R&D Intensity and Finance: Are Innovative Firms Financially Constrained?

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The assumption of perfect capital markets is least likely to be satis¯ed for the class of ¯rms which devote resources towards the development of innovative products or processes. Existing tests of the impact of capital market imperfections on innovative ¯rms cannot distinguish between two alternative hypotheses: (i) that capital markets are perfect, and that di®erent factors drive the ¯rm's di®erent expenditures, and (ii) that capital markets are imperfect, and that the di®erent expenditures of the ¯rm repond disproportionately to a common factor, namely shocks to the supply of internal ¯nance. However, an implication of the perfect capital markets assumption is that each of the ¯rm's expenditures should be equally insensitive to °uctuations in internal ¯nance. Therefore, to distinguish between these hypotheses, the sensitivity of physical investment expenditures to internal ¯nance is compared across innovative and non-innovative ¯rms. For robustness, several investment equations are estimated. The results support the hypothesis that innovative ¯rms are ¯nancially constrained.

Keywords: Investment, R&D , Financing Constraints

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1 Introduction

Arguably, the class of ¯rms for which the assumption of perfect capital markets is least likely to be satis¯ed is the class of innovative ¯rms - ¯rms which devote resources towards the production of innovative products or processes. For this reason economists have long thought that a ¯rm's supply of internal ¯nance will be one of the main determinants of its R&D expenditures. However, there is little empirical support for this belief. R&D expenditures are far less sensitive to °uctuations in internal ¯nance than other expenditures, such as investment in physical capital. In their survey of the R&D literature, Kamien and Schwartz (1982) conclude that \the empirical evidence that either liquidity or pro¯tability are conducive to innovative e®ort or output appears slim".

These ¯ndings are consistent with the assumption of perfect capital markets, together with the hypothesis that di®erent expenditures are driven by di®erent factors. However, they are also consistent with the alternative hypothesis that ¯nancially constrained ¯rms adjust di®erent expenditures disproportionately in response to a common factor, namely changes in supply of internal ¯nance. Innovative ¯rms may choose to smooth R&D expenditures by using other expenditures as a bu®er against °uctuations in internal ¯nance, either because the costs of adjusting R&D are higher or because the elasticity of the marginal bene¯t to R&D is higher than that of other factors of production.

Simply by comparing the statistical properties of the R&D and investment processes, it is not possible to distinguish between these hypotheses. However, an implication of the perfect capital markets assumption is that each of the ¯rm's expenditures should be equally insensitive to °uctuations in the ¯rm's supply of internal ¯nance. Therefore, a possible test is to compare individually the sensitivities to internal ¯nance of di®erent expenditures of innovative ¯rms with those of non-innovative ¯rms.

For the purpose of this study, an innovative ¯rm is de¯ned to be a ¯rm with a research agenda to develop global innovations. While the assumptions underlying the theory on capital market imperfections may apply equally to ¯rms which develop local innovations, much of this innovative activity may not be carried out within a formal R&D framework, and therefore would not be identi¯ed by the strati¯cation criterion which uses as a measure of R&D intensity the ratio of R&D to total investment. Firms with an average R&D intensity over 1990{1993 higher than their respective average industry R&D intensity are classi¯ed as innovative. Averaging R&D intensity is designed to minimize the potential asymptotic bias in the estimator which would arise if the strati¯cation criterion were endogenous.

The sensitivity of physical capital investment expenditures to °uctuations in internal ¯nance is then compared across the two classes of ¯rms.[1] For robustness, three di®erent investment equations are estimated. Two of these are derived from the Adjustment Costs model of investment, Tobin's Q equation and the Euler equation corresponding to the model, and the third is derived from an Accelerator model.

The results are consistent with the alternative hypothesis that innovative ¯rms are ¯nancially constrained. Both the results from the Q model and from the Accelerator model show that the sensitivity of investment expenditures to internal ¯nance is much higher for innovative ¯rms than non-innovative ¯rms. The Euler equation results show that the Adjustment Costs model is rejected for both sub-samples. However, there is evidence that the model does ¯t the data of non-innovative ¯rms better than that of innovative ¯rms.

The test in this paper is not a direct test of whether or not ¯nancially constrained ¯rms underinvest in R&D. However, viewed in conjunction with other empirical work the results provide indirect evidence that this is true. The presence of ¯nancing constraints may reduce the returns to R&D by hindering the ability of innovative ¯rms to establish a large market share for a successful innovation before competitors

[1] In my sample the number of observations on R&D across time is insu±cient to enable a similar analysis of the sensitivity of R&D to internal ¯nance. A new accounting standard, SSAP 13, obligating large ¯rms to disclose their R&D expenditures in their company accounts, came into e®ect in the UK only in 1989.

introduce rival products. The responses to a survey of innovative ¯rms in the U.S. conducted by Levin, Klevorick, Nelson, and Winter (1987) show sales and service e®orts to be one of the most important means of appropriating the returns to R&D.

The rest of the paper is organised as follows. Theoretical issues regarding capital market imperfections and the determinants of R&D expenditures and physical capital investment are addressed in section two. The empirical models and estimators are discussed in section three. A description of the sample selection criteria and the results are given in section four. The ¯nal section concludes.

2 Theoretical Issues

2.1 Capital Market Imperfections

One of the main assumptions upon which rest many of the results in the literature on capital market imperfections is the assumption of asymmetric information. When ¯rms possess more information about the quality of an investment project than do potential investors, or when the ¯rm can control variables which are not observable to the investor but which a®ect the return to the project, capital markets will be ine±cient. Arguably, such conditions are most likely to be satis¯ed by ¯rms which devote resources to innovating. The production of an innovation is more di±cult to predict from observable inputs than is the production of most other types of output. There is greater scope for inputs which are not observable to all parties, such as a researcher's skill level or the choice of research agenda, to a®ect the returns to an investment in the development of an innovation. Moreover, given that many innovations are produced in very technologically advanced industries, there are potentially large di®erences in the information sets of the di®erent parties to a ¯nancial contract. This will limit the extent to which monitoring can reduce possible agency problems.

