Does the diversification penalty crowd out R&D value?

Robert Brooks[a], Sinclair Davidson[b] and Matt Taylor[c]

a Department of Econometrics and Business Statistics, Monash University
b School of Economics, Finance and Marketing, RMIT University
c Social Policy Analysis, Evaluation and Research Centre, Australian National University

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Keywords: R&D; Diversification discount; Valuation; Tax concessions

JEL Classification: C24; G32; H25; O32

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Correspondence to: Sinclair Davidson, School of Economics, Finance and Marketing, RMIT University, GPO Box 2476V, Melbourne VIC 3001, Australia,
Phone: 61-3-99255869, Fax: 61-399255986
Email: Sinclair.davidson@rmit.edu.au

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1. Introduction

Despite a positive relationship between R&D expenditure and firm value (see Chan, Martin and Kensinger (1990) and Eberhart, Maxwell and Siddique (2004) for examples of event-based studies, Griliches (1981), Hall (1993), Chung, Wright and Kedia (2003), Hall and Orani (2006) for cross-section studies and Chan, Lakonishok and Sougiannis (2001) for an asset–pricing approach) it is commonly believed that firms underinvest in R&D. The standard economic solution to underinvestment is some form of government subsidy. In Australia that subsidy takes the form of a non-debt tax shield. Firms can earn a 125 percent deduction on some types of R&D expenditure. In some instances that deduction may rise to 175 percent. The reason Australia provides the tax incentive is "to make eligible companies more internationally competitive" (Auditor-General 2003). This objective implies that firms with export earnings are the primary intended recipients of the R&D tax concession. Bosworth and Rogers (2001) indicate that Australian firms undertaking R&D do tend to be large. They do not, however, investigate whether R&D firms have large export earnings. Nor do they investigate the value relevance of R&D for such firms. In this paper we investigate the R&D value relevance of firms that are industrially and internationally diversified. Australia is a small open economy; many firms are likely to exhibit some form of diversification. If the R&D tax concession is aimed at making firms "internationally competitive" then the impact of that policy needs to evaluated relative to those firms.

The conventional financial wisdom indicates that corporate diversification destroys wealth, and diversified firms are less valuable than comparable stand-alone firms (see Martin and Sayrak 2003 for an extensive survey). The generally accepted rationale for the diversification discount is the inefficient investment hypothesis (Lamont 1997, Shin and Stulz 1998 and Rajan et al. 2000). The (related) corporate focus hypothesis argues that inefficient investments, inefficient cross-subsidisation and poor managerial incentives drive the diversification discount (Berger and Ofek 1995, and Dittmar and Shivdasani 2003). Denis, Denis and Sarin (1997) and Scharfstein (1998) argue, using US data, that agency problems cause the diversification discount. Some studies, however, indicate that the diversification penalty is driven by omitted variable bias (Graham, Lemmon and Wolf 2002) or measurement error (Maksimovic and

Phillips (2001) and Villalonga (2004)). The literature is unsettled and some evidence of premia also exist. Morck and Yeung (2002), for example, document a diversification premium, but only for those firms that have firm-specific intangible assets (i.e. assets with similar characteristics to R&D). Fauver, Houston and Naranjo (2004) examine diversification penalties across 35 economies and report that high income, and common law, economies are more likely to exhibit diversification penalties. Fleming, Oliver and Skourakis (2003) using Australian data report that the diversification penalty only appears in some diversified (under-performing) firms. Christophe and Pfeiffer (2002) and Denis, Denis and Yost (2002) report that geographic diversification reduces firm value in the same way as does industrial diversification.

This discussion suggests our research question: How does R&D activity interact with diversification penalties/premia? In answering this question we will need to consider a series of sub-questions. For example, to what extent are R&D firms diversified, either industrially and/or geographically? How does the value relevance of R&D vary by size, industrial diversification and geographic diversification?

2. Model and Data

(i) Empirical Strategy

A treatment effects model can be used to model the decision to undertake R&D expenditure and the decision to diversify. Firms do not undertake R&D, or choose to diversify at random. Therefore it is not appropriate to simply compare the sample firm value mean for firms that undertake R&D, and firms that do not, and conclude that the entire difference between the two sample means is the R&D premium. Naturally we expect other variables to determine firm value in addition to R&D and it would be reasonable to expect that these characteristics might be more concentrated amongst firms that undertake R&D expenditure. The method we use to obtain consistent estimates of the effect of R&D and diversification involves adopting a latent variable approach employing a probit specification in order to model the latent propensity associated with the decisions to undertake R&D and to diversify.

If we are to consider positive R&D expenditure and diversification a form of 'treatment' then our sample selection problem is not that of missing or censored data, but rather of self-selection into treatment (Wooldridge, 2002: p. 606). If the decision to undertake R&D is correlated with unobserved variables that increase the market valuation of a firm then R&D firms are likely to be more valuable for reasons other than the fact that they undertake R&D. Consequently a least squares regression will over estimate the R&D premium due to omitted variables bias. This is a somewhat different sample selection problem to that which arises because we do not observe a random sample of the population owing to data censoring in either the dependant variable or one of the regressors. In these instances we are only able to observe a sub set of the population because the sample has been selected for us through sample design or non-response. It is this second problem described by Heckman (1979) in his seminal work on the omitted variable bias that is induced in such situations that is associated with the Heckit procedure. We employ a maximum likelihood estimation of Heckman's dummy endogenous variable model (Heckman, 1978).

The following set of equations provides a general framework within which to explore some of the challenges that modelling R&D expenditure poses.

$$V_i = \mathbf{x}'_i\beta + RD_i\theta + u_i \tag{1}$$

$$RD_i = \mathbf{z}'_{1i}\gamma_1 + v_{1i} \tag{2}$$

$$RD_i^* = \mathbf{z}'_{2i}\gamma_2 + v_{2i} \tag{3}$$

Here V_i is an observed measure of firm value for which we choose Tobin Q and RD_i the level of R&D expenditure, a potentially endogenous regressor. RD_i^* is an unobserved latent propensity that determines the probability that positive R&D expenditure is observed. RD_i is observed via the specification of the following selection rule

$$RD_i = \begin{cases} RD_i & \text{if } RD_i^* > r_i \\ r_i & \text{if } RD_i^* \leq r_i \end{cases}$$

The scalar r_i is an unobserved threshold propensity. When a firm's latent propensity exceeds this point the propensity is then realised as some positive level of R&D

expenditure. The vectors of explanatory variables, $\mathbf{x}$, $\mathbf{z}_1$ and $\mathbf{z}_2$, are assumed exogenous in their respective equations. $\mathbf{x}$ is a vector of control variables that are thought to determine firm value and $\mathbf{z}_1$ a vector of variables that determine the level of R&D expenditure of firms. The vector $\mathbf{z}_2$ contains variables that determine the decision to undertake R&D, these would normally be expected to overlap with those contained in $\mathbf{z}_1$. This selection rule combined with equations (1) to (3) nest many distinct micro-econometric models, however, we will limit ourselves to a discussion of the two that are most appropriate for the modelling of R&D before describing our chosen specification[1].

