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PATENT QUALITY AND RESEARCH PRODUCTIVITY: MEASURING INNOVATION WITH MULTIPLE INDICATORS*

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We analyse the determinants of the decline in research productivity using panel data on manufacturing firms in the US for the period 1980–93. We focus on three factors: the level of demand, the quality of patents and technological exhaustion. We develop an index of patent 'quality' using detailed patent information and show that using multiple indicators substantially reduces the measured variance in quality. Research productivity at the firm level is inversely related to patent quality and the level of demand, as predicted by theory and patent quality is positively associated with the stock market value of firms.

Research productivity, as typically measured by the ratio of patents to R&D, has declined sharply over the last 40 years, in many different industries and countries (see Figure 1 for US experience). By 1990 the number of patents produced per US scientists and engineers (S&E) had fallen to just 55% of its 1970 level, with even steeper declines in Europe (Evenson, 1984, 1993). At any time there are also large cross-sectional differences in measured research productivity across industries and firms (Evenson, 1984; Griliches, 1990). These facts have attracted increasing attention from academics and international organisations such as the OECD (1991) because of concern about the apparent slowdown in total factor productivity since the late 1960s. But scholarly observers have voiced concerns about the decline in research productivity for a long time. As Griliches (1990) points out, aggregate patent numbers have fluctuated widely and have grown more slowly than investments over much of the twentieth century.

This fall in research productivity could simply derive from diminishing returns in the 'knowledge production function'. As markets expand, the private returns to R&D increase. The induced rise in the level of R&D investment leads to a fall in research productivity. A number of quality-ladder growth models have formalised this relationship, showing that in equilibrium research productivity should fall with growth in demand (Caballero and Jaffe, 1993; Kortum, 1993). Empirical studies using sector-level data for the US and other countries typically find that market size does matter. However, demand growth is not sufficient to explain the observed declines in R&D productivity as measured by the ratio of patents to R&D inputs (Evenson, 1993; Kortum, 1993).

Thus the evidence of declining research productivity raises the spectre of technological exhaustion – getting less inventive output for any *given* level of

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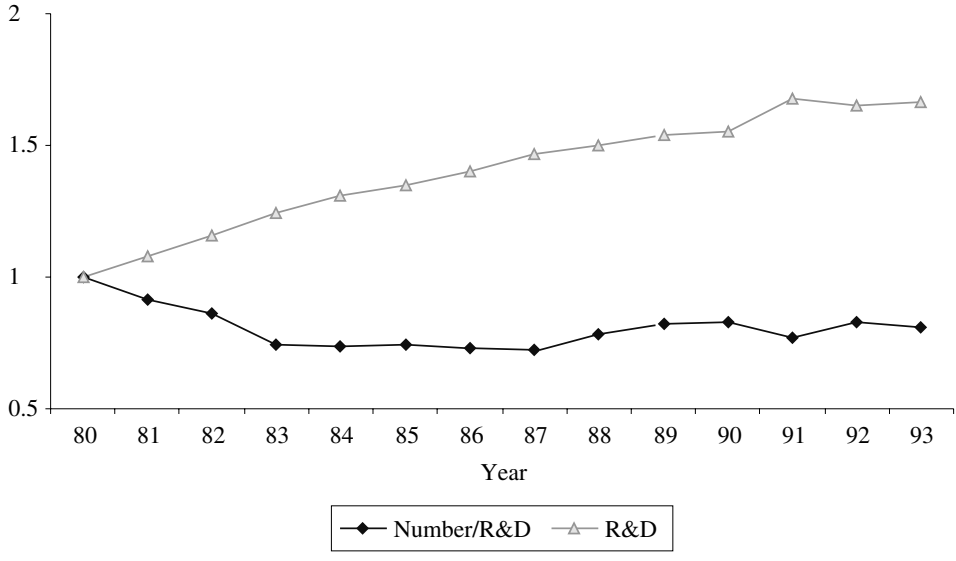

Fig. 1. *R&D and Patenting*

R&D investment. This is of great concern. A process of technological exhaustion would lower innovative output directly and, by reducing the private returns to R&D, it would also bring down the equilibrium level of private R&D investment. These two features of technological exhaustion could undermine our ability to sustain growth in total factor productivity. This process could be countered with government policies to provide stronger R&D incentives, recharging the pool of invention potential through government-funded R&D and programmes to strengthen industry-government research links. Therefore, a key question is whether we can take the decline in the ratio of patents to R&D as indicating a decline in the fecundity of R&D – i.e., as deterioration in the underlying knowledge production function.

In considering this question it is useful to break the patent to R&D ratio into its two component parts: the patent to invention ratio and the invention to R&D ratio. A fall in measured research productivity may be real – a declining invention/R&D ratio – or only apparent – a declining patent/invention ratio. Since we do not normally have information on the number of inventions, there is an identification problem in interpreting changes in the patent to R&D ratio. What appears to be technological exhaustion may simply be mismeasurement. Inventors may be making less use of an patent system, perhaps because the costs of obtaining and enforcing patents have risen relative to alternative protection mechanisms; see Cohen *et al.* (2000) for discussion and survey evidence. If so, the observed growth in the number of patents over time understates growth in innovation. Further, the average value of an innovation covered by a patent may be increasing over time. Both of these 'measurement' issues imply that counting

patents can give a misleading impression of the true output of the research process.[1]

When looking for evidence of technological exhaustion, a common approach taken in the literature is to look for a decline in the R&D elasticity in production function or total factor productivity regressions. Focusing on R&D inputs avoids the potential pitfalls of measuring invention output. However, it involves other serious problems associated with productivity measurement (Griliches, 1979). Moreover, the R&D elasticity in a production function reflects two distinct factors: the impact of R&D on invention, which could exhibit technological exhaustion, and the effect of invention on productivity. The latter depends on other characteristics of the firm and market, including the level of demand and the ability of the firm to appropriate the rents from invention. Both technological exhaustion and a decline in demand or appropriation imply that the rate of return to R&D would fall. Econometric estimates at the firm and industry level do not show any systematic decline in the output elasticity of R&D through the mid-1980s, and thus the evidence of 'exhaustion' is at best inconclusive (Griliches, 1994; Hall, 1993*a, b*), see Griliches (1990) for an excellent review of relevant studies.

In this paper we use a large panel data set to examine the relationships between research productivity, market size and technological exhaustion at the firm level. Studying the micro level data allows us to avoid changes in composition of more aggregate data (e.g., growth in markets may encourage marginal firms to enter R&D activity). We also develop a new control for the changes in the quality of patented output in order to separate real and apparent changes in research productivity.

In micro data various indicators have been used to adjust for variation in the quality of patents. Schankerman and Pakes (1986) use patent renewal data to estimate the value of patent rights and found that adjusting for quality at the country level accounted for most of the observed decline in patents per scientist and engineer. Other important indicators that have been used include the number patent citations (Trajtenberg, 1990; Hall *et al.* 1999*b*), patent family size (the number of countries in which the patent is taken out) (Putnam, 1996) and the number of claims in the patent application (Tong and Frame, 1994).

In this paper we develop a composite index of patent quality using multiple characteristics of patents. We use the term *quality* to emphasise both the technological and value dimensions of an innovation. We formulate a factor model with four separate indicators of a patent's underlying, unobservable quality: the number of claims, forward citations to the patent, backward citations in the patent application, and family size. Each indicator has quality-related and unrelated variation, or 'measurement error'. The factor model is estimated using over 100,000 patents applied for during the period 1975–93 in seven technology areas – drugs, biotechnology, other health, chemicals, electronics, computers and communications, and mechanical. The parameter estimates are used to construct a

[1] Evenson (1991) argues that it is reasonable to interpret variations in the patent/R&D ratio that are common across industries (country-year effects) as due to changes the patent/invention ratio and those that are common across countries (industry-year effects) as due to variation in true research productivity. He finds evidence of negative industry-specific time trends, pointing to exhaustion.

minimum-variance estimator of quality for each patent, conditional on its observed characteristics. We show that using the composite index reduces the variance in patent quality substantially, to as little as one-quarter of the unconditional variation.

