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The Market Valuation of Innovation: The Case of Indian Manufacturing

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Abstract

We revisit the relationship between market value and innovation in the context of manufacturing firms in a developing country, using data for Indian firms from 2001 through 2010. Surprisingly, we find that financial markets value the R&D investment of Indian firms the same or higher than it values such investment in developed economies like the US. The paper explores the use of a proxy for the option value of R&D and finds that this can account for a very small part of the R&D valuation (5 per cent at most). We also find that the market value-R&D relationship does not vary significantly across industry groups, although these results are rather imprecise.

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1. Introduction

Innovation is often considered to be the prime motive force behind economic growth. Firms spend large amounts of scare resources on innovative activities, and it is therefore desirable to know whether financial markets value innovating firms differently from non-innovating ones. Of course, innovative activity tends to be highly risky by its very nature, and may take time to yield returns. Hence the interest in examining market value, which should reflect the present discounted value of the expected profits that all such investments are likely to generate (Griliches 1981; Hayashi 1982). While there is persuasive empirical evidence that stock markets in advanced economies do value innovative activity by firms, can we expect the same in the context of less developed economies? A major reason for doubt is the fact that the predominant share of intellectual capital appears to be generated in a handful of developed economies, whether measured in terms of the inputs into innovation (such as research and development expenditure[3]) or in terms of the outputs of innovation (such as patents, WIPO 2014).

Nevertheless, the literature does recognize the existence of some innovative activity in a few developing countries, even though this may manifest itself primarily in the form of process patents, or utility models, or even smaller innovations which may not qualify for formal protection of any sort (Bogliacino *et al.* 2009). Although these innovations may be small in the larger scheme of things, they appear to have value insofar as they contribute to increasing firm productivity and profitability. Moreover, innovation may be directed towards imitation and diffusion in some cases, which may be just as important in generating profits and hence market value, even though such activity may not generate any patents. In view of these arguments, therefore, questions about the stock market's responsiveness become as relevant in the developing country context as they have historically been in the context of developed economies. Thus, are more innovative firms valued more highly than less innovative ones, ceteris paribus? Is the market valuation responsive to the success or quality of innovation spending? Does the relationship between firm market value and innovative activity vary across industries, and if so, how? Is the variation in the market value–innovation relationship across industries, if any, related to variations in economic performance across these industries? In this study we explore these questions in the context of manufacturing industries in the BRIC economy of India.

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[3] See Wikipedia, which suggests that 3 countries (US, China, and Japan) accounted for 90 per cent of R&D worldwide in 2010:
http://en.wikipedia.org/wiki/List_of_countries_by_research_and_development_spending

The prior literature on the market valuation of the intangible assets of the firm has been informative on a number of counts. Griliches (1981), using US data, reports that a dollar increase in R&D raises market value of the firm by about $2 in the long run. Bloom and Van Reenen (2002) confirm these findings with UK data, finding that patents have a significant (immediate) impact on firm market value, such that doubling the citation-weighted patent stock raises firm value (per unit of physical capital) by about 43%. Hall (1993a) highlights the fact that the relationship is not stable over time, while Hall, Jaffe and Trajtenberg (2005) report a smaller increase of about 25% with a doubling of the (normalized) stock of knowledge capital.

Further studies show that the stock market valuation differs considerably across UK industries (Greenhalgh and Rogers 2006), that the market may well value intangible assets more than a firm's tangible assets (Hall 1993), and that the average value of patents fell whereas that of trademarks rose for a sample of Australian firms (Griffiths and Webster 2006). An exception to these studies appears to be that of Hall and Oriani (2006) who report only a weak relationship for the market valuation of intangible assets in Italy. Hall (2005) emphasizes the fact that the relationship between market value and R&D (or other proxies for innovation) is that of a hedonic equilibrium rather than a causal relationship, and that interpretation of the valuation coefficient depends heavily on the assumed depreciation rate for R&D assets.[4]

It is striking, however, that the predominant bulk of the empirical evidence relates to the US, with a small fraction for some European economies such as the UK and Italy (see Czarnitzki *et al.* 2006 for a recent survey). Do similar results apply to less developed countries as well, at least those where firms are engaged in some innovative activity and the stock market is reasonably well functioning? In view of the recent trend for multinationals to locate some of their innovative activity in certain developing countries, these are questions that might be of interest to developed country entities as well.

This study contributes to this literature by adding evidence for firms in the BRIC economy of India, for which there has only been one prior such study (Chadha and Oriani 2010). We use data for a more recent time period than theirs, during which GDP growth averaged 7.5% per annum and the economy has displayed numerous signs of higher productivity (Topalova and Khandelwal 2005; and the references therein), and innovativeness (The Economist 2010). This performance inevitably leads to the question whether the higher productivity and innovativeness have been reflected in the domestic stock market movements during this period. We also have data for both the Bombay and National Stock Exchanges, whereas their data were

[4] See also Rosen (1974) for a discussion of price determination in hedonic models.

from the Bombay exchange only, in addition to a number of other differences in the model specifications and estimation techniques.

What distinguishes our context from those in the developed country literature is precisely the fact that while the firms may have become more oriented towards innovation, they have still not displayed a strong innovative performance as reflected by patents, which makes it far from obvious that the stock market would place any differential value on such innovation as there might have been. Thus, we do not follow the literature that uses patent counts – raw or citation-weighted – in studying the relationship between innovation and market performance, precisely because few Indian firms take out patents, especially product patents. Despite that, it may be the case that these firms are indeed innovative, although those innovations may not be enough of an advance over the international state of the art to merit formal protection in the form of patents. Alternatively, it is possible that patenting has been viewed in the past as somewhat ineffective and costly in India, especially prior to the expansion of subject matter coverage under TRIPS (Lanjouw 1998). It is also worth noting that India does not and never has had a "utility model" or petty patent, unlike China (Lei 2012). Therefore, because patents are not really a useful proxy for innovative success in the context of India, we explore the use of a measure based on unexpected profitability as a proxy for the "quality" of the R&D output, as well as of a measure of risk to explore the option value of R&D.

Our data cover a large sample of 380 Indian firms in the manufacturing sector during the period 2001-2010. We find that both R&D and advertising capital are highly valued in these firms, with the marginal value of R&D slightly higher than its share, and the marginal value of advertising slightly lower. We find relatively little variation across sectors in these relationships, largely because the estimates are rather imprecise once we break up the sample of firms. Most intriguing, we do find a positive impact of market uncertainty on market value, as predicted by the various real options models of R&D in the literature.

The detailed analysis is presented in the following sections. Section 2 develops the relationship to be estimated. Section 3 details the data set and explains the computation of the model variables. Section 4 discusses the detailed empirical results, as well as their economic significance. Section 5 examines the heterogeneity of the relationship across industry groups. Section 6 studies whether this variation across industries is explained by variations in expected firm/industry performance. Finally, section 7 briefly presents the conclusions.

2. The market value model

On the premise that the innovative activity of firms leads to the generation of 'knowledge capital', we measure the private value of firm innovation in terms of the marginal effect of a unit change in knowledge capital on the capitalized market value of a firm, following Griliches (1981) and Hall (1993a). If stock markets are efficient and the firm is pursuing an optimal investment strategy, in any given period the market values the assets owned by the firm (physical capital, *knowledge capital*, and *other intangible capital*) as the present discounted value of the expected returns to those assets. The notion of physical capital is well-defined (plant, equipment, inventories, etc.) and does not require further elaboration. *Knowledge capital* refers to the stock of knowhow embodied in the ideas, innovations, and inventions that a firm has title to, where this entitlement may be explicit as in the case of ownership of formal intellectual property rights such as patents, design rights, or copyrights, or else implicit as with trade secrets or other informal knowledge. *Other intangible capital* refers to factors such as reputation capital, which are too amorphous to be easily conceptualised.

In addition to the magnitudes of these capital stocks, the market's valuation of a firm could also depend on the quality of the capital stocks; just as the market value of a consignment of apples would depend both on their quality as well as their quantity. Although the quality of all three types of capital may differ across firms and over time, one would expect this to be particularly true of the stock of knowledge capital, in part because of the stochastic nature of the innovation process. For instance, some R&D investment might result in very small innovations, whereas other R&D investment might generate major breakthroughs. Even though the stock of knowledge capital generated in both these cases may be of similar magnitude, the quality of the capital stock would be much higher in the latter case.