The first specification that may appear useful in modelling the relationship between firm value and R&D is that of the corner solution regressor a slight variation on what Amemiya (1984) refers to as the Type III Tobit. It seems natural to assume that some firms will undertake a positive level of R&D expenditure while many firms will optimise at the corner solution and not undertake R&D. Here we observe RD_i according to the rule $\max(0, RD_i)$ setting $r_i = 0$ for all i. This is not a latent variable model as interest centres on R&D expenditure itself. The high proportion of zeros observed for this variable suggests a censored variable best modelled by a mixture of a discrete and a continuous distribution to capture the density at zero. It is for this reason that equation (3) contains the same regressors as equation (2) we therefore set $\mathbf{z}_1 = \mathbf{z}_2$[2]. The second specification is a sample selection model that involves incidental truncation of RD_i. This term comes from the fact that whether we observe R&D expenditure is determined by another variable, the incidence of undertaking R&D as determined by the variables contained in $\mathbf{z}_2$. Whether we observe RD_i is governed by the latent variable RD_i^* via the selection rule $\max(r_i, RD_i)$. RD_i^* need not be determined by the same variables as $\mathbf{z}_1$ but we would expect that many of these variables would overlap. A more fundamental difference is that r_i is an unobserved

[1] Although not appropriate for modelling Tobin's Q the familiar Tobit model of Tobin (1958) is found within this framework. In Tobin's model it is the dependent variable of equation (1) that is a corner solution variable. Here we drop equation (2) and allow equation (3) to determine the density associated with the censoring point of the dependent variable. This occurs via the specification of the selection rule $\max(c_i, V_i)$. Tobit model assumes $c_i = 0$ for all i and $x_i = z_2$.

[2] In the instance of a censored variable we have mixture of discrete and continuous distribution equation (3) is used to model the discrete component. Both of these components together integrate to one. This censoring point need not be at zero however in most applications it is or can be normalised as such. The distribution of a censored random variable is distinct from that of a truncated variable. Truncation involves the entire distribution lying on one side of a particular point such that the truncated distribution integrates to one over this range.

random variable specific to each observation and should not be assumed to equal 0. This censoring point is however assumed to be exogenous with respect to equation (1).

The sample selection specification requires a minor redefinition of the latent propensity. We now let RD_i^o be the latent propensity to undertake R&D and it is only when RD_i^o is greater than r_i that we observe RD_i. This value will be specific to individual firms, however, we would expect that the point at which undertaking R&D becomes worthwhile for a firm will be similar within an industry where firms are expected to face a similar cost structure and regulatory environment. That is we observe R&D expenditure if $RD_i^* > 0$ where $RD_i^* = RD_i^\circ - r_i$ providing the selection rule

$$RD_i = \begin{cases} RD_i \text{ if } RD_i^* > 0 \\ 0 \quad \text{if } RD_i^* \leq 0 \end{cases}$$

This normalisation is standard in the literature; see for example Amemiya (1973).

Heckman (1976) casts the endogeniety that sample selection and corner solution variables give rise to in terms of an omitted variable bias. We can write the expectation of V_i for the sub sample for which we observe selection as

$$E(V_i|\text{sample selection rule}, \mathbf{x}_i) = \mathbf{x'}_i\beta + E(u_i|\text{sample selection rule}, \mathbf{x}_i) \qquad (4)$$

If the conditional expectation of u_i is zero then a least squares regression on the selected sample will yield consistent estimates of the population regression function. If we observe a random sample of the population then we do not have a selection problem and V_i is conditional only upon $\mathbf{x}_1$. The omitted variable bias arises in the case of a corner solution regressor because observation of the relationship between V_i and RD_i relies on $RD_i > 0$, with $RD_i = 0$ being the case for a nontrivial proportion of the sample. This suggests that the conditional expectation of u_i is equal to $E(u_i|v_{2i} > RD_i – \mathbf{z'}_{2i}\gamma_2, \mathbf{x}_i)$. If we take incidental truncation as the appropriate specification, then this relationship is only observed when $RD_i^* > 0$. This provides us with a slightly different term equal to $E(u_i|v_{2i} > – \mathbf{z'}_{2i}\gamma_2, \mathbf{x}_i)$[3]. Heckman (1976) shows that it is

[3] This difference arises because in a Tobit Type III specification selection is determined by the continuous range of a corner solution variable. We can only observe the relationship between V_i and

possible to derive an expression for this under the assumption that u_i and v_{2i} are bivariate normal. With a normalisation of the variance of v_{2i} to 1 this can be shown to equal

$$E(u_i|v_{2i} > -\mathbf{z'}_{2i}\gamma_2, \mathbf{x}_i) = \rho\sigma_\varepsilon\lambda_i \qquad (5)$$

Where ρ is the correlation between the two distributions, σ_ε he dispersion of u_i and λ_i the Inverse Mills Ratio (IMR) equal to $\frac{f(-\mathbf{z'}_{2i}\gamma_2)}{1-\Phi(-\mathbf{z'}_{2i}\gamma_2)}$. The denominator of λ_i is the probability that we observe data on RD_i and can be shown to be an increasing function of $-\mathbf{z'}_{2i}\gamma_2$. It is precisely this term that is omitted were we to perform a least squares regression on (1). A least squares regression would provide inconsistent estimates of θ in so far as the determinants of undertaking R&D contained in $\mathbf{z}_2$ are correlated with R&D expenditure. This would not be a concern if we thought that these decisions were completely independent of each other. This, we suspect, would be unlikely. The parameter ρ has an important interpretation. If u_i is not correlated with v_{2i} such that $\rho = 0$ then we do not have a sample selection problem and selection is independent with respect to V_i, at least under the assumption of normality. Fortunately the full information maximum likelihood estimator of this parameter is asymptotically normally distributed under the null of no selection bias ensuring this an easily tested hypothesis.