Developing a composite quality index is an 'information-reduction' exercise. This is most useful when a single index is needed to construct a quality-adjusted patent measure to be used, for example, in generating more meaningful measures of research productivity or in econometric studies where quality-adjusted patents appear on the left-hand side of a regression. Even where it would be reasonable to use the component indicators as separate controls without imposing weighting restrictions, the composite may be preferred. Individual indicators may have links to the dependent variables that are not associated with quality, and in such cases a composite index would be more informative about the specific effect of quality differences.

We find that adjusting for a rise in patent quality accounts for some of the time series variation in research productivity at the sector level, except in pharmaceuticals where there was especially fast growth in R&D. We find some support for the theoretical prediction that the level of research productivity at the firm level is inversely related to the level of demand and average patent quality. At the same time we find no evidence of technological exhaustion at the micro level, i.e., there are no negative time trends in research productivity, conditional on the level of R&D. We find that differences in (average) patent quality *across firms* are strongly associated with the market valuation of firms, with an especially large effect in pharmaceuticals. However, these relationships do not hold up in the time series dimension at the firm level. The general conclusion that emerges is that the patent quality index is most useful when one averages – either the mean over time for a given firm or the mean over firms for a given year. While the results are not uniformly strong, they are encouraging and suggest that the quality index may be useful in empirical studies that require innovation measures.

The paper is organised as follows. In Section 1 we outline a simple model of the relationship between R&D, market size and innovation quality. This serves to highlight the difference between technological exhaustion and demand growth explanations for a decline in research productivity. Section 2 describes the data and the indicators used. Sections 3 to 5 describe the construction of our index of innovation quality and discuss changes in the index over time. In Sections 6 to 8 we explore how the quality index relates to research productivity and the market value of firms. The final Section concludes.

1. Analytical Framework

In this Section we present a stylised model of research productivity that incorporates patent quality. Assume that each firm has the following patent production function:

$$\mathrm{E}(N_{ft}|R_{ft}) = \mathrm{e}^{-\tau t} R_{ft}^{\beta(t)} \quad 0 < \beta(t) < 1, \tag{1}$$

where $E(N|R)$ is the expected flow of patents and R_{ft} is R&D expenditure in year t by firm f.[2] Technological exhaustion can take the form of an increase in the parameter τ, or a decline in the R&D elasticity $\beta(t)$.

Each innovation is endowed with a given quality level, which can be thought of as a measure of the maximum potential rent the innovation can generate. Let q_{fti} denote the quality of innovation i of firm f in year t. We assume that innovation quality is drawn from a distribution with a firm-specific and time-varying mean:

$$q_{fti} = q_f + q_t + u_{fti},$$

where u_{fti} has zero mean and constant variance and q_t may be correlated over time. The mean of this distribution is unrelated to R&D (this is consistent with micro evidence presented in Section 7). Let q^*_{ft} denote the expected mean quality for the firm in a given year.

The expected profit flow per invention depends on expected innovation quality and the relevant market size for the firm, S. For simplicity, we assume that market size is exogenous and non-stochastic. Demand for each invention is specified as monotonic in the level of sales of the firm:

$$E(\pi_{fti}) = q^{*\alpha}_{ft} S^{\sigma}_{ft} \quad \text{where} \quad \alpha > 0 \text{ and } \sigma \in [0, 1]. \tag{2}$$

This specification of how demand affects the profitability of R&D is standard in the empirical literature (Cohen and Levin, 1995). In the extreme case where an invention applies to whole of the firm's market, we have $\sigma = 1$ and flow profits would be proportional to sales. However, in general an innovation will be relevant only to some part of the firm's market (e.g. the innovation may represent a new variety of product that appeals to a subset of tastes). In such cases we expect $\sigma < 1$.[3]

We assume that each innovation enjoys patent protection for T years. The flow profit π_t depreciates at rate δ during the patent life, and no rent is earned after the patent expires. The expected present value of innovation rents net of R&D costs for all innovations made by firm f in time t is

$$E(\Pi_{ft}|R_{ft} = \phi q^{*\alpha}_{ft} S^{\sigma}_{ft} e^{-\tau t} R^{\beta(t)}_{ft} - R_{ft}, \tag{3}$$

where $\phi = (1 - e^{-(r+\delta)T})/(r+\delta)$ is the present value of a dollar of rent over the patent life with discount rate r.[4] We assume diminishing returns to R&D, as supported by numerous empirical studies; see, Griliches (1990) for a summary. The firm chooses optimal R&D, $R^*_{ft} = \text{argmax } E(\Pi_{ft}|R_{ft})$. From the first-order condition, we get

$$R^*_{ft} = [e^{-\tau t}\beta(t)\phi q^{*\alpha}_{ft} S^{\sigma}_{ft}]^{1/[1-\beta(t)]}. \tag{4}$$

Let $P_{ft} = N_{ft}/R_{ft}$ denote the number of patents per R&D dollar, which is the standard measure of research productivity. From (1) and (4), we get

[2] The empirical evidence indicates that the average lag in the relationship between patents (by date of application) and R&D is very short (Hall *et al.*, 1986).

[3] In principle the relevant market size could be larger than current sales (e.g., if a radical innovation captured a large part of other firms' market shares). We are modelling the 'typical' innovation.

[4] This is a simplification in two respects. First, some innovations may not be patented (this can easily be absorbed in the parameter ϕ). Second, most patents are terminated by non-payment of patent renewal fees before the maximum statutory lifespan is reached.

$$\mathrm{E}(P_{ft}|R^*_{ft}) = [\phi\beta(t)q^{*\alpha}_{ft}S^{\sigma}_{ft}]^{-1}. \quad (5)$$

In equilibrium, observed research productivity depends on the ability of the firm to appropriate innovation rents (ϕ), R&D elasticity (β), expected quality of inventions (q^*), and demand (S). An increase in any of these factors raises equilibrium R&D spending, reducing research productivity when there are diminishing returns.

Adding a multiplicative error term, we write observed research productivity as

$$\log P_{ft} = -\log \phi\beta(t) - \alpha \log q^*_{ft} - \sigma \log S_{ft} + v_{ft}, \quad (6)$$

where v is assumed to be a normal, independently and identically distributed error. Given an index of patent quality, we can estimate parameters and test the basic predictions of the model: $\alpha > 0$ and $\sigma \in [0,1]$. We can also test the null hypothesis that technological exhaustion is not a source of change in research productivity once quality has been controlled by checking whether there are trended year-effects in (6).

2. Description of the Data

The patent data cover US patents applied for during the period 1975–93 and issued by the beginning of 2000. It includes those held by all publicly listed corporations that had a firm identification code (CUSIP) in the Standard & Poor's CRISP data set in 1989, including all patents assigned to these firms or any of their subsidiary bodies, as determined by their corporate structure in 1989.[5] These firms held 434,108 patents. By drawing on several data sources, we obtained information on a range of characteristics for each patent-owning firm and patent. For all firms, we know from the US Patent and Trademark Office (PTO) whether it is foreign or domestic, and for a subset we have annual R&D expenditure, sales, capital stock and market value. For patents, the variables include:

Claims: The claims in the patent specification delineate the property rights protected by the patent. The principal claims define the essential novel features of the invention and subordinate claims describe detailed features of the innovation. The patentee has an incentive to claim as much as possible in the application but the patent examiner may require that the claims be narrowed before granting. The number of claims is available on a PTO-CD.

Citations: An inventor must cite all related prior US patents in the application. A patent examiner is responsible for insuring that all appropriate patents (and other prior art) have been cited. Like the claims, these identify the rights of the patentee. For each patent, we obtained the number of prior patents cited in the application (*backward citations*). We obtained the same information on all subsequent patents that had cited a given patent in their own applications, as of the end of 1998 (*forward citations*). We construct two forward citation measures. *Fwd*5 includes all forward cites to the patent that occur within five years of the patent

[5] Thus, if firm *A* acquired firm *B* after 1989, the existing patent portfolio of firm *B* would not become a part of the portfolio of firm *A* in our data. Further, firm *B* would continue as a separate entity in our data but would appear to obtain no patents after it was acquired. We thank Adam Jaffe for making these data available to us. For details see Hall *et al.* (1999*a*).

application date, a period which we call the 'citation span'. *Fwd*610 includes citations that occur between six and ten years of patent application. The latter can be calculated for fewer cohorts but each indicator treats all patents within eligible cohorts symmetrically. These variables are constructed from data on a PTO-CD.

