E C O N O M I C S   B U L L E T I N

Innovation and market value: a quantile regression analysis

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Abstract

We construct a new database by matching firm-level Compustat data to NBER patent data, for four 2-digit complex technology sectors. Whilst conventional regression estimators show that the stock market does recognise efforts at innovation, quantile regression analysis adds a new dimension to the literature, suggesting that the influence of innovation on market value varies dramatically across the market value distribution. For firms with a low value of Tobin's q, the stock market will barely recognize their attempts to innovate. For firms with the highest values of Tobin's q, however, their market value is particularly sensitive to innovative activity.

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1 Introduction

The impact of firm-level innovative activity on firm performance has received much attention over the last 25 years. One strand of the literature, beginning with Griliches (1981), has measured post-innovation performance by considering Tobin's q (i.e. market value divided by book value of assets). Given that it may take a long time for a successful innovation to be transformed into a profitable finished product, Tobin's q is a useful proxy for firm performance because the (expected) future profit stream is already taken into account. Indeed, there is evidence that the market can evaluate firm-level innovative activity reasonably well (Chan *et al.* 2001).

The regression methodology of this literature has typically been based on standard least-squares estimators. However, given that the distribution of Tobin's q is highly skewed, the usual assumption of normally distributed error terms is not warranted and could lead to unreliable estimates. Indeed, the variability in Tobin's q is even higher for high-tech firms than for other firms. Furthermore, firms are fundamentally heterogeneous and it may make little sense to use regression estimators that implicitly focus on the 'average effect for the average firm' by giving summary point estimates for coefficients. Instead, we apply quantile regression techniques that are robust to outliers and are able to describe the influence of the regressors over the entire conditional distribution of Tobin's q. Results obtained from conventional regressions do not show the whole picture. Quantile regression analysis is much more informative and shows that, while low-q firms' efforts at innovation are virtually ignored by financial markets, those few super-star firms with exceptionally high market valuation owe a lot of their success to innovative activity.

A major challenge facing research into firm-level innovative activity is the construction of suitable databases. In particular, it has proved difficult to gather meaningful quantitative indicators of innovation. While R&D expenditures and Patent statistics both shed light on the processes of innovation, they also contain a lot of specific variation (for surveys, see Dosi 1988 and Griliches 1990). For example, one statistical discrepancy is that patent series are typically more erratic and more skewed than R&D expenditures. In this study, we use Principal Component Analysis to create a summary 'innovativeness' variable that extracts the common variance from both R&D and patent statistics (levels and stocks) while discarding the irrelevant variance that includes measurement error and idiosyncratic variation.[1] In addition, we restrict our analysis to four 'complex technology' sectors (Cohen *et al.* 2000) that are known for their intense R&D and patenting activity. By concentrating on these sectors we attempt to get the best possible observations on firm-level innovation.

2 Database Description and Summary Statistics

This paper uses an original database that we created by matching the NBER patent database with the Compustat file database.[2] The patent data has been obtained from the NBER Database (Hall *et al.* 2001b). The NBER database comprises detailed information on almost 3,416,957 U.S. utility patents in the USPTOs TAF database granted during the period 1963 to December 2002.

[1]For a more detailed discussion of how to measure firm-level innovative activity, and why we generate this 'innovativeness' indicator, see Coad and Rao (2006).

[2]We would like to thank Bronwyn Hall for providing us with her calculations of Tobin's q for the Compustat data used in this paper.

Table 1: Summary statistics before and after data-cleaning, SIC's 35-38

	sample before cleaning n=1852 firms			sample used n=1331 firms		
	mean	median	std. dev.	mean	median	std. dev.
Total Sales	846.61	61.78	4334	983.05	71.81	4747
Patent applications	9.31	0	54.94	11.22	0	61.89
R&D expenditure	46.18	2.21	254.59	50.38	2.50	264.65
Tobin's q	3.77	1.52	19.35	3.31	1.46	14.04

Table 2: The Distribution of Firms by Total Patents, 1963-1999 (SIC's 35-38)

	0 or more	1 or more	10 or more	25 or more	100 or more	250 or more	1000 or more
Firms	1331	877	614	457	229	131	57

The initial sample of firms was obtained from the well-known Compustat database for the 'complex technology' sectors. These firms were then matched with the firm data files from the NBER patent database and we found all the firms[3] that have patents. The final sample thus contains both patenters and non-patenters.

