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Distance to Frontier and Appropriate Business Strategy

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Abstract:
This paper is an empirical test of the hypothesis that the appropriateness of different business strategies is conditional on the firm's distance to the industry frontier. We use data on four 2-digit high-tech manufacturing industries in the US over the period 1972-1999, and apply semi-parametric quantile regressions to investigate the contribution of firm behavior to market value at various points of the conditional distribution of Tobin's q. Among our results, we observe that innovative activity, measured in terms of R&D expenditure or patents, has a strong positive association with market value at the upper quantiles (corresponding to the leader firms) whereas the innovative efforts of laggard firms are valued significantly less. Laggard firms, we suggest, should instead achieve productivity growth through efficient exploitation of existing technologies and imitation of industry leaders. Employment growth in leader firms is encouraged whereas growth of backward firms is not as well received on the stock market.

Keywords: Distance to frontier; Strategy; Market value; Innovation; Firm growth
Jel codes: L25 ; L21 ; D21 ; O31

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1 Introduction

Firms differ widely in terms of their performance, and there is a case to be made for prescribing different strategies for firms conditional on the distance to the industry frontier. Leader firms, at the technological frontier, may be better suited to innovation, whereas laggard firms can experience relatively rapid productivity growth by exploiting existing technologies and imitating frontier technologies. Furthermore, backward firms should focus on improving production efficiencies whereas leader firms can seek to apply their proven competences to new areas, through growth, diversification, and exporting.

This paper is an empirical test of the hypothesis that different business strategies and management practices are more or less appropriate conditional on the business firm's distance to the industry frontier. We use data on four 2-digit high-tech manufacturing industries in the US over the period 1972-1999, and apply semi-parametric quantile regressions to investigate the contribution of firm behavior to market value at various points of the conditional distribution of Tobin's q. We observe that innovative activity, measured in terms of R&D expenditure or patents, has a strong positive association with market value at the upper quantiles (corresponding to the leader firms) whereas the innovative efforts of laggard firms are valued significantly less. Employment growth in leader firms is encouraged whereas growth of backward firms is not as well received on the stock market. While firm size may be an advantage for backward firms, this appears to be more of a liability for leader firms, for whom the emphasis is on innovation and adaptation in a highly turbulent market environment.

The originality of this paper lies in the application of the distance-to-frontier framework at the firm-level of analysis. We acknowledge, however, that previous work in the development macroeconomics literature prescribes different growth policies conditional on a country's distance to the world technological frontier (see Appendix A for a survey of this literature). Section 2 develops a set of testable hypotheses. Section 3 describes the database and empirical methodology, as well as the results. The rich implications of our empirical findings are discussed in Section 4, while Section 5 concludes.

2 Hypotheses

We now formulate some possible hypotheses according to which distance to frontier has important conditioning effects on appropriate firm behavior.

Distance to frontier and innovation Innovative activity undertaken by firms plays a key role in the dynamics of modern capitalism. Successful innovation can push forward the existing technological frontier, bestowing competitive advantage upon the innovator in the form of privileged knowledge on new products or production techniques. However, innovation is also a very uncertain activity, requiring large investments but in many cases offering modest returns (Coad and Rao (2008)). These features of innovation are germane to our present discussion. Leader firms, who are at the industry frontier, have already reached the limits of productive efficiency that can be achieved through existing production techniques. Being at the frontier, they can only improve their performance if they move the industry frontier forward. Leader firms also have the financial resources available to make such investments. Far from the frontier, however, there is considerable leeway for backward firms to improve their productivity levels merely through the application of existing knowledge on production techniques (i.e. 'imitation'). Furthermore, these firms do not have sufficient 'slack' resources to invest in R&D. Instead, they should focus on steadily improving their operating efficiency and thus improving their chances of survival. A similar idea was recently expressed by (Levinthal, 2007, p. 302):

> "Young, small, vulnerable firms have an acute survival problem. They need to exploit whatever modicum of wisdom they have about the world if they are to survive. Exploration, we suggest, is for the richer, more established firm."

An illustration of the special roles of innovation and imitation is provided by the Japanese electronics firm Matsushita (owner of the 'Panasonic' and 'National' brands). Matsushita started out by imitating existing technologies and became famous for its 'me-too' products, to the point where it earned itself the derogatory nickname 'Maneshita', meaning 'copycat' (Hall (2006)). Having achieved productive efficiency, however, it has focused on the design of new innovative products and has thus been able to establish itself as a world leader.[1]

This discussion leads us to formulate two hypotheses:

Hypothesis 1 *Investment in R&D is a more valuable strategy for leader firms than for backward firms*

Hypothesis 2 *Patenting activity is a more valuable strategy for leader firms than for backward firms*

Distance to frontier and firm size Having a large size may to be an advantage for backward firms feeling the threat of exit (i.e. 'the shadow of death'), since larger firms have 'deeper pockets', more market power, and a greater probability of survival. In contrast, having a large size is less useful for leading, innovative firms. Larger firms may suffer from bureaucratic inertia and be more rigid and less able to adapt to the changing market environment (which

[1]Panasonic won six awards at the 2006 Industrial Design Excellence Awards, more than any other company (Hall (2006)).

changes very rapidly at the frontier). Furthermore, larger firms may suffer from 'cognitive' inertia in the sense that they may not be able to see the value of a novel technology. In this vein, it has often been suggested that innovation is the domain of relatively small firms (e.g. Acs and Audretsch (1990)).

Hypothesis 3 *Firm size is a disadvantage for frontier firms but may be an advantage for backward firms*

Distance to frontier and firm growth High-productivity firms have incentives to expand, because they are capable of efficient production and can increase total profits by increasing their sales base. Less productive firms do not have such incentives to grow, however, and they should focus their attention on improving the efficiency of their existing production routines and avoid being distracted by growth projects.[2] Poor performers may nonetheless seek to grow if they are run by self-interested managers whose personal satisfaction increases with the size of the firm.[3]

In the case of leader firms, then, shareholders would value firm growth, whereas in the second case they would not benefit from firm growth.

Hypothesis 4 *Firm growth is a valuable strategy for leader firms but is not valuable for laggard firms*

We are aware that there may be a tension between hypotheses 3 and 4. These two hypotheses state that employment growth among leader firms is encouraged, but that large size among leaders can be a hindrance. This tension is reminiscent of some early perspectives on firm growth,[4] according to which firms take up additional growth opportunities that are attractive on the margin, even if there is no long term advantage associated with a larger size.

3 Empirical analysis

3.1 Database description

The following analysis draws from the database of US manufacturing firms in high-tech sectors used in Coad and Rao (2006). Most of the variables come from the Compustat database.

[2] An exception, however, would be the case of laggard small firms who are struggling to reach the industry minimum efficient scale (MES). For such firms, growth would be advantageous because it would be associated with increasing productivity.

[3] Managers of larger firms tend to receive larger remuneration as well as other advantages such as power and prestige. For a survey of the 'managerialist' theory of firm growth, see Coad (2007a).

[4] See, among others, Dixon's theory of firm growth through 'creep' (Dixon (1953)), Penrose's theory of 'economies of growth' despite constant returns to scale (Penrose (1959)), or the 'will o' the wisp' models of firm growth described in Starbuck (1971).

In order get information on patent applications, we matching the NBER patent database with the Compustat file database.[5] The patent data has been obtained from the NBER Database (Hall et al. (2001)), and we have used the updates available on Bronwyn Hall's website[6] to obtain data until 2002. Because of the lag between patent application and grant, however, we end our analysis in 1999. Since the reporting of R&D expenditures became compulsory in 1972, we only use data after this date in order to minimize sample selection biases. Our dataset thus covers the period 1972-1999. To take into account sectoral specificities in production technology, we focus on four different 2-digit sectors. By conducting our analysis at a sectoral level, we aim to avoid problems of aggregating across heterogeneous firms, with the advantage of being able to compare the results obtained for the four sectors. We focus on high-technology sectors characterized by high R&D levels and high patenting activity in the hope of getting meaningful quantitative measurements of firm-level innovative activity. These sectors are: SIC 35 (industrial and commercial machinery and computer equipment), SIC 36 (electronic and other electrical equipment and components, except computer equipment), SIC 37 (transportation equipment) and SIC 38 (measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks).