Theory does not necessarily provide an explicit form for the market value equation except under very restrictive assumptions (Hayashi and Inoue 1991). We follow the empirical literature and use a first order approximation that allows for returns to scale. Thus, the market value of a firm (V) may be expressed as a function of its stocks of physical capital (K_P), knowledge capital (K_K), and other intangible capital (K_{OI}), as well as the quality of its capital stocks (S), according to the relation

$$V = p(K_P + \beta K_K + \gamma K_{OI} + \delta S)^{\sigma} \quad (1)$$

where p is the market premium of the firm's stock value over its replacement cost of capital, β is the shadow price of the knowledge capital, γ is the shadow price of other intangible capital, δ is the shadow price of the quality of capital, and σ is the scale factor in this valuation relation. Although one could have considered three different quality variables corresponding to the three different stocks of capital, we preferred to be circumspect in our modelling, knowing the data limitations. Taking logarithms and subtracting $ln\ K_P$ from both sides, this relationship may be rewritten as

$$\ln\left(\frac{V}{K_P}\right) = \ln(p) + \sigma \ln(K_P + \beta K_K + \gamma K_{OI} + \delta S) - \ln K_P \qquad (2)$$

or

$$\ln\left(\frac{V}{K_P}\right) = \ln(p) + \rho \ln K_P + \sigma \ln\left(1 + \beta \frac{K_K}{K_P} + \gamma \frac{K_{OI}}{K_P} + \delta \frac{S}{K_P}\right) \qquad (3)$$

where $\rho \equiv \sigma - 1$. The market premium p would be one in equilibrium (if all capital measurements are correct and there is some kind of steady state). However, usually it will differ from one because of overall macroeconomic shocks and other things that cause market volatility.

Allowing for firm and year effects, the estimating equation corresponding to the above specification is the following:

$$\ln\left(\frac{V}{K_P}\right)_{it} = \rho \ln(K_P)_{it} + \sigma \ln\left[1 + \beta \left(\frac{K_K}{K_P}\right)_{it} + \gamma \left(\frac{K_{OI}}{K_P}\right)_{it} + \delta \left(\frac{S}{K_P}\right)_{it}\right] + \alpha_i + \mu_t + \epsilon_{it} \qquad (4)$$

where α_i signifies firm-specific 'time constant' factors such as (possibly) management skills or tax rates, μ_t references factors that affect the sample firms similarly but may vary over time such as the 'depth' of stock markets, and ϵ_{it} is the stochastic error term.

Given the twin simplifying claims that $\sigma = 1$, and that $ln(1+x) \approx x$ when x is 'small',[5] as in some of the literature reviewed earlier, the model in (4) yields the alternative estimating equation:

$$\ln\left(\frac{V}{K_P}\right)_{it} \approx \beta \left(\frac{K_K}{K_P}\right)_{it} + \gamma \left(\frac{K_{OI}}{K_P}\right)_{it} + \delta \left(\frac{S}{K_P}\right)_{it} + \alpha_i + \mu_t + \epsilon_{it} \qquad (5)$$

To appreciate the difference between estimating equations (4) and (5), note that the implied (partial) elasticities of firm market value with respect to knowledge capital ($\partial lnV/\partial lnK_K$) are

$$\sigma\beta K_K/(K_P + \beta K_K + \gamma K_{OI} + \delta S) \qquad (6)$$

[5] The approximation $ln(1+x) \approx x$ holds true only for $|x| \leq 0.1$, and is quite close for $|x| \leq 0.2$. Our data include a number of observations with knowledge or other capital that is much greater than physical capital, leading to values of x that are much larger than unity, so the approximation will not be very good in those cases.

and $\beta K_K/K_P$, respectively. Thus, if in fact σ is found to be close to unity, one would expect specification (5) to yield upwardly biased estimates of the change in the capitalized market value of a firm as a result of a change in the stock of its knowledge capital. But if σ differs from unity, the elasticity estimate from (5) could be upwardly or downwardly biased. Of course, from the policy perspective total elasticities would serve better than partial elasticities, for they would include not just the direct impact of a change in knowledge capital on market value, but the indirect impacts as well. For instance, an increase in the stock of knowledge capital may lead to a reduction in physical capital insofar as it raises the efficiency of use of physical capital. If this indirect effect dominates the direct effect of the first round increase in knowledge capital, the total impact may be a decline in market value. Alternatively, an increase in the stock of knowledge capital may lead to an increase in the stock of reputation capital, and the total impact would be a larger increase in market value than in the absence of the indirect effect. Incorporating such indirect effects, however, would require a more elaborate model that allows for interactions between the different types of capital stocks, and that is beyond the scope of this paper.

To render estimating equations (4) and (5) estimable, we need to be able to measure knowledge capital, other intangible capital, and the overall quality of capital. As we discussed in the introduction, researchers have attempted to capture knowledge capital either in terms of the inputs into the innovation process – namely, research and development investment – and/or in terms of the output of the innovation process – namely, patents (and other intellectual property) that firms acquire based on the innovation (Hall and MacGarvie 2010, Greenhalgh and Rogers 2006, Hall *et al.* 2005, Bloom and Van Reenen 2002, Blundell *et al.* 1999, Cockburn and Griliches 1988). In the case of India, where patents have been relatively unimportant until recently, it is preferable to use R&D data to proxy for innovation assets, and we describe the exact construction of our knowledge capital variable using R&D data in Section 3.1 below. Similarly, we measure the stock of other intangible (reputational) capital using the firm's advertising expenditure, as described in Section 3.2 below.

The quality aspect of capital, specifically knowledge capital, has most often been captured in terms of patent citations. Citation weights are found to considerably improve non-weighted patent-based measures of knowledge capital, even though such weights are only a proxy for the relative importance of particular innovations (Hall *et al.* 2005), and may not reflect knowledge that is fully appropriable by the firm.[6] What appears to make such measures particularly

[6] In fact, as Hall *et al.* (2005) show, citations by a firm's patents to its own patents are indeed worth more than other citations.

inappropriate in the less developed country context such as that of India, is that few firms file patents at all, making patent citations a poor measure for most firms. However, a much larger percentage does undertake R&D investment, so it is useful to look beyond patent citations for a different quality or innovative success measure. As a first approximation, we represent the quality of capital (S) by the post-tax profit of firms *appropriately modified*, for better quality capital (or that associated with 'meaningful' innovations from the production viewpoint) should increase profit more than poorer quality capital (or that associated with no innovations or else innovations that are not practically useful). The method we use to construct an input-adjusted profit measure as a proxy for innovation quality is explained in Section 3.3 below.

3. Data and Variables

The data we use are based on a large sample of firms drawn from the 'Prowess' database, sold by the Centre for Monitoring Indian Economy (CMIE 2012). They pertain to firms traded on the Bombay and National Stock Exchanges of the country.[7] Only firms for which data were available for physical capital and R&D for the full ten-year period 2001-2010 were retained. This left us with data on 380 firms for the period 2001-2010, or 3800 observations.[8] To minimize the influence of outliers, observations with a market value to physical capital ratio exceeding 20 or a debt to assets ratio exceeding 5 were dropped,[9] which left us with a sample of 3551 observations relating to 380 firms, with an average of 9.4 years of data for each firm. Some of these observations clearly indicated a break in the firm data (reorganization, bankruptcy, possible major errors in reporting, etc.); when this occurred we defined a new firm going forward, to avoid measurement error bias in the dynamic models. We also required at least three years of data per firm, to ensure identification of the dynamic models, which removed a few more observations. After this data cleaning, we are left with a sample of 3,494 observations relating to 380 firms, an average of 9.2 years per firm. The firms were spread across 22 manufacturing industries (mostly) at the broad 2-digit and (some at the) 3-digit levels of the National Industrial Classification (NIC). The list of industries and the number of firms in each is shown in Appendix A.

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[7] A brief description of the Indian stock exchanges can be found at Investopedia:
http://www.investopedia.com/articles/stocks/09/indian-stock-market.asp

[8] As section 3.1 explains, the knowledge capital variable was constructed using R&D data. Though we started off with R&D data on 380 firms for the period 2000-2010, the first observation was lost in constructing the knowledge capital variable, leaving us with data for 2001-2010.