Descriptive statistics of the sample before and after cleaning is shown in Table 1. Initially using the Compustat database, we obtain a total of 1852 firms which belong to the SICs 35-38 and this sample consists of both patenting and non-patenting firms. These firms were then matched to the NBER database. After this initial match, we further matched the year-wise firm data to the year-wise patents applied by the respective firms (in the case of patenting firms) and finally, we excluded firms that had less than 7 consecutive years of good data. Thus, we have an unbalanced panel of 1331 firms belonging to 4 different sectors. Since we intend to take into account sectoral effects of innovation, we will proceed on a sector by sector basis, to have (ideally) 4 comparable results for 4 different sectors.

We find that 34% of the firms in our sample have no patents. Thus the intersection of the two datasets gave us 877 patenting firms who had taken out at least one patent between 1963 and 1999, and 454 firms that had no patents during this period. (See Table 2 for more details on the distribution of firms by total patents.) The total number of patents taken out by this group over the entire period was 291,555, where the entire period for the NBER database represented years 1963 to 2000, and we have used 217,770 of these patents in our analysis i.e. representing about 75% of the total patents ever taken out at the US Patent Office by the firms in our sample.

[3]The patent ownership information reflects ownership at the time of patent grant and does not include subsequent changes in ownership. Also attempts have been made to combine data based on subsidiary relationships. However, where possible, spelling variations and variations based on name changes have been merged into a single name. While every effort is made to accurately identify all organizational entities and report data by a single organizational name, achievement of a totally clean record is not expected, particularly in view of the many variations which may occur in corporate identifications. Also, the NBER database does not cumulatively assign the patents obtained by the subsudiaries to the parents, and we have taken this limitation into account and have subsequently tried to cumulate the patents obtained by the subsidiaries towards the patent count of the parent. Thus we have attempted to create an original database that gives complete firm-level patent information.

Table 3: Contemporaneous correlations between Patents and R&D expenditure

	SIC 35	SIC 36	SIC 37	SIC 38
CORRELATIONS				
ρ	0.5281	0.3834	0.4475	0.7766
p-value	0.0000	0.0000	0.0000	0.0000
RANK CORRELATIONS				
ρ	0.4227	0.4672	0.4574	0.4587
p-value	0.0000	0.0000	0.0000	0.0000
Obs.	5986	6219	1972	5241

Table 4: Contemporaneous correlations between patents/sales and R&D/sales

	SIC 35	SIC 36	SIC 37	SIC 38
CORRELATIONS				
ρ	0.3446	0.3297	0.0900	0.3230
p-value	0.0000	0.0000	0.0001	0.0000
RANK CORRELATIONS				
ρ	0.0851	0.2153	0.2322	0.1336
p-value	0.0000	0.0000	0.0000	0.0000
Obs.	5986	6219	1972	5241

Table 5: Extracting the 'innovativeness' index used for the quantile regressions - Principal Component Analysis results (first component only, unrotated)

	SIC 35	SIC 36	SIC 37	SIC 38
R&D / Sales	0.4097	0.4127	0.4208	0.4408
Patents / Sales	0.4060	0.3740	0.3898	0.3607
R&D stock / Sales ($\delta = 15\%$)	0.4121	0.4307	0.3921	0.4397
Patent stock / Sales ($\delta = 15\%$)	0.4029	0.4002	0.4249	0.3787
R&D stock / Sales ($\delta = 30\%$)	0.4133	0.4280	0.3951	0.4401
Patent stock / Sales ($\delta = 30\%$)	0.4055	0.4012	0.4250	0.3810
Prop^n Variance explained	0.6270	0.5865	0.5588	0.5404
No. Obs.	5094	5305	1702	4467