In the previous literature surveyed above, a firm's distance to frontier is operationalized using indicators of performance such as labour productivity (e.g. Amable et al. (2007)) or multifactor productivity (Nicoletti and Scarpetta (2003)). In this paper, however, we prefer to measure a firm's distance to frontier using its Tobin's q value. Tobin's q is the ratio obtained by dividing a firm's market value by its book value of assets. Tobin's q is the preferable variable here because future performance gains obtained through 'appropriate' behaviour can be anticipated on the stock market and can thus be included into a firm's current market value (and hence Tobin's q). In this way, we minimize problems related to the time lags between firm behaviour and changes in performance. Furthermore, there is evidence that the stock market can evaluate firm-level innovative activity reasonably well (Chan et al. (2001), Hall (2000)). Another reason for this choice is that we lack the detailed information on inputs required to construct an accurate productivity indicator at the firm-level.

The Tobin's q variable used here comes from Bronwyn Hall's calculations (see Coad and Rao (2006)). The R&D stock variable is constructed over a 3-year period, whereby R&D expenditure (deflated to 1980 dollars) is depreciated at the conventional 15% rate. The 3-year patent stock variable is also depreciated at the conventional 15% rate. To control for size effects, these stock variables were scaled down by a firm's sales. Firm size is measured in terms of (log of thousands of) employees, and employment growth rates are measured the

[5] 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.

[6] See http://elsa.berkeley.edu/∼bhhall/bhdata.html

Table 1: Summary statistics for the main variables.

									Correlation matrix				
Variable	Mean	Std. Dev.	10%	25%	Median	75%	90%	Obs	Tobin's q	R&D stock	Patent stock	Empl	Empl. gr.
SIC 35: Machinery & Computer Equipment													
Tobin's q	3.4592	23.8976	0.6193	0.8747	1.3864	2.5341	5.3990	5551	1.0000				
R&D stock	0.1377	0.2809	0.0158	0.0340	0.0746	0.1669	0.2871	4858	0.1117	1.0000			
Patent stock	0.0673	0.1933	0.0000	0.0000	0.0018	0.0547	0.1724	4858	0.0193	0.0914	1.0000		
Empl	0.2395	1.8855	-2.1716	-1.0818	0.1196	1.4586	2.8332	5551	-0.0976	-0.2342	-0.0277	1.0000	
Empl. gr.	0.0560	0.2374	-0.1748	-0.0523	0.0379	0.1423	0.3102	5234	0.0470	-0.0628	-0.0097	0.0030	1.0000
SIC 36: Electric/Electronic Equipment													
Tobin's q	3.0900	6.5281	0.6464	0.9365	1.4633	2.8040	5.7988	5856	1.0000				
R&D stock	0.1764	0.8909	0.0144	0.0393	0.0951	0.1876	0.3196	5115	0.1532	1.0000			
Patent stock	0.0818	0.3899	0.0000	0.0000	0.0000	0.0626	0.1962	5115	0.1435	0.2459	1.0000		
Empl	-0.0765	1.8913	-2.3126	-1.4106	-0.3341	0.9783	2.6967	5856	-0.1504	-0.0903	-0.0530	1.0000	
Empl. gr.	0.0466	0.2357	-0.1909	-0.0609	0.0380	0.1472	0.2897	5507	0.1777	-0.0342	0.0318	0.0633	1.0000
SIC 37: Transportation Equipment													
Tobin's q	1.4589	1.8142	0.5999	0.7772	1.0675	1.5405	2.4047	1841	1.0000				
R&D stock	0.0511	0.0664	0.0000	0.0145	0.0341	0.0701	0.1141	1654	0.0670	1.0000			
Patent stock	0.0483	0.1654	0.0000	0.0000	0.0019	0.0325	0.1211	1654	-0.0359	0.1821	1.0000		
Empl	1.5974	1.9980	-0.9163	0.1823	1.3460	3.1135	4.3399	1841	-0.1938	0.0435	-0.1157	1.0000	
Empl. gr.	0.0331	0.1873	-0.1498	-0.0541	0.0241	0.1024	0.2167	1761	0.1802	-0.0083	-0.0278	-0.0380	1.0000
SIC 38: Measuring Instruments													
Tobin's q	4.0755	8.1767	0.7100	1.0518	1.7593	3.7371	9.1015	4913	1.0000				
R&D stock	0.2707	2.0313	0.0361	0.0686	0.1327	0.2121	0.3463	4256	0.2052	1.0000			
Patent stock	0.1447	0.4920	0.0000	0.0000	0.0146	0.1103	0.3328	4256	0.2184	0.1178	1.0000		
Empl	-0.5510	1.8742	-2.8473	-1.9241	-0.7614	0.5939	2.1342	4911	-0.2674	-0.1034	-0.1374	1.0000	
Empl. gr.	0.0629	0.2156	-0.1431	-0.0392	0.0411	0.1487	0.2979	4595	0.1941	-0.0341	0.0190	-0.0289	1.0000

usual way by taking the log-differences of firm size (i.e. employees). Summary statistics and a pairwise correlation matrix for the key variables used in this analysis are presented in Table 1. The correlations between the variables are generally rather low. (For more information on the database construction procedure and supplementary statistics on patent applications, see Coad and Rao (2006).)

3.2 Results

The regression equation we estimate is the following:

$$
\begin{aligned}
q_{i,t} = \quad & \alpha + \beta_1 R\&Dstock_{i,t} + \beta_2 PATstock_{i,t} \\
& + \beta_3 EMPL_{i,t} + \beta_4 EMPLGR_{i,t} \\
& + \gamma_1 IND_{i,t} + \gamma_2 y_t + \varepsilon_{it}
\end{aligned} \tag{1}
$$

where q is the value of Tobin's q for firm i in year t, $R\&Dstock$ and $PATstock$ are the three-year stocks of R&D and patents, $EMPL$ is the number of employees, and $EMPLGR$ is the employment growth rate.[7] IND represents a full set of 3-digit industry dummies, y is a year dummy that controls for common macroeconomic trends, and $\varepsilon_{i,t}$ is the residual error term. The coefficients of interest are β_1, β_2, β_3, and β_4, and they are obtained for various quantiles by estimating the quantile regressions at different quantiles of the conditional distribution of the dependent variable (Tobin's q).

For the benefit of those readers who are not familiar with quantile regression, we begin with some basic pooled OLS regressions where, for each industry, the sample is split into two groups – firms with below-median values of Tobin's q, and firms with above-median values of q. The results are generally in line with our hypotheses (see Table 2). For firms with relatively high values of Tobin's q, investment in R&D as well as patenting activity are associated with a higher premium on a firm's market value. Our results also suggest that a large firm size is associated with lower market values, and that this effect is particularly strong for the leading high-q firms. Employment growth is also better received when it is undertaken by leading firms.

We also repeat the analysis splitting firms according to labour productivity (also in Table 2). Due to data limitations, the best indicator of productivity we can construct is a rather crude indicator of labour productivity defined as deflated sales[8] per employee. We then examine the contribution of the explanatory variables to market value for the low productivity and high productivity groups. In all sectors, R&D activity has a strong positive association with

[7]Employment growth is calculated in the usual way by taking log-differences of employment levels.
[8]Sales is deflated according to the Consumer Price Index in each year.