[9] Varying these thresholds did not change the results qualitatively – the signs and significance of the variables of interest remained unchanged.

The market value of firms was computed as the sum of equity and the book value of debt. Physical capital was measured as the book value of net fixed assets. Knowledge capital, other intangible capital, and the quality measure were computed as described in the next three sections.

3.1 Measuring knowledge capital

We construct the stock of knowledge capital from the flow of R&D expenditure using the usual perpetual inventory relation (Hall 1990):

$$K_{Kt} = (1-\theta)K_{K(t-1)} + RD_t \quad (7)$$

where K_K is the stock of knowledge capital, RD is research and development investment, θ is the rate of depreciation of knowledge capital, and t is the time subscript. To employ this relation, we need to resolve a number of issues. First, it is difficult to determine an appropriate rate of depreciation for knowledge capital, and we follow the literature in employing a rate of 15% per annum. Later in the paper we use 30% per annum as a robustness check. Second, if there are only one or two missing values in the R&D series for a firm, we interpolate these, since even a single missing value for R&D for a firm will cause all the associated stocks to be missing. Third, to derive the value of the stock in the 'first' period, we divide the R&D investment in that period by the sum of the rate of depreciation of knowledge capital and the pre-sample rate of growth of R&D. We employ the sample period R&D data (along with the few pre-sample observations that are available for some firms) to compute a proxy for the pre-sample rate of growth of R&D. This proxy is the average of R&D growth rates within each of the 22 industries; the values are shown in Appendix A. With the exception of a few outliers based on very small samples, they range from 0.5% for metals to 2.7% for pharmaceuticals (compared to the 8% per annum that Hall (1990) suggests for the U.S.). Having computed the value of the stock in the first period, we then employ equation (7) to derive the complete series, using R&D data deflated by the industry sales deflator.

3.2 Measuring other intangible capital

The stock of other intangible capital (K_{OI}) is even more problematic to measure, given its amorphous nature. We attempt to capture it in terms of the stock of reputation capital (K_R) generated by its advertising expenditure. To estimate this, we again employ the perpetual inventory relation. However, since such capital is subject to relatively rapid depreciation in comparison to knowledge capital, we take depreciation to be 30% per annum, and employ the sample period rate of growth of advertising expenditure to capitalize the first period of advertising expenditure. The latter is found to range between -1.0% per annum and 2.7% per annum across the 22 industry groups. Having derived the first period stock of reputation capital (using the same methodology as that outlined in the previous sub-section for knowledge capital), we then derive the reputation capital series for each firm in the sample using the perpetual inventory equation and deflated advertising data.

Because the advertising expenditure variable is zero for about 40 per cent of the observations, in the regressions we also include a dummy for zero advertising, to check whether these firms are somehow different from the others. The coefficient of this variable was invariably insignificant, leading us to conclude that these firms did indeed have zero advertising that was captured well by the zero stock measure of advertising capital.

3.3 Measuring the quality of intangible capital

Although R&D-based measures of the stock of knowledge capital may reflect the importance of the associated innovations better than patent-based measures, there may still be need to control for quality; for a given amount of R&D expenditure by different firms may not all be the same, if only because it may be spent in different ways. As a first pass, we propose to capture the quality of capital (S) by the post-tax profit of firms in excess of that predicted by its capital stocks. Because current profit is itself likely to be influenced by the stocks of knowledge capital and other intangible capital of the firm, we regress the ratio of post-tax profit to physical capital on the ratios of knowledge capital and other intangible capital to physical capital (as well as a full set of year dummies), and then take the residual from this regression as a proxy for the unobserved quality of capital.[10] This measure also accounts to some extent for (semi-)permanent differences in managerial capabilities across firms.

3.4 Sample statistics

Summary statistics for each of the variables are presented in Table 1. It is very difficult to put these statistics in perspective by comparing their magnitudes across countries, because one would be comparing physical capital of rather different kinds and vintages, knowledge capital with very different implications for raising productivity, stock markets with hugely varying depths and levels of development, and more. Nevertheless, some comparison might be helpful, for which we use the recent studies of Hall and Oriani (2006), and Chadha and Oriani (2009). We find the so-called Tobin's average q (V/K_P) to be 4.4 on average, which is much larger than the magnitudes reported by Hall and Oriani for the UK, France, Germany and Italy, and even larger than that for the US. It is also larger than the 2.4 found by Chadha and Oriani for the

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[10] Real post-tax profit is derived as post-tax profit deflated by the (industry-specific) wholesale price index for output.

earlier period in India, which doubtless reflects shifting expectations about firm growth following the various economic liberalizations of the 1990s.

The ratio of knowledge capital to physical capital (K_K/K_P) is small, averaging 0.12, as one would expect for a country where firms do not invest a great deal in R&D. It is no surprise then, that this figure is only about one-fourth or one-third that for the US, Germany and France, although it is about the same as that for the UK, and it is larger than the 0.03 reported by Chadha and Oriani for 1991-2005. The mean ratio of other intangible capital to physical capital (K_{OI}/K_P) is fairly high at 0.17, exceeding those for the US, UK, Germany, and Italy, although the category of other intangible capital is quite ill-defined and varies across different accounting systems, so this comparison is not really appropriate. The mean of the profit surprise to physical capital ratio (S/K_P) is zero by construction, but it is slightly skewed to the left, with a median of -0.03. We have no comparators as this is a new measure.

That most of the variables in question have highly skewed distributions becomes evident from considering their median values. At 3.2, the median value of Tobin's average q is much smaller than its mean. The median ratio of the stock of knowledge capital to physical capital is a mere 0.05, and that of the stock of other intangible capital to physical capital even smaller at 0.0, largely because many of the firms have no spending on advertising at all. The correlation matrix suggests a positive association between market value and the intangible capital variables, while discounting the possibility of any significant collinearity between the regressors.

The final column in the table of means shows that with the exception of the profit surprise variable and possibly the dependent variable (q), all the variables exhibit much higher variance across firms than within firms. This fact affects the identifiability of models based on within-firm data, and we will return to this issue after we present some of these results.

4. Empirical Results

4.1 Econometric issues

Several issues arise when estimating market value equations using panel data. The first is the presumed presence of permanent (or slowly changing) differences across firms that may be correlated with the regressors. The second is the fact that the capitals on the right hand side are at best predetermined and may even be contemporaneously correlated with the disturbances. The latter problem, although present in principle, is not an issue once it is recognized that the market value relationship is a hedonic one that describes the current equilibrium of supply and demand for claims on the underlying assets, and as such should be interpreted as a conditional expectation of price given the associated assets of the firm. Thus, the contemporaneous capitals will be uncorrelated with the disturbances by construction. In addition, since the capitals are very slow to adjust and the market value is determined instantaneously in the stock market, we can argue that what is being estimated by the hedonic equation is the *demand* for particular firm assets, rather than their *supply*, although of course future investment decisions will depend to some extent on current market value.

To return to firm effects, the usual solution to this problem offered in the literature is the use of estimation methods that control for permanent differences across firms. However, these methods to some extent violate the spirit of the hedonic model, whose identification is based on variations across firms in the bundles of assets they possess. A second issue is the well-known fact that within-firm R&D and intangible investments tend to be highly correlated over time, leading to even more highly correlated R&D and other intangible capitals, which leaves little variation in these variables to explain shifts in market value after firm effects are removed. Even small amounts of measurement error can, therefore, cause large downward biases in the estimated coefficients (Griliches and Hausman 1986). A second problem is that fixed effects estimation itself is inconsistent in the presence of predetermined right hand side variables, and the solution to both problems is to use GMM estimation on a first-differenced version of the model, with lagged values of the variables as instruments (Arellano and Bond 1991, Blundell and Bond 2000). This ensures that non-correlation between the dependent variable and future values of the independent variables is allowed, permanent firm effects are removed, and transitory measurement error is instrumented.

Unfortunately, in the case of the market value equation (unlike production functions), it has proved impossible in the past to find suitable instruments among the lagged variables in the model. For all these reasons, and because including firm dummies is inappropriate when estimating a pure hedonic model, our preferred estimates are those based on ordinary or nonlinear least squares, although we also present estimates of our preferred specification with fixed and random effects, in addition to some exploratory GMM estimates.

