_t, Δpq^2_t and Δs_t in the first difference equation, and Δpq^1_t in the levels equation. In (B) nine instruments were used: lags 1-3 of Δq^1_t , lags 2-3 of growth in value added, Δq^2_t, Δy_t, and growth in gross profit, and Δs_t.. Hence, the Hansen J test is distributed $\chi^2(13)$ in part (A) and $\chi^2(6)$ in part (B).

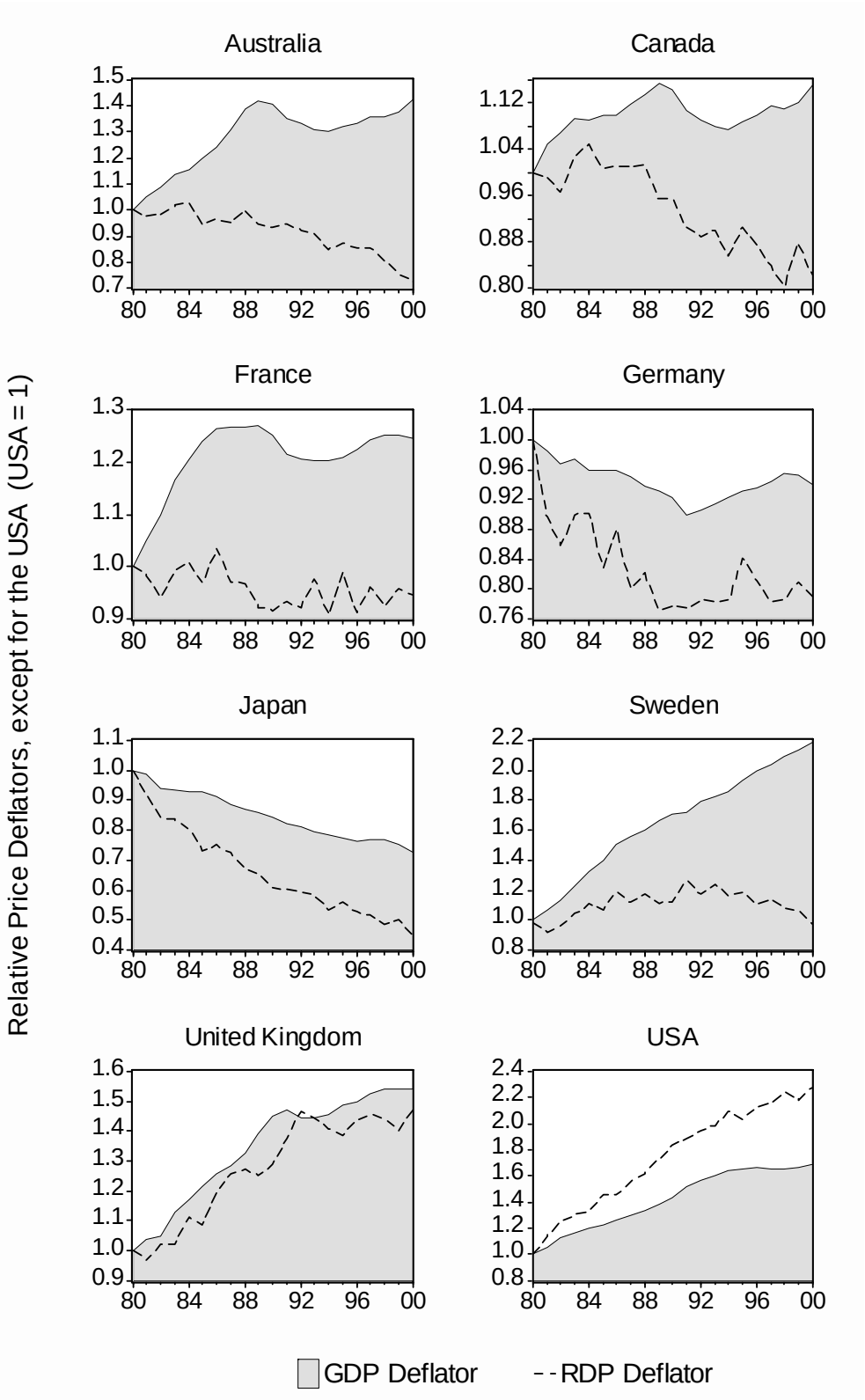

Figure 1. Relative R&D Price Inflation: Pharmaceuticals, 1980-2000

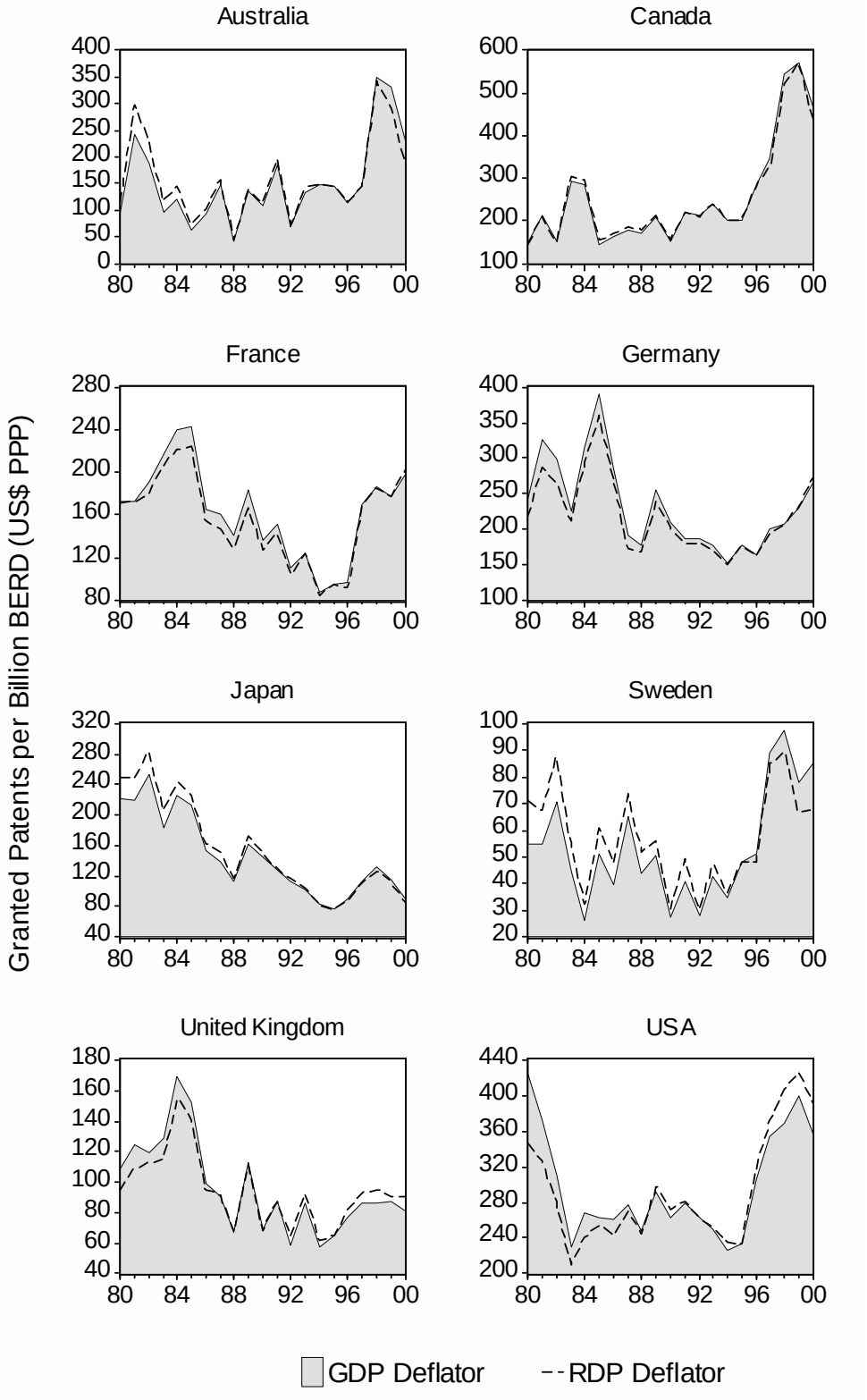

Figure 2. Real BERD and R&D Productivity: Pharmaceuticals, 1980-2000

Appendix: Data Description

Labour Compensation

OECD Health Data is the source of Australian data for the period 1980-1995. Unpublished Australian Bureau of Statistics (ABS) data on 'wages and salaries' are used to extend the sample to 2000. The ABS data, however, combines the 'Medicinal and Pharmaceutical Product Manufacturing' industry (code 2543) with 'Pesticides' (2544) and only since 2000-01 the two are separated. Based on the 2000-01 estimates, we adjust the wages and salaries figures by a factor of 0.902. The STAN series of 'labour compensation' are used for all other countries. For Spain, data are not available during 1980-1985 and we extrapolate on the basis of growth in labour costs in France. All series for United Germany are the result of splicing in 1991 that extends the STAN data on the basis of the West Germany data.

Employment

The OECD Health Data provide Australian data for the period 1980-1992 and ABS covers the period 1996-2000. We resort to linear interpolation for missing values. STAN is the source of total employment data. Given these are not available for the UK, we use total number of employees as a proxy. For Belgium they are only available for the period 1994-2000. We extrapolate the Belgian data back to 1980 on the basis of yearly growth in France.