Table 2: OLS regression of equation (1) with Tobin's q as the dependent variable. Firms are sorted into two classes according to their values of Tobin's q or labour productivity. Coefficients significant at the 5% level appear in bold ink. OLS regressions are robust to heteroskedasticity (Huber/White/sandwich estimator).

	Below-median q		Above-median q		Below-median lab. prod.		Above-median lab. prod.		Full sample	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
SIC 35: Machinery & Computer Equipment										
R&D stock	-0.0084	-0.11	**6.1293**	2.51	**6.8017**	2.65	**6.7095**	2.65	**7.3022**	2.72
Patent stock	-0.0050	-0.20	2.0314	0.63	-0.5469	-0.28	**7.3674**	2.33	1.7488	1.19
Empl	**0.0230**	7.64	**-1.4174**	-2.69	-1.1315	-1.82	**-0.5360**	-5.90	**-0.7866**	-2.89
Empl. gr.	**0.2437**	8.46	**6.9350**	4.21	**3.3979**	2.24	**6.0802**	5.28	**5.0637**	5.38
Obs.	2536		2322		2396		2462		4858	
R^2	0.2018		0.0415		0.0518		0.1879		0.0360	
SIC 36: Electric/Electronic Equipment										
R&D stock	0.0311	0.51	0.6420	1.63	0.6647	1.70	**6.0429**	5.65	0.7525	1.72
Patent stock	**0.1430**	3.51	1.4701	1.77	1.6707	1.85	1.5309	1.75	**1.7471**	1.96
Empl	**0.0365**	11.37	**-0.5737**	-6.42	**-0.2537**	-3.12	**-0.2204**	-3.50	**-0.2379**	-5.10
Empl. gr.	**0.1503**	4.90	**5.2919**	2.50	4.1076	1.91	**5.3843**	5.53	**4.3872**	3.60
Obs.	2672		2443		2551		2564		5115	
R^2	0.1789		0.1612		0.1632		0.1856		0.1615	
SIC 37: Transportation Equipment										
R&D stock	0.0855	1.27	1.4917	1.62	0.8325	1.53	**2.7888**	2.84	**1.1861**	2.42
Patent stock	**-0.1266**	-4.15	1.2962	1.40	0.1352	0.69	**2.1154**	1.97	0.1576	0.87
Empl	**0.0214**	7.26	**-0.2030**	-5.34	**-0.0545**	-3.14	**-0.1440**	-4.09	**-0.0933**	-4.67
Empl. gr.	**0.1498**	5.09	**1.5273**	2.58	**0.8443**	4.03	**1.9821**	3.04	**1.3093**	4.24
Obs.	839		815		818		836		1654	
R^2	0.2920		0.1989		0.2453		0.2611		0.2343	
SIC 38: Measuring Instruments										
R&D stock	-0.0010	-0.81	**0.8740**	3.55	0.5498	1.77	**5.1798**	2.69	0.5744	1.84
Patent stock	0.0241	0.73	**2.1987**	3.31	**2.4773**	3.85	**1.9409**	2.57	**2.5045**	4.27
Empl	**0.0398**	9.27	**-0.9547**	-10.44	**-0.8312**	-9.12	**-0.3407**	-5.29	**-0.5718**	-11.00
Empl. gr.	**0.3600**	8.56	**7.8736**	5.98	**5.2984**	4.64	**7.6770**	7.70	**6.1475**	7.92
Obs.	2239		2014		2067		2186		4253	
R^2	0.1806		0.1904		0.2624		0.1179		0.1856	

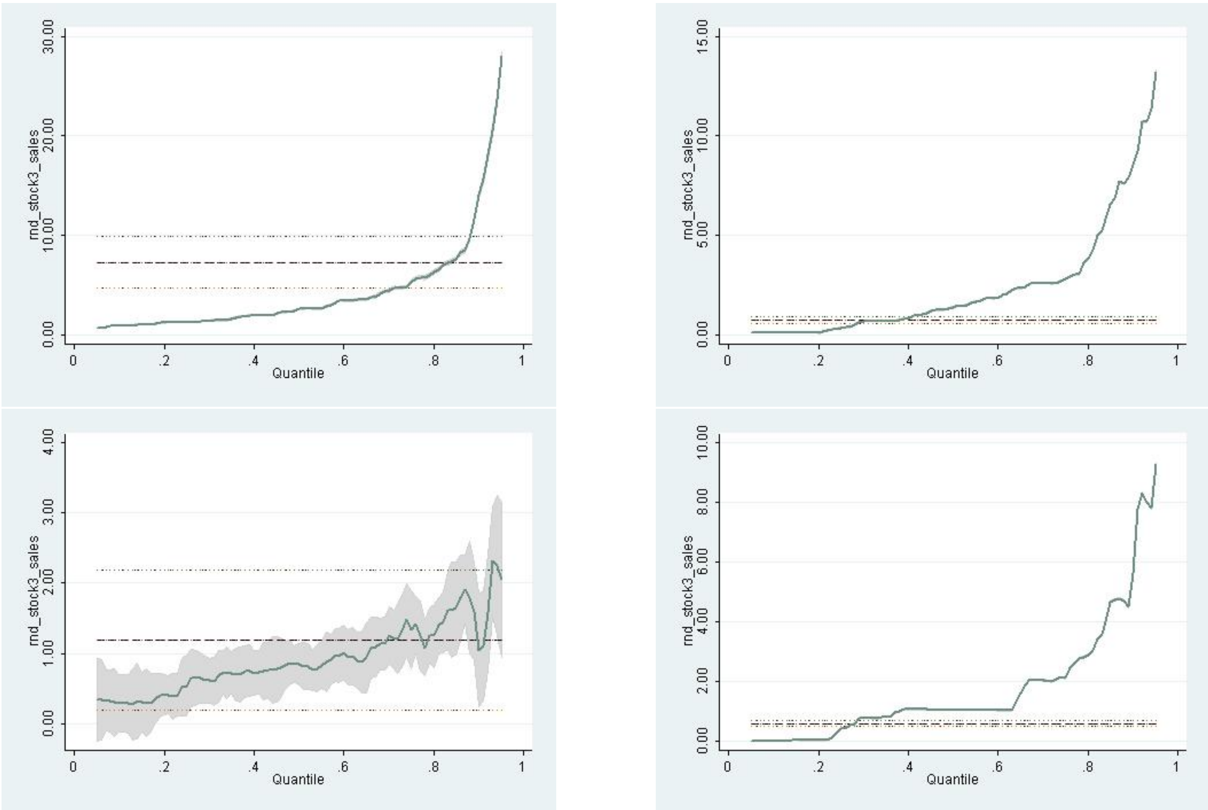

Figure 1: Variation in the coefficient on 3-year R&D stock (i.e. β_1 in Equation (1)) over the conditional quantiles of Tobin's q. Confidence intervals (non-bootstrapped) extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: Machinery & 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)).