Under the assumption that managers have an informational advantage over investors regarding the quality of the potential investment projects the ¯rms may undertake, Myers and Majluf (1984) show that equity markets will be ine±cient. Given its informational disadvantage, the market requires all ¯rms to issue equity at a discount. The discount can imply such a heavy dilution of the existing shareholders stake in the existing assets of the ¯rm that it is not in their interest to undertake a positive NPV project. Stiglitz and Weiss (1981) show that asymmetric information leads to similar outcomes in debt markets. Again the key assumption in this model is that the market is at an informational disadvantage vis-µa-vis the ¯rm regarding the quality of the investment project for which debt ¯nance is being sought (speci¯cally, projects di®er according to the variance of their returns). Creditors react to excess demand by rationing some borrowers rather than by raising interest rates. Raising interest rates increases the riskiness of the average investment project in the pool of credit applicants because applicants with \safe" projects drop out. Again in equilibrium positive NPV projects will be forgone.

An inherent part of an R&D project is the accumulation of knowledge. Knowledge is a public good, and the existence of patent systems is typically justi¯ed as a mechanism whereby ¯rms which invest in knowledge capital can protect their investment (in legal parlance, the ¯rm's intellectual property). However, patents work only imperfectly. In a survey of R&D investing ¯rms in the U.S., Levin, Klevorick, Nelson, and Winter (1987) report that managers believed non-patent methods of protecting knowledge capital to be more important than patents. Those methods include the lead time a ¯rm has over its rivals (i.e. di®erences in their knowledge capital), and the speed with which they accumulate knowledge. According to their study, innovative ¯rms clearly possess intellectual property which is unprotected by patents, and which has an important impact on the value of its investment projects. It is equally true that such property cannot be appropriated by another party; it is the inalienable property of the ¯rm.[2]

Hart and Moore (1994) have shown that, even in a model of debt with full information,

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[2]Strictly speaking, this type of intellectual property is the asset of the research sta® within the ¯rm. For simplicity, I assume that the researchers are also owner-managers of the ¯rm.

positive NPV projects may still be forgone. The results of this model rest upon two assumptions: ¯rst, that the entrepreneur possess an asset which a creditor is unable to appropriate, and second, that this \inalienable" asset a®ect the value of assets that can be appropriated (i.e the ¯rm's collateralisable assets). The threat that the entrepreneur may withdraw the inalienable asset from the production process can limit the debt capacity of the ¯rm below the cost of the investment project.[3] Therefore, whether or not such an investment project is undertaken depends upon the amount of internal ¯nance available to the entrepreneur.

Even if innovative ¯rms could mitigate the e®ect of capital market imperfections by, for example, revealing some of their knowledge capital to parties outside the ¯rm, doing so may not be optimal. Levin, Klevorick, Nelson, and Winter (1987) report that secrecy is also an important way ¯rms protect their intellectual property, particularly for process innovations. Indeed, the importance of lead time over rivals suggests that revealing information may be reduce the value of the innovation. Bhattacharya and Ritter (1983) and Horstmann, MacDonald, and Slivinski (1985) present theoretical models in which it is not optimal for a ¯rm to reveal all of its information, either through a third party such as a ¯nancial intermediary, or through patenting its innovations.

These theoretical arguments imply that internal funds will be an important source of ¯nance for innovative ¯rms. However, to what extent will ¯rms be able to separately ¯nance investment projects other than R&D projects? Firms which conduct R&D typically produce the product innovations and implement the process innovations which are the corresponding outputs of the ¯rm's R&D input. Hence, the ¯rm's innovations will a®ect the returns to its physical capital, and the returns to investment in new physical capital will depend upon the ¯rm's future innovations. It is therefore

[3]The strength of the threat to withdraw the inalienable asset depends upon the outside options available to the two parties. Levin, Klevorick, Nelson, and Winter (1987) report that one of the main channels of information spillover is through the hiring of rival ¯rms R&D sta®. This would indicate that the ¯rm's bargaining position vis-à-vis creditors is strong. Other things being equal, such a ¯rm's debt capacity would be low.

unlikely that firms will be able to separately finance R&D projects and physical capital investment projects. If capital markets are imperfect for R&D projects, those imperfections will impact upon the firm's physical investment projects due to the interdependence of the returns to the two projects.

2.2 Determinants of R&D and Investment

The above theoretical arguments suggest that fluctuations in internal finance should be highly correlated with at least some of the expenditures of innovative firms. The arguments do not imply that all expenditures will be sensitive to internal finance. Moreover, they do not place any testable restrictions on differences in the statistical properties of different expenditures. Therefore, one cannot test the hypothesis of imperfect capital markets by comparing the statistical properties of different expenditures such as R&D and physical capital investment.

There is considerable empirical evidence showing that actual expenditures on R&D and physical capital respond to different, as well as to common, factors. For example, Lach and Schankerman (1989) show that while both R&D and investment respond to a shock which is permanent (in the sense that its impact is highly persistent), investment is influenced strongly by an idiosyncratic shock as well.[4]

Such evidence is consistent with both the null and alternative hypotheses. In general, under the null hypothesis that innovative firms are not financially constrained, desired expenditures on R&D and physical capital will respond to different, as well as common, factors. For example, physical capital may be subject to productivity shocks which do not affect the expected marginal value of knowledge capital. How-

[4]Similar evidence has been reported by other authors. Pakes (1985) found that changes in R&D were associated with large changes in the market value of the firm, indicating the market expected a persistant change in profits. Himmelberg and Petersen (1994) found evidence that R&D expenditures were sensitive to permanent (i.e highly persistent) changes in cash flow, not transitory changes. They interpreted this as evidence of higher costs of adjustment for R&D, although it is also consistent with the above null hypothesis.

ever, it is equally plausible that ¯rms adjust only their physical capital expenditures in response to a shock to its internal ¯nance. Under the alternative hypothesis, the responses of actual expenditures on R&D and physical capital to shocks to the ¯rm's internal ¯nance will be proportionate only in the restricted case where the functions governing the ¯rm's production and its costs of adjusting inputs are homothetic. There does not seem to be much evidence that this restriction is valid. If innovative ¯rms' production functions were homothetic, the ratio of R&D to output wou the common determinant of internal ¯nance shocks. Therefore, an appropriate test to distinguish between them is to examine the sensitivity of the expenditures to changes in the ¯rm's supply of internal ¯nance. In view of the lower within-¯rm variability of R&D, performing this test on investment will be more powerful.