4.2 Nonlinear Specification

We first present the estimation results using equation (4), where the parameter estimates are derived using nonlinear least squares. The results are reported in Table 2. All regressions allow for year fixed effects, and report robust standard errors. Not surprisingly, the null hypothesis that all slopes are simultaneously zero is strongly rejected for all regressions. Column (1) shows that the (normalised) stock of knowledge capital (K_K/K_P) has a strongly significant positive association with Tobin's q (measured as V/K_P). Inclusion of the advertising capital variable

(K_{OI}/K_P) in the column (2) regression, and the real profit surprise variable (S/K_P) in the column (3) regression, weakens the results somewhat. In addition, both the added regressors are also found to be strongly associated with market value, whereas the dummy for no advertising and the scale parameter are insignificantly different from zero. Thus, we find constant returns to scale in the basic market value relationship. The inclusion of the 22 industry dummies in column (4) reduces the R&D coefficient by about one quarter, but leaves the advertising capital coefficient largely unchanged.

This table also shows the estimated elasticities for R&D capital and advertising capital below the coefficient estimates. Both these elasticities and their standard errors are computed using the formula in equation (6) and the "delta" method, observation by observation, and then averaged over all observations. Taking column (3) as an example, the elasticity of market value with respect to R&D capital has a mean value of 0.13 with a standard error of 0.02, although the median is much lower at 0.07 with a standard error of 0.01 (not shown). The implication of the estimates in this table is, that on average, doubling R&D is expected to increase value by about 11-14 per cent, which is very roughly equivalent to the average R&D capital share, implying a normal rate of return to R&D. In contrast, advertising capital has an average elasticity of about 0.05-0.06, which is considerably less than the advertising share, although this interpretation is clouded by the number of zeroes in this variable.

In column (5) of Table 2, we present results for a regression with all the variables lagged one period, in order to assess the extent of bias due to transitory measurement error and simultaneity. With the exception of the R&D coefficient, which declines by about 7 per cent, the results are largely unchanged (compare column 3 with column 5). In column (6), we present instrumental variable (IV) estimates with the lagged variables as instruments. The estimated R&D coefficient is approximately the same as in column (3), but the advertising capital coefficient is lower, and the profit surprise coefficient is higher. We conclude that transitory measurement error and endogeneity are more likely to affect advertising and profits than the R&D capital variable.

In the bottom panel of the table we have reported the average of the within-firm Durbin-Watson statistics. These are valid in this context, given the large sample size in the cross-section dimension. They suggest that substantial serial correlation remains in the disturbances even after inclusion of the measure of profit surprise. We will explore this symptom of misspecification later in the paper after we present the results of estimating the linear version of the model.

4.3 Linear Specification

Table 3 presents the results of estimating the model in equation (5) for the same set of specifications as in Table 2. Although the coefficient estimates are different because the specification is different, the main features of the estimation are the same. The average elasticity of market value with respect to advertising is roughly the same as in the nonlinear case, whereas the elasticity with respect to R&D capital is somewhat lower, around 0.12 for the instrumental variable estimates, as compared with 0.14 in the nonlinear case. There is still substantial serial correlation in the residuals, and the standard error of the estimate is approximately 0.55, implying that unexpected movements in market value have a standard deviation of 55%. This last result is similar to estimates that have been obtained for other countries.

4.4 Estimation with firm effects

In Table 4 we present various estimates of the linear model that allow for firm effects. For these and subsequent estimations we dropped the zero advertising dummy, as it was almost always insignificant and it does not vary much within firm. The first column shows the estimates with two-digit industry effects only, for comparison. The next two columns are those for conventional fixed and random effects models. Compared to those with industry effects only, they show the downward bias in the coefficients that is customary when working with firm panel data, higher for fixed effects than random effects, of course. This implies correlation between any left out differences among firms and the included independent variables, but it may also imply measurement error in the independent variables, whose impact is larger in the within-firm dimension.

Including firm effects also reduces the residual serial correlation, but it is still quite significant. In an effort to model this feature of our data, in columns (4) and (5) we show estimates of a dynamic panel model that includes the lagged dependent variable. Column (4) has the usual fixed effects model, which is well-known to be inconsistent in this case (Blundell and Bond 2001), while column (5) shows GMM-SYS estimates, where the level equation is instrumented with first differences of lagged variables and the first-differenced version of the equation is instrumented by lagged level variables. Clearly the fixed effects model does eliminate much of the serial correlation. In principle, the GMM estimates would be consistent for our underlying model, provided they pass two specification tests: non-correlation of the lagged instruments with their contemporaneous residuals (the AR(2) test in the table), and the over-identification test due to Sargan. Here we use Hansen's robust variant of the test for over-identification. It is apparent that the Hansen test fails dramatically, and the residuals are slightly correlated at lag 2 (p-value = 0.05).

In Appendix B, we explore various versions of the GMM system estimation in an attempt to find a set of instruments that can pass the over-identification test, but without success. The version with the lowest Sargan test (adjusted for degrees of freedom) is the one we report in Table 4. Long run R&D and advertising coefficients for this version of the model (the estimated coefficient divided by one minus the lagged log dependent variable coefficient) are slightly higher than those obtained with instrumental variable estimation (1.03 and 0.50). The scale coefficient is once again insignificant, contrary to the fixed effects estimates where it was strongly downward biased. Based on these explorations, our conclusions are twofold: first, in general it is not possible to obtain consistent estimates of the market value equation using the GMM panel methodology; and second, nevertheless, and taking all the results together, transitory measurement error does not affect the cross-section estimates very much (compare OLS and IV without firm effects).

4.5 Economic significance

Analysis of the estimates can be done in several ways and we focus on the two most common: 1) coefficient estimates, and 2) the implied elasticities. As we showed in section 2 of the paper, the elasticity of Tobin's q (V/K_P) with respect to the R&D capital intensity K_K/K_P is given by $\beta K_K/K_P$ in the linear model and by $\sigma\beta(K_K/K_P)/(1+\beta K_K/K_P+\gamma K_{OI}/K_P+\delta S/K_P)$ in the nonlinear case. The implication in both cases is that the elasticity depends on the level of R&D capital relative to tangible capital. In the nonlinear case, the equation allows for the fact that the total value of the capital is based significantly on the intangibles as well as on the tangibles, so the denominator of the term differs. In contrast, the linear model assumes that capitals other than tangible are small and do not affect the total capital measure very much. Because these elasticities depend on the R&D capital intensity, it is necessary to choose a summary statistic when presenting the results. We have chosen to use the average elasticity in the sample. In the linear case, this is just the elasticity evaluated at the average R&D capital intensity, but in the nonlinear case, it is the average over the sample of equation (6). These average values, together with the average standard errors, are shown in Tables 2 to 4, below the coefficient estimates for R&D capital and advertising capital, respectively.

The elasticity estimates pertaining to knowledge capital are fairly consistent across the alternative linear and nonlinear specifications, although somewhat lower in the linear model, as is evident from Tables 2 and 3. Controlling also for advertising and scale, the magnitude of the average estimates ranges from 0.11 to 0.14, with the preferred nonlinear IV estimate of 0.14.

This implies that a doubling of the knowledge capital stock (per unit of physical capital) would lead to an increase in market value of approximately 14%, which is slightly greater than the R&D capital share in total capital (0.12/1.12 = 0.11). The corresponding advertising capital elasticity ranges from 0.05 to 0.06, although this variable is so highly skewed and has so many zero values that the median elasticity is zero.

How do these estimates compare with those reported for the US and other developed countries? Take equation (1) with the scale coefficient σ equal to unity as the basic relation implied by the theory in Hayashi (1982) and Hayashi and Inoue (1991).[11] In equilibrium, and assuming correct measurement of the capitals, we expect two things to be true: first, adding a dollar (or rupee) to any of the capitals should raise market value by one dollar (or rupee); and second, overall Tobin's q should be unity. The implication of these assumptions is that p, β, and γ should all be equal to unity. Of course, the market is never in equilibrium, and our choice of capital measures is not perfect, but this is a useful baseline against which to compare the estimates for different countries, as it can be informative about the market for intangible assets and about the depreciation rates we use to construct them.