Family Size: In order to protect an innovation in multiple countries, a patentee must secure a patent in each country. We call the group of patents protecting the same innovation its 'family' (also referred to as parallel patents). More than two-thirds of patentees do not seek protection outside their home markets. A small fraction finds it worthwhile to patent widely - about 5% of US patent owners apply for protection in more than ten countries. International agreements give inventors at most 30 months to file applications worldwide, so family size captures information available to the patentee up that date.[6] Information on family size was provided by Derwent, a private data base vendor. Due to limitations on access, we have family data for a random sample of just over 100,000 patents, or about 20% of our total population of patents.

Technology Area (*USPC*): The patent examiner assigns each patent to one or more 9-digit technology groups, based on the USPC system. Using these detailed assignments, we classify each patent into one of seven, more aggregated classes: Pharmaceuticals, Biotechnology, Other Health, Chemicals, Computers, Other Electronic, and Mechanical.[7] For patents with more than one, we use the primary technology classification.

Table 1 presents the correlation matrix for the indicators for the pooled sample (results are similar by technology group). Since the raw data are skewed, we log transform the indicators.[8] The numbers of claims, forward cites, backward cites and family size vary substantially both across patents within a given technology area and across technology fields. The correlation between forward citations and the other indicators does not fall off when we use a longer citation span – compare *Fwd*610 and *Fwd*5 – which suggests a payoff to using forward citations over a longer span when the information is available.

3. Specification and Estimation of the Factor Model

We use a multiple-indicator model with one latent common factor:

$$y_{ki} = \mu_k + \lambda_k q_i + \boldsymbol{\beta}' \boldsymbol{X}_i + e_{ki}, \tag{7}$$

where y_{ki} indicates the value of the kth indicator for the ith patent (in logs, $k = 1,\ldots,K$); q is the common factor with factor loadings λ_k, and $\boldsymbol{X}$ denotes a vector of controls. Since q is unobservable, we normalise by setting its variance equal to

[6] The Paris Convention gives applicants twelve months to apply in other signatory countries after having made the first, or priority, application. The Patent Cupertino Treaty allows a 25-month period after a priority PCT application, increased to 30 months in the late 1980s.

[7] This classification updates an earlier aggregation by Adam Jaffe. The computer classes are readily identifiable new additions to the USPC system. The classes designated as biotechnology follow the PTO's identification for examination purposes. These were also checked against the distribution across classes of patents owned by biotechnology companies. We thank Josh Lerner for providing the latter information.

[8] When there are zero forward citations, we set the log of this varible to zero. Results are similar if we drop such observations.

Table 1

Correlation Structure of Indicators

	Claims	*Family*	*Fwd5*	*Fwd610*
Family	0.103			
Fwd5	0.138	0.098		
Fwd610	0.115	0.099	0.390	
Bwd Cites	0.143	0.044	0.093	0.083

Notes: Entries are correlation coefficients for the pooled sample. All are statistically significant at the 1% level. Variables are in logarithms.

one: $q \sim N(0,1)$.[9] Each indicator contains an idiosyncratic error, $e_k \sim N(0, \sigma_k^2)$, that captures any variation that is not common to the other indicators in the model.

The common factor is simply the unobserved characteristic of a patented innovation that influences *all* four of the indicators we use: the number of forward cites, backward cites, claims and family size. Because applying for protection in each country is costly, family size should be directly related to the expected (private) value of protecting an innovation and thus to the value of the innovation itself; see Putnam (1996). This should reflect both the technological importance of the innovation and market opportunities. Forward citations are related most directly to technological importance. Forward citations over the long term indicate an innovation has contributed to future research. Citations soon after patent application suggests rapid recognition of its importance as well as the presence of others working in a similar area, and thus the expectation of a valuable technological area. This is also true of backward citations, although large numbers of citations to others also suggests that the particular innovation is likely to be more derivative in nature (Lanjouw and Schankerman, 2001). The number of claims is also an indication that an innovation is broader and of greater potential profitability.

We call the common factor '*quality*' because we find it difficult to think of any other characteristic that would be common to *all four* indicators. While advances in information technology might increase the number of backward and forward citations per patent, by making it easier to search for relevant prior art, there is no reason that this would also increase the number of claims per patent. Similarly, changes in patent application fees would affect patent family size and, possibly, the number of claims per patent (as ideas are repackaged into 'broader' patents) but this would not directly affect the number of citations.

The theoretical covariance matrix for the indicators is

$$\mathbf{\Lambda} = E(\mathbf{y}\mathbf{y}') = \boldsymbol{\lambda}\boldsymbol{\lambda}' + \mathbf{\Phi}, \tag{8}$$

where $\mathbf{y}$ is the vector of indicators, now demeaned to control for nationality (domestic or foreign) and cohorts, and $\mathbf{\Phi} = E(\mathbf{e}\mathbf{e}')$ is not constrained to be

[9] The interpretation is the same under an alternative normalisation, such as $\lambda_k = 1$. For technical discussion of latent variable models and their uses, see Bartholomew (1987).

diagonal.[10] We estimate by maximum likelihood (estimated parameters make the theoretical covariance matrix as close as possible to the observed covariance structure). The k-indicator model has $K(K+1)/2$ covariance terms and $2K$ parameters, and thus $K(K-3)/2$ over-identifying restrictions. In our study $K=4$, so there are two testable restrictions.

The latent variable and K indicators have the joint normal distribution

$$\begin{bmatrix} q \\ y \end{bmatrix} \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Sigma}), \quad \text{where } \boldsymbol{\Sigma} = \begin{bmatrix} 1 & \lambda' \\ \lambda & \Lambda \end{bmatrix}. \tag{9}$$

The posterior mean and variance of the latent variable, conditional on the observed indicators, $\mathbf{y}$, are

$$\mathrm{E}(q|\mathbf{y}) = \boldsymbol{\lambda}'\boldsymbol{\Lambda}^{-1}\mathbf{y}, \tag{10}$$

$$\mathrm{Var}(q|\mathbf{y}) = 1 - \boldsymbol{\lambda}'\boldsymbol{\Lambda}^{-1}\boldsymbol{\lambda}. \tag{11}$$

Given $\boldsymbol{\lambda}$, (10) provides an estimate of the latent variable for each patent (as a deviation around mean zero), which we will use as a measure of its quality. The conditional posterior mean of the latent variable is a linear combination of the set of indicators, where weights depend on the factor loadings. The conditional posterior variance of quality is a constant that can be estimated. The term $\boldsymbol{\lambda}'\boldsymbol{\Lambda}^{-1}\boldsymbol{\lambda}$, represents the percentage reduction in the variance of quality due to conditioning on the set of indicators, $\mathbf{y}$ (since the unconditional variance is normalised to one).

3.1. *Parameter Estimates*

Table 2 presents the parameter estimates for each technology group. We include nationality and cohort effects, and estimate each model separately for two sub-periods, 1975–85 and 1986–93, to allow for changes over time in the covariance matrix of the indicators. We tested for parameter stability across the sub-periods and include pooled estimates in the Table when the test is not rejected. Results are robust to alternative definitions of the sub-periods.[11]

We conduct a sequence of tests and interpret the statistics using both the conventional significance criterion and the alternative measure proposed by Leamer (1978), which we call the Bayesian-F. Leamer's criterion has the property that, given a diffuse prior distribution, the critical value is exceeded only if the posterior odds favour the alternative hypothesis.[12] This is useful as any null hypothesis will be rejected in large enough samples if the significance level is not adjusted for sample size.

[10] The assumption of constant variance in the measurement error is not critical. Since identification of $\boldsymbol{\lambda}$ comes from the *covariance* terms in $\boldsymbol{\Lambda}$, the important assumption is that each covariance is constant across patents (within a given technology field, as we estimate separately). Of course, if the measurement error variances are not constant, the estimates are not efficient and the estimated standard errors may be inconsistent.

[11] Since indicators are in logs, in estimating the factor model we drop observations that have zero values for forward citations (other indicators are always positive).

[12] The critical value is $F = (T/p)(T^{p/T} - 1)$ where T is the sample size, $T-k$ is degrees of freedom, and p is the number of restrictions being tested.