3 Empirical Speci¯cation

3.1 Model Speci¯cation

To distinguish between the alternative and null hypotheses, this paper examines how di®erent empirical models of investment ¯t the data of di®erent subsamples of ¯rms. Since investment decisions are forward looking, these models should be structural in the sense of Lucas. Otherwise it is not theoretically possible to isolate the e®ect of shocks to the supply of internal ¯nance from the e®ect of new information contained in changes in internal ¯nance regarding the future marginal pro¯tability of capital (demand shocks). In common with much of the empirical investment literature, two of the empirical models used in this are derived from the Adjustment Costs model of investment (expositions of this model are given in Eisner and Strotz (1963), Lucas (1967), and Gould (1968)): the Q model, and the Euler equation corresponding to the costs-of-adjustment model.

The Q model of investment is a test of the ¯rst-order condition of the Adjustment Costs model under two assumptions: (i) linear homogeneity of the pro¯t and cost of adjustment functions, and (ii), perfect capital markets.[5] Under the second assumption the market value of the ¯rm equals its fundamental value (the expected present discounted value of future cash °ows), while under the ¯rst condition the

[5] These functions are de¯ned in the appendix, where both the ¯rst-order condition and the Euler equation are derived. Su±cient conditions for the linear homogeneity of the pro¯t function are constant returns to scale and perfect competition in all input and output markets. An assumption in this particular derivation of the model is that newly installed capital becomes productive immediately.

average and marginal products of capital are equal (see Lucas and Prescott (1971), Hayashi (1982)). The following quadratic form for the cost of adjustment function is commonly assumed, $G(I; K; \varphi) = \frac{\varphi}{2}(\frac{I}{K} - \alpha - \epsilon)^2 K$, where I is investment, K the existing stock of capital, α a firm specific constant, and ϵ a random variable. With this functional form, the first order condition can be written as,

$$\left(\frac{I}{K}\right)_{it} = \alpha_i + \beta Q_{it} + \epsilon_t; \tag{3.1}$$

where β is the inverse of the marginal cost of adjustment, φ, and Q_{it} is the ratio of the market value of the firm to the replacement cost of its existing assets.

Under the null, the theory predicts that Q_{it} is a sufficient statistic for the firm's investment rate. Under the alternative hypothesis, capital markets will still be weak-form efficient. In this case it is not generally true that the market value of the firm will equal the fundamental value. However, Q_{it} will represent the expected marginal value of capital conditional on all public information.[6] Therefore, under the alternative, the reported cash flow variable reflects the effect of shocks to the firm's supply of internal finance. Moreover, instrumenting cash flow with its own lagged values ensures that any possible informational affect is eliminated.[7]

An advantage of the Q model is the existence of a well specified alternative. However, in practice the measurement error under the alternative hypothesis may be very large. Factor analytic empirical studies show that the factor common to the stock price and investment accounts for only a small percentage to the total variation in the stock price. The vast majority of price variation is accounted for by an idiosyncratic factor (see Blanchard, Rhee, and Summers (1990) and Lach and Schankerman (1989)). An advantage of estimating the Euler equation is that it can be done without using

[6] Under the alternative hypothesis, Q_{it} can be thought of as measuring with error the fundamental value of the firm. Valid instruments will depend on the degree of serial correlation in both the measurement error and ϵ.

[7] In theory, there will be no such effect if all variables are dated under according to the same convention. However, in the empirical work in this paper, Q_{it} refers to the beginning-of-period whereas all other variable dated t refer to end-of-period values.

observations on the firm's stock price.

To make the Euler equation estimable, either a functional form for the profit function can be assumed (as in Abel (1980)), or the linear homogeneity assumption made above can be maintained (as in Bond and Meghir (1994)). In fact, the linear homogeneity of the profit function can be relaxed to allow for imperfect competition.[8] Using the same functional form for the costs of adjustment function, the Euler equation can be written as,

$$\left(\frac{I}{K}\right)_{it} = \beta_1 \left(\frac{I}{K}\right)_{it-1} + \beta_2 \left(\frac{I}{K}\right)^2_{it-1} + \beta_3 \left(\frac{CF}{K}\right)_{it-1} + \beta_4 \left(\frac{Y}{K}\right)_{it-1} + \alpha_i + d_t + v_t; \quad (3.2)$$

where I represents investment, CF cash flow, and Y output. All variables are weighted by the firm's capital stock, K. The term α_i picks up firm specific effects, while d_t is a time dummy to control for fluctuations in the omitted price and user cost of capital terms (see Appendix). One interpretation for the error term, v_t, is that it is an expectational error (i.e it represents the effect of new information acquired in period t). As such v_t should be i.i.d. However, v_t may also summarise the effects of random variables such as the error term in the costs of adjustment function, and therefore may not be i.i.d.

The theoretical model places the following restrictions on the signs of the coefficients in the above equation: (i) the coefficient on the lagged investment rate, β_1, is positive and greater than one; (ii) the coefficient on the square of the lagged investment rate, β_2, is negative and greater that one in absolute value; (iii) the coefficient on cash flow, β_3, is negative, and (iv) the coefficient on output, β_4, is positive if there is imperfect competition (otherwise it is zero). A disadvantage of the Euler equation test is that the model is not well specified under the alternative. In other words, if the restrictions are not satisfied it is not possible to determine which assumption, linear homogeneity or perfect capital markets, has been violated.

[8] Both the production function and the costs of adjustment functions are still assumed to be linear homogeneous, and input markets perfectly competitive.

As a check on the results of the regressions based on the Adjustment Costs model, a third and simpler model of investment is estimated: the Sales Accelerator model. A theoretical justification for this model can be derived under similar assumptions above, but without the assumption of adjustment costs (a good reference for this and other investment models is Nickell (1978)). Dropping that assumption eliminates the need to deal with expectations since the capital stock can be costlessly adjusted instantaneously. The factors driving investment are then the exogenous processes driving prices, the user cost of capital, and demand for the firm's output. Moreover, with no adjustment costs and under the null, changes in output are driven entirely by exogenous shocks to demand. The empirical model can be written as,

$$\left(\frac{I}{K}\right)_{it} = \alpha_i + d_t + \left(\frac{\Delta Y}{Y}\right)_{it} + \mu_t \tag{3.3}$$

where again α_i picks up a firm specific effect, d_t picks up fluctuations in prices and the user cost of capital, and the growth rate of sales, $\Delta Y/Y$, captures exogenous demand shocks. Under the null hypothesis, cash flow contains the same information as the growth rate of sales and therefore should not enter significantly. However, under the alternative hypothesis cash flow will enter significantly if financing constraints are binding.