R&D Business Expenditure

The OECD ANBERD database is the source for most OECD-15 countries. A change of classification from *ISIC Rev. 2* (code 3522) to *ISIC Rev 3* (code 2423) in ANBERD 2001 apparently maintains compatibility for pharmaceuticals. *Rev 2* of ANBERD 2001 is the primary source for the period 1973-1986 and *Rev 3* for the period since. Due to data limitations, there are some exceptions. We draw more extensively from ANBERD 2001 *Rev 2* for Germany and Italy for the period 1980-94. Belgium data for 1980-1986 come from OECD Health Data 2003 and are only available bi-annually up to 1985; we linearly interpolate to complete the series. For Germany, there is a break in the series due to the unification of Germany. We used 1991-99 data for 'UDEU' (ANBERD code) in order to arrive at a (multiplicative) spliced series with 1991 as the base year. Thus, 'Germany' stands for Unified Germany.

R&D Cost Structure

The SIRF, Hay Group, Ernst &Young (2001) study covers nine countries. We use the mean of the France and Germany estimates as a proxy for Italy, Netherlands and Spain, the mean of France, Germany and the UK as a proxy for Belgium, the mean of Germany and Sweden for Denmark and the Sweden estimate for Finland and Norway.

In order to allow the R&D input cost shares to vary across nations and over time, we also estimate R&D business enterprise personnel. The OECD *Main Science and Technology Indicators* database is the primary source for the period 1987-2000. We supplement this source with data from PhRMA (2003) and DiMasi *et al.* (2003) to obtain estimates for the USA. Missing observations have been filled on the basis of the mean annual growth rate in France and Germany for Belgium, Italy and Netherlands; the mean growth rate of France and USA for Canada and the UK, and the growth rate in Sweden for Denmark and Finland. For the period 1980-1986, we exploit information on the R&D personnel share of total employment in the industry and changes in the ratio of BERD to Value Added to expand the R&D personnel series.

National Sales and Sales Price Index

This is the sum of 'total expenditures on pharmaceuticals & other non-durables' (OECD *Health Data* 2004) and net exports (OECD *STAN*). When available, the annual growth rate of 'pharmaceutical sales' (*Health Data* 2004) is used to fill gaps in the former (Italy in 1980-1987, and Norway and Spain in 1998-2000). Missing observations for Belgium, France, Japan and the UK are filled by interpolation/ extrapolation on the basis of annual growth rates in adjacent data points. Regrettably, we cannot control for re-exports; i.e., imported goods exported without further transformation. The 'total expenditures on pharmaceuticals & other non-durables' price index (OECD *Health Data* 2004) was used. Missing data are filled on the basis of the mean of growth rates of France and Germany for Belgium, the mean of Germany and Switzerland for Italy, the mean of Denmark and Sweden for Norway and the mean of France and Italy for Spain. Missing observations in France (1981-1984 and 1986-1989) and Japan (1998-2000) are filled by interpolation and extrapolation respectively.

Value Added Implicit Price Deflators

Implicit value added deflators are derived from value-added estimates and value-added volume indices $VAP_{i,t} = 100*VALU_{i,t} /(VALK_{i,t}*VALU_{i,95})$ where $VALU_i$ is the STAN code for value added in industry *i* at national currency units, $VALK_{it}$ is the value added volume index at time *t* and the $VALU_{95}$ is value added in 1995, the base year. Note that VALK data are only available for Canada, Denmark, France, Norway and the UK. VALK data for chemicals industries are used for other countries. These data were not available for Australia and Norway. We used the mean of VAP estimates of Canada and the USA for the former and the pharmaceutical industry deflator for the latter. Also, we extrapolated to fill data gaps for France (1980-1991), Spain (1980-1994) and Sweden (1980-1992) on the basis of annual growth rates in Belgium, Italy and Finland respectively.

USPTO Patents

USPTO patents data were collected in early 2005 at http://patft.uspto.gov/netahtml/search-adv.htm. The pharmaceutical industry was defined to comprise of technology classes 424 and 514. Patent data for the USA is the sum of patent counts in individual US states. The inventor collaboration series was defined as the number of patents granted for which at least on of the inventors lived in one of the other OECD countries in the sample plus Switzerland, given the status of the latter as a leading player Due to limitations in the USPTO search engine, only the twenty eight leading US states were considered as international locations of patent collaboration for non-US countries. These US states are as follows: AL, AZ, CA, CO, CT, DE, FL, GA, IL, IN, LA, MD, MA, MI, MN, MO, NH, NJ, NY, NC, OH, PA, TN, TX, UT, VA, WA, WI.