Table 2

Parameter Estimates for the One-Factor Model, By Technology Field

Independent Variable (log)	Drugs	Biotech	Other Health	Chemicals	Computers	Electronic	Mechanical
Fwd5 (1975–85)	*0.49* (0.043)	*0.19* (0.066)	*0.29* (0.028)	*0.29* (0.013)	*0.18* (0.048)	*0.25* (0.028) *0.32* (0.014)	*0.22* (0.012)
Claims (1975–85)	*0.30* (0.030)	*0.84* (0.20)	*0.52* (0.042)	*0.48* (0.019)	*0.29* (0.066)	*0.54* (0.054) *0.41* (0.016)	*0.52* (0.022)
Family (1975–85)	*0.12* (0.025)	*0.14* (0.060)	*0.19* (0.028)	*0.16* (0.012)	*0.35* (0.077)	*0.17* (0.011)	*0.14* (0.032) *0.23* (0.013)
Bwd Cites (1975–85)	*0.30* (0.037)	*0.37* (0.099)	*0.35* (0.030)	*0.23* (0.024) *0.31* (0.014)	*0.11* (0.045)	*0.19* (0.021) *0.29* (0.012)	*0.12* (0.028) *0.28* (0.013)
No. Obs.	4,709	453	3,858	28,106	2,326	39,070	34,237
1FM, $\chi^2(2)$ (p-value)	12.8 (0.002)	0.6 (0.76)	14.7 (0.001)	91.2 (<0.001)	0.7 (0.69)	90.1 (<0.001)	78.6 (<0.001)
Generalised 1FM, $\chi^2(1)$ (p-value)	4.0 (0.045)		7.6 (0.006)	15.2 (0.005)		47.8 (<0.001)	0.7 (0.41)
S_{fwd}	*0.28* (0.049)	0.053 (0.037)	*0.17* (0.017)	*0.12* (0.011)	*0.04* (0.02)	*0.08* (0.018)	*0.07* (0.007)
S_{clm}	*0.13* (0.027)	*0.82* (0.38)	*0.29* (0.066)	*0.37* (0.029)	*0.13* (0.059)	*0.51* (0.10)	*0.42* (0.035)
S_{fam}	*0.01* (0.003)	0.01 (0.01)	*0.056* (0.007)	*0.02* (0.003)	*0.13* (0.056)	*0.03* (0.004)	*0.02* (0.008)
S_{bwd}	*0.10* (0.025)	0.16 (0.085)	*0.17* (0.034)	*0.08* (0.016)	0.02 (0.017)	*0.06* (0.013)	0.02 (0.011)

Note: Nationality and cohort dummies included. Estimated standard errors are in parentheses. Italics indicates statistical significance at the 5% level. The signal rate for indicator k (period 1986–93) is $S_k = \lambda_k^2/\sigma_k^2$ where the point estimate of λ_k is used. The approximate standard error is computed as $2\lambda_k\sigma(\lambda_k)/\sigma_k^2$. $\chi^2(2)$ tests the over-identifying restrictions in the one-factor model. $\chi^2(1)$ tests the restriction in a 'generalised' one-factor model that allows non-zero covariance between measurement errors in forward citations and family size.

First we test the hypothesis that there is no common factor linking the four indicators. This is decisively rejected in every technology group (p-values <0.001). Second, we test whether cohort controls are important. Cohort dummies are jointly significant in all technology fields, so we include them in the subsequent analysis. Finally, we test the two over-identifying restrictions of the one-factor model. We reject the restrictions at the 5% significance level except in biotechnology and computers. In the other five technology groups we relax one of the zero-constraints in the error covariance matrix $\mathbf{\Phi}$ (the choice was made on the basis of the associated gradient of the likelihood function) and test the remaining restriction. We introduce flexibility in this way because we cannot identify a two-factor model without another indicator. The error covariance chosen to be unrestricted always turned out to be the covariance between forward cites and patent family size. This is not surprising, as these two indicators both reflect information that accumulates after the patent is applied for. When we allow for the desired free covariance between forward cites and family size, the remaining restriction is not rejected for drugs, other health, chemicals and mechanical patents, using the Bayesian-F. We reject the remaining restriction in electronics and tried relaxing different zero constraints in $\mathbf{\Phi}$ without success. We include that category for completeness but those results should be viewed with some caution.

The lower panel in the Table presents estimated signal rates, defined as the percentage of variance in an indicator accounted for by the common factor. Signal rates vary both across indicators and technology fields. Forward citations have largest signal rate in drugs, whereas patent claims dominate in all of the other fields.[13]

4. The Patent Quality Index and Gains from Multiple Indicators

The composite quality index is a linear combination of observed indicators. In this Section we describe the weights used for the quality index, and discuss two advantages of using multiple indicators. The weight for each indicator corresponds to the increase in the expected value of quality associated with a unit increase in that indicator $\partial \mathrm{E}(q|\mathbf{y})/\partial y_k$. Using (10), the weights (normalised to sum to unity) are $\mathbf{\Lambda}^{-1}\boldsymbol{\lambda}/\boldsymbol{\iota}'\mathbf{\Lambda}^{-1}\boldsymbol{\lambda}$, where $\boldsymbol{\lambda}$ is the column vector of estimated factor loadings, $\mathbf{\Lambda}$ is the covariance matrix of the indicators and $\boldsymbol{\iota}$ a unit vector.

Table 3 presents the weights based on the parameter estimates in Table 2. For drug patents, forward citations get about 48% of the weight, with claims taking another 28%, backward citations nearly 20%, with about 5% to family size. In the other technology fields, claims are much more important than forward cites, the former accounting for more than half the weight. Patent family size gets very little

[13] Controlling for claims reduces the *variance* in the forward citations indicator (also holds for backward cites). The between-group variance (groups defined by the number of claims) accounts for 7–12% of the total variance in forward citations and about 20% in drugs and chemicals. However, controlling for claims does not increase the *signal rate* for forward citations. Letting $z_{fwd} = y_{fwd} - y_{clm}$ denote (log) forward cites per claim, the signal rates for z_{fwd} and y_{fwd} are $(\lambda_{fwd} - \lambda_{clm})^2/\sigma^2_{z,fwd}$ and $\lambda^2_{fwd}/\sigma^2_{y,fwd}$. Using the estimated parameters, we find that forward cites *per claim* are much noisier than either claims or forward cites in all technology groups except mechanical patents.

Table 3

Weights in the Patent Quality Index

% Weight on (log):	Drugs	Biotech	Other Health	Chemicals	Computers	Electronics	Mechanical
Claims	29.8	72.0	53.1	49.2	37.3	44.5	52.3
*Fwd*5	46.1	12.8	13.6	23.0	16.2	21.3	14.7
Bwd Cites	21.2	13.9	29.4	23.7	15.3	27.1	24.8
Family	2.9	1.2	3.9	4.1	31.2	7.1	8.3

Notes: Based on cohorts 1986–93. Weights are estimated values for $\Lambda^{-1}\lambda/\iota'\Lambda^{-1}\lambda$, where λ is the column vector factor loadings, Λ is the covariance matrix of the indicators, net of nationality and cohort effects, and ι a unit vector. Each weight corresponds to $\partial E(q|y)/\partial y_k$, summed to one.

weight in the index in drugs, biotechnology and chemicals, but plays a larger role for computer patents and, to a lesser extent, in electronics and mechanical.

4.1. *Greater Variance Reduction with Multiple Indicators*

Because putting together sets of indicators is costly, we analyse the potential information gains from using multiple indicators. It is not necessary to have four indicators – the single latent variable model is estimable with any subset of $K = 3$ indicators.[14] Moreover, it might be convenient to apply the parameters estimated here to construct an estimate of q from *any available* subset of these indicators without re-estimating the model, provided it is reasonable to assume a similar correlation structure holds across the different sets of data. Therefore, we analyse how the conditional variance of quality, given in (11), varies when using different subsets of the indicators to predict the latent variable (Table 4). The unconditional variance is normalised to unity, so the entries in the Table represent the percentage reduction in variance we get by using different subsets of indicators.