For US data, Hall et al. (2005) report R&D capital coefficients of 1.74 for the 1976-1984 period, and 0.55 for the 1985-1992 period. Using a slightly different formulation with beginning of year capitals and a larger dataset, Hall (2005) reports coefficients ranging between 0.4 and 0.8 for the 1974-2003 period, and Hall and Oriani (2006) report 0.8 for the 1989-1998 period. The conclusion reached in Hall (2005) is that the primary reason that these coefficients are biased downwards from unity is that the depreciation rate used to construct R&D capital is too low in some sectors, notably the information technology sectors where technical change has been quite rapid due to Moore's Law and the falling price of semiconductors over the period. The relatively high coefficient for 1976-1984 may be explained by some data problems during that period, due to the phase-in of R&D reporting, as well as disequilibrium in the market for these assets (that is, lack of sufficient R&D investment).

Hall and Oriani (2006) also report estimates of the R&D capital coefficient for France, Germany, Italy, and the UK for the 1989-1998 period. These are quite variable, ranging from insignificant for Italy to 1.92 for the UK (for France, Germany, and the US they are 0.41, 0.36, and 0.80 respectively). The UK estimate is the closest to that for Indian firms, which is 1.75 (standard error 0.31) based on instrumented nonlinear least squares (column 6 of Table 2). Estimates of this magnitude carry the strong implication that there may be underinvestment in R&D in these

[11] Many critics have pointed out that this functional form ignores the fact that there may be interaction effects among the capitals, which is true. It is best considered as a first order approximation to a more complex valuation formula. In practice, interaction effects tend to be extremely imprecisely measured.

countries, because increasing R&D would more than pay for itself in market value increases. The result itself implies either that the 15% depreciation rate used to construct R&D capital was too high (which is unlikely) or because the market requires a much higher rate of return to capital for R&D-intensive firms than for other firms, probably because of risk and uncertainty. The question then is why the markets in these countries, the UK and India, but not in other countries, behave in this way.

Although the focus of this paper is on R&D spending, we have also estimated the coefficient of advertising capital, with the estimation based on a fairly high depreciation rate of 30%. A typical estimate from the nonlinear model is approximately 0.8, which suggests undervaluation or a more rapid depreciation rate than we used to construct the variable. We can compare this estimate to some for the US. For example, Servaes and Tamayo (2013) estimate a Tobin's q regression with advertising intensity (a flow measure) and a measure of corporate social responsibility (CSR) for US firms during the 1991-2005 period, obtaining an average coefficient of about 5.5 (corrected for the average level of CSR). Converting this flow coefficient to a stock coefficient of unity (the theoretical value) would require a depreciation rate of 18 per cent, somewhat lower than what we find. Hirschey and Weygandt (1985), using data for 1977, obtain depreciation (amortization) rates for advertising that are very similar to those for R&D. On the other hand, Hall (1993b) uses a large sample of US firms for the period 1973-1991 and obtains an advertising coefficient that is one-quarter to one-third that for R&D, which suggests a much higher depreciation rate. However, she also shows yearly estimates that increase steadily to parity at the end of the period, consistent with the Servaes and Tamayo result.

5. Variation Across Sectors

One of the important determinants of variations in R&D intensity is variation across industrial sectors in the importance of R&D spending that is internal to the firm. Thus, it is useful to look at the market valuation of intangible assets at a more disaggregated level. We chose to classify our sample firms into the four groups described by Pavitt (1984):[12] (1) supplier dominated industries, (2) production intensive (scale intensive) industries, (3) production intensive specialised suppliers industries, and (4) science-based industries. The precise classification is given in Table A1. The idea behind this typology is the contention that although firms vary in their technological trajectories, there is still sufficient basis to group them in a meaningful manner. For example, Pavitt (1984) identifies groups (2) and (4) as those primarily concerned with in-house R&D, whereas group (1) innovates by acquiring new process technology, and

[12] See also Greenhalgh and Rogers (2006).

group (3) is more dependent on customers for product design and development. In our data, there is a somewhat different pattern: the R&D and advertising capital intensities for the four groups are the following:

Pavitt Sector	R&D to Physical Capital ratio	Advertising to Physical Capital ratio
Supplier-dominated industries	0.041	0.094
Scale-intensive industries	0.093	0.247
Specialised-suppliers industries	0.153	0.043
Science-based industries	0.161	0.083

Clearly the specialized suppliers in this sample are more R&D-oriented than was contemplated by the Pavitt classification. In addition, the scale intensive firms are also highly advertising intensive, which turns out to be due primarily to the brand-oriented personal care industry. Otherwise, the ranking of sectors is as we might have expected.

Table 5 presents the nonlinear estimation results for our preferred specification including R&D capital, advertising capital, and the profit surprise. We discuss the results for each Pavitt sector in turn. Group (1) is relatively small, with only 32 firms, most of which are in textiles. For this group, the R&D capital coefficient is large and extremely imprecisely determined, whereas the advertising capital coefficient is large and fairly significant. Apparently these low-tech supplier-dominated firms are quite heterogeneous in their R&D behavior (e.g., Bata, a shoe manufacturer, has quite high R&D, whereas most other firms in the sector have very little), and in its valuation. Because most of their production is consumer-oriented, advertising is quite important and valued.

The other 3 groups have significant and similar R&D capital coefficients, somewhat lower for the specialized suppliers. The average elasticities of market value with respect to R&D capital are in fact roughly equal to the R&D capital shares in the table above, which does not suggest underinvestment. The advertising capital coefficients are more variable, with that for the specialized suppliers insignificant. The others are fairly precise and the average elasticities are roughly consistent with the advertising capital shares. The coefficient of the profit surprise variable is remarkably consistent across the sectors, which implies that valuation of success or failure at achieving returns from the various firm assets is neutral across sectors.

6. Risk and Uncertainty

More than one researcher has emphasized that the uncertainty associated with the outcome of R&D programmes implies that the right way to value R&D is to use a real options approach that recognizes the option value of continuing or shutting down the various projects (Bloom and Van Reenen 2002, Oriani and Sobrero 2008). These two papers take different approaches: Bloom and Van Reenen (2002) focus on the valuation of patents and the associated option value of waiting to bring the product to market, whereas Oriani and Sobrero (2008) build a more complex model of multiple real options, due to both market (demand) uncertainty and technological uncertainty. Bloom and Van Reenen's model predicts both that profit uncertainty and its interaction with R&D or patent intensity will increase market valuation, because higher volatility increases the likelihood that expected profit from investing in development will cross the profitability threshold. However, their empirical results, based on UK firm data from 1986 to 1996, do not support this prediction, and they suggest that other causes of uncertainty, such as increased costs of capital, may be the source of the negative coefficients.

Oriani and Sobrero identify three options arising from R&D: the growth option, the option to switch, and the option to wait. The growth option is similar to that described by Bloom and Van Reenen, and is positively affected by market uncertainty. The option to switch is affected only by technological uncertainty, whereas the option to wait increases with both types of uncertainty. Although all these options suggest positive valuation for volatility or uncertainty, the basic net present value of profit flows from the firm's activities is affected negatively by uncertainty, due to the higher discount rates applied to evaluate it. They use this model to predict a U-shaped relationship between market uncertainty and market valuation of R&D, and an inverse U-shaped relationship between technological uncertainty and market valuation of R&D. Their results, based on data for UK firms from 1989 to 1998, confirm these relationships.

These two papers used a range of methods to measure firm-level volatility. Bloom and Van Reenen (2002) used a firm-specific measure of the variance of profits or the stock market return, with similar results. Oriani and Sobrero (2008) measured market uncertainty using a GARCH autoregressive model of industry output, and computed uncertainty as the absolute value of the difference between actual and predicted industry output that year. Technological uncertainty was measured using the technology cycle time developed by CHI Research (Narin 1999). Owing to data limitations, we have chosen to investigate the role of uncertainty using a slightly different uncertainty measure, but one in the spirit of the market uncertainty measures described above.

Our measure of uncertainty is based on a GARCH model whose estimates are reported in Appendix Table B3. We model the logarithm of sales as a function of its lag and the year dummies, and then allow the variance of the disturbance in this model to evolve as a GARCH process, where the coefficients depend on firm size (as measured by the log of net fixed assets). We then average the estimates of the variance of this model over industry and year, and include these in our basic market value model as a control for market uncertainty in that industry and time period.