3.2 Estimators

An instrumental variables estimator is required for both of the empirical models derived from the Adjustment Costs model. In the Q model, if ϵ_t is realised at the beginning of the period (i.e. is in the firm's information set in period t), then Q_{it} will be endogenous through the effect ϵ_t has on the actual amount of capital installed.[9] Valid instruments for Q_{it} will be variables with a lag or lead of j or greater, where j is the lowest lag for which $cov(\epsilon_t; \epsilon_{t-j}) = 0$. The theory places no restrictions on serial correlation in the ϵ process.

[9]The error term, ϵ_t, is interpreted as factors which are observable to the firm, but not to the econometrician. Alternatively, it can be assumed that ϵ_{t-1} is in the firm's information set and that ϵ is serially correlated.

Similarly in the Euler equation, the standard within-groups estimator is biased due to the presence of the lagged dependent variable. Differencing the model to remove the fixed effect necessitates the use of instruments for the lagged dependent variable terms. As in the estimation of the Q model, lagged values can be used as instruments. The validity of the instruments will depend on the degree of serial correlation in the error term.

Unlike the first two models, an instrumental variables estimator is not theoretically required for the Sales Accelerator model, since sales growth in that model is strictly exogenous. However in this model, as in the previous two models, under the alternative hypothesis the cash flow terms may be endogenous. These terms are instrumented in all regressions, and can therefore be interpreted as the effect of predictable cash flow on investment.

All of the above models are differenced to remove the firm-specific effect, α_i, and an Anderson-Hsiao estimator is used (Anderson and Hsiao (1982))(except for the basic Sales Accelerator model, which is estimated by OLS). While this estimator is not efficient, it is consistent. Monte Carlo experiments done by Arellano and Bond (1991) show that in dynamic models the loss of efficiency is not great if the coefficient on the lagged dependent variable is not too close to one (a condition which is satisfied in all of the estimated dynamic models).

The Anderson-Hsiao estimator differs from the efficient estimator in two ways. First, the GMM estimator which imposes the moment condition for each available instrument in each time period is the efficient estimator in the class of instrumental variable estimators which use only linear combinations of instrumental variables (see Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991)).[10] In contrast, the

[10] For example, if there were five observations per firm, and instruments of lag two or greater were valid then this estimator would impose six moment conditions: there is one valid instrument for the observation in period 3 (lag 2), two for the observation in period 4 (lags 2 and 3), and three for the observation in period 5 (lags 2, 3 and 4). If the instrument set were restricted to only the second lag, there would be three moment conditions.

the moment conditions imposed by the Anderson-Hsiao estimator are the sum of the individual time period moment conditions corresponding to a particular lagged value of the instrument (i.e. there is one moment condition per instrument, as opposed to one moment condition for each year in which the instrument is available).

Second, the e±cient GMM estimator uses an estimate of the optimal weighting matrix based on the residuals generated by an initial consistent estimator. The (arbitrarily chosen) weighting matrix for the Anderson-Hsiao estimator has two's on the principal diagonal, and one's on the main o®-diagonals.[11] The standard errors of this estimator are White-corrected for heteroscedasticity.

The choice of the less e±cient Anderson-Hsiao estimator was made for two reasons. First, the standard errors of the e±cient GMM estimator produced by the estimation routine employed in this paper are biased downwards.[12] Second, in practice the large set of valid instruments typically available to the e±cient estimator can raise di±culties. One of the problems encountered in this paper was the unreliability of test statistics, such as the Sargan statistic, when a large set of instruments were used.

One of the speci¯cation tests reported is the Sargan statistic (referred to as the J-statistic in Hansen (1982)). However, because the validity for the instruments depends crucially on serial correlation in the error term, two estimates of this serial correlation are also reported: a test for ¯rst-order serial correlation, the m1 statistic, and a test for second-order serial correlation, the m2 statistic (see Arellano and Bond (1991)). If the error term in the undi®erenced model is white noise, then the error term in the di®erenced model should exhibit ¯rst-order, but not second-order, serial correlation.

[11] If the models are exactly identi¯ed, then the orthogonality conditions are set exactly to zero and the weighting matrix is the identity matrix.

[12] Estimation was performed using the DPD routine developed by Manuel Arellano and Stephen Bond (Arellano and Bond (1988)). The bias in the standard errors of the two-step GMM estimator is reported in Arellano and Bond (1991).

4 Data and Results

4.1 Sample Design

The empirical methodology is the same as that which is commonly used in the literature on liquidity constraints and investment. A sample of ¯rms is ¯rst identi¯ed, and then strati¯ed according to a particular criterion, which in this analysis is whether or not the ¯rm is innovative. Conclusions are then based on a comparison of the results from the group of \controls" (non-innovative ¯rms) with those from the group of \experimentals" (innovative ¯rms). This methodology requires sampling choices be made concerning the class of ¯rms from which the initial sample is drawn, and the criteria used to stratify the sample.

For the purpose of this study, an innovative ¯rm is de¯ned to be a ¯rm with a research agenda to develop global innovations.[13] While the assumptions underlying the theory on capital market imperfections may apply equally to ¯rms which develop local innovations, much of this innovative activity may not be carried out within a formal R&D framework, and therefore would not be identi¯ed by a strati¯cation criterion based on ¯rm R&D expenditures. For this reason each ¯rm, even those in the control group, was required to have at least one positive observation on R&D to be included in the sample. This is designed to reduce the number of ¯rms which develop local innovations (and therefore may be ¯nancially constrained), but which either do not expense the costs under R&D in their accounts, or are not required to report their R&D expenditures.[14]

[13]Paul Stoneman o®ers the following distinction. \ Global innovation would be the ¯rst occurrence in an economy (or even wider in the world economy) of a particular event...Local innovation would be the the ¯rst occurrence of the event in the unit of observation." Stoneman (1995), p.3.

[14]In January 1989 a new standard of accounting practice was introduced in the United Kingdom, the Statement of Standard Accounting Practice (SSAP 13), which requires certain ¯rms to report their R&D expenditures. SSAP 13 did not alter the conditions under which R&D may be capitalized rather than expensed. Few ¯rms in the sample reported capitalized R&D expenditures.