Using all four indicators reduces the conditional variance of quality by about a third in drugs and by more than half in the other technology fields except com-

Table 4

Information Content in Alternative Sets of Indicators: Percentage Reduction in Variance of Patent Quality

Subset of Indicators	Drugs	Biotech	Other Health	Chemicals	Computers	Electronics	Mechanical
*Fwd*5, *Claims, Family, Bwd Cites*	42.1	83.9	55.0	48.9	28.8	47.6	53.5
Drop *Fwd*5	21.6	82.3	52.5	43.1	26.3	40.9	50.7
Drop *Claims*	34.8	21.2	26.3	23.9	18.2	26.5	21.8
Drop *Family*	41.9	83.8	54.7	48.6	18.3	46.7	52.1
Drop *Fwd*5 and *Family*	21.3	82.2	51.9	42.3	15.1	39.4	48.9

Notes: Computed as $\lambda'\Lambda^{-1}\lambda = \mathrm{Var}(q) - \mathrm{Var}(q|y)$, using estimated λ for cohorts 1986–93 and covariance matrix Λ, net of cohort effects, for the relevant set of indicators.

[14] Of course, the common factor will depend on the subset of indicators used, as will the composite quality index. The model with three indicators is exactly identified and thus not testable.

puters (see first row in the Table). Forward citations are the most important indicator for drugs – if they are dropped from the quality index, the reduction in variance is cut in half. In contrast, dropping forward cites has only a modest effect in the other technology fields. In those areas, claims are the key indicator – dropping them from the quality index cuts the original reduction in variance by two-thirds. Patent family size is much less important than forward cites or claims, except for computer patents.[15]

In short, there is a substantial information gain from using multiple indicators to measure the quality of innovations. Their relative importance is also fortuitous since it tracks their relative cost. Information on the number of claims and backward citations is available in the patent application and inexpensive to obtain. Even if we use only these two indicators, we get most of the reduction in the conditional variance of quality, except in drugs. Forward citations are also straightforward to obtain, but have the added drawback of taking time to accumulate. Family size requires considerable effort to construct.

4.2. *Improved Understanding of Time Trends*

Most studies that adjust for variation in the quality of patented innovation use the single indicator, forward citations. A difficulty with using any single indicator over time is that the cost of 'producing' the indicator may change. For instance, computerisation reduces the cost of citing. It is difficult to disentangle this from changes in underlying quality. On the other hand, for a change in the production of an indicator to influence our quality index it would have to affect *all four* indicators and it is difficult to think of plausible examples. As a result, using the indicators together enables us to interpret changes in citation rates (or any other single indicator) over time.

For example, in a study of patent citation rates, Hall *et al.* (1999*b*) show that a patent would have been 1.63 times more likely to be cited in 1985–93 than in 1977–85, conditional on characteristics of the patent and the size of the patent population. As they recognise, this finding combines two very different factors: changes in the underlying quality of patents, and changes in the ease of citation. The multiple-indicator factor model allows us to isolate the quality-related changes in citation rates. To do this we allow the coefficients in the factor model to vary across sub-periods, and use the estimated coefficients to compute $\partial \mathrm{E}(q|\mathbf{y})\partial \mathbf{y} = \mathbf{\Lambda}^{-1}\boldsymbol{\lambda}$ for each period. Weighting the estimates across all technology fields, we find that an average first-period citation is equivalent to 1.10 second-period citations in terms of implied patent quality. Comparing this estimate with the 1.63 figure from Hall *et al.*, we conclude that about 16% of the

[15] We also re-estimated the model using forward citations over a five-year span and then a ten-year span (on a common sample of earlier cohorts) and compared the signal rates. Doubling the citation span roughly doubles the signal rate in each technology area and the differences are statistically significant. Thus it is possible to achieve an even greater reduction in the conditional variance of quality with longer-term forward citations, so longer spans should be used when feasible.

increase in citation is due to changes in innovation quality, with the remaining 84% reflecting an increase in the 'propensity to cite'.

5. Changes in the Patent Quality Index

We demonstrate below that there has been a substantial growth in the quality index over time. We would like to interpret this as the reflection of an upward shift in the underlying distribution of innovation. However, the increase in the index over time could be the result of rising patent application and enforcement costs that cause lower-quality patents to drop out. To discriminate between these explanations note that, under the assumption that the quality index is correlated with innovation value, shifts in the underlying distribution of innovation should shift the composite index for patents throughout the distribution. In the special case where there is a proportional shift in the innovation distribution (so the coefficient of variation is constant) and the quality index is proportional to innovation value, the percentage change in the quality index should be similar in different percentiles of the quality distribution. On the other hand, changes in the cost of patenting that shifted the cut-off point on the distribution of innovations that are patented would primarily affect patents in the lower quantiles of the distribution.

Thus, to examine the issue we draw a (fixed size) random sample of patents from each cohort in a technology field and compute the mean value of the quality index for various percentiles of the distribution of sampled patents, say $\bar{q}(\kappa, t)$ for the κ-percentile for cohort t. The 'test' involves comparing the percentage change in $\bar{q}(\kappa, t)$ for different value of κ both over the whole sample period and for cohort sub-groups. Table 5 presents results for the cumulative changes over the period 1975–93. In each technology area, the changes in the quality index are evident *both* in the upper and lower ends of the distribution. This also holds for different sub-periods (not reported). There is some evidence that increases in the cost of patenting may be at work – the changes in the quality index are higher in the lower tail of the distributions for electronic and mechanical patents but not for drugs and chemicals. One would expect changes in patenting costs to affect all

Table 5

Changes in Patent Quality Index, by Percentile (%)

Percentile	Drugs	Chemicals	Electronics	Mechanical
Top 5%	24.5	27.0	19.7	16.0
10%	21.3	24.3	20.1	16.7
50%	23.2	21.6	21.9	19.7
90%	27.1	24.1	25.3	23.0
95%	27.9	24.9	25.9	23.8

Notes: Each cell gives the mean percentage increase in the average quality for a randomly drawn (without replacement) sample of 787 patents per year in each technology field, 1975–93. 787 is the minimum number of patents in any year in any technology area. Three technologies are excluded due to small numbers in the early years. Similar patterns hold for sub-periods 1975–84 and 1984–93, although changes are smaller for the second period.

technology areas in a roughly similar way. This non-parametric evidence suggests that variations in the patent quality index are related to changes in the underlying value of innovations.

6. Understanding Research Productivity at the Sector Level

For the remainder of the paper, we focus on the five largest technology fields and allocate our firms to these groups. Firms classified in a given SIC industry may have patents in multiple technology fields. In order to assign a given firm to a technology field (e.g., to treat it as a drug firm), we require that a plurality of its patents during the period 1975–93 fall into that field. Of such assigned firms, it turns out that about three-quarters have at least a majority of their patents in one field, and the minimum share is about 25%.[16] Table 6 presents descriptive statistics for these data. There is large variation in firm size as measured by sales, R&D intensity (R&D/sales) and research productivity (patents/R&D) both across technology fields and within a given field.

The patent quality index used in the analysis that follows is constructed with *three* indicators – claims, forward citations and backward citations – using renormalised weights from Table 3. We do not use family size here because we only have family data for a subset of patents and, to compare to R&D aggregates, we must have complete patent coverage for each firm.[17]

Figures 2–6 present the time paths of R&D expenditures, unadjusted research productivity (the number of patents divided by R&D), and a patent quality-adjusted measure of research productivity for each technology field over the period 1980–93. In pharmaceuticals, R&D increased 2.5 times during the period, mostly from 1980–7. There was a concurrent, sharp decline in the patents to R&D ratio, by about 50%. Adjusting for patent quality in this sector makes a very modest difference in measured research productivity over the sample period, and the

Table 6

Descriptive Statistics: Firm-Level Sample

Median of:	Drugs	Other Health	Chemicals	Electronics	Mechanical
Sales (1998 $m)	109.2	39.6	418.8	122.5	302.3
R&D/Sales (%)	13.2	8.0	2.3	5.8	1.4
Patents/R&D (per $m)	0.27	0.59	0.58	0.46	0.54
Number of firms	69	68	322	410	664

Notes: Both sales and R&D data are deflated. The reported number of firms is the maximum available for any single variable. Actual sample sizes vary in the different regression analyses.

[16] When a merged company takes on a new name, the R&D and patent data are not always merged to produce a consistent series for the new firm. We dropped two pharmaceutical firms with abnormal breaks in the R&D and patent series after confirming they were involved in mergers.

[17] In constructing the weighted patent counts, the log of zero-valued indicators were set to zero rather than missing to avoid dropping firms' lowest-valued patents. In the estimation of the factor model, such observations were dropped.