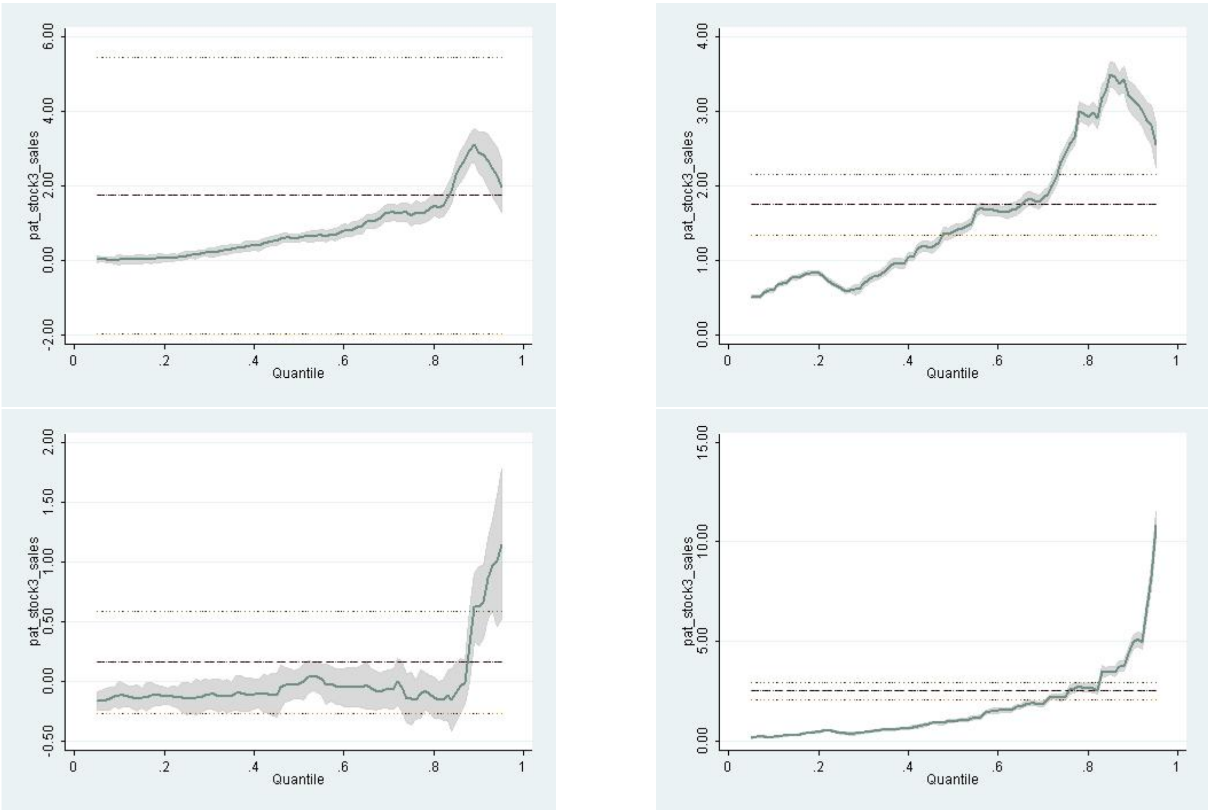

Figure 2: Variation in the coefficient on 3-year patent stock (i.e. β_2 in Equation (1)) over the conditional quantiles of Tobin's q. Confidence intervals (non-bootstrapped) extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: 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)).

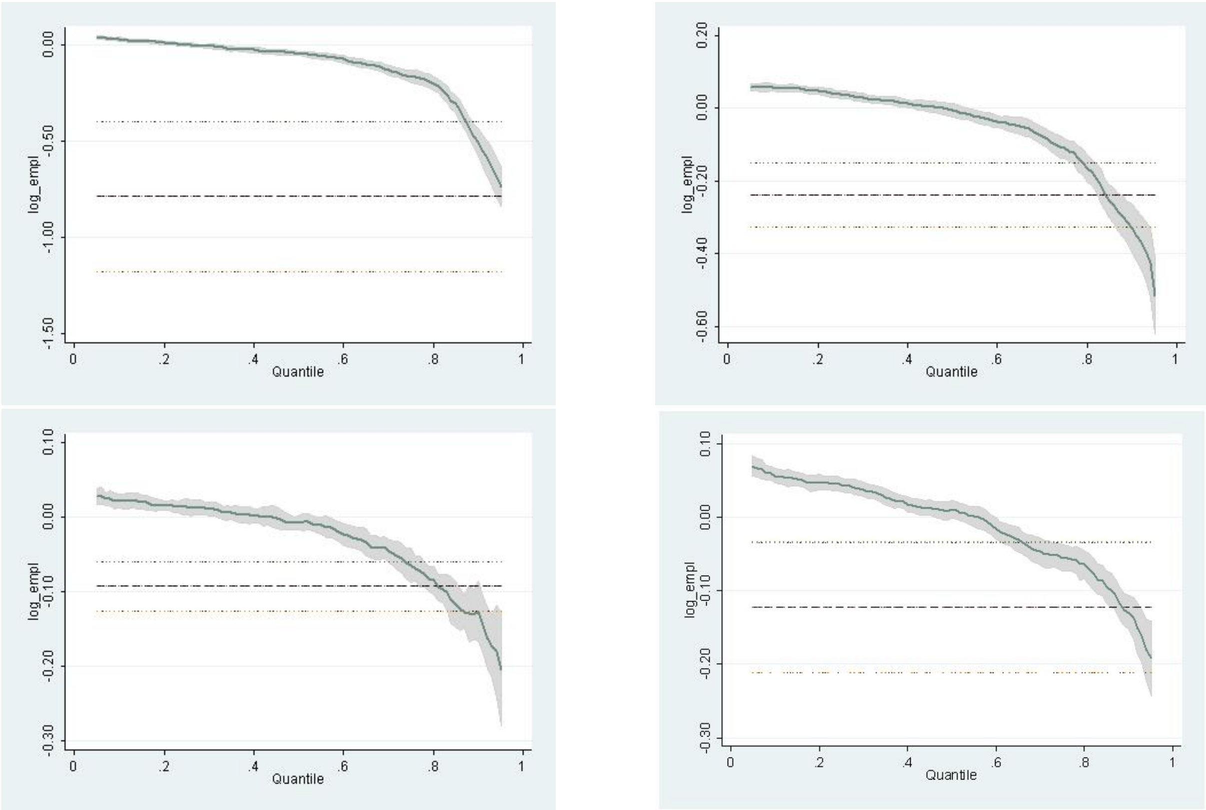

Figure 3: Variation in the coefficient on number of employees (i.e. β_3 in Equation (1)) over the conditional quantiles of Tobin's q. Confidence intervals (non-bootstrapped) extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: 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)).

market value for the most productive firms, whereas R&D undertaken by less productive firms has no significant association with market value (in the majority of cases). Similar results are found for the patent stock variable. While the results for our firm size variable are not clear-cutting, we observe that in each case employment growth undertaken by the productive firms has a larger positive association with market value than employment growth undertaken by the less productive firms.

There are several drawbacks to this type of OLS estimation, however. First, OLS assumes normality and the coefficient estimates are sensitive to outliers – this is indeed a problem in our case because the distribution of Tobin's q is highly skewed. Quantile regression, however, is robust to outliers on the dependent variable that tend to $\pm\infty$. Second, by sorting firms into distinct categories we introduce class boundaries which are an arbitrary source of discontinuity in the data. Third, by classifying firms into groups for OLS regressions we reduce the number of observations in each regression. In order to take these econometric issues into consideration, we perform quantile regressions. An introduction to quantile regression is provided in Appendix B.