Though the NBER database provides the data on patents applied for from 1963 till 2000, it contains information only on the granted patents and hence we might see some bias towards the firms that have applied in the end period covered by the database due the lags faced between application and the grant of the patents. Hence to avoid this truncation bias (on the right) we consider the patents only till 1999 so as to account for the average 3-year gap between application and grant of the patent.[4]

Table 3 shows that patent numbers are well correlated with (deflated) R&D expenditure, albeit without controlling for firm size. To take this into account, Table 4 reports the correlations between firm-level patent intensity and R&D intensity (conventional correlations and also rank correlations that are more robust to extreme observations). For each of the sectors we observe positive and highly significant rank correlations, which nonetheless take values of 0.23 or lower. These results would thus appear to be consistent with the idea that, even within industries, patent and R&D statistics do contain large amounts of idiosyncratic variance and that either of these variables taken individually would be a rather noisy proxy for innovativeness. Indeed, these two variables are quite different not only in terms of statistical properties (patent statistics are much more skewed and less persistent than R&D statistics) but also in terms of economic significance. However, they both yield valuable information on firm-level innovativeness.

As a result, we use Principal Component Analysis to create a composite summary index of

[4]This average gap has been referred to by many authors, among others Bloom and Van Reenen (2002) who mention a lag of two years between application and grant, and Hall *et al.* (2001a) who state that 95% of the patents that are eventually granted are granted within 3 years of application.

firm-level innovative activity. Our synthetic innovativeness index is created by extracting the common variance from a series of related variables: both patent intensity and R&D intensity at time t, and also the actualized 3-year stocks of patents and R&D. These stock variables are calculated using the conventional amortizement rate of 15%, and also at the rate of 30% since we suspect that the 15% rate may be too low (Hall and Oriani 2006). Information on the factor loadings is shown in Table 5. We consider the summary innovativeness variable to be a satisfactory indicator of firm-level innovativeness because it loads well with each of the variables and explains between 54% to 63% of the total variance. An advantage of this composite index is that a lot of information on a firm's innovative activity can be summarized into one variable (this will be especially useful in the following graphs). A disadvantage is that the units have no ready interpretation (unlike 'one patent' or '$1 million of R&D expenditure'). In this study, however, we are less concerned with the quantitative point estimates than with the qualitative variation in the importance of innovation over the conditional distribution of Tobin's q (i.e. the 'shape' of the graphs).

A more detailed discussion of the drawbacks of using either patent counts or R&D on their own as indicators of innovation, and why we prefer the composite 'innovativeness' variable, is provided in Coad and Rao (2006).

3 Quantile Regression

We begin this section with a brief introduction to quantile regression, and then apply it to our dataset.

3.1 An Introduction to Quantile Regression

Standard least squares regression techniques provide summary point estimates that calculate the average effect of the independent variables on the 'average firm'. However, this focus on the average firm may hide important features of the underlying relationship. As Mosteller and Tukey explain in an oft-cited passage: "What the regression curve does is give a grand summary for the averages of the distributions corresponding to the set of x's. We could go further and compute several regression curves corresponding to the various percentage points of the distributions and thus get a more complete picture of the set. Ordinarily this is not done, and so regression often gives a rather incomplete picture. Just as the mean gives an incomplete picture of a single distribution, so the regression curve gives a correspondingly incomplete picture for a set of distributions" (Mosteller and Tukey 1977:266). Quantile regression techniques can therefore help us obtain a more complete picture of the underlying relationship between innovation and market value.

In our case, estimation of linear models by quantile regression may be preferable to the usual regression methods for a number of reasons. First of all, we know that the standard least-squares assumption of normally distributed errors does not hold for our database because the values for Tobin's q follow a skewed distribution (see the evidence in Table 1). While the optimal properties of standard regression estimators are not robust to modest departures from normality, quantile regression results are characteristically robust to outliers and heavy-tailed distributions. In fact, the quantile regression solution $\hat{\beta}_\theta$ is invariant to outliers of the dependent variable that tend to $\pm\infty$ (Buchinsky 1994). Another advantage is that, while conventional regressions focus on the mean, quantile regressions are able to describe the entire conditional distribution of the dependent variable. In the context of this study, high-q firms

Table 6: Quantile regression estimation of equation (4): the coefficient and t-statistic on 'innovativeness' reported for the 10%, 25%, 50%, 75% and 90% quantiles. t-statistics are computed using bootstrapped standard errors (500 replications). Coefficients significant at the 5% level appear in bold.