It is clear from (5) that the sign and magnitude of ρ and $\gamma 2$ simultaneously determine this bias[4]. Heckman (1976) suggested a two-step procedure that uses the fact that observation of RD_i conditional upon $\mathbf{z}_2$ is a binary variable that is observed for the entire sample to model that probability that RD_i is observed. The procedure involves taking a probit estimate of λ_i for inclusion in a least squares estimation of (1). It is this procedure that has since been immortalised as the Heckit procedure. The asymptotic distribution for the Heckit estimator is subsequently derived in Heckman (1979). The full information maximum likelihood estimator of ρ is asymptotically

RD_i where we have $RD_i > 0$ this ensures that we only observe $v2i > RD - \mathbf{z'}_{2i}\gamma_2$ when $RD_i > 0$. If we adopt the sample selection approach then selection is determined by the incidence of undertaking R&D expenditure. This is a binary variable that we have chosen to define in terms of an unobserved latent variable, here we only know that $v_{2i} > -\mathbf{z'}_{2i}\gamma_2$ when $RD_i > 0$. Regardless of our chosen specification we do not observe v_{2i} for the unselected sample we only know that $v2i \leq -\mathbf{z'}_{2i}\gamma_2$.

[4] If the probability that we have data on RD_i for the entire sample is quite high then this term will be small suggesting little bias in a least squares estimation of the parameter vectors β and θ. If the probability of selection is equal across the entire sample then we will only observe a biased estimate of the intercept contained in β.

normal under the null of no selection bias. In the two-step procedure it is t-distributed and does not suffer from the generated regressors problem of Murphy and Topel (1985).

The estimation of the Type III Tobit can also be implemented in two steps. With the assumption that $r_i = 0$ and $\mathbf{z}_1 = \mathbf{z}_2$ we obtain the selection rule max(0, RD_i) which is of a Tobit form rather than the probit used in the Heckit procedure. Here it is the residuals from a Type I Tobit estimation of (2) $\hat{v}_{2i}$ that we insert into a least squares estimation of (1). Another difference in estimation is that in the Type III Tobit we do not require an instrument be placed in $\mathbf{z}_2$. We see from $E(u_i|v_{2i} > -\mathbf{z}'_{2i}\gamma_2, \mathbf{x}_i)$ that variation in an estimate of v_{2i} is ensured by the presence of approximately continuous variable RD_i in this conditional expectation. This is not the case when we use the probit selection equation of Heckman for obvious reasons. Strictly speaking the model is still identified but only due to the nonlinearity of the IMR and would be not be if we used a linear probability in place of the Heckit procedure.

Despite the differences in these specifications the R&D variable is assumed to be exogenous in equation (1). Within the context of firm value and R&D, however, there are potentially two distinct causes of endogeniety that may be present in equation (1). First it may be the case that R&D expenditure is itself endogenous in equation (1). Alternatively R&D expenditure may be exogenous conditional upon the firm undertaking R&D, with the decision to undertake R&D endogenous in equation (1)[5]. If the decision to undertake R&D is correlated with unobserved variables that increase the market valuation of a firm then R&D firms are likely to be more valuable for reasons other than the fact that they undertake R&D thereby inducing an endogeniety bias.

With regards to the endogeniety of R&D expenditure, once undertaken, the Type III Tobit specification will provide consistent estimates if we include instruments in $\mathbf{z}_1$ (recall that here $\mathbf{z}_1 = \mathbf{z}_2$) in addition to $\hat{v}_{2i}$. The Type III specification will not provide

[5] In addition to this there is also the possibility that both the decision to undertake R&D and the level of R&D expenditure once undertaken are endogenous. Another potential cause of endogeniety is that firm value and R&D expenditure and decision to undertake R&D are jointly determined giving rise to endogeniety bias.

consistent estimates if it is the decision to undertake R&D that is endogenous in equation (1) as this specification assumes that $r_i = 0$ for all firms thereby assuming the R&D decision is exogenous with respect to firm value. With the assumption $\mathbf{z}_1 = \mathbf{z}_2$ we are not permitted to specify a separate instrument for the R&D decision. The sample selection framework is more flexible, however, at least admitting r_i to be a random variable. This normalisation does not however change the endogeniety associated with firms having crossed their individual thresholds. As before the possible endogeniety of R&D expenditure for R&D firms requires the inclusion of an instrument in $\mathbf{z}_1$ along with the probit estimates of the IMR. The omitted variable bias caused by the endogeniety of the decision to undertake R&D requires the specification of an additional instrument for $\mathbf{z}_2$ that does not appear in $\mathbf{z}_1$. This underlines the main difference between these two specifications. The type III Tobit only deals with the complication of an omitted variable bias induced by the presence of a censored regressor, whereas sample selection is able to model the R&D decision at both the extensive and intensive margin.

Our interest is in the effect that undertaking R&D has on firm value rather than the marginal return to R&D expenditure. We therefore drop equation (2) but keep the latent variable specification implied by (3) and take RD_i to be a binary variable set equal to 1 where we observe firms to undertake some positive level of R&D expenditure that is

$$RD_i = \begin{cases} 1 \text{ if } RD_i^* > 0 \\ 0 \text{ if } RD_i^* \leq 0 \end{cases}$$

This specification implies structural equations

$$V_i = \mathbf{x}'\beta + RD_i\theta + u_i \quad (6)$$

$$RD_i^* = \mathbf{z}'_{2i}\gamma_2 + v_{2i} \quad (7)$$

This is the Heckman's (1978) Dummy Endogenous Variable Model. In terms of Heckman's (1976) general formula given by equation (4) we have

$$E(V_i|\mathbf{x}_i, \mathbf{z}_{2i}, RD_i) = \mathbf{x}'\beta + RD_i\theta + E(u_i|\mathbf{x}_i, \mathbf{z}_{2i}, RD_i) \quad (8)$$

Heckman (1978) sets out the required conditions for identification of the coefficients and provides a full information maximum likelihood estimator for an endogenous indicator. The maximum likelihood estimator is consistent, asymptotically efficient and normal. This specification sits neatly within our general framework and was originally intended for instances such as ours where an endogenous binary variable is the realisation of a continuous latent variable crossing a stochastic threshold. This model is often called the Treatment Effects Model and finds application where selection into treatment does not occur at random and is correlated with the variable of interest in our case firm value.