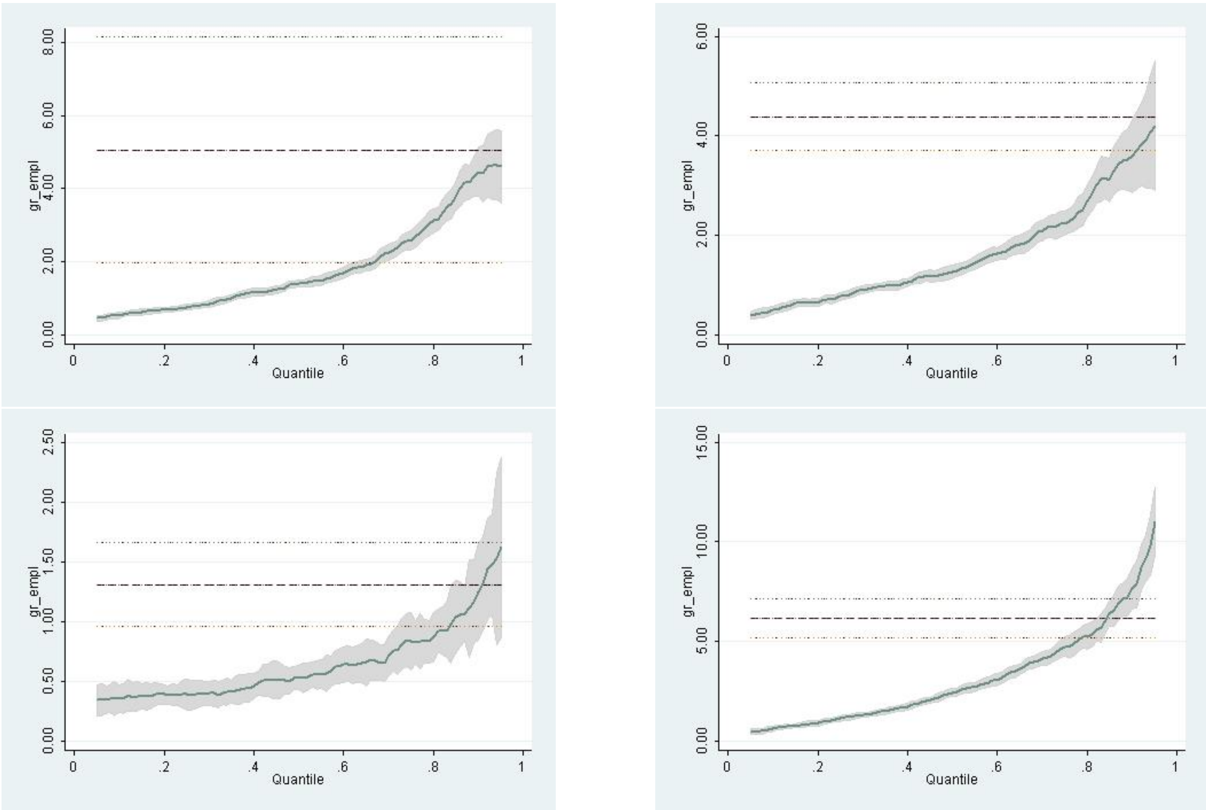

Figure 4: Variation in the coefficient on employee growth (i.e. β_4 in Equation (1)) over the conditional quantiles of Tobin's q. Confidence intervals (non-bootstrapped) extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: Machinery & 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)).

The quantile regression results for the coefficients $\beta_1 - \beta_4$ are shown in Figures 1 – 4 respectively. The interpretation of these figures is quite intuitive. The regression quantile is shown along the x-axis, with low-q firms at the left and high-q firms at the right. The magnitudes of the coefficients are indicated referring to the y-axis. These plots also show the 95% confidence intervals of the quantile regression estimates, as well as OLS estimates (horizontal line) and OLS 95% confidence intervals.

For extra precision in statistical inference, we repeat the regressions using the computationally-intensive 'bootstrap' resampling technique which yields more reliable standard errors. Bootstrapped quantile regression results are reported in Table 3.

Figure 1 presents the results concerning the stock market's reaction to firm-level R&D expenditure for firms at different points of the distribution of Tobin's q. A similar pattern is observed for each of the four sectors. At the lowest quantiles (corresponding to the low-q firms), the coefficient on R&D expenditure is close to zero, indicating that for firms with relatively low market valuations, their attempts at innovation are virtually ignored by the stock market. Moving up the quantiles, however, the coefficient rises, taking relatively large positive values at the upper quantiles. For firms with high values of Tobin's q, their stock market valuation is particularly sensitive to investment in R&D. R&D investment is perceived by the stock market as being a much more valuable undertaking when performed by leader firms as compared to laggard firms. Laggard firms, it seems, do not benefit much from R&D investment. Given the implicit opportunity cost of investment in R&D, laggard firms would do better to refrain from R&D activity.

Similar results are obtained when innovative activity is measured in terms of a firm's 3-year patent stock (see Figure 2). Patenting activity appears to have large effects on the market value of leader firms, but appears to be a relatively futile undertaking for laggard firms. Nevertheless, our results do not hold for all four sectors since we observe that the results for the transportation equipment sector (SIC 37) are insignificant at all quantiles.[9]

Figure 3 compares the benefits of firm size (proxied here by number of employees) for firms at different quantiles of Tobin's q. At the lowest quantiles, the coefficients are small but significantly positive (see also the bootstrapped results in Table 3). For laggard firms, larger firms tend to have lower exit hazards, and size may also confer other advantages such as market power, access to financial resources ('deep pockets') or the existence of a large internal labour market. Moving up the quantiles, however, the coefficients decrease dramatically in

[9]This could be due to a smaller number of observations in this sector, and perhaps also due to the peculiarities of the composition of this sector. SIC 37 (Transportation Equipment) contains manufacturing sectors as diverse as ship-building, bicycles, and guided missiles. Furthermore, while the three other 2-digit 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, p. 1667).

Table 3: Quantile regression estimation of Equation (1), 1972-1999. The coefficient and t-statistic reported for the 10%, 25%, 50%, 75% and 90% quantiles. Coefficients significant at the 5% level appear in bold. Standard errors are obtained using 1000 bootstrap replications.

	Quantile regression				
	10%	25%	50%	75%	90%
SIC 35: Machinery & Computer Equipment (4858 obs)					
R&D stock	**0.9243**	**1.3089**	**2.5877**	**5.3153**	**14.0576**
	7.66	6.48	6.17	6.32	3.24
Patent stock	0.0136	0.1267	**0.6054**	**1.2080**	**2.8926**
	0.28	1.29	3.73	3.45	2.46
Empl	**0.0298**	0.0032	**-0.0439**	**-0.1633**	**-0.5058**
	4.98	0.54	-5.42	-9.62	-10.10
Empl. gr.	**0.5459**	**0.7580**	**1.4122**	**2.5766**	**4.4667**
	7.60	9.30	12.23	12.36	8.81
R^2	0.0520	0.0650	0.0914	0.1346	0.1984
SIC 36: Electric/Electronic Equipment (5115 obs)					
R&D stock	0.1098	0.3506	**1.3819**	**2.8080**	**8.5090**
	0.41	1.03	2.30	2.42	3.66
Patent stock	**0.5978**	**0.6276**	**1.3858**	**2.4353**	**3.1541**
	4.58	3.03	4.26	3.66	3.65
Empl	**0.0572**	**0.0378**	**-0.0047**	**-0.1105**	**-0.3307**
	10.23	6.14	-0.55	-6.42	-9.78
Empl. gr.	**0.5016**	**0.7766**	**1.2728**	**2.2462**	**3.5898**
	8.16	9.20	11.26	10.55	7.66
R^2	0.0583	0.0669	0.1034	0.1729	0.2715
SIC 37: Transportation Equipment (1654 obs)					
R&D stock	0.2920	0.5382	**0.8498**	**1.3378**	1.0486
	1.04	1.70	2.19	2.05	0.81
Patent stock	**-0.1131**	**-0.1426**	-0.0238	-0.1461	0.6282
	-2.33	-2.56	-0.23	-0.80	0.99
Empl	**0.0212**	**0.0132**	-0.0078	**-0.0647**	**-0.1262**
	3.86	2.46	-1.07	-5.11	-5.23
Empl. gr.	**0.3527**	**0.3897**	**0.5336**	**0.8369**	**1.2500**
	6.12	5.66	5.64	6.40	6.39
R^2	0.1567	0.1651	0.1961	0.2348	0.3000
SIC 38: Measuring Instruments (4253 obs)					
R&D stock	0.0012	0.4235	1.0471	2.1006	**5.5885**
	0.00	0.93	1.53	1.43	2.08
Patent stock	0.2032	0.3999	**0.9968**	**2.2468**	**4.9557**
	1.93	1.93	3.42	2.72	2.36
Empl	**0.0313**	0.0060	**-0.0837**	**-0.3076**	**-0.6562**
	3.15	0.68	-5.33	-8.31	-8.91
Empl. gr.	**0.6162**	**1.1251**	**2.4308**	**4.7518**	**7.6505**
	6.24	9.28	12.07	13.17	9.93
R^2	0.0412	0.0539	0.1025	0.1793	0.2604

all four sectors. Large size appears to be a disadvantage for the leader firms, because a large number of employees is associated with a negative effect on Tobin's q. These leader firms, at the technological frontier, operate in a turbulent and innovative environment and need to be flexible and adapt quickly to new developments. For these firms, a large number of employees may have the drawback of being a factor of inertia.