	OLS	FE	Quantile regression 10%	25%	50%	75%	90%
SIC 35	**1.2919**	-0.1965	0.0271	**0.0942**	**0.2307**	**0.6873**	**1.2807**
(4648 obs.)	3.36	-0.34	1.76	3.36	5.14	6.65	5.07
[Pseudo-]R^2	0.0290	0.0145	0.0381	0.0519	0.0727	0.1111	0.1742
SIC 36	**0.7277**	-0.1736	**0.1537**	**0.2946**	**0.4590**	**1.1032**	**2.2329**
(4848 obs.)	3.30	-1.10	4.02	8.75	4.66	5.87	6.68
[Pseudo-]R^2	0.1430	0.0498	0.0406	0.0560	0.0880	0.1470	0.2351
SIC 37	**0.0593**	-0.0281	0.0013	0.0079	**0.0384**	**0.0364**	0.0453
(1567 obs.)	2.72	-1.44	0.19	0.58	3.02	2.18	1.46
[Pseudo-]R^2	0.1938	0.1588	0.1231	0.1394	0.1784	0.2113	0.2634
SIC 38	**0.9341**	**0.4715**	0.0309	**0.2281**	**0.6619**	**1.4918**	**3.5843**
(4080 obs.)	3.67	2.50	0.75	2.03	4.20	5.34	5.36
[Pseudo-]R^2	0.1283	0.0674	0.0336	0.0430	0.0760	0.1353	0.2037

are of interest in their own right, we don't want to dismiss them as outliers, but on the contrary we believe it would be worthwhile to study them in detail. This can be done by calculating coefficient estimates at various quantiles of the conditional distribution. Finally, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Relaxing this assumption allows us to acknowledge firm heterogeneity and consider the possibility that estimated slope parameters vary at different quantiles of the conditional distribution of Tobin's q.

The quantile regression model, first introduced by Koenker and Bassett (1978), can be written as:

$$y_{it} = x'_{it}\beta_\theta + u_{\theta it} \qquad \text{with} \qquad \text{Quant}_\theta(y_{it}|x_{it}) = x'_{it}\beta_\theta \tag{1}$$

where y_{it} is the growth rate, x is a vector of regressors, β is the vector of parameters to be estimated, and u is a vector of residuals. $Q_\theta(y_{it}|x_{it})$ denotes the θ^{th} conditional quantile of y_{it} given x_{it}. The θ^{th} regression quantile, $0 < \theta < 1$, solves the following problem:

$$\min_\beta \frac{1}{n}\left\{ \sum_{i,t:y_{it}\geq x'_{it}\beta} \theta|y_{it} - x'_{it}\beta| + \sum_{i,t:y_{it}<x'_{it}\beta} (1-\theta)|y_{it} - x'_{it}\beta| \right\} = \min_\beta \frac{1}{n}\sum_{i=1}^{n} \rho_\theta u_{\theta it} \tag{2}$$

where $\rho_\theta(.)$, which is known as the 'check function', is defined as:

$$\rho_\theta(u_{\theta it}) = \left\{ \begin{array}{ll} \theta u_{\theta it} & \text{if } u_{\theta it} \geq 0 \\ (\theta-1)u_{\theta it} & \text{if } u_{\theta it} < 0 \end{array} \right\} \tag{3}$$

Equation (2) is then solved by linear programming methods. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y, conditional on x