We face an analogous problem if one is to consider undertaking R&D as a form of treatment. One of the advantages of focusing solely on the decision to do R&D is that we avoid the problem of potential endogeniety in the intensity of R&D expenditure. This is advantageous in that we only require an instrument for the decision to undertake R&D for which we choose the ratio of Earnings to Total Assets and Debt to Assets. This model has the same identification requirements as the selection model. Although the model is identified in the absence of an instrument due to the non-linearity of the IMR a robust estimation requires an instrument. No such requirement exists for the Type III Tobit as our estimate of v_{2i} is calculated from RD_i in addition to $\mathbf{z}_2$.

We hypothesise that the relationship between firm value R&D and diversification can be described as follows

$$V_i = \mathbf{x'}_i \beta + \theta RD_i + \delta D_i + u_i \qquad (9)$$

Where V_i is Tobin Q and $\mathbf{x}_i$ a vector of characteristics that determine firms value. RD_i is the binary variable defined in terms of a latent propensity described above. Here we now include D_i, a binary indicator that captures diversification. Our interest centres on finding consistent estimates of the coefficients that measure the impact of R&D and diversification on firm value in the face of possible endogeniety. It is for this reason we include a second equation that captures the determinants of R&D

$$RD_i = \mathbf{z'}_i \gamma + v_i \qquad (10)$$

$\mathbf{z}_i$ is a vector of variables that are thought to drive the latent propensity to undertake R&D in addition to an appropriate instrumental variable.

(ii) Operational Model

We use Tobin Q as a proxy for firm value. In addition to R&D and the presence of diversification, Tobin's Q is expected to vary quadratically with firm size as measured by the natural logarithm of the book value of total assets Log(Assets) and its square Log(Assets)^2 which are included as control variables. In addition to this we include indicators for industry groupings and year dummies to control for time effects.

We wish to estimate the following operational equation,

$$\begin{aligned} Q_{it} = {} & \alpha_0 + \alpha_1 \text{Log}(\text{Assets}_{it}) + \alpha_2 \text{Log}(\text{Assets}_{it})^2 + \alpha_3 \text{RD}_{it} + \alpha_4 \text{D}_{it} + \alpha_5 \text{RD}_{it} \times \text{D}_{it} \\ & + \text{Industry Dummies} + \text{Annual Dummies} + \varepsilon_{it} \end{aligned} \quad (14)$$

Where interest centres on consistent estimation of both α_3 and α_4. We estimate equation (4) using two separate specifications. The first addresses the problem of selectivity bias in the estimation of the impact of R&D on firm value using the latent variable approach described above. This involves the simultaneous maximum likelihood estimation of equation (4) with the following probit specification that captures the determinants of investment in R&D.

$$\begin{aligned} \text{RD}_{it} = {} & \alpha_0 + \alpha_1 \text{Log}(\text{Assets}_{it}) + \alpha_2 \text{Log}(\text{Assets}_{it})^2 + \alpha_3 \text{RoA}_{it} + \alpha_4 \text{Debt - Assets}_{it} \\ & + \text{Industry Dummies} + \text{Annual Dummies} + v_{it} \end{aligned} \quad (15)$$

In this specification we use the binary indicator D to control for diversification and do not interpret the coefficient α_4 literally owing to the sample selection issues raised above. The interaction RDXD in equation (4) is included in order to control for the possibility that market valuation of R&D expenditure is different across diversified firms. Return on Assets (RoA) and Debt - Assets are included as instruments for R&D in the structural equation[3].

In our second specification we augment equation (4) with an equation that captures those variables associated with diversification given by the following equation.

[3] We favour the inclusion of RoA in the selection equations as we find it to be statistically significant in only two unreported treatment effects estimations of equation (14), using equation (15) to correct for endogeniety in RD where RoA was omitted from the selection equation. The results that follow in tables 4 and 5 suggest that RoA has greater utility in equations (15) and (16).

$$D_{it} = \alpha_0 + \alpha_1 \text{Log}(\text{Assets}_{it}) + \alpha_2 \text{Log}(\text{Assets}_{it})^2 + \alpha_3 \text{RoA}_{it} + \alpha_4 \text{Debt - Assets}_{it} + \text{Industry Dummies} + \text{Annual Dummies} + v_{it} \quad (16)$$

We report results for the estimation of both specifications for four different categories of diversification. First we estimate these models where the diversification indicator is defined as those that are either industrially diversified or internationally diversified. Second, we report estimates where the diversification estimates are defined for only those firms that are industrially diversified. Third, we estimate these models for only those firms that are internationally diversified. Finally we estimate models for those firms that are both internationally and industrially diversified. We calculate White (1980) heteroskedasticity robust standard errors and p-values for all estimated equations.

(iii) Data

The data contained in our analysis was extracted from the Osiris (September 2005 release), a database owned by the business data publisher Bureau Van Dijk. We collect financial data for all listed Australian firms from 1997/98 to 2001/02. Our panel includes a maximum of 1,516 firms per year with five years worth of data providing us with 7,580 observations in total. This number, however, is expected to change from year to year as new firms list and some firms delist. From this database we collect information on the Market Value of Equity, Book Value of Shareholder Equity, Total Assets, Return on Assets (RoA), and Total Revenue (Sales). From these variables we calculate our estimate of Tobin's Q equal to the market value of equity plus book value of assets less book value of shareholder equity all divided by the book value of assets. We take the natural Log of Total Assets, Log(Assets), as a proxy for firm size. In addition to this we construct ten industry classification indicators to control for industry specific group effects using the four-digit primary SIC codes obtained from Osiris.

Osiris includes a breakdown of financial data for individual industrial segments. While the coverage of segment specific financial data is not ideal it is all we require to quantify industrial diversification. We obtain this measure by simply counting the number of unique entries within the market segment data. Naturally the number of segments that a firm is involved in will vary over time as firms diversify or divest. Counting only the unique entries avoids any duplication that might arise due to the panel nature of our data set. Strictly speaking, however, we should interpret this variable as the maximum level of diversification that we observe over the five years of our sample period. Osiris provides a similar breakdown for each foreign market from which we construct a measure of international diversification. We use this data to construct diversification indicators. A firm is defined as industrially diversified if it is involved in more than one industrial segment and defined as internationally diversified if it has a presence in more than one country.