The differential effects of employment growth on market value are shown in Figure 4. For firms that are far from the frontier (represented by the lower quantiles), employment growth is not associated with the creation of stock market value. This could be because laggard firms should concentrate on increasing their productive efficiency of their existing output rather than looking to expand by replicating their 'bad' production routines. Once they improve the efficiency of their existing production techniques, then they can seek to replicate these routines to gain larger profits from a larger sales base. Employment growth by laggard firms may thus be frowned upon by the stock market because this could signal 'managerial' behavior on the part of the firm, whereby the executives are less concerned about shareholder interests than they are about the personal advantages they receive from heading a large firm (e.g. larger salary, more power and prestige). The story is quite different for leader firms, however. In all four sectors, the coefficient on employment growth increases substantially with the quantiles. Leader firms have already proven their productive efficiency, and expansion of these firms is likely to lead to commensurate increases in profits.

Our coefficient estimates for the low quantiles are generally closer to zero than those for higher quantiles. One reason for this could be that backward firms are particularly idiosyncratic, and that as such it is difficult to generalize across types of backwardness. Indeed, firms may underperform for a wide variety of reasons. For example, some backward firms may be run by managers who are excessively averse to innovation whereas others may be run by fanatical innovators. Increases in innovative activity may be beneficial for the former whereas it would be harmful for the latter – thus, the net effect is unclear. Among backward firms, we may also find one firm who are averse to employment growth whereas another is overly enthusiastic, again leading to an ambiguous overall result. Leading firms, however, have a more objective management and are less susceptible to being led astray by irrational idiosyncratic fads and whims.

3.3 Robustness analysis

We verify the robustness of our results in a number of ways. To begin with, it is worth investigating the robustness of our results to temporal disaggregation, in order to control for structural changes in the relationships between the variables considered (such as differences in patenting activity brought on by institutional changes in the protection of intellectual property rights, for example). To this end, we repeat the analysis using shorter subperiods: 1972-1979, 1980-1989, and 1990-1999. Results are reported in Appendix C. Within each subperiod we observe qualitatively similar regression results, however, which suggests that our results are not being driven by temporal aggregation effects.

In our baseline regressions we investigate the hypothesis that firm behaviour *influences* different effects on a firm's performance outcome (market value), and that these different effects are *associated* with different positions on the distribution of firm performance. We cannot rule out the possibility that our results are misleading in the sense that they might be capturing reverse causality from performance outcome on firm behaviour. We suspect that these effects are not large for the innovation variables, since in our baseline regressions we consider the association between the stocks from $t-2{:}t$ and Tobin's q at time t. We also suspect that market value is not a major determinant of firm size, because market value is much more volatile than firm size. There is also evidence suggesting that market value is not an important predictor of firm growth.[10] Nevertheless, as further evidence on the robustness of our findings we lag each of our four dependent variables by one period and repeat the regressions. Given that we have no suitable instrumental variables at hand, this seems to us to be the best feasible way of dealing with the issue of endogeneity. The regression results are presented in Appendix D and are similar to those obtained previously.

4 Discussion

Table 4 presents a summary of our empirical results as well as formulating some further conjectures that these results might imply.

Innovation was seen to play a role in firm performance that varies with distance to frontier. Our analysis showed how investment in R&D, as well as patenting activity, were rewarded quite significantly for firms close to the frontier. For backward firms, however, efforts at innovation are not greeted with much enthusiasm by the stock market. Following on from these findings, it would be interesting to investigate whether environmental innovation and environmental performance are also relatively effective strategies for leader firms, or whether the importance of these strategies is independent of distance to frontier.

Does the relaxation of selection pressures increase innovation? Some scholars might consider that having more diversity in the population of surviving firms will foster innovation. We suggest, however, that firms must pass the competitive test before they start to innovate in an effective way; or, in other words, that they must first prove themselves as efficient pro-

[10] Geroski et al. (1997) analyze the sales growth of a panel of large listed UK firms 1976-82 and, although they do detect a small and statistically significant influence of current and lagged market value on sales growth, they conclude that firm growth is best modelled as a random walk.

Table 4: Distance to frontier and strategic orientation: normative prescriptions

LAGGARDS	FRONTIER / LEADER FIRMS
Imitation	**Innovation**
Imitate the industry best-practice	Competitive advantage through innovation
Application of existing technologies	Higher R&D investments, more patents
Improvements in basic production methods	Managers should keep up with latest trends
Minimize slack	Creative slack
Steep hierarchy	**Flat hierarchy**
Catch-up to the technological leaders	Employees are a source of creativity
Monitoring, specific goals, performance pay	Harness the intrinsic motivation of employees
Large Firm Size	**Small Firm Size**
Large size improves chances of survival	Lean, flexible, innovative firm
'Deep pockets' and market power	
Improve efficiency rather than grow	**Pursue expansion**
Focus on improving production efficiency	Production efficiency has been achieved
Perfection of existing production routines	Replication of existing routines
Quality management	
Defect reduction	
Develop capabilities	Apply existing capabilities to new areas
	Profit opportunities in new markets
Diversification likely to destroy value	Diversify, export, seek new markets
Threat of exit	**Turbulence**
Risk-taking should be minimized	Threat of loss of market share
	Innovate to get ahead of competitors

ducers before they can engage in worthwhile attempts at innovation. Innovation undertaken by backward, inefficient firms does not seem to be effective.

We suggest that imitation is more appropriate for backward firms than innovative activity. Imitation is a widespread practice and can provide an effective alternative means for backward firms to profit from innovation. Mansfield et al. (1981) observe that about 60% of patented successful innovations were imitated within four years. The development costs incurred by the imitator were about 35% lower and the development time about 40% lower. Further evidence on imitation can be found in the survey of R&D managers conducted by Levin et al. (1987), who report that approximately 65% of 'typical' unpatented innovations could be imitated in less than one year. Backward firms can thus reduce the costs of technological progress, and also limit their exposure to uncertainty, by imitating the industry leaders rather than performing their own innovation. If backward firms do decide to engage in R&D activity, then we suggest that this R&D should be directed towards imitation of existing products or practices, rather than the introduction of new products.

Another interesting result, pregnant with consequence, is that employee growth is much more positively valued for leader firms than for backward firms. Whilst growth of leading firms leads to the replication of profitable production patterns, growth of backward firms may be little more than an aimless organizational drift or, perhaps worse, the ambitious projects of 'managerial' administration. An implication of this finding is that specific forms of growth strategy, such as diversification or entry into export markets, should be the domain of leading firms. Backward firms should first address the causes of their lower productivity before seeking to replicate their business model on new markets. Before exporting, a firm's product needs to be competitive enough to overcome difficulties such as transport costs, foreign tastes, costs of contracting with distributors, and so on. Furthermore, diversification (and especially unrelated diversification) undertaken by backward firms is likely to be a value-destroying strategy undertaken for managerial motivations (see for example the evidence in Blanchard et al. (1994)). To be sure, diversification and exporting are enough of a challenge for industry leaders, without backward firms also having a crack. If indeed we were to observe that the most productive firms undertook expansion whereas the least productive firms renounced growth opportunities, however, then this felicitous state of affairs would correspond to a net reallocation of productive assets to the most productive firms, and would thus be a source of productivity growth for the economy as a whole (Coad (2007b)).