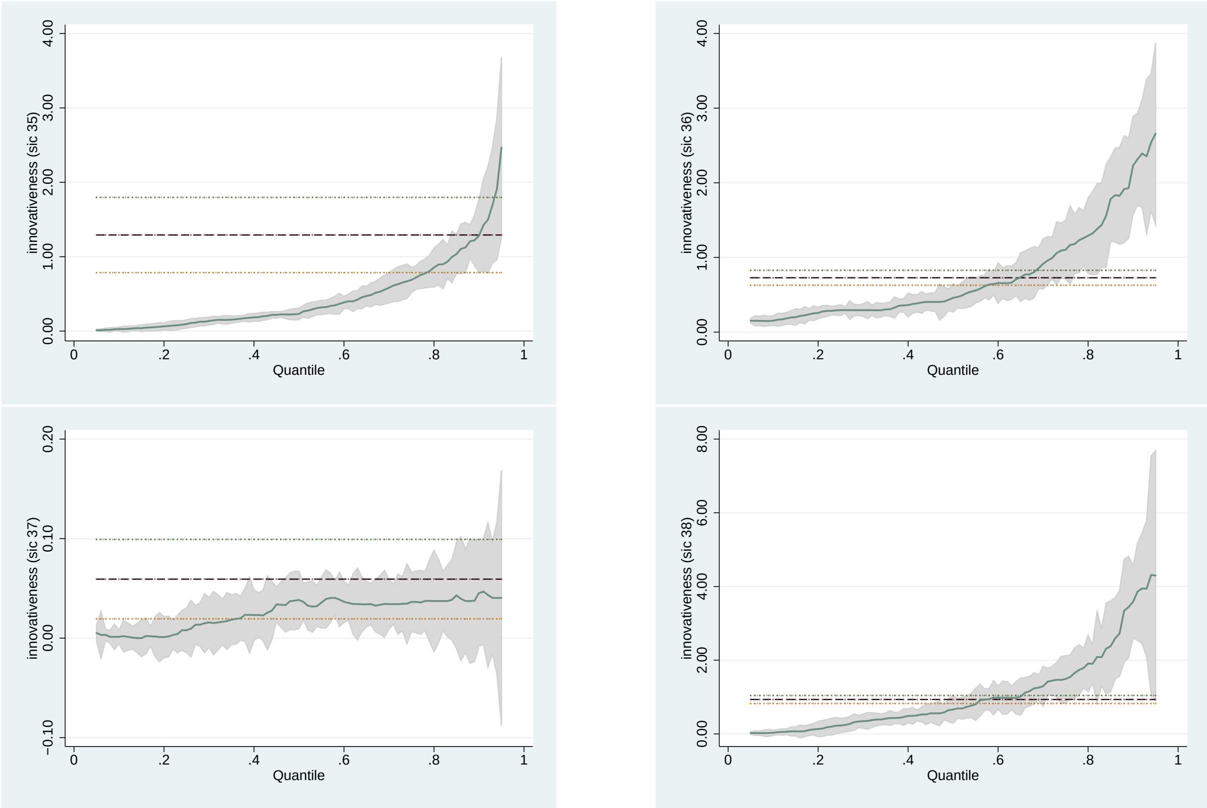

Figure 1: Variation in the 'innovativeness' coefficient (β_1 from Equation (4)) over the conditional quantiles. Confidence intervals extend to 95% confidence intervals in either direction (for computational manageability, we use the Stata default setting of 20 replications for the bootstrapped standard errors). Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: Machinery & Computer Equipment (top left), SIC 36: Electric/Electronic Equipment (top right), SIC 37: Transportation Equipment (bottom left), SIC 38: Measuring Instruments (bottom right). Graphs made using the 'grqreg' Stata module (Azevedo 2004).

(Buchinsky 1998). More on quantile regression techniques can be found in the surveys by Buchinsky (1998) and Koenker and Hallock (2001); for applications see Buchinsky (1994), Mata and Machado (1996), Coad (2006) and also the special issue of *Empirical Economics* (Vol. 26 (3), 2001).