Let y denote the log of sales, x the log of net fixed assets (K_P), and j the industry to which the i^{th} firm belongs. Then our full GARCH model is:

$$y_{it} = \mu_t + \beta_1 y_{i,t-1} + \varepsilon_{it} \tag{8a}$$

$$\varepsilon_{it} \sim \Phi(0, h_{it}) \tag{8a}$$

$$h_{it} = \exp(\mu_j + \alpha_1 x_{it}) + (\pi_0 + \pi_1 x_{it})(\hat{\varepsilon}_{i,t-1})^2 + (\gamma_0 + \gamma_1 x_{it})h_{i,t-1} \tag{8c}$$

where μ_t are the year dummies, and μ_j the industry dummies. We estimate this model by maximum likelihood on the pooled panel. Note that unlike the usual GARCH model, identification here rests on the cross-section variation rather than on the time series variation, as our panel is quite short.[13] In practice, we found that the coefficients of x (log of net fixed assets) were insignificantly different from zero in the $\hat{\varepsilon}_{t-1}^2$ and h_{t-1} terms (i.e., the second and third terms on the right hand side of equation 8c), and so we dropped those coefficients. Our preferred estimates were the following:

$$y_{it} = \mu_t + 1.00 y_{i,t-1} + \varepsilon_t$$

$$h_{it} = \exp(\mu_j - 0.24 x_{it}) - 0.06(\hat{\varepsilon}_{i,t-1})^2 + 1.08 h_{i,t-1} \tag{9}$$

These estimates imply several things: (1) sales appears to evolve as a simple random walk; (2) the variance of the sales process is highly serially correlated and growing, with the growth dampened slightly by the actual draw on the disturbance variance in the previous period; (3) the variance varies across industry (compare columns (4) and (5) in Table A3); and (4) the variance is declining in firm size as measured by net fixed assets.

Given these estimates, we computed the industry-year means of the variance h predicted by the model and included them in our market value regression, both alone and interacted with the R&D capital variable. The results, estimated by OLS with robust standard errors clustered on the firm, are presented in Table 6. The sample size is slightly different from that in Table 3 due

[13] Brownlees (2013) suggests estimating such a model for financial institutions during 2007-2009, where the panel dimension is quite short.

to the need to use lagged values in the model, so column (1) simply repeats the regression in column (3) of Table 3. Column (2) shows that the industry average sales variance enters positively in the market value equation, as predicted by the real options theory. The average value of this variable is 0.02, with a standard deviation of 0.01. Therefore, this result implies that a one standard deviation increase in the industry average sales variance is associated with a 5 per cent increase in the market value of the firms in that industry, other things equal, which seems both plausible and non-negligible. However, the standard error on this prediction is also large, on the order of 2 per cent.

This imprecision carries over to columns (3) and (4), where we investigate the shape of the relationship and the interaction with R&D. Neither effect is significant, and the standard errors are very large, so the estimates neither confirm nor rule out such a relationship. There is a slight hint that firms with higher R&D intensity receive a somewhat lower premium from uncertainty, which may indicate that they face higher discount rates or costs of capital, as suggested by both Bloom and Van Reenen (2002) and Oriani and Sobrero (2008). Column (3) also shows that the inclusion of the interaction effect reduces the raw R&D capital coefficient slightly, consistent with an interpretation that the size of this coefficient is partly due to the option value of R&D.

7. Conclusion

This paper revisits the relationship between market valuation and innovation in the context of manufacturing firms in India, using recent data for the period 2001 to 2010. In a milieu where most firms do not obtain patents, and where utility model or petty patents are not available, the concern was whether R&D-related innovations would be visible to potential investors in the stock market. Interestingly, despite these mitigating aspects, we find that the stock market does value the R&D capital created by these firms, and that the magnitude of the premium appears to be larger than that reported by studies on developed economies, with the exception of the UK. There are several possible interpretations of this result. The first and most obvious is that the depreciation rate used to construct R&D capital was too high (Hall 2005), leading to values of the independent variable that were too low. But this is unlikely, because other studies have found higher depreciation rates in most sectors in other countries.

A second explanation is that Indian firms underinvested in R&D for some reason, or that R&D turned out to be more profitable *ex post* than was predicted *ex ante*, during this period. This is certainly a possibility worth exploring in future work. It is consistent with what was observed in the United States during the period when R&D became salient to financial investors because of changes in reporting requirements (1970s-1980s). A third possibility, for which we found weak support, is that R&D-intensive firms are valued more highly due to the option value of R&D programs. In assessing this possibility it is useful to recall that our sample consists only of R&D firms, so that our finding of a positive association with a risk measure could indeed be related to the fact that they perform R&D. India may be different, but it seems unlikely to differ in that way.

Looking across sectors using the industry groupings due to Pavitt, we actually found relatively little variation in the coefficients of the market valuation that was significant. The supplier-dominated sector, a low-tech manufacturing sector, showed some differences, but it was a very small sector and the differences from the other sectors were largely insignificant.. The one implication one can draw from this result is, that the allocation of R&D across sectors is not obviously inefficient in India.

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Table 1
Sample statistics (3,494 observations on 380 firms, 2001-2010)

Variable	Mean	Median	Standard Deviation	Minimum	Maximum	Share Variance Within††
V/K_P	4.36	3.23	3.43	0.16	19.82	0.265
K_K/K_P	0.12	0.05	0.20	0.00	2.72	0.159
K_K'/K_P	0.17	0.06	0.32	0.00	5.39	0.181
K_{OI}/K_P	0.13	0.00	0.42	0.00	7.38	0.078
S/K_P	0.00	–0.03	0.31	–1.94	2.02	0.427
K_P (M rupees)	1140.7†	1110.8	1.71	2.30	1,500,007	0.050
D (K_{OI} = 0)	42.4%					0.052

Correlation Matrix

	$\ln(V/K_P)$	K_K/K_P	K_K'/K_P	K_{OI}/K_P	S/K_P	$\ln K_P$
$\ln(V/K_P)$	1					
K_K/K_P	0.330	1				
K_K'/K_P	0.338	0.906	1			
K_{OI}/K_P	0.302	0.112	0.077	1		
S/K_P	0.391	–0.004	–0.140	–0.001	1	
$\ln K_P$	–0.024	–0.131	–0.045	–0.039	0.004	1

Definitions:
V = Market value = Equity + Book Debt
K_P = Net fixed assets
K_K = Knowledge capital at 15% depreciation
K_K' = Knowledge capital at 30% depreciation
K_{OI} = Advertising capital at 30% depreciation
S = Quality of capital = Profit surprise
† Geometric mean
†† Within-firm variance as a proportion of total variance (controlling for overall year means)

Table 2
Nonlinear Regressions
Dependent Variable: ln (V/K_P)

	(1)	(2)	(3)	(4)	(5)	(6)
Regressor	NLLS	NLLS	NLLS	NLLS	NLLS, lag RHS	NLIV
K_K/K_P	2.275***	2.009***	1.790***	1.473***	1.661***	1.764***
	(0.389)	(0.375)	(0.330)	(0.336)	(0.324)	(0.329)
	[0.164] ***	[0.140] ***	[0.134] ***	[0.114] ***	[0.126] ***	[0.137] ***
	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)
K_{OI}/K_P		0.988***	0.817***	0.974***	0.815***	0.640***
		(0.224)	(0.183)	(0.191)	(0.185)	(0.145)
		[0.058] ***	[0.052] ***	[0.059] ***	[0.051] ***	[0.044] ***
		(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
D $(K_{OI} = 0)$		–0.028	–0.037	–0.004	–0.031	–0.083***
		(0.057)	(0.053)	(0.056)	(0.055)	(0.053)
S/K_P			0.508***	0.464***	0.527***	0.709***
			(0.103)	(0.101)	(0.095)	(0.031)
ln K_P	0.020	0.020	0.012	0.015	0.013	0.012
	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.016)
Industry dummies	No	No	No	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.199	0.267	0.318	0.383	0.286	0.270
Standard Error	0.608	0.582	0.561	0.536	0.571	0.579
Panel Durbin-Watson	0.266	0.285	0.316	0.345	0.360	0.346
Observations	3494	3494	3494	3494	3114	3114
Firms	380	380	380	380	380	380