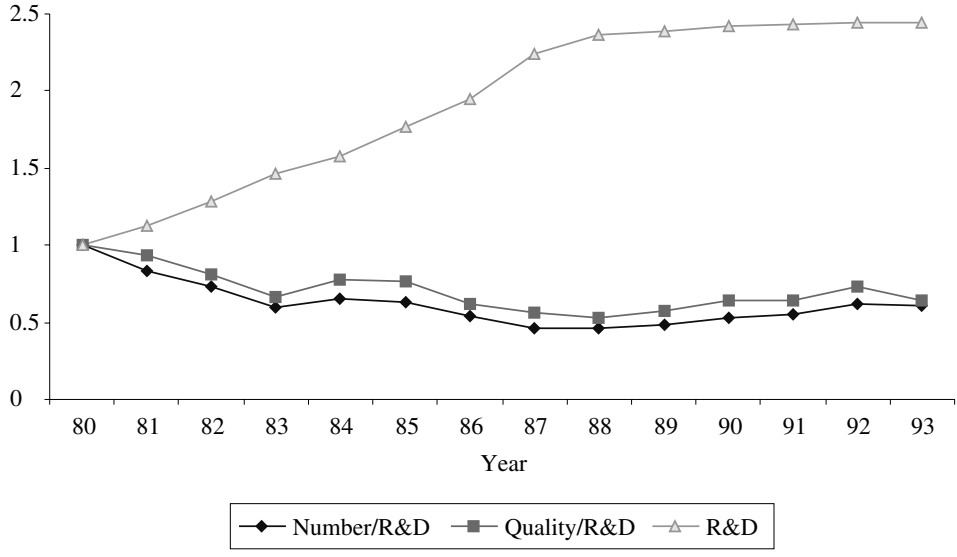

Fig. 2. *Pharmaceuticals*

difference disappears by the end of period. In the other sectors the quality adjustment is more important in accounting for changes in research productivity. In both other health and electronics the patents to R&D ratio fell sharply and then rose, ending the period 13 and 20% higher, respectively. After adjusting for quality, the increase in their productivity by the end of the period was more than twice as large. In chemicals, patents/R&D declined by 20%, but the quality adjustment reduces this fall to 7%. Finally, the mechanical field experienced quite rapid growth in R&D, nearly doubling over the period. This was accompanied by a 40% decline in unadjusted research productivity but a moderated 29% fall when the quality adjustment is made.

Thus, it appears that an increase in the quality of patented innovation accounts for a sizable share of declines in research productivity when they are observed at the sector level, apart from drugs. We emphasise that the interpretation of trends does *not* rest on an identifying assumption that there is a stable relationship between quality and the four indicators. (We allow the coefficients in the factor model to vary by sub-period. See Section 3.)

7. Research Productivity and Innovation Quality: Micro Evidence

We next examine the role of patent quality and sales in explaining the micro level variations in research productivity. The model of Section 1 assumed that R&D affects the number of innovations but not their quality (1). We first explore this relationship and then turn to the equilibrium research productivity equation (6).

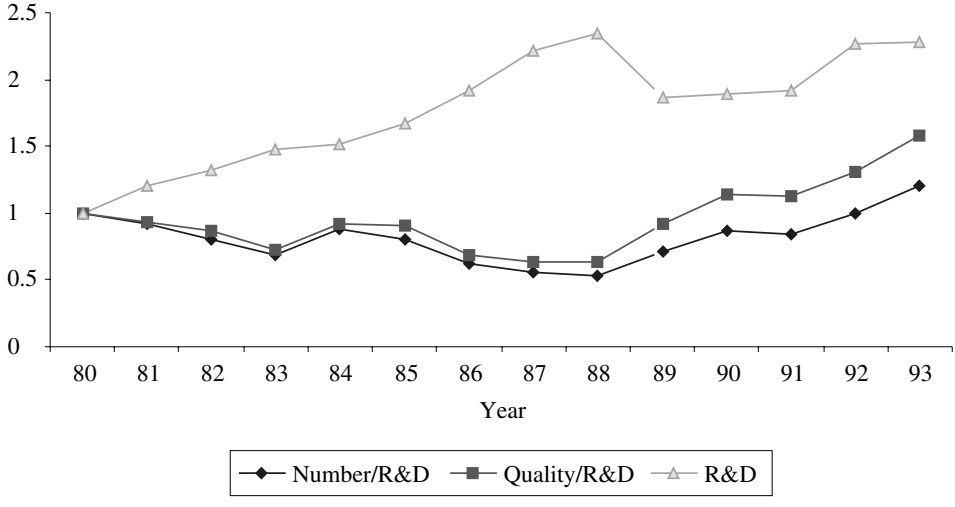

Fig. 3. *Other Health*

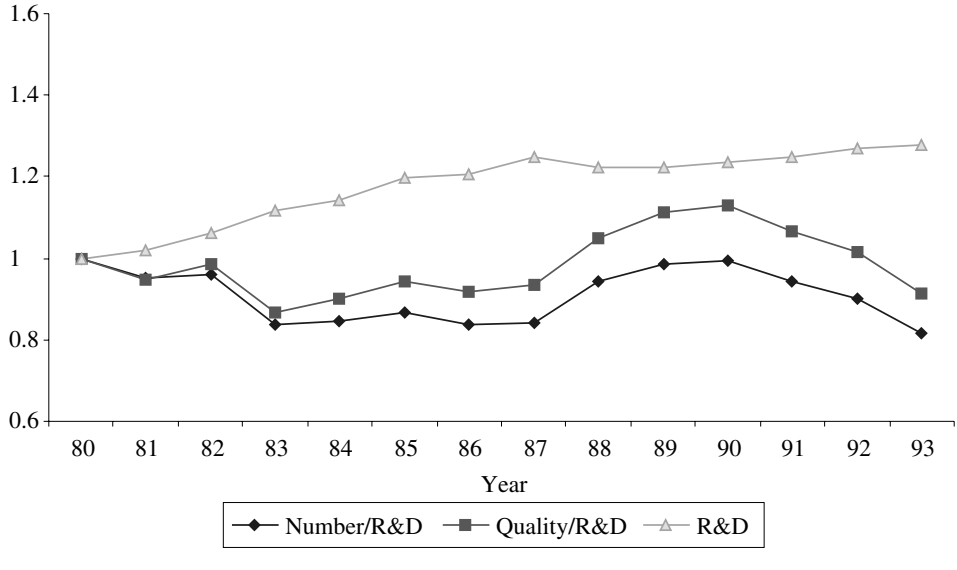

Fig. 4. *Chemicals*

7.1. *R&D Investment and Quality*

Quality-adjusted patent counts can be either more or less closely correlated with R&D than simple patent counts. This depends on whether there are differences in the *ex ante* distributions of innovation quality faced by firms. This would occur if firms adopt research strategies for trading off quantity for quality of innovation, in which case we expect R&D to be more strongly correlated with quality-adjusted patents than with unadjusted patents counts. If, on the other hand, the *ex ante*