3.2 Quantile regression results

In keeping with the literature,[5] we estimate the following linear regression model:

$$q_{i,t} = \alpha + \beta_1 INN_{i,t-1} + \beta_3 SIZE_{i,t-1} + \beta_4 IND_{i,t} + y_t + \epsilon_{i,t} \tag{4}$$

where q_{it}, the dependent variable, is the value of Tobin's q for firm i at time t. INN represents the 'innovativeness' index, and the control variables are lagged size (measured in sales (deflated dollars)) and 3-digit industry dummies. We also control for common macroeconomic shocks by including year dummies (y_t).

[5] See, among others, Griliches (1981), Pakes (1985), Jaffe (1986), Cockburn and Griliches (1988), Hall (1993a, 1993b), Hall *et al.* (2005) and Hall and Oriani (2006).

The numerical results for OLS, fixed-effects and quantile regression estimation are reported in Table 6. OLS regressions estimate a positive and significant influence of innovative activity on Tobin's q, for each of the four sectors. Fixed-effects regressions, on the other hand, only detect a significant (positive) influence for SIC 38.[6] Median (50%) quantile regression results, which correspond to the Minimum Absolute Deviation (MAD) estimator, are significantly lower than the OLS estimates for each of the four sectors. This suggests that the OLS estimates, which are not robust to extreme observations or non-gaussian distributions of residuals, may be biased upwards.

Quantile regression results are always positive and mostly statistically significant. The quantile regression coefficients can be interpreted as the partial derivative of the conditional quantile of y with respect to particular regressors, $\Delta Q_\theta(y_{it}|x_{it})/\Delta x$. Put differently, the derivative is interpreted as the marginal change in y at the θ^{th} conditional quantile due to marginal change in a particular regressor (Yasar *et al.* 2006). For each of the four sectors, the coefficient on innovativeness is much larger at the higher quantiles. The coefficient estimates at the 75% quantiles are over three times bigger than those at the 25% quantiles, for each of the four sectors. Values for the pseudo-R^2 also rise as we move to the upper quantiles.

Figure 1 allows a visual appreciation of the quantile regression results. All four of the sectors show a common pattern, although the plot for SIC 37 is much less elegant than for the other sectors (this is in part due to the smaller number of observations, and perhaps also due to the peculiarities of this sector[7]). At the lowest quantiles of the conditional Tobin's q distribution, the coefficients on innovativeness are very low, close to zero, which suggests that these firms' efforts at innovation are barely recognized by the stock market. As we move up the conditional distribution, however, the coefficient rises significantly, especially at the extreme upper quantiles. For those firms with the highest values of Tobin's q, additional efforts at innovation result in relatively large gains in market value. It is plain to see that the OLS point estimates, shown here as horizontal lines with 95% confidence intervals, provide limited information on the relationship between innovation and market value.

Our results appear to be quite robust, not only across the four 'complex technology' sectors, but also using different data. We repeated the analysis using either 3-year R&D stocks or 3-year patent stocks (instead of combining them in a composite index) and we obtained qualitatively similar results. Furthermore, we repeated the analysis using the Hall *et al.* (2005) database,[8] and obtained similar results (although with fewer observations).

To sum up, previous research using conventional regression estimators shows that the stock market does recognize innovative activity undertaken by firms. However, quantile regression analysis adds a new dimension to the literature and suggests that the influence of innovation on market value varies dramatically across the market value distribution. For firms with a low value of Tobin's q, the stock market will barely recognize their attempts to innovate. For firms with the highest values of Tobin's q, however, their market value is particularly sensitive to innovative activity.

[6]See Hall *et al.* (2005:26) for a discussion of the poor performance of the fixed-effect estimator in this particular case.

[7]SIC 37 (Transportation Equipment) contains manufacturing sectors as diverse as ship-building, bicycles, and guided missiles. Furthermore, while the other 3 sectors are bona fide 'high-tech' sectors, many subclasses of SIC 37 have rather more mature technological bases. For an amusing anecdote on the diversity of industries grouped together in the 'Transportation Equipment' class, see Griliches (1990:1667).

[8]This database is publicly available (subject to conditions) from Bronwyn Hall's website: http://elsa.berkeley.edu/∼bhhall/bhdata.html

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