Note: Robust standard errors clustered on firm in parentheses below each coefficient
Elasticity at the means in square brackets, with its standard error below it
In column (5), all right hand side (RHS) variables are lagged one year
In column (6), the instruments are the right hand side variables lagged one year
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test

Table 3
Linear Regressions
Dependent Variable: ln (V/K_P)

	(1)	(2)	(3)	(4)	(5)	(6)
Regressor	OLS	OLS	OLS	OLS	OLS, lag RHS	IV
K_K/K_P	1.025***	0.939***	0.943***	0.790***	0.912***	0.964***
	(0.136)	(0.129)	(0.116)	(0.118)	(0.118)	(0.120)
	[0.128] ***	[0.117] ***	[0.117] ***	[0.098] ***	[0.114] ***	[0.118] ***
	(0.017)	(0.016)	(0.014)	(0.015)	(0.015)	(0.015)
K_{OI}/K_P		0.368***	0.368***	0.393***	0.392***	0.385***
		(0.062)	(0.051)	(0.055)	(0.055)	(0.053)
		[0.049] ***	[0.049] ***	[0.053] ***	[0.053] ***	[0.051] ***
		(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
D $(K_{OI} = 0)$		–0.079	–0.079	–0.054	–0.076	0.039
		(0.051)	(0.047)	(0.047)	(0.049)	(0.050)
S/K_P			0.704***	0.633***	0.686***	0.500***
			(0.076)	(0.071)	(0.074)	(0.100)
ln K_P	0.006	0.007	0.007	0.010	0.009	0.011
	(0.015)	(0.015)	(0.013)	(0.015)	(0.014)	(0.014)
Industry dummies	No	No	No	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.177	0.238	0.339	0.396	0.301	0.318
Standard Error	0.616	0.593	0.552	0.530	0.565	0.559
Panel Durbin-Watson	0.265	0.282	0.364	0.385	0.413	0.335
Observations	3494	3494	3494	3494	3114	3114
Firms	380	380	380	380	380	380

Note: Robust standard errors clustered on firm in parentheses
Elasticity at the means in square brackets, with its standard error below it
In column (5), all right hand side variables are lagged one year
In column (6), the instruments are the right hand side variables lagged one year
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test

Table 4
Regressions with Firm Effects
Dependent Variable: ln (V/K_P)

	(1)	(2)	(3)	(4)	(5)
Regressor	OLS with industry fixed effects	OLS with random firm effects	OLS with firm fixed effects	OLS with firm fixed effects	GMM-SYS with lag 2+ instruments
Lagged dependent variable				0.484***	0.706***
				(0.023)	(0.036)
K_K/K_P	0.785***	0.688***	0.428***	0.315***	0.302***
	(0.117)	(0.117)	(0.140)	(0.087)	(0.071)
K_{OI}/K_P	0.413***	0.353***	0.250***	0.192***	0.146***
	(0.054)	(0.048)	(0.064)	(0.054)	(0.028)
S/K_P	0.631***	0.428***	0.352***	0.239***	0.251***
	(0.071)	(0.053)	(0.051)	(0.045)	(0.056)
ln K_P	0.011	–0.047***	–0.158***	–0.182***	–0.005
	(0.015)	(0.018)	(0.042)	(0.032)	(0.014)
Long run coefficient: K_K/K_P				0.609***	1.026***
				(0.172)	(0.221)
Long run coefficient: K_{OI}/K_P				0.372***	0.495***
				(0.107)	(0.091)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3494	3494	3494	3114	3096
Firms	380	380	380	380	379
R^2	0.395	0.372	0.381	0.522	
Standard Error Within	0.530	0.347	0.321	0.271	
Share variance across firms	0.566	0.602	0.737	0.662	
T-stat for AR(1) test	69.9***	29.0***	30.1***	1.8***	
Hansen test (df)					255.1 (206)**
AR(1) test (p-value)					–10.7 (0.000)***
AR(2) test (p-value)					2.0 (0.050)**

Note: Robust standard errors clustered on firm in parentheses.
Hausman test for correlated effects: χ^2_8 = 137.0 (p-value = 0.000).
The instruments in column (5) are lags 2 and earlier (level and differenced) of the dependent and independent variables.
***,** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test.

Table 5
Nonlinear Regressions by Pavitt Sector
Dependent Variable: ln (V/K_P)

	(1)	(2)	(3)	(4)
		Pavitt Sector		
Regressor	Supplier-dominated	Scale-intensive	Specialized-supplier	Science-based
K_K/K_P	4.24	1.80***	1.28***	1.73***
	(3.45)	(0.65)	(0.38)	(0.50)
	[0.102]	[0.093] ***	[0.152] ***	[0.155] ***
	(0.063)	(0.025)	(0.034)	(0.034)
K_{OI}/K_P	2.74***	0.73***	0.83	1.51**
	(0.89)	(0.18)	(0.56)	(0.64)
	[0.097] ***	[0.077] ***	[0.030]	[0.055] **
	(0.022)	(0.013)	(0.019)	(0.016)
S/K_P	0.41	0.50***	0.48***	0.48***
	(0.46)	(0.18)	(0.13)	(0.18)
ln K_P	0.08	0.03	–0.10***	0.03
	(0.06)	(0.02)	(0.04)	(0.02)
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.450	0.352	0.357	0.289
Standard Error	0.464	0.549	0.541	0.581
Panel Durbin-Watson	0.350	0.329	0.343	0.294
Observations	316	1,235	690	1,253
Firms	32	134	78	136

Note: NLLS regressions. Robust standard errors clustered on firm in parentheses
Elasticity at the means in square brackets, with its standard error below it
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test

Table 6
Market Value Regressions Allowing for Uncertainty
Dependent Variable: ln (V/K_P)

Regressor	(1)	(2)	(3)	(4)
K_K/K_P	0.959***	0.945***	0.925***	1.227***
	(0.110)	(0.110)	(0.120)	(0.220)
K_{OI}/K_P	0.380***	0.374***	0.378***	0.376***
	(0.050)	(0.050)	(0.050)	(0.050)
$\hat{h}$†		5.790**	–5.540	8.300***
		(2.640)	(8.310)	(3.180)
$\hat{h}^2$			203.6	
			(144.0)	
$\hat{h}$ x (K_{OI}/K_P)				–13.240
				(8.390)
S/K_P	0.727***	0.716***	0.713***	0.716***
	(0.080)	(0.078)	(0.078)	(0.078)
ln K_P	0.009	0.013	0.012	0.014
	(0.014)	(0.014)	(0.014)	(0.014)
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.329	0.335	0.337	0.337
Standard Error	0.553	0.551	0.550	0.550
Panel Durbin-Watson	0.351	0.329	0.345	0.294
Observations	3114	3114	3114	3114
Firms	380	380	380	380

Note: OLS regressions. Robust standard errors clustered on firm in parentheses
† Industry sales variance estimated as shown in Appendix A, Table A3.
***,** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test

Appendix A: Industry Coverage

Table A1
Observations by Industry and Pavitt sector

Pavitt sector	Industry	Observations	Firms	Mean R&D growth	Mean ADV growth
(i) supplier-dominated	Gems and jewellery	7	1	0.23%	4.81%
(i) supplier-dominated	Leather products	30	3	3.21%	0.60%
(i) supplier-dominated	Rubber products	20	2	0.91%	–0.88%
(i) supplier-dominated	Textiles and textile products	259	26	1.42%	–1.08%
(ii) scale-intensive	Domestic appliances	60	7	1.29%	4.11%
(ii) scale-intensive	Automobiles	101	12	1.59%	0.96%
(ii) scale-intensive	Cement	140	14	1.33%	0.78%
(ii) scale-intensive	Food and agricultural products	352	39	0.89%	0.51%
(ii) scale-intensive	Glass and glassware	25	3	–1.97%	7.93%
(ii) scale-intensive	Metals and metal products	217	22	0.51%	1.03%
(ii) scale-intensive	Other consumer goods	30	3	–2.80%	–0.17%
(ii) scale-intensive	Other construction products	171	18	0.62%	2.71%
(ii) scale-intensive	Paper and paper products	129	13	1.79%	0.08%
(ii) scale-intensive	Personal care	10	3	–2.92%	1.46%
(iii) specialized supplier	Automobile ancillaries	419	43	1.58%	1.18%
(iii) specialized supplier	Non-electrical machinery	271	35	2.59%	1.94%
(iv) science-based	Chemicals	600	62	0.79%	0.08%
(iv) science-based	Electrical machinery	129	15	2.36%	2.32%
(iv) science-based	Electronics	68	8	1.39%	0.83%
(iv) science-based	Petroleum products	64	7	–0.36%	2.58%
(iv) science-based	Drugs and pharmaceuticals	268	31	2.72%	1.76%
(iv) science-based	Plastic products	124	13	1.21%	0.09%
Total		3494	380	1.32%	1.00%