The lot of the backward firm is certainly not as exciting as that of the leader firms. Backward firms should resist the urge to dabble in innovation, but instead should seek out the most productive techniques available and try to learn from them through imitation. Imitation, however, requires a clear template on which to base the replication. If accurate imitation proves to be too difficult (due to lack of a clear template), then backward firms should at least aim to improve the efficiency of their production processes by reducing slack wherever they can find it, as well as reducing the number of defects in their production batches. They should also seek to inprove the quality of their goods.

Managers of backward firms must improve productivity, preferably by committing themselves to a path of productivity growth in the existing technological trajectory, and sticking to this plan. It is no doubt more exciting to be at the frontier, among the 'superstars' of the industry; to be a growing firm grasping at new opportunities and formulating new ideas. Instead, backward firms face the pressure of sudden death and get but a distant glimpse of the new technologies being developed on the horizon. Backward firms should not attempt to grow, but instead seek to use their existing resources more efficiently. This will not be easy, given that employees generally prefer to be part of a growing organization.[11]

In the light of this discussion, backward firms should have a relatively routinized existence. Production activities can be coordinated and executed through the use of authority, in the context of a relatively strict hierarchy. Whereas frontier firms should orient themselves towards innovation and tap the creativity of their employees, we suggest that backward firms should focus on the task of 'catch-up' through the exploitation of existing technologies. As a result, one might suggest that 'performance pay' schemes combined with strict hierarchical command would be appropriate here, because of the nature of production in backward firms. These firms do not require creativity or intrinsic motivation of their employees, but merely ask that these employees perform relatively dull tasks. At the frontier, however, work can be more interesting and rewarding in itself, and intrinsic motivation plays a more important role. Performance pay would not be appropriate in the case of leader firms because the provision of financial incentives may crowd out intrinsic motivation and have adverse effects on search activity and innovation (Frey and Jegen (2001)). (This latter point notwithstanding, however, employees in frontier firms should receive higher pay to reflect their higher productivity.)

Our discussion draws us on to distinguish between the notions of 'creative slack' and 'just plain old slack.' Repetitive work and imitation does not require slack in the same way that creative work does. As a result, backward firms have less need for 'creative slack'. Frontier firms, however, can only improve their performance by pushing the frontier forward through innovation, and the search activity they undertake does require some slack.

Future work may consider the relevance of other business strategies as distance to frontier changes. How does advertising expenditure and product differentiation fit into this framework? It may be that investment in advertising is more appropriate for backward firms than investment in R&D: "a rapidly expanding firm is in a better position to wait for R&D's distant and uncertain payoffs. Turning the argument around, the slowly expanding firm, feeling much more concerned about the future, may place heavier reliance on advertising with its more rapid

[11] Roberts (2004) puts it this way (p. 243): "Work is more fun in a growing company."

and predictable returns." (Mueller, 1967, p. 75). However, firms that are extremely backward stand a lot to gain by simply aiming at improving their production efficiency, irrespective of advertising expenditure.

There may also be life-cycle considerations that can be incorporated in this framework. New firms may enter the industry with more familiarity of the latest technologies, although if they are very small their small size may put them at a disadvantage. New firms have a distinct lack of experience, however. It may be that new, small firms choose to take on outsourcing contracts from established leader firms, allowing them to gain familiarity with the industry through the execution of standard manufacturing tasks. Once they gain experience, and their productivity rises, they may move into more innovation-intensive activities.[12]

5 Conclusion

Some first steps were taken to explore the hypothesis that certain strategies and behaviors may be more appropriate for different business firms conditional upon their distance to the industry frontier. In this paper, we operationalize the concept of distance to frontier by sorting firms according to their market value (Tobin's q). Firms at the frontier are encouraged to undertake innovative activities, such as investments in R&D or patent applications. Innovative efforts made by backward firms, however, are valued significantly less. This is consistent with the suggestion that innovation is a more appropriate strategy for industry leaders than for backward firms. Our results also suggest that leading firms are encouraged to grow whereas backward firms should abstain from expansion. Nonetheless, backward firms benefit from having a large size (whilst size appears to be a disadvantage for leading firms). We also observed that the market value of leader firms is sensitive to their operating margins, whereas the stock market is less sensitive to the financial performance of backward firms.

The empirical strategy used in this paper is different from conventional analysis in several respects. First, the 'average firm' is of little interest in our framework. Instead, heterogeneity of business firms is the main organizing theme. As a result, standard regression techniques such as OLS that focus on calculating the 'average effect on the average firm' will be of limited use. Second, whereas standard econometric investigations focus on the average and the distance to average, our focus has been on the frontier and distance to frontier. The technological frontier is pushed forward by firms at the frontier, and the others follow. In this sense, it is the outliers that are the key drivers of industrial evolution.

[12] The case of electronics firm Flextronics is illustrative. It started out as an OEM (original equipment manufacturer) undertaking relatively routine manufacturing and assembly operations for large incumbents, gradually gained competences and experience, and has now strategically repositioned itself in innovation and design activities.

There may well be many different maladies at the source of a firm's backwardness. To generalize strategy conditional upon distance-to-frontier is, in some sense, to generalize across all possible causes of backwardness. Backward firms should recognize their poor performance and try to find out what the problem is. As they seek to come to terms with their specific predicaments, however, we recommend that they renounce innovative activity and forego expansion projects. Instead they should focus on imitating more successful competitors and improving their basic production efficiency. As backward firms face up to their shortcomings, "by turning inwardly and analyzing information about the assets a firm already controls" (Barney, 1986, p. 1239), they may also discover some of their idiosyncratic capabilities and resources that they can use to gain competitive advantage. Indeed, different firms have unequal abilities to pursue heterogeneous paths of progress. The greatest challenge in all of this, however, may well be the humble admission of unsatisfactory performance and recognition of the need for reform.

The distance to frontier framework developed here is also related to the 'Carnegie School' perspective developed by organizational theorist such as Simon, Cyert, and March. This latter approach emphasizes behavioural factors such as aspiration level and achievement, the construction of goals and their readjustment in the light of recent performance. Can the 'industry frontier' be related to the aspiration level? Do firms have something of an 'equilibrium distance to frontier' such that, once they have comfortably attained this position they are satisfied and have no further aspirations? It may well be that being behind is a spur to improvement (although our results do suggest that backwardness is not a spur to effective innovation). Further work on these topics would clearly be welcome.

Appendices

A Origins of the distance-to-frontier concept

The origins of the distance-to-frontier approach can be traced back to the macroeconomic literature, where the unit of analysis is national economies or specific industries. In the following we present the background to this concept and survey some specific predictions that have emerged from theoretical work or have been investigated in empirical studies.

Although the distance-to-frontier concept has previously been applied at the level of national economies or industrial sectors, we argue in this paper that it is also a useful concept in the analysis of business strategies. There are of course several differences between analyses performed at the levels of countries or individual businesses. (These differences may make catch-up more difficult for backward firms than for backward countries.) First, entry and exit phenomena, as well as life-cycle considerations, are less relevant at the country level than at the firm-level. Second, employment growth and mergers/acquisitions in firms don't have accurate analogues at the country level. Third, backward countries often have a cheaper supply of labour with respect to more advanced nations, but this is not likely to be true in a comparison of backward vs. frontier firms in a single economy. Other differences may also be envisaged.

A.1 Background

The prescription of specific policies for economies conditional upon their distance to the world technological frontier has proven to be a useful concept in the macroeconomics literature. Following on from the failure of the 'Washington consensus', which has been criticised for prescribing 'one-size-fits-all' neo-liberal policy recommendations to a wide variety of economies, the distance-to-frontier approach has gained popularity in recent years, because it acknowledges the specific role of 'appropriate institutions' (Aghion and Howitt (2006)) at different stages of development. (Protectionism, for example, can be seen as an 'appropriate institution' for emerging economies but is less appropriate for world leaders.) According to the distance-to-frontier view, a cross-section of countries is ordered according to their distance to the world technological frontier, and countries at different stages are assumed to face distinct challenges.