By focusing on the aims of the ¯rm's research agenda, the de¯nition of an innovative ¯rm includes ¯rms which may not actually develop a global innovation. The successful development of an innovation may serve to mitigate the e®ect of capital markets imperfections. For example, in an hidden information context successful innovation may reveal the ¯rm's type. Consequently, constraints on the access to external capital may not di®er between groups of ¯rms identi¯ed as innovative and non-innovative according to a de¯nition based on innovative output (patent counts or innovation counts).[15]

Accordingly, the strati¯cation criterion appropriate for this study uses only information on a ¯rm's inputs to the innovation process. The following measure of a ¯rm's R&D intensity was used: the ratio of R&D expenditures to total investment (physical investment plus R&D expenditures). Innovative ¯rms were de¯ned to be those ¯rms whose R&D intensity was above its corresponding industry mean for each year in which the ¯rm reported a positive R&D expenditure. Implicit in this strati¯cation criterion is the assumption that ¯rms attempting to develop global innovations must spend more on R&D than other ¯rms within the same industry. Firms with a low R&D intensity are assumed to have research programs aimed at replicating the existing technology of competitors. Using this criterion, 42 of 144 ¯rms in the sample were identi¯ed as innovative. Tables 1a{1c show the breakdown of observations for the entire sample, and for the two subsamples. Details of the sample selection procedures are given in the Data Appendix.

4.2 Results

Tables 2 and 3 show the results for the Q regression (equation (3.1)) for innovative and non-innovative ¯rms respectively. Comparing the ¯rst column of the two tables we see that the point estimates of Q are very similar for the two classes of ¯rms. However,

[15] Using data on actual innovations, Blundell, Gri±th, and Van Reenen (1993) found that the probability of a ¯rm producing an innovation in a period is greatly increased if the ¯rm had innovated in previous periods.

the test statistics for the class of non-innovative firms clearly reject the instrument set. The Sargan statistic rejects at the 1% level. The m2 statistic narrowly fails to reject at the 5% level. To deal with the potential serial correlation, it is assumed that the error term in equation (3.1) follows an AR(1) process, $\epsilon_t = \rho\epsilon_{t-1} + \nu_t$; and a Cochrane-Orcutt transformation is performed. Using equation (3.1) to solve for ϵ gives,

$$\left(\frac{I}{K}\right)_{it} = (1-\rho)\alpha_i + \beta Q_{it} + \rho\left(\frac{I}{K}\right)_{it-1} - \rho\beta Q_{it-1} + \nu_t. \qquad (4.4)$$

This specification is used in column 2 of Table 3. Although the m2 statistic now gives no indication of second order serial correlation flow terms at the 1% level.

These results are consistent with the hypothesis that innovative firms either have a preference for internal finance or face greater constraints on their access to external capital. The significance of cash flow for non-innovative firms indicates that the assumption of perfect capital markets may be inappropriate for this class of firms as well. It is possible that some innovative firms were included in the non-innovative group.[16]

The results for the Euler equation regression, given in Table 4, are consistent with the Q equation results.[17] Looking at the first and fourth columns, it can be seen that the Adjustment Costs model does not fit the data well for either class of firm. None of the estimated coefficients are within two standard errors of the range predicted by the theory. Moreover, the coefficient on the cash flow term has the wrong sign. The Euler equation results show that the previous results are not due to the poor empirical performance of Q.

As with the Q equation results, there is some evidence that the model fits the data for non-innovative firms somewhat better than that for innovative firms. In the second and fifth columns, the second lag is removed from the set of instruments. Although the specification tests do not reject the validity of instruments dated $t-2$, dropping these instruments changes the point estimates of the two lagged endogenous variable terms for the non-innovative class.[18] The point estimates are now within the range

[16] The estimated coefficients on the cash flow terms of non-innovative firms is very close to those reported by Blundell, Bond, Devereux, and Schiantarelli (1992) in their study of the Q equation using UK manufacturing firms.

[17] In their paper on firm investment, Bond and Meghir (1994) show that the firm's debt policy can be incorporated into the Euler equation by including the term $(B/K)^2_{t-1}$. All the regressions reported in Table 4 were run with this term included, but its coefficient was never statistically significant.

[18] If the error term were an MA(1) process, values of the the regressors in period $t-2$ would be invalid, but higher order lags would remain valid. Most of the bias arising from using the invalid $t-2$ instruments is likely to be manifested in the coefficients on the lagged endogenous terms.

predicted by the theory. Though less precisely estimated, both coe±cients are still signi¯cant at the 5% level. By comparison, in column 5 the coe±cients estimated from the data on innovative ¯rms remain well outside the range predicted by the theory. Moreover, for this class of ¯rms the only coe±cient which is statistically signi¯cant in either speci¯cation is that of cash °ow.

It is not possible to deduce from this evidence which of the assumptions underlying the model is violated.[19] However, the most likely reason for the di®erence in the model's ¯t to the data of the di®erent classes of ¯rms the greater impact of ¯nancing constraints on innovative ¯rms. In columns 3 and 6, the cash °ow term is replaced by free cash °ow (the di®erence being interest payments and taxes). This has no e®ect on the coe±cient estimates for non-innovative ¯rms, but increases the value of the estimate of the cash °ow coe±cient of innovative ¯rms. This indicates that revenue lost to taxes and interest payments a®ects the investment expenditures of these ¯rms. Second, while it is plausible that the costs of adjusting physical capital may be associated with R&D intensity, it is more likely that much of the variation in adjustment costs is between industries. Since the strati¯cation rule compared a ¯rm's R&D intensity to its industry average, most industries are represented in both subsamples. To control for any residual inter-industry variation industry dummies were included in the estimation.

The results for the Accelerator Model, presented in Table 5, also support the hypothesis that innovative ¯rms are ¯nancially constrained. Columns 1 and 4 show the results for the basic model, estimated using ordinary least squares. The sales growth term is positive and signi¯cant in both regressions. The results with free cash °ow included in the speci¯cation are in columns 2 and 5.[20] As with the Q model results,

However, the Hausman test statistic also fails to reject the validity of these instruments, taking a value of 3.118 with 2 degrees of freedom.

[19]Note that because the (Y/K) controls for either imperfect competition or departures from a constant returns to scale production function, the only remaining assumptions are the assumed form of the cost of adjustment function, and perfect capital markets.

[20]Unlike the Q model, there is no theoretical argument that the sales growth term is endogenous.

the e®ect of free cash °ow on the investment of innovative ¯rms is quantitatively much larger (0.676 as opposed to 0.2996). Although this is not a forward looking model, by instrumenting free cash °ow any information about the future marginal productivity of capital has been purged from the contemporaneous free cash °ow terms. The results in columns 3 and 6 show that lagged free cash °ow is also signi¯cant, although it has a negative sign for innovative ¯rms. This con¯rms that the results in the Q equation regressions are not due to the poor empirical performance of the measured Q variable.