Appendix B: Robustness Checks and GARCH Estimation

B.1 GMM Estimates

Table B1
GMM-SYS regressions
Dependent Variable: ln (V/K_P)

	(1)	(2)	(3)	(4)	(5)	(6)
				Estimation Method		
Regressor	GMM-SYS with lag 2+ instruments	GMM-SYS with lag 3+ instruments	GMM-SYS with lag 3/4 instruments	GMM-SYS with lag 2+ instruments	GMM-SYS with lag 3+ instruments	GMM-SYS with lag 3/4 instruments
Lagged regressand				0.706^{***}	0.694^{***}	0.677^{***}
				(0.036)	(0.039)	(0.045)
K_K/K_P	0.991^{***}	0.711^{***}	0.668^{***}	0.302	0.326^{***}	0.238^{***}
	(0.174)	(0.130)	(0.144)	(0.071)	(0.094)	(0.110)
K_{OI}/K_P	0.336^{***}	0.287^{***}	0.287^{***}	0.146^{***}	0.169^{***}	0.165^{***}
	(0.055)	(0.073)	(0.079)	(0.028)	(0.039)	(0.039)
S/K_P	0.793^{***}	0.802^{***}	0.821^{***}	0.251^{***}	0.181^{***}	0.203^{***}
	(0.115)	(0.149)	(0.153)	(0.056)	(0.073)	(0.085)
ln K_P	0.002	–0.024	0.018	–0.005	–0.011	0.001
	(0.035)	(0.035)	(0.035)	(0.014)	(0.016)	(0.019)
Long run coefficient: K_K/K_P				1.026^{***}	1.067^{***}	0.735^{***}
				(0.221)	(0.286)	(0.312)
Long run coefficient: K_{OI}/K_P				0.495^{***}	0.553^{***}	0.510^{***}
				(0.091)	(0.133)	(0.125)
Observations	3494	3494	3494	3096	3096	3096
Firms	380	380	380	379	379	379
Hansen test (df)	279.3 (216)***	224.1 (184)***	165.1 (96)***	255.1 (206)***	220.2 (170)***	155.1 (95)***
AR(1) test (p-value)	–6.7 (0.000)***	–6.9 (0.000)***	–6.8 (0.000)***	–10.7 (0.000)***	–10.4 (0.000)***	–9.9 (0.000)***
AR(2) test (p-value)	–1.0 (0.328)	–0.9 (0.357)	–0.9 (0.365)	2.0 (0.050)**	1.9 (0.065)*	1.9 (0.065)*

Note: Robust standard errors in parentheses
The instruments are lags (level and differenced) of the dependent and independent variables – in columns (1) and (4) they include lag 2 and earlier values, in columns (2) and (5) lag 3 and earlier values, and in columns (3) and (6) lags 3 and 4 only.
***,** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test

B.2 GARCH Model for Sales

Table B2 presents the estimation results based on the GARCH model 8a-8c, outlined in the main text. Our preferred estimates are those in column (5), which allow for industry and size differences in the mean variance, but not in the lagged variances, for reasons discussed in the main text above.

Table B2
GARCH Model for log(Sales)

Parameter	(1)	(2)	(3)	(4)	(5)
β_1	0.999***	1.000***	1.002***	1.002***	1.001***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
α_0	–3.070***	–2.980***	–5.030***	–4.600***	
	(0.190)	(0.150)	(0.480)	(0.580)	
α_1	–0.064***	–0.078***	–0.321***	–0.384***	–0.235***
	(0.026)	(0.021)	(0.072)	(0.086)	(0.076)
π_0	0.904***	0.636***	–0.050***	–0.049***	–0.056***
	(0.348)	(0.075)	(0.003)	(0.003)	(0.003)
π_1	–0.040				
	(0.049)				
γ_0			1.063***	1.029***	1.075***
			(0.008)	(0.034)	(0.008)
γ_1				0.005	
				(0.004)	
Year fixed effects	In equation (8a)	In equation (8a)	In equation (8a)	In equation (8a)	In equation (8a)
Industry fixed effects	No	No	No	No	In equation (8c)
Observations	2752	2752	2752	2752	2752
Log-likelihood	466.9	466.5	1172.7	1173.2	1216.5

Parameters above pertain to equations (8a)-(8c) in the text, reproduced below:

$$y_{it} = \mu_t + \beta_1 y_{i,t-1} + \varepsilon_{it}$$

$$\varepsilon_{it} \sim \Phi(0, h_{it})$$

$$h_{it} = \exp\left(\mu_j + \alpha_1 x_{it}\right) + (\pi_0 + \pi_1 x_{it})(\hat{\varepsilon}_{i,t-1})^2 + (\gamma_0 + \gamma_1 x_{it}) h_{i,t-1}$$

where y is log(sales), x is log(K_P), j is the industry to which the i^{th} firm belongs, μ_t are the year dummies, and μ_j are the industry dummies.

5.3 Varying the Depreciation Rate of Knowledge Capital

As a further robustness check, we compute an alternative measure of the stock of knowledge capital, allowing for a 30% per annum rate of depreciation instead of the earlier 15% per annum. This transformed regressor is denoted K'_K/K_P. The results are reported in Table B3, which duplicates Table 3 (the linear model). The results are exactly as expected – the only coefficient that changes appreciably is that for R&D, which nearly doubles. Note that if R&D grows at a constant rate g and depreciates at a constant rate θ, R&D capital is simply $K_{Kt} = RD_t/(g+\theta)$, which implies that $K_K/K'_K = (g+0.30)/(g+0.15)$, so that the corresponding coefficients will be approximately in the inverse ratio of 2 = 0.30/0.15 if g is small. Our conclusion is that a depreciation rate of 15 per cent is more appropriate, as it corresponds to the expected value of the coefficient, which is unity, and is more useful for comparison to prior work by others.

Table B3
Linear Regressions
Dependent Variable: ln (V/K_P)

	(1)	(2)	(3)	(4)	(5)	(6)
Regressor	OLS	OLS	OLS	OLS	OLS, lag RHS	IV
K'_K/K_P†	1.847***	1.733***	1.703***	1.418***	1.607***	1.785***
	(0.203)	(0.191)	(0.163)	(0.177)	(0.175)	(0.182)
K_{OI}/K_P		0.379***	0.380***	0.398***	0.402***	0.395***
		(0.061)	(0.050)	(0.056)	(0.055)	(0.052)
D ($K_{OI}=0$)		–0.077	–0.077	–0.053	–0.074	0.039
		(0.050)	(0.047)	(0.048)	(0.049)	(0.052)
S/K_P			0.691***	0.624***	0.673***	0.500***
			(0.076)	(0.072)	(0.075)	(0.100)
ln K_P	0.004	0.005	0.005	0.008	0.007	0.009
	(0.015)	(0.015)	(0.013)	(0.015)	(0.014)	(0.014)
Industry dummies	No	No	No	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.184	0.249	0.346	0.399	0.304	0.325
Standard Error	0.614	0.589	0.550	0.529	0.564	0.556
Panel Durbin-Watson	0.269	0.288	0.366	0.385	0.415	0.340
Observations	3494	3494	3494	3494	3114	3114
Firms	380	380	380	380	380	380

Note: † K'_K = Knowledge capital at 30% depreciation
Robust standard errors clustered on firm in parentheses
Elasticity at the means in square brackets, with its standard error below it
In column (5), all right hand side variables are lagged one year
In column (6), the instruments are the right hand side variables lagged one year
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, for a two-tail test