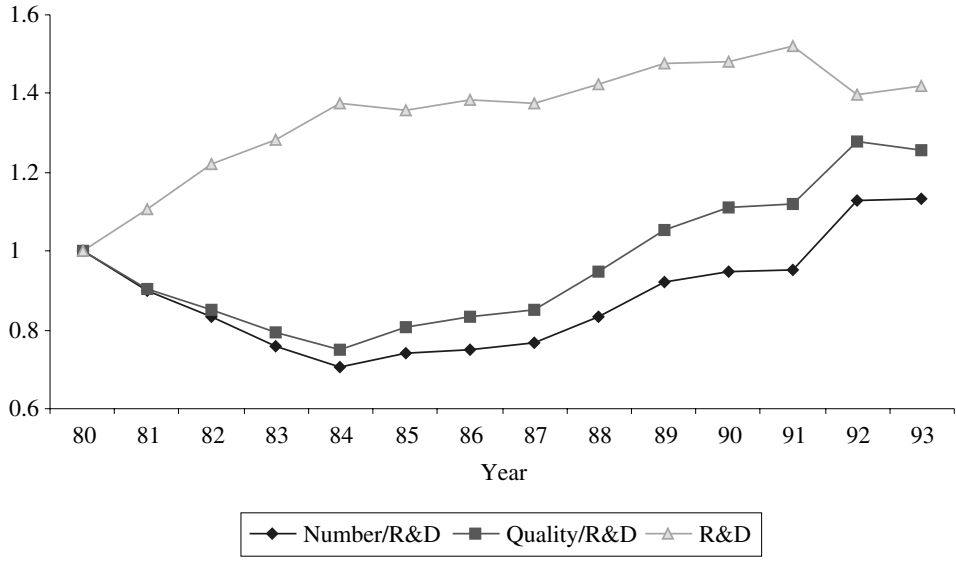

Fig. 5. *Electronics*

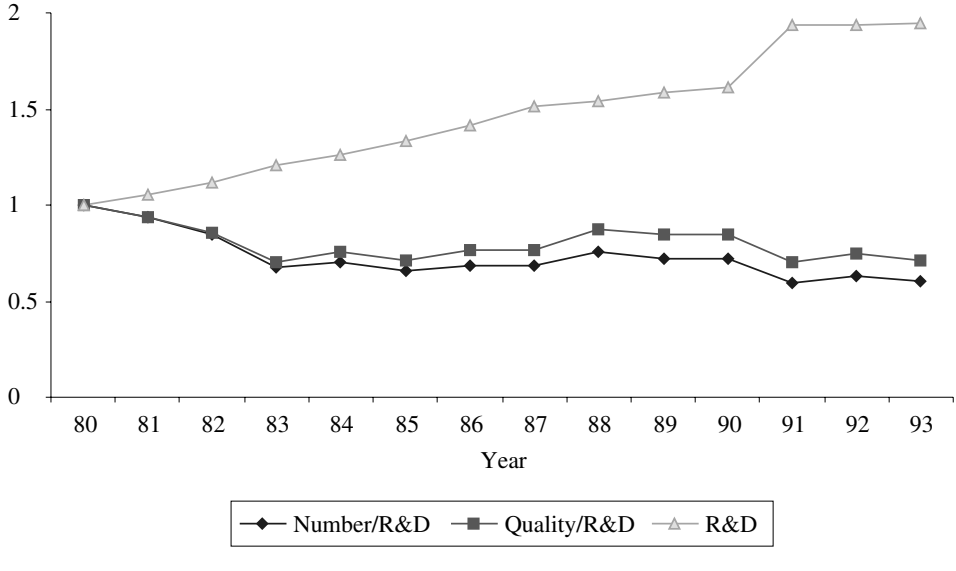

Fig. 6. *Mechanical*

distribution of quality is the same across firms, differences in the *ex post* average quality of their patents simply reflect stochastic R&D outcomes. Then making a quality adjustment would not strengthen the correlation between patents and R&D. The latter is what we find: the simple correlation between firm R&D and quality-adjusted patent count in the pooled sample is 0.68, which is virtually

identical to the correlation with unadjusted patent counts. This conclusion also holds in each technology field.

If there is a trade off between the quality and quantity of innovation we would also expect a negative relationship between patent counts and mean patent quality at the firm level, conditional on R&D. This would generate a different relationship between R&D and simple patent counts as compared to R&D and quality-adjusted patents. We explored this by estimating a 'patent production function' for each technology field. Using the deviations around firm means, we regressed the (log) number of new patent applications against the stock of R&D and year dummies.[18] We also estimated the between-firm regression. For brevity we summarise the relevant results. As in many other studies, we find decreasing returns to R&D in both the within- and between-firm regressions.[19] What is striking is that we obtain virtually identical coefficients on R&D when we use quality-adjusted patent counts, both in the within and the between-firm regressions. This evidence suggests that *variations in patent quality over time* at the micro level are dominated by stochastic factors rather than by variations in R&D expenditures.

Because variations in patent quality over time (for a given firm) may be largely noise, we also investigate whether *cross-firm differences* in the patent quality index are related to the number of patents, conditional on the firm's R&D level. Again, if firms choose between quality and quantity then we expect a negative relationship. We test this by including in the patent production function regressions the mean value of the patent quality index for the firm, computed over the firm's patents applied for during the entire sample period: $\hat{q}_f = \sum_t \hat{q}_{ft}/N_f$. In the within-firm regressions the coefficient on mean patent quality is completely insignificant in all technology fields, except drugs where it is positive. This positive coefficient probably reflects unobserved heterogeneity in research capability, for which the mean patent quality for a firm is serving as a proxy. There is no relationship evident in the between-firm regressions. Thus again we find no evidence that firms target different quality levels in their R&D strategies. We conclude that differences in the (average) quality of their innovations are not related to R&D, or that whatever differences are present get swamped by the stochastic element in the R&D process.

7.2. *Research Productivity at the Firm Level*

The equilibrium equation (6) predicts that the log of research productivity should be inversely related to the level of log sales and average patent quality, and that the coefficient on sales should be less than unity in absolute value. Table 7 presents

[18] Results are similar using the R&D flow. The R&D stock is computed using a declining balance formula with a depreciation rate of 0.15. To construct the initial stock we assume constant past growth rate equal to the average growth in R&D for the firm during the first five years of the sample. Results are not sensitive to alternative assumptions.

[19] In the within-firm regressions, the estimated R&D elasticity of patents and its standard error are 0.77 (0.18) in drugs, 0.37 (0.095) in other health, 0.55 (0.07) in chemicals, 0.64 (0.068) in electronics, and 0.36 (0.05) in mechanical. The between-firm estimates are not statistically different from these in drugs or electronics but are larger in the other three fields (this is not surprising since measurement error in R&D gets amplified in the 'within' dimension).

Table 7

Research Productivity, Patent Quality and Market Demand

	Drugs		Other Health		Chemicals		Electronics		Mechanical	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Within-Regression										
$\hat{q}$	0.02 (0.085)	*0.46* (0.23)	−0.18 (0.094)	0.05 (0.37)	*−0.14* (0.06)	−0.03 (0.14)	−0.01 (0.05)	−0.19 (0.17)	*0.09* (0.045)	0.26 (0.14)
Log Sales	*−0.23* (0.05)	*−0.22* (0.05)	*−0.25* (0.06)	*−0.14* (0.07)	0.068 (0.05)	*0.30* (0.07)	−0.03 (0.04)	0.01 (0.04)	*−0.08* (0.03)	*−0.08* (0.04)
R^2	0.12	0.12	0.07	0.04	0.02	0.03	0.02	0.02	0.014	0.003
F-test $H_0: \beta(t) = \beta$	0.91		0.85		1.48		*2.64*		1.80	
No. Obs.	460	385	394	291	1,469	1,170	1,906	1,461	2,208	1,681
Between-Regression										
$\hat{q}$	0.71 (0.48)	1.36 (0.95)	−0.25 (0.51)	0.97 (1.42)	0.02 (0.28)	0.04 (0.50)	*−0.80* (0.22)	*−0.95* (0.53)	*−0.67* (0.20)	*−0.84* (0.41)
Log Sales	*−0.14* (0.06)	*−0.16* (0.06)	*−0.38* (0.06)	*−0.37* (0.06)	*−0.33* (0.034)	*−0.31* (0.034)	*−0.32* (0.03)	*−0.31* (0.034)	*−0.39* (0.30)	*−0.37* (0.30)
R^2	0.19	0.20	0.38	0.38	0.29	0.27	0.24	0.22	0.31	0.29
No. Obs.	63	62	63	63	226	218	312	311	387	381

Notes: OLS uses no instrument for q. IV uses lag q as the instrument for q – the R^2 in the first-stage regression varies from 0.12 to 0.24. 'Within' denotes the regression with fixed firm and year effects. Italic indicates statistical significance at the 5% level. The F-statistic tests the null hypothesis that there are no year effects (no technological exhaustion) in the OLS model. 'Between' is the regression done on firm means of variables.

parameter estimates for both within-firm and between-firm regressions. We include year dummies in the within-firm regressions to capture technological exhaustion over the period and report F-tests of the null hypothesis that these coefficients are jointly zero.