4.3 Robustness Checks

Reservations concerning the validity of the inferences made thus far arise from two potential problems in the sample design. The estimator used may be inconsistent due to endogenous sampling (selection bias). Alternatively, the results may be spurious due to inadequate control of other exogenous ¯rm characteristics which a®ect the ¯rm's access to external capital.

There are two potential sources of selection bias: (i) survivorship in the panel, and (ii) the endogeneity of the sample strati¯cation rule. The ¯rst source is due to the new accounting standard, SSAP 13. Prior to its introduction in 1989 no ¯rm was obligated to report R&D expenditures. Consequently, ¯rms which conducted R&D prior to 1990, but which did not survive until this time, are excluded from the sample. Moreover, SSAP 13 does not require all ¯rms to report their R&D expenditures, though it applies to all the ¯rms in this sample.[21]

The free cash °ow terms, however, may still be endogenous. Therefore, cash °ow is instrumented with its lagged values in the subsequent regressions. The m2 statistic indicates that these instruments may not be valid for low intensity ¯rms. A Cochrane-Orcutt transformation was performed. This eliminated the second order serial correlation. The point estimates of the coe±cients on the free cash °ow and sales growth terms were unaltered.

[21]The standard applies \in e®ect to companies which are public limited companies, or special category companies, or subsidiaries of such companies, or which exceed by a multiple of ten the criteria for de¯ning a medium-sized company under the Companies Act 1985".

Unfortunately, simple tests of selection bias suffer heavily from a lack of power.[22] However, it is not necessarily the case that non-randomness in the sample implies that conventional estimators are inconsistent. Inconsistency results only if the sample selection rule is dependent on the endogenous variables in the structural equations.[23] Unlike samples derived from survey data such as the income experiment data used for early studies of attrition bias (e.g. Hausman and Wise (1979)), there are few a priori reasons to believe this is true for this sample. Moreover, potentially biased estimates due to survivorship or attrition affects all studies which use panel data collected from publically available company accounts. Restricting analysis to balanced panels, as many studies have done, does not affect the consistency of the estimator.

Another possible source of selection bias is the potential endogeneity of the rule used to split the sample into high and low intensity classes of firms. Since the measure of R&D intensity was defined to be the ratio of R&D to R&D plus investment, this measure may not be independent of the endogenous variables in the structural equations (i.e. $\Delta(I/K)_{it}$). However, the potential asymptotic bias for the fixed-effect estimator used in the analysis may not be very severe. Since the the stratification rule compared the average R&D intensity over the period 1990 to 1993 with the firm's corresponding industry average over the same period, most of the variation in R&D intensity is between-firm.[24] Firm specific fixed effects explain approximately 95% of the variance of R&D intensity.[25] The greater the proportion of R&D intensity

[22] Verbeek and Nijman (1992b) suggest "quasi-hausman" tests comparing, for example, the estimates from a fixed effect estimator for the unbalanced panel and the balanced sub-panel. The term "quasi-hausman", and the tests' lack of power, stem form the fact that unlike hausman tests both estimators are inconsistent under the alternative.

[23] For a detailed discussion see Verbeek and Nijman (1992a).

[24] The averaging will have removed much of the within-firm source of variation. However, because the period over which R&D intensity was averaged is so short (for some firms there was only 1 observation) not all of the within-firm source of variation will have been removed.

[25] This estimate is from a simple one way error components model. All data on R&D intensity was used, even that for firms excluded from the sample. Other empirical studies have found similar results. For example, using a slightly different measure of R&D intensity, the R&D to sales ratio,

explained by a ¯rm-speci¯c e®ect, the smaller will be the asymptotic bias of the ¯xed-e®ect estimator (see Verbeek and Nijman (1992b)). In the limit the ¯xed-e®ect estimator will be consistent.

Another reservation about the conclusions drawn is the degree to which they may be ascribed to factors other than innovativeness. One factor which has been commonly found to be associated with the presence of ¯nancing constraints is ¯rm size. Table 6 show the average ¯rms sizes for the two groups at in 1987 and 1993 (over these seven years the panel was at its maximum width). Looking at either the book value of the capital stock or total sales the average non-innovative ¯rm is twice as large as the average innovative ¯rm. Perhaps the di®erence in the results of the structural regressions is due to this size di®erence.

To check this the sample was strati¯ed according to the initial observation of a ¯rm's capital stock. The 48 ¯rms in the lowest third of the distribution were classi¯ed as small. The results of the Q equation regressions for small and large ¯rms are given in table 7. In contrast to many of the results in the investment literature, the coe±cient on free cash °ow is insigni¯cant for small ¯rms, but is strongly signi¯cant for large ¯rms. Since the division of small and large ¯rms is roughly proportionate across the innovative and non-innovative classes of ¯rms (thirteen small ¯rms are in the group of innovative ¯rms) it is unlikely that those results may be attributed to the discrepancy in average size.

5 Conclusions

The assumption of perfect capital markets is least likely to be satis¯ed for the class of ¯rms which devote resources towards the development of innovative products or processes. An implication of this assumption is that each of the ¯rm's expenditures should be insensitive to °uctuations in internal ¯nance. To test this hypothesis

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Pakes and Schankerman (1984) found that over 95% of the structural variance in R&D intensity was accounted for by the variance of a ¯rm-speci¯c structural parameter.

existing empirical work either has examined the sensitivity of R&D expenditures to internal ¯nance or has compared the properties of the statistical process of R&D with those of the processes of other expenditures such as physical capital investment. Neither of these procedures can distinguish between the two hypotheses: (i) that capital markets are perfect, and that di®erent factors drive the ¯rm's di®erent expenditures, and (ii) that capital markets are imperfect, and that the di®erent expenditures of the ¯rm repond dispr

Tables 1a - 1c

Table 1a - Full Sample

No. of obs	7	8	9	10	11	12	13	15	16	18	19	21	22
No. of companies	9	10	7	4	4	5	3	2	2	4	2	5	87

Table 1b - High Intensity Firms

No. of obs	7	8	9	10	11	12	15	18	19	21	22
No. of companies	4	3	2	1	2	1	1	2	2	1	21

Table 1c - Low Intensity Firms

No. of obs	7	8	9	10	11	12	13	15	16	18	21	22
No. of companies	5	7	5	3	2	4	3	1	2	2	4	66