While the financial data contained in Osiris is quite comprehensive its coverage of R&D expenditure for Australian firms is less than satisfactory. For this reason we augment the financial data contained in Osiris with R&D expenditure sourced from the Intellectual Property Research Institute of Australia (IPRIA) for listed and unlisted Australian firms. We take data for our sample period 1996/97 to 2001/2002. The IPRIA data set is widely regarded as the most comprehensive database of R&D data in Australia and gathered from annual reports supplemented by telephone surveys. Despite this the IPRIA data set has its limitations (Griffiths & Webster 2004). The greatest challenge is how to deal with missing R&D expenditure data, which represent a large proportion of the sample. As Griffith and Webster (2004) note “it is not possible to discern whether these represent true zeros, R&D spending below a threshold limit or the non reporting of values above this threshold”. Griffith and Webster suggest that firms that do not report R&D while simultaneously making patent applications during the same year can reasonably be considered non-reporting and that R&D reporting is largely time invariant. While this may be thought to induce a sample selection problem Griffith and Webster argue that in so far as the characteristics that determine reporting of R&D expenditure are time invariant then fixed effects panel data methods will capture these characteristics in the firm specific intercepts. Table 1 provides the estimated probabilities that firms having undertaken R&D (or not undertaken R&D) in previous years will be observed to undertake R&D in subsequent years. These estimated probabilities refer to average probabilities over the entire sample period.

The top right cell of Table 1 suggests that firms that do not report R&D in any one-year rarely do so in the years that follow. The bottom left cell indicates that firms reporting R&D expenditure in any year have a 0.24 probability of not reporting R&D in the following year. For firms that do report R&D expenditure it is estimated that approximately 76 percent will report R&D expenditure in subsequent years. In contrast to Griffith and Webster, who obtain a larger sample of years we do not find that gaps R&D reporting represent small proportion of R&D firm years. Table 2 provides the number of observations of R&D expenditure for each R&D firm in the sample.

Only 25 of the 145 R&D firms observed in the sample enjoy full coverage, of the 110 that do not have full coverage 49 have a single value for R&D expenditure over the sample period. The column headed Gaps provides the total number of R&D firms for which we do not obtain five years of R&D expenditure for the full sample and for the diversification sub samples. As stated above we are not able to determine whether these missing values for R&D expenditure are 'true zeros' or non- reporting of R&D expenditure. It is possible that the 49 firms for which we observe a single R&D value did in fact undertake R&D in a single year over the sample period. These gaps apply to the reporting of R&D for firms that undertake R&D while the transition table indicates that the vast majority of firms that do not undertake R&D will generally not report R&D for the entire sample period. This would seem to support Griffiths and Webster's assertion that the characteristics that drive the reporting of R&D are most likely time invariant, however the reporting of R&D by R&D firms varies considerably at least over our sample period.

Our measures of diversification, defined above, are used to construct four different diversification indicators. Our first diversification indicator captures those firms that have been involved in more than one industry segment or have a presence in more than one country, that is firms that are diversified in some way. The second indicator we include captures only those firms that are industrially diversified defined as firms involved in more than one industrial segment. In addition to this we would expect some of these firms to be internationally diversified however not all of these firms will be. We include a third indicator for international diversification defined as those firms with a presence in more than one nation, firms that are not necessarily industrially diversified. This allows us to observe the differential impact that specific categories of diversification might have upon firm value. Finally we include an indicator that captures those firms that are both industrially and internationally diversified. These indicators are interacted with our two separate measures of R&D, the binary indicator RD and the ratio RD-Sales. The state of dual industrial and international diversification is quite common as the cross tabulation below illustrates.

Panel A of table 3 shows the number of firm years spread across the various types of diversification for both R&D and non R&D firms. The table is more easily interpreted when we keep in mind that these types of diversification are not mutually exclusive. We would expect to find that the four cells that pertain to each type of diversification sum to the number of firm years. As stated above our diversification indicators do not vary over the sample period while not all R&D firms are observed to undertake R&D in every year of the sample period.

The table indicates that of the 7,580 total firm years we find over two thirds of the sample to be diversified either industrially or internationally. Just under a third of firm years are found to be industrially and internationally diversified representing 44 percent of diversified firms. The sample is also about evenly balanced between industrially and internationally diversified firms with 3,938 and 3,510 firm years respectively. We find that relatively few firms undertake R&D expenditure over the 5 years of our sample. Of the 398 firm years where we observe positive R&D expenditure 376 are diversified in some way, while 277 of these are both industrially and internationally diversified. We also find R&D firm years to be spread fairly evenly across industrial and international diversification with 332 and 321 firm years respectively.

Panel B of table 3 provides a cross tabulation of R&D and diversification for firms. Of the 1,516 firms in our sample only 154 are observed to undertake R&D in at least one of the years of the sample period. Recall from table 2 that 49 firms had positive R&D expenditure in only one year, and a total of 35 are found to consistently undertake R&D over the entire sample period. As in panel A, the majority of firms are industrially diversified with only 482 involved in a single industrial sector. About 44 percent of industrially diversified firms are simultaneously internationally diversified. Internal diversification is not quite as common as industrial diversification with 702 firms found to be internationally diversified compared to a total of 787 industrially diversified firms. What is clear from table 3 is that there is a less than ideal sampling of non-diversified R&D firms. We only have 13 R&D firms that are not diversified in any way with just 22 firm years distributed across these firms. This provides us with an average of 1.7 observations for each firm in this cell. This suggests that the within transformation of a fixed effects panel data model is inappropriate for our dataset. We argue below that this would not be particularly informative for our purposes anyway.

Prior to estimation we delete some observations that are likely to be outliers. As with all accounting data we encounter a large number of missing values in our data set in addition to the thin coverage of R&D expenditure. Of the 3,326 valid observations for which we have a full set of data we find 188 have values for Tobin Q that are greater than ten. We also find 132 values for RoA that are less than negative 100. In addition to this we find that a least squares estimation of (14) reveals 65 standardised residuals that are larger than three standard deviations from zero which we also choose to delete. In some preliminary treatment effects estimations we find the selection equation is quite sensitive to the inclusion of industry indicators for Finance, Insurance, and Real Estate in addition to the miscellaneous category Service (Other) Industries that we also choose to delete. Placing these conditions on our data set reduces our sample size from 3,326 observations to 2,331 at the outset. Summary statistics for all variables included in the estimation sample are shown below in table 4. Fortunately applying these conditions to the sample does not reduce the number of R&D firm years by very much.