In the within-firm dimension, the evidence is not very strong. The variation in research productivity over time is very noisy – the regressions explain very little of the within-firm variance. This is not surprising, since we expect a large stochastic element in R&D outcomes that lead to patenting. Nonetheless, changes in research productivity are negatively and significantly related to the level of sales in the drugs, other health and mechanical technology fields. However, the patent quality index does not explain any of the within-firm variation in research productivity. The results are more encouraging in the between-firm regressions. The sales and patent quality variables account for between 20 and 40% of the *cross-firm* variation in research productivity. Differences across firms in research productivity are negatively and significantly related to differences in the level of sales in all technology fields and all of the estimated sales coefficients are less than unity, as predicted. In addition, research productivity is strongly and negatively related to the patent quality index in the electronics and mechanical technology fields and weakly so in other health (with no relationship in drugs or chemicals). We do not reject the hypothesis that there are no year effects in the within-firm regression for drugs, chemicals and mechanical fields. Although we do reject the hypothesis for electronics, the estimated year effects (not reported) do not show any *systematic* decline over the sample period. In the context of the model in Section 1 equation (6), this evidence provides no support for the hypothesis of technological exhaustion at the micro-level, once we control for sales and patent quality.[20]

8. Stock Market Value and Innovation Quality

In this Section we examine whether differences in patent quality help explain differences in the stock market valuation of patenting firms.[21] We use the approach developed by Griliches (1981) and applied in many subsequent studies. We estimate an equation that relates the value of Tobin's Q for the firm (the ratio of market value to capital stock) to the stock of patents, plus year and technology field effects. Following Hall *et al.* (1999*b*), we compute market value as the sum of the values of common stock, preferred stock, long-term debt and short-term debt net of assets. Book value of capital includes net plant and equipment, inventories, investments in unconsolidated subsidiaries and intangibles (other than R&D).

[20] We also tested the hypothesis that there are no year effects in the within-firm regression that excludes the sales and patent quality index. The finding for drugs is reversed – the F-statistic rises from 0.91 to 2.81 when we drop sales and the patent quality index. The conclusions are unchanged in the other fields.

[21] We also examined whether the quality of innovations is related to the firm's decision to maintain patent protection by paying periodic renewal fees. Patent renewal models imply that, at any age, the likelihood of renewal should increase in the profit associated with the patent, equation (2), e.g., Schankerman and Pakes (1986). We estimate probit regressions for patent renewals at various ages (four, eight and twelve, as required in the United States). The coefficient on q_f is positive and significant in all technology areas.

The market value of firm f in year t is the sum of the value of the stocks of physical and knowledge capital:

$$MV_{ft} = (\eta_t C_{ft} + \rho_t K_{ft})^{\psi}, \tag{12}$$

where η and ρ denote the shadow prices of physical and knowledge capital, respectively. Assuming constant returns to scale ($\psi = 1$) and that the shadow price of each capital stock is equalised across firms in equilibrium,

$$\log(MV/C)_{ft} = \eta_t + \log(1 + \mu_t K_{ft}/C_{ft}). \tag{13}$$

MV/C is the conventional measure of Tobin's Q and $\mu_t = \rho_t/\eta_t$ is the shadow price of knowledge capital relative to physical capital in year t. The equation is estimated by non-linear least squares. We include either the cumulative number of patents or of quality-adjusted patents (*Nstk* and *Vstk*, respectively) as our measure of the knowledge stock.[22] Since the mean quality is not unity, we have scaled the estimated coefficients (and standard error) on *Vstk* in Table 8 so that they can be compared directly to the coefficients on *Nstk*. We include year effects in the regression to pick up variation in η_t. The baseline specification treats μ as constant over time. We also allowed it to vary across three sub-periods in the sample and the results were similar to those reported here. In the drugs, electronics and mechanical fields, the estimated μ increased from the early period 1980–4 to 1985–9 and then declined, while in other health and chemicals it rose throughout the sample period. For related evidence on the returns to R&D, see Hall (1993*b*). We also include the firm's average patent quality index, $\bar{q}$, in the regression. This allows us to examine whether cross-section differences in patent quality are valued by the stock market, in addition to any over time variations in patent quality.[23] These between-firm differences account for a substantial part, about 40%, of the overall variance in the patent quality index in each technology field.

As expected, the results show that the market value is positively related to the stock of patents held by the firm (before any quality adjustment). In each of the technology fields, when we use the quality-adjusted patent stock, we find that there is relatively little change in the estimated coefficient on the patent stock variable and virtually no improvement in the regression fit. Not surprisingly, the coefficient on average patent quality index, $\bar{q}$, falls somewhat since some of the effect is being picked up by the new patent stock. This evidence indicates that variations over time in a firm's patent quality (i.e., averaged over its patents) are mostly swamped by idiosyncratic variation and, as such, are not be well identified by investors.

However, in four out of five technology areas, the stock market value is positively related to the *mean quality* at the firm level, given the stocks of capital and quality-adjusted patent counts (the exception is chemicals). This finding is robust – it also

[22] The patent quality index used in these regressions is constructed with three indicators – claims, forward citations and backward citations – using the renormalised weights from Table 3. We do not use family size because it is only available for about 20% of patents. We checked robustness by running the regressions using only the subset with family data, and the qualitative results were similar. All patent stocks are computed using a depreciation rate of 0.15.

[23] This means that the market value in year t is a function of the firm's mean quality index for patients applied for after t. This is reasonable if the market has enough accumulated information to estimate firm-specific quality.

Table 8

Stock Market Value and Patent Quality

	Drugs		Other Health		Chemicals		Electronics		Mechanical	
Nstk/C	0.070 (0.013)		0.072 (0.012)		0.052 (0.008)		0.072 (0.006)		0.174 (0.013)	
Vstk/C		0.076 (0.014)		0.067 (0.011)		0.059 (0.007)		0.069 (0.006)		0.164 (0.013)
$\bar{q}$	*0.302* (0.11)	*0.242* (0.11)	*0.479* (0.10)	*0.422* (0.11)	*−0.070* (0.028)	*−0.082* (0.028)	*0.137* (0.024)	*0.119* (0.024)	*0.074* (0.019)	*0.058* (0.019)
R^2	0.62	0.63	0.60	0.60	0.21	0.22	0.50	0.50	0.28	0.29
No. Obs.	489	489	575	575	2,360	2,360	3,209	3,209	4,731	4,831

Notes: Estimated by non-linear least squares, with year effects included. Italic indicates statistical significance at the 5% level. *Nstk* is the stock of patents, *Vstk* is the stock of quality-adjusted patents, *C* is capital stock, and $\bar{q}$ is the mean value of the patent quality index for a firm. The quality index is computed using three indicators, without patent family size, with weights renormalised.

holds when we drop the year effects and we allow the relative shadow price μ to change over time. This result implies that investors have enough information to distinguish differences in mean patent quality across companies. The estimated effects of the cross-sectional differences in quality on market value are large, especially for drug and other health patents. For example, using the point estimates from the regression with *Nstk* and $\bar{q}$, we find that increasing $\bar{q}$ for a firm from the 50th percentile to the 75th percentile in the distribution would increase its market value by 9.4% for drugs, 7.7 in other health, 2.5 in electronics and 1.3 for mechanical. Improving the firm's average patent quality index from the 50th to the 95th percentile would raise its market value by 20.2% for drugs, 19.6 in other health, 7.3 in electronics and 3.9 in mechanical. This strong empirical link between the firm-specific patent quality index and market value may be useful in developing techniques for valuing patent portfolios held by firms, for trading and other purposes.

9. Concluding Remarks

In this paper we analyse the determinants of research productivity (the patent/R&D ratio) using panel data on manufacturing firms in the US for the period 1980–93. We focus on three factors: the level of demand, the quality of patents and technological exhaustion. We first develop an index of patent 'quality' using detailed information on patents in the US in seven technology fields during 1975–93. Using a factor model, we construct a minimum-variance index based on four patent characteristics – the numbers of claims, forward citations, backward citations, and patent family size – and we demonstrate that using multiple indicators substantially reduces the measured variance in patent quality. Forward citations are the most important indicator for drug patents while the number of claims is the most important in the other six technology fields. Using multiple indicators reduces the variance in patent quality by between 20 and 73%, which confirms that there is large information gain from exploiting detailed patent characteristics.

The patent quality index helps account for part of the time series variation in *research productivity at the sector level* but the explanatory power varies across technology fields. There is also some evidence that differences in research productivity at the *micro level* are inversely related to demand and patent quality, as predicted by theory. But the results are mixed – the main variable of interest, quality of patents, does not appear to have a strong impact on *research productivity at the firm level*. However, patent quality is strongly associated with variations in market value of firms, with an especially large effect in the pharmaceuticals and other health sectors. This suggests that the quality index may be useful for understanding stock market valuation of patent stocks, and for evaluating bundles of patents for cross licensing and patent pooling arrangements.

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