Table 2

Q Equation - High Intensity Firms

	1	2	3	4	5	6	7
Q_t	0.0161	0.0066	0.0093	0.0086	0.0076	0.0038	0.0032
	(0.0064)	(0.0081)	(0.0044)	(0.0054)	(0.0107)	(0.0077)	(0.0079)
$(FCF/K)_t$	-	0.5712	-	0.1306	0.6174	-	-0.2545
	-	(0.1506)	-	(0.4791)	(0.1763)	-	(0.6389)
$(FCF/K)_{t-1}$	-	-	0.3707	0.2958	-	0.5684	0.7478
	-	-	(0.0832)	(0.2897)	-	(0.1385)	(0.437)
m1	-3.652	-3.53	-3.772	-3.296	-3.676	-3.815	-4.326
m2	0.614	0.902	0.187	0.321	0.933	-0.171	-0.356
Sargan	2.773	1.664	2.894	2.471	1.543	0.656	0.269
prob	(0.25)	(0.797)	(0.576)	(0.481)	(0.462)	(0.72)	(0.604)

(i) The dependent variable is $(I/K)_t$. Sample period is 1972-1993. There are 686 observations.

(ii) Time and Industry dummies included in estimation. White-corrected standard errors are in brackets.

(iii) Lags 2,3, and 4 of the regressor are used in columns 1 to 4. Lags 3 and 4 in columns 5 to 7.

(iv) The m1 and m2 test statistics are normally distributed around zero.

(v) The Wald test statistic for the joint significance of the two cash flow terms in column 4 is 19.627, and in column 7 is 13.131.

Table 3

Q Equation - Low Intensity Firms

	1	2	3	4	5	6	7
Q_t	0.0193	0.0221	0.129	0.0223	0.0177	0.0171	0.0136
	(0.0071)	(0.008)	(0.1446)	(0.0077)	(0.0065)	(0.0064)	(0.0107)
$(I=K)_{t¡1}$	-	0.2011	-0.2331	0.1751	0.1674	0.1717	0.1985
	-	(0.036)	(0.2102)	(0.0414)	(0.0414)	(0.0387)	(0.0444)
$Q_{t¡1}$	-	-0.0092	-0.0746	-0.005	-0.004	-0.0054	-0.0159
	-	(0.0042)	(0.0925)	(0.0042)	(0.0042)	(0.0041)	(0.0118)
$(FCF=K)_t$	-	-	-	-	0.1502	-	-1.2373
	-	-	-	-	(0.0778)	-	(1.1255)
$(FCF=K)_{t¡1}$	-	-	-	-	-	0.1061	0.9045
	-	-	-	-	-	(0.0486)	(0.7542)
m1	-6.393	-7.575	-1.165	-7.459	-7.281	-7.236	-1.807
m2	-1.838	-0.589	-1.967	-0.777	-0.867	-0.812	0.9
Sargan	9.261	11.01	0.045	2.875	5.777	5.57	0.706
prob	(0.01)	(0.012)	(				

Table 4

Euler Equation

	Low Intensity			High Intensity		
$(I/K)_{t-1}$	0.5554	1.2064	0.5864	0.0818	0.3659	0.1055
	(0.134)	(0.5387)	(0.1386)	(0.2112)	(0.9165)	(0.2182)
$(I/K)^2_{t-1}$	-0.5192	-1.919	-0.5577	-0.0224	-0.0956	-0.0243
	(0.2127)	(0.9493)	(0.2205)	(0.2836)	(1.3172)	(0.2928)
$(CF/K)_{t-1}$	0.2198	0.3232	0.2195	0.2475	0.1839	0.3363
	(0.056)	(0.1084)	(0.0726)	(0.0714)	(0.2155)	(0.078)
$(Y/K)_{t-1}$	-0.0067	-0.0165	0.0001	0.0105	0.0015	0.0199
	(0.0055)	(0.0098)	(0.0048)	(0.0114)	(0.0151)	(0.0078)
m1	-7.443	-2.215	-7.604	-4.522	-1.726	-4.479
m2	-0.749	-1.875	-0.826	1.259	0.699	1.177
Sargan	5.441	0.708	7.284	2.816	2.976	3.47
prob	(0.71)	(0.95)	(0.506)	(0.945)	(0.562)	(0.902)

(i) The dependent variable is $(I/K)_t$. Sample period is 1972-1993. There are 686 observations for high intensity firms and 1894 observations for low intensity firms.

(ii) Time and Industry dummies included in estimation. White-corrected standard errors are in brackets.

(iii) Lags 2,3, and 4 of the regressors are used in columns 1,3,4 and 6. Lags 3 and 4 in columns 2 and 5.

(iv) The m1 and m2 test statistics are normally distributed around zero.

(v) The Hausman test statistic for the validity of the lag 2 instruments is 3.118 (2) for low intensity firms and 0.557 (2) for high intensity firms.

Table 5

Sales Accelerator Model

	Low Intensity			High Intensity		
$(¢Y=Y)_t$	0.0608	0.037	0.0541	0.1245	0.0442	0.1381
	(0.0264)	(0.0251)	(0.0258)	(0.0408)	(0.0448)	(0.0415)
$(FCF=K)_t$	-	0.2996	-	-	0.676	-
	-	(0.0871)	-	-	(0.154)	-
$(FCF=K)_{t¡1}$	-	-	0.2116	-	-	-0.0706
	-	-	(0.0598)	-	-	(0.0224)
m1	-6.267	-6.209	-6.219	-3.549	-3.614	-3.529
m2	-1.859	-1.955	-1.793	0.634	0.88	0.663
Sargan	-	3.035	4.137	-	0.018	1.029
prob	-	(0.219)	(0.126)	-	(0.991)	(0.598)

(i) The dependent variable is $(I=K)_t$. Sample period is 1972-1993. There are 686 observations for the high intensity ¯rms and 1894 observations for the low intensity ¯rms.

(ii) Time dummies included in estimation. White-corrected standard errors are in brackets.

(iii) Lags 2,3, and 4 of free cash °ow are used in columns 2,3,5, and 6. OLS is used in columns 1 and 4.

(iv) The m1 and m2 test statistics are normally distributed around zero.