Average Tobin Q for the full estimation sample is found to be two. Mean Log(Assets) is 11.38 that corresponds to average assets of $872M with mean return on assets equal to negative 4 percent. Were we to drop firms with a negative RoA below 40 percent we would have a mean RoA of 1.84 percent, this would however come at the cost of an additional 218 firm years. The mean ratio of R&D to Sales is found to be 0.32 percent for the full sample a low but not altogether surprising figure since we find R&D expenditure for only 4.3 percent of firm years across a total of 145 firms. Naturally this changes dramatically when we consider only the 339 firm years in the estimation sample where we find RD expenditure to be 2.17 percent of Sales on average. We also find that R&D firms have a greater return to assets and carry more debt on average. As is expected they are also considerably larger in size with mean assets of 7.6B.

3. Empirical Results

(i) Firm Value Premium for R&D expenditure

We begin by estimating equation (14) employing the probit specification of equation (15) to account for the potential endogeniety that might be associated with the R&D decision. We do this for each of the diversification indicators with results shown in table 4. The results in the bottom panel indicate quadratic size effects in the R&D decision with statistically significant estimates for the coefficients on both Log(Assets) and Log(Assets)^2 in all of the regressions. The estimated turning points for this quadratic relationship are extremely large and together with the negative coefficient estimates for the quadratic terms indicate a negative relationship between assets and the propensity to undertake R&D that applies to all of the firms in the sample. We also find intuitive results for RoA and Debt-Assets that suggest the propensity to undertake R&D is positively related to the firm's ability to finance R&D expenditure.

Table 5 also indicates quadratic size effects in the value equation. The estimates of equation (14) have positive quadratic terms with turning points that lay well above the estimation sample maximum. This indicates a negative relationship between firm size and Tobin Q. The largest of these extrema are for those regressions that control for international diversification. This is intuitive as it implies a less pronounced size discount.

We find statistically significant coefficient estimates for R&D in all of our regressions ranging from just under 0.987 in the international diversification regression to 1.328 for industrial diversification. These endogeniety corrected coefficient estimates might at first seem to suggest a value premium that is extremely high, however these estimates cannot be directly interpreted as the effect of undertaking R&D. The positive coefficient estimates do however imply an R&D value premium regardless of what type of diversification we choose to control for.

In addition to diversification indicators we include the interaction of diversification with R&D so that we might observe whether R&D firms that are also diversified incur the same value discount as non R&D firms. Here we find only two of the diversification indicators to be statistically significant, Industrial Diversification and International Diversification. The coefficient estimate for Industrial Diversification is negative in contrast to that of International diversification, which is positive albeit very small in magnitude and on the cusp of statistically significance at a 10 percent level.

We also find only two interactions to be statistically significant. The interaction of Industrial Diversification with R&D is statistically significant and negative suggesting that industrially diversified firms that undertake R&D receive a lower return to R&D than do undiversified firms. This is an important finding since table 1 indicates that the vast majority of R&D firm years are associated with some level of industrial diversification. The second is that for simultaneously industrially and internationally diversified firms this is also negative despite finding the joint diversification indicator not statistically significant. It may be that the diversification discount for jointly diversified firms only applies to those firms that undertake R&D, however it is more likely, given the absence of statistical significance for the estimate of the international diversification indicator in the second regression, that the diversification discount is driven solely by industrial diversification and that it is this that has an adverse effect on the R&D premium.

Our concern that R&D might be endogenous in equation (4) seems well founded as we find our estimate of ρ to be statistically significant in all of the regressions. Since our specification is estimated by optimising the likelihood we can also perform a likelihood ratio test of the null hypothesis that $\rho = 0$. The relevant likelihood ratios are reported in the second panel and concur with our finding that there is statistically significant correlation between the residuals of equation (14) and (15). As indicated earlier this parameter is an estimate of the correlation between the residuals of equations (4) and (5) highlighting the presence of omitted variables common to the error terms of both equations. We show below that the negative sign of this correlation indicates that an OLS estimation of equation (14) would underestimate the R&D premium.

We now compute the marginal effect of undertaking R&D and the various types of diversification on firm value. The first panel of table 5 displays the average value of Tobin Q for a firm with mean assets that is not diversified and does not undertake R&D, using our treatment effects estimates from table 5 and estimation sample mean characteristics for non R&D firms. It is important to note that the coefficient estimates of equation (14) do not by themselves provide the expected percentage increase in Tobin Q attributed to undertaking R&D. In the treatment effects framework the expected value of the dependent variable without treatment is equal to

$$\mathrm{E}(\mathrm{V}_i | \mathrm{RD}_i = 0) = \mathbf{x'}_i \beta + \rho\sigma_\varepsilon \left[\frac{-f(\mathbf{z'}_{2i}\,\gamma_2)}{1-\Phi(\mathbf{z'}_{2i}\,\gamma_2)} \right] \tag{17}$$

and it is this that is calculated in the first row of table 5. The second term of this equation can be thought of as a correction factor that is added on to the value of non R&D firms and is included in the calculation of average $\ln(\mathrm{Q})$ for non R&D firms found in table 5. Equation (12) is equal to the expected value with treatment; the final term of this equation provides the correction for R&D firms. These correction terms are equal to 0.21 and -0.21 for all of these estimations. These correction terms combine to reduce the effect of undertaking R&D by increasing the expected value of non R&D firms and reducing the value of R&D firms such that the increase in firm value due to R&D is not equal to the full value of the estimated coefficient. The effect of treatment is therefore equal to

$$\mathrm{E}[\ln(\mathrm{V}_i) | \mathrm{RD}_i = 1] - \mathrm{E}[\ln(\mathrm{V}_i) | \mathrm{RD}_i = 0] = \theta + \rho\sigma_\varepsilon \left[\frac{f(\mathbf{z'}_{2i}\,\gamma_2)}{\Phi(\mathbf{z'}_{2i}\,\gamma_2)[1-\Phi(\mathbf{z'}_{2i}\,\gamma_2)]} \right] = g \tag{18}$$