Table 6

Summary Statistics

	Innovative Firms		Non-Innovative Firms	
	Mean	S.d.	Mean	S.d.
Capital Stock 1987	99.2	22.8	284.9	93.6
Capital Stock 1993	238	73.9	566.7	189.5
Total Sales 1987	371.6	76.4	861.2	309.1
Total Sales 1993	689.7	158.7	1348.2	489.6
R&D Intensity	0.257	0.196	0.239	0.187

Table 7

Q Equation - Robustness Check

	Small Firms			Large Firms		
Q_t	0.0177	0.0156	0.015	0.0358	0.0294	0.03
	(0.0057)	(0.005)	(0.0046)	(0.009)	(0.0081)	(0.0075)
$(FCF=K)_t$	-	0.1102	-	-	0.3778	-
	-	(0.1054)	-	-	(0.1186)	-
$(FCF=K)_{t\ i\ 1}$	-	-	0.076	-	-	0.2221
	-	-	(0.0727)	-	-	(0.0688)
m1	-4.441	-4.378	-4.481	-5.504	-5.387	-5.746
m2	-0.456	-0.456	-0.466	-1.034	-0.965	-1.292
Sargan	0.124	0.079	0.153	1.718	3.565	4.24
prob	0.725	0.961	0.926	0.19	0.168	0.12

A Costs of Adjustment Model

The firm's problem is to maximise,

$$V_t = E_t \sum_{j=0}^{\infty} \beta^{-j} \Pi_{t+j}, \tag{A.5}$$

where β is a discount factor, assumed constant, and

$$\Pi_t = p_t F(K_t, L_t, \mu_t) - p_t G(I_t, K_t, \epsilon_t) - w_t L_t - p_t^I. \tag{A.6}$$

$F(\cdot,\cdot,\cdot)$ is the firm's production function, $G(\cdot,\cdot,\cdot)$ the cost of adjustment function, I investment, K the capital stock, L labour, p output price, p^I the price of new capital, w the wage, and μ and ϵ are random disturbances. The firm's problem can be formulated as the following dynamic programming problem,

$$V(K_{t-1}, \mu_t, \epsilon_t) = \max_{I,L} \{\Pi_t + \beta E_t[V(K_t, \mu_{t+1}, \epsilon_{t+1})]\}, \tag{A.7}$$

subject to (i) (A.6), (ii), the law of motion for capital,

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{A.8}$$

and (iii), the stochastic processes governing the two disturbance terms. Assuming that capital invested in period t also becomes productive in period t, the first-order condition for investment is,

$$\left(\frac{\partial \Pi}{\partial I}\right)_t + \left(\frac{\partial \Pi}{\partial K}\right)_t + \beta E_t \left(\frac{\partial V}{\partial K}\right)_{t+1} = 0, \tag{A.9}$$

and the Euler equation is,

$$\left(\frac{\partial V}{\partial K}\right)_t = (1-\delta)\left(\frac{\partial \Pi}{\partial K}\right)_t + \beta(1-\delta)E_t \left(\frac{\partial V}{\partial K}\right)_{t+1}. \tag{A.10}$$

Using equation (A.10), the first-order condition can be re-written as,

$$-(1-\delta)\left(\frac{\partial \Pi}{\partial I}\right)_t = \left(\frac{\partial V}{\partial K}\right)_t. \tag{A.11}$$

This is the equation tested by the empirical Q model equation. To derive the latter from equation (A.11), assume that both the production function and the costs of adjustment function are linearly homogeneous in their arguments. This implies that the profit function $\Pi(I; K; L)$ is also homogeneous of degree one. Under this assumption it is straightforward to show that the value function is also homogeneous of degree one in K (see Stokey, Lucas, and Prescott (1989)). From Euler's theorem it follows that the marginal value of capital, $\partial V/\partial K$, equals the average value of capital, V/K. Assuming efficient capital markets allows market prices to be used to construct the average value of capital. Finally, assuming the functional form for $G(\cdot; \cdot; \cdot)$ gives equation (3.1).

To derive the Euler equation used in the text, substitute equation (A.11) into equation (A.10) to get,

$$(1 - \delta) E_t \left(\frac{\partial \Pi}{\partial I} \right)_{t+1} = \left(\frac{\partial \Pi}{\partial I} \right)_t + \left(\frac{\partial \Pi}{\partial K} \right)_t . \tag{A.12}$$

Under the same linear homogeneity assumptions, the assumption of a perfectly competitive labour market and a monopolistic output market, and the assumed functional form for $G(\cdot; \cdot; \cdot)$ equation (3.2) in the text is derived.

B Data Appendix

The data used is from the published accounts of UK listed firms and was collected from Datastream. From the sampling frame of firms covered by Datastream, a primary sample of firms was identified with the following criterion: the firms chosen for the sample were required to have at least one positive recorded R&D expenditure between the years 1990–1993. Very few firms reported R&D expenditures prior to the introduction of the new accounting standard, SSAP 13, in 1989. The initial sample consisted of approximately 340 firms, the vast majority of which had fewer than four positive observations on R&D .

Two further selection criteria were applied to this primary sample. First, all firms with fewer than seven consecutive positive observations on all of the main variables were deleted. Data on firms which have been acquired, or which have gone out of business, are not readily available from Datastream. Consequently, all firms have seven or more observations leading up to 1993 (the ¯nal observation for each ¯rm is 1993). Second, ¯rms with large one period changes in their capital stock were also deleted. This was done to exclude ¯rms with major mergers or acquisitions. Firms whose change in their book value of lay outside three times the interquartile range above and below the median were removed. The ¯nal sample is an unbalanced panel consisting of 144 ¯rms with observations ranging between seven and twenty-two. Approximately half of the sample had observations available for the full sample period (1972{1993).

In splitting the sample, Datastream's ¯nest industrial classi¯cation, level 6,was used.

The de¯nitions of the data used in the construction of the variables is as follows (Datastream codes are in square brackets).

Tobin's Q (Q): The market value of ordinary shares [HMV] plus the book value of total loan capital [321] less deferred tax [301] divided by the book value of capital [339].

Investment (I) : Total new ¯xed assets [435].

Cash Flow (CF) : Provision for depreciation of ¯xed assets [136], plus operating pro¯t before tax, interest and preference dividends [137].

Free Cash Flow (FCF) : Cash Flow less total interest charges [153] and total tax charge [172].

Output (Y) : Total sales [104].

R&D : Research and Development (expensed) [119].

Capital Stock (K) : Book value of net total ¯xed assets [339].

Market value of ordinary shares (V) : Historic market value of the ¯rm [HMV].

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