Since our regression is estimate in the natural log of Tobin Q the coefficients on the binary variables have a percentage change interpretation. We therefore estimate the R&D premium as

$$\%\Delta \mathrm{V}_i = 100 \cdot [\exp(\gamma) - 1] \tag{19}$$

providing a biased, but consistent, estimate of the expected percentage change. The correction factors are always calculated from the mean characteristics of the selected (R&D firm) sample. The estimated R&D premium for each regression is shown in the second row of table 6. This can be interpreted as the average percentage increase in Tobin Q that a firm with non R&D firm characteristics would receive were it to undertake R&D. There is a degree of variability in these estimates of the R&D premium. Diversification seems to bring about a 36 percent increase in firm value; this drops to just 11.42 percent if the firm is simultaneously industrially and internationally diversified. Undertaking R&D is associated with a considerable increase of 35 percent in firm value for industrially diversified firms while internationally diversified firms incur a small but statistically significant 2.65 percent value discount. While the market may not value R&D undertaken by internationally diversified firms as highly as it does industrially diversified firms we know from table 4 that international diversification is associated with a value premium and this appears to be more than enough to offset the R&D discount. It may be that the market has an expectation that internationally diversified firms will undertake some level of R&D expenditure.

Before we proceed to a discussion of the R&D premium for diversified firms we will first assess the diversification discount for non R&D firms. The estimate of the diversification discount is calculated as in (19) with the treatment γ replaced with the estimated coefficient on the diversification indicator. As stated previously diversification and international diversification do not incur a value discount. Industrial diversification on the other hand is found to be associated with a reduction in firm value of almost 8 percent.

We now turn to the R&D premium for diversified firms. The R&D premium for diversified firms is calculated using (19) including the coefficient estimates on the diversification indicators and the diversification-R&D indicators in addition to the R&D treatment γ. It was found above that the only interaction terms that are statistically significant are those for industrial diversification and joint industrial and international diversification. Industrial diversification has the effect of reducing the R&D premium from about 35 percent to a discount of 17 percent. The effect is slightly less pronounced for joint diversification, however this too involves an offsetting interaction that results in an 11 percent value discount. These are significant results when one considers that the vast majority of Australian R&D firms are industrially diversified.

(iii) Ordinary Least Squares Estimates

We now compare the treatment effects estimates of table 5 and 6 with a pooled OLS regression where the endogeniety of the decision to undertake R&D and to diversify are not considered. OLS results are shown in table 7. Once again we find a statistically significant size discount implied by the sign and statistical significant of the quadratic terms and locations of the turning points.

In contrast to the treatment effects estimates of table 5, the R&D coefficient estimates for the OLS regressions do provide the estimated increase in average Tobin Q associated with undertaking R&D. As expected we find the OLS estimates to underestimate the R&D premium. Previously when we controlled for diversification the increase in Tobin Q associated with undertaking R&D is 0.3663, we now estimate that premium to be just over half of this at 0.17 (see table 8).

4. Conclusion

From an initial government policy standpoint of subsidising the R&D activities of companies in Australia to make them internationally competitive we have explored the value relevance of R&D expenditure in companies that are both industrially and internationally diversified. A challenge in the empirical analysis of this problem is that companies do not decide to undertake R&D expenditure or diversify at random, and as such appropriate econometric treatment of the selectivity issues in this decision is required. For all specifications of the model we find a positive R&D value premium. In addition our modelling approach shows that an OLS estimation of the value premium underestimates the size of that premium. However we also find a negative interaction relationship between R&D and industrial diversification.

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Table 1: Transition Table for R&D Over Sample Period		
	Non $R\&D_t$	$R\&D_t$
Non $R\&D_{t-1}$	98.39	1.61
$R\&D_{t-1}$	23.75	76.25
Total	94.71	5.29

Table 2: Coverage of R&D Firm Years

	1	2	3	4	5	Gaps	R&D Firms
R&D Firm Years							
Full Sample	49	28	14	19	35	110	145
Diversified	41	25	13	19	34	98	132
Industrially Diversified Firms	30	21	11	18	31	80	111
Internationally Diversified Firms	34	19	10	16	31	79	110
Internationally & Industrially Diversified Firms	23	15	8	15	28	61	89

Table 3: Cross Tabulation of RD & Non R&D Firms and Firm years with respect to Diversification

	Non R&D Firms	R&D Firms	Total
Panel A: Firm Years			
Diversified	4,794	376	5,170
Not Diversified	2,388	22	2,410
Industrially Diversified Firms	3,603	332	3,935
Not Industrially Diversified	3,579	66	3,645
Internationally Diversified Firms	3,189	321	3,510
Not Internationally Diversified	3,993	77	4,070
Internationally & Industrially Diversified Firms	1,998	277	2,275
Sole Diversification and Non Diversified Firms	5,184	121	5,305
Total R&D Firm Years	1,177	339	7,580
Panel B: Firms			
Diversified	902	132	1,034
Not Diversified	469	13	482
Industrially Diversified Firms	676	111	787
Not Industrially Diversified	695	34	729
Internationally Diversified Firms	592	110	702
Not Internationally Diversified	779	35	814
Internationally & Industrially Diversified Firms	366	89	455
Sole Diversification and Non Diversified Firms	1,005	56	1,061
Total R&D Firms	1,371	145	1,516

Table 4: Estimation Sample Summary Statistics.

Variable	Mean	Median	Std. Dev.	Minimum	Maximum	N
Full Sample						
Tobin's Q	2.00	1.39	1.65	0.12	9.97	2311
Log(Assets)	11.38	11.17	2.22	6.53	17.44	2311
Log(Assets)^2	134.34	124.78	52.59	42.63	304.24	2311
RD-Sales	0.32	0.00	2.18	0.00	60.50	2311
Return on Assets (RoA)	-4.00	3.62	23.86	-99.11	85.67	2311
Debt to Assets	42.05	46.41	23.57	0.22	99.77	2311
R&D Firms						
Tobin's Q	1.62	1.22	1.24	0.47	9.02	335
Log(Assets)	13.54	13.50	1.78	9.87	17.44	335
Log(Assets)^2	186.57	182.34	48.75	97.43	304.24	335
RD-Sales	2.17	0.44	5.38	0.00	60.50	335
Return on Assets (RoA)	6.71	6.37	14.42	-88.63	85.67	335
Debt -Assets	54.70	56.90	13.52	11.21	94.32	335

Table 5: Results of a Treatment Effects estimation of equation (14). Dependant variable is the natural log of Tobin Q. Independent variables are Log(Assets) and Diversification Indicators with endogeniety corrected estimates of the R&D coefficient. Industry and year dummies are included. White (1980) p-values are included in parentheses. Stars indicate 5 and 10 percent levels of significance.

	Diversified	Industrial	International	Joint
Tobin Q Equation				
C	4.547	4.716	4.506	4.659
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000) **
Log(Assets)	-0.547	-0.577	-0.548	-0.574
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Log(Assets)^2	0.016	0.018	0.016	0.018
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
R&D	1.328	1.325	0.987	1.128
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Diversified	-0.050			
	(0.2330)			
Industrial Diversification		-0.0807		
		(0.0140)**		
International Diversification			(0.050	
			(0.1030)	
International & Industrial Diversification				0.0096
				(0.7610)
Diversified*R&D	-0.374			
	(0.2860)			
Industrial Diversification*R&D		-0.4059		
		(0.0030)**		
International Diversification*R&D			-0.0408	
			(0.6530)	
International & Industrial Diversification*R&D				-0.2339
				(0.0090)**
Turning Point for Assets (Billion)				
Industry Dummy	Yes	Yes	Yes	Yes
Annual Dummy	Yes	Yes	Yes	Yes
Wald Test	983.08	1015.49	985.11	975.62
	0.0000	0.0000	0.0000	0.0000
Selection equation				
C	-12.068	-12.252	-11.939	-11.774
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Log(Assets)	1.327	1.359	1.307	1.283
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Log(Assets)^2	-0.041	-0.042	-0.040	-0.039
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
RoA	0.022	0.021	0.022	0.022
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Debt-Assets	0.014	0.014	0.014	0.014
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
ρ	-0.835	-0.847	-0.833	-0.838
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
σ	0.698	0.697	0.698	0.698
Log-Likelihood	-2591.09	-2575.04	-2593.55	-2588.71
Turning Point for Assets (Billions)				
N	2120	2120	2120	2120

Table 6: Marginal effects computed from a Treatment Effects Estimation. Percentage change in average Tobin's Q for non diversified firms that undertake R&D relative to non diversified firms that do not undertake R&D followed by, percentage change in average Tobin's Q for diversified firms that do not undertake R&D relative to diversified firms that do not undertake R&D and finally the percentage change in average Tobin Q for diversified firms that undertake R&D with respect to diversified firms that do not undertake R&D. Percentages changes are calculated for four different types of diversification.

Research & Development	Diversified	Industrial	International	Joint
Average Q for a Non Diversified Firm That Does Not Undertake R&D	1.845	1.883	1.720	1.766
Average Q for a Non Diversified Firm That Undertakes R&D	4.594	4.739	3.008	3.602
Increase in average Q relative to a non diversified firm that does not undertake R&D				
Percentage Change	36.63	34.93	-2.65	11.42
Average Q for a Diversified Firm That Does Not undertake R&D	1.755	1.737	1.809	1.783
Increase in average Q relative to a non diversified firm that does not undertake R&D				
Diversification Discount	-4.87	-7.76	5.15	0.96
Average Q for a Diversified Firm That Also Undertakes R&D	3.006	2.913	3.036	2.878
Increase in average Q relative to a non diversified firm that does not undertake R&D				
Combined Percentage Change	-10.59	-17.06	-1.73	-10.97

Table 7: Results of an OLS estimation of equation (14). Dependant variable is the natural log of Tobin Q. Independent variables are Log(Assets) and Binary R&D and Diversification Indicators. Industry and year dummies are included. White (1980) p-values are included in parentheses. Stars indicate 5 and 10 percent levels of significance

	Diversified	Industrial	International	Joint
Tobin Q Equation				
C	4.347	4.501	4.314	4.449
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Log(Assets)	-0.565	-0.593	-0.568	-0.592
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
$Log(Assets)^2$	0.020	0.022	0.020	0.021
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
R&D	0.164	0.292	0.046	0.162
	(0.4840)	(0.0170)**	(0.5230)	(0.0300)**
Diversified	-0.070			
	(0.1030)*			
Industrial Diversification		-0.1134		
		(0.0010)**		
International Diversification			0.0325	
			(0.3300)	
International & Industrial Diversification				-0.0293
				(0.3890)
Diversified*R&D	-0.120			
	(0.6110			
Industrial Diversification*R&D		-0.2820		
		(0.0250)**		
International Diversification*R&D			-0.0103	
			(0.8980)	
Industrial & International Diversification*R&D				-0.1663
				(0.0440)**
Turning Point for Assets (Billions)				
Industry Dummies	Yes	Yes	Yes	Yes
Annual Dummies	Yes	Yes	Yes	Yes
F test	20.33	22.09	19.96	20.62
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.12	0.13	0.12	0.12
N	2120	2120	2120	2120

Table 8: Marginal effects computed from OLS Regression. Percentage change in average Tobin's Q for non diversified firms that undertake R&D relative to non diversified firms that do not undertake R&D followed by, percentage change in average Tobin's Q for diversified firms that do not undertake R&D relative to diversified firms that do not undertake R&D and finally the percentage change in average Tobin Q for diversified firms that undertake R&D with respect to diversified firms that do not undertake R&D. Percentages changes are calculated for four different types of diversification.

Research & Development	Diversified	Industrial	International	Joint
Average Q for a Non Diversified Firm That Does Not Undertake R&D	1.588	1.659	1.453	1.529
Average Q for a Non Diversified Firm That Undertakes R&D	1.871	2.221	1.522	1.799
Increase in average Q relative to a non diversified firm that does not undertake R&D				
Percentage Change	17.78	33.90	4.70	17.63
Average Q for a Diversified Firm That Does Not undertake R&D	1.481	1.481	1.486	1.485
Increase in average Q relative to a non diversified firm that does not undertake R&D				
Diversification Discount	-6.77	-10.72	3.30	-2.89
Average Q for a Diversified Firm That Also Undertakes R&D	1.313	1.117	1.501	1.258
Increase in average Q relative to a non diversified firm that does not undertake R&D				
Combined Percentage Change	-2.61	-9.83	7.05	-3.27