An early contribution to this literature was made by Gerschenkron (1962). Gerschenkron's analysis investigated different degrees of backwardness in a cross-section of countries, and focused on the 'advantages of backwardness' of countries far from the world technological frontier. These advantages mainly revolve around the application of technologies imported from developed countries. Backward countries can thus experience rapid productivity growth and catch up to leading countries if they learn to imitate and apply frontier technologies.

Gerschenkron (1962) acknowledged that there may be difficulties in operationalizing the theoretical concept of 'level of backwardness' – "'degree of backwardness' defies exact measurement" (p. 43) – but nonetheless this is not an indomitable task:

> "And, indeed, as we look upon the economic scenery of nineteenth-century Europe, riveting our attention, say, to the midpoint of that century, few would disagree that Germany was more backward economically than France; that Austria was more backward than Germany; that Italy was more backward than Austria; and that Russia was more backward than any of the countries just mentioned. Similarly, few would deny England the position of the most advanced country of the time. ... In practice, we *can* rank the countries according to their backwardness and even discern groups of similar degree of backwardness." (Gerschenkron, 1962, p. 44)

Abramovitz (1986) provides further elucidation on Gerschenkron's 'catch-up hypothesis', emphasizing in particular the role of technological know-how embodied in new capital vintages on the international transfer of frontier technologies. Abramovitz (1986) also discusses the importance of 'social capital' as a prerequisite for periods of rapid productivity growth – "a country's potential for rapid growth is strong ... when its is technologically backward but socially advanced" (Abramovitz, 1986, p. 387). Indeed, before a country can embark upon a 'catch-up' trajectory, it must recognize that its performance has been, to date, less than satisfactory. 'Catch-up' requires a flexible and progressive attitude. A humble assessment of current shortcomings is a necessary prerequisite for obtaining a mandate for change. Society must accept the superiority of machinery and techniques coming from abroad and make the necessary efforts to learn about these new production techniques.

In general, then, the advantages of backwardness include the following factors: access to frontier production technologies, the opportunity to invest in more recent capital vintages, the ability to learn from leader's mistakes, as well as the freedom to choose between technological trajectories in the absence of being 'locked-in' to any particular trajectory. Among the drawbacks of backwardness, however, we can mention a lack of skilled labour, and more generally the far-reaching and multifaceted institutional failure (what we might call a 'culture of backwardness'). (Note that these factors are also relevant at a firm-level analysis of heterogeneous performance.)

A.2 Specific predictions

The theories of Gerschenkron (1962) and Abramovitz (1986) have since been further developed and have yielded several specific implications, which we will briefly explore.

Distance to frontier and innovation The concepts of innovation and imitation are central to the distance-to-frontier analysis. At the simplest level, the theory is that there exists a continuum of entities that are sorted according to productivity levels. Nations at the world technological frontier occupy one extreme of this continuum, and those far from this extreme strive to it. Whilst backward economies can experience productivity growth through the application of existing technologies, frontier economies can only experience productivity growth by pushing the world frontier forward. The basic conjecture that emerges, therefore, is that frontier economies should engage in innovative activity whereas backward economies should instead try to catch up to the frontier through imitation.

A casual look at the concentration of innovative activity offers strong support this conjecture. (Coe et al., 1997, p. 134) report that "In 1990, the industrial countries accounted for 96% of total world R&D expenditures" and that "within the OECD the seven largest economies accounted for 92% of R&D in 1991." The bulk of world R&D expenditure seems to be invested by frontier economies. R&D expenditure may also have a role in backward economies, however, if such R&D can build up the 'absorptive capacity' required for the adoption of new technologies (Griffith et al. (2004)).

Distance to frontier and human capital Bearing in mind the relationship between distance to frontier and innovative performance, some implications for the analysis of human capital composition are seen to emerge. An early contribution by Nelson and Phelps (1966) contains a theoretical model in which education plays a role in reducing the distance to the technological frontier, since education facilitates the adoption of foreign technologies. More recently, cross-country empirical work has provided support for this hypothesis. Benhabib and Spiegel (1994) observe that the importance of human capital varies considerably with distance-to-frontier. Backward countries benefit from investment in human capital through a 'catch-up' effect that effectively reduces the relative productivity gap through the application of frontier technologies. Their findings thus offer an explanation for the observation that "education [is] statistically significantly and positively associated with subsequent growth only for the countries with the lowest level of education" (Krueger and Lindahl (2001))– an observation that had previously baffled economists. Vandenbussche et al. (2006) provide further evidence on the role of education conditional on distance to frontier. They consider the specific contribution of skilled labour and observe that skilled labour has a higher growth-enhancing effect closer to the technological frontier, for a panel of 19 OECD countries. This is taken as support for the hypothesis that innovation is the domain of frontier countries whereas imitation is more appropriate further from the frontier (see also the empirical analysis in Aghion et al. (2005)).

The hypothesis that education plays different roles conditional on the distance to frontier has led some economists to suggest that one of the sources of the widening productivity gap between Europe and the US is the fact that Europe invests less in higher education than the US does. The intuition is that lower levels of higher education in Europe dampen the innovative performance of the European economy relative to the US economy (Aghion et al. (2007)).

Distance to frontier and competition/regulation The distance-to-frontier perspective has several implications regarding the role of competition and regulation. Consider first the role of protectionism. Protectionist policies are typically justified as a means of temporary support to infant industries as they develop capabilities. In the early stages of development, an industry needs to invest heavily in new capital. Once infrastructure has been developed, however, and skills and knowhow have been accumulated, these industries need to be opened up to competition in order to provide incentives to incumbents to innovate and achieve productivity gorwth. As such, protectionism is a policy designed to assist backward sectors as they move closer to the technological frontier. Once these sectors are close enough to the frontier to be able to compete against the world leaders, then protectionist policies have accomplished their purpose and should be dismantled. Aghion and Howitt (2006) criticise protectionist policies in developed countries, because this adversely affects the incentives for competitive advanced state-industries of investing in new production and management practices. Aghion et al. (2004) show that the entry of foreign firms has a productivity-enhancing effect in frontier economies. Closer to the frontier, innovation becomes more important than capital accumulation, and thus selection plays a more important role (Acemoglu et al. (2006)).

Distance to frontier and the structure of firms Acemoglu et al. (2003) suggest that a firm's distance to frontier will also have an influence on the appropriate organizational structure of the firm. Firms near the frontier should focus on innovation, and innovation is in turn associated with flat hierarchies in which information flows from employees are to be valued. Further from the frontier, however, firms seek to apply and exploit existing technologies rather than discover technologies of their own. For such firms, the appropriate organizational form would be a steep hierarchy.

B 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), p. 266). Quantile regression techniques can therefore help us obtain a more complete picture of the underlying relationship between firm performance and market value.

In our case, estimation of linear models by quantile regression is preferable to conventional regression methods because we are concerned with differential effects across the distribution of Tobin's q rather than a single point estimate which would correspond to a population average. Intuitively, quantile regression is a weighted regression whereby a judicious choice of weights yields regression solutions corresponding to various points of the (conditional) distribution of the dependent variable. In our specific case, quantile regression allows us to evaluate the differences in stock market reaction to firm-level behavior (e.g. R&D investment, employment growth) for poorly performing firms and industry leaders.

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 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 some 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 in Koenker and Bassett (1978), can be written as:

$$y_{it} = x'_{it}\beta_\theta + u_{\theta it} \qquad \text{with} \qquad \text{Quant}_\theta(y_{it}|x_{it}) = x'_{it}\beta_\theta \tag{2}$$

where y_{it} is the dependent variable, 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:

$$\min_\beta \frac{1}{n}\left\{ \sum_{i,t:y_{it}\geq x'_{it}\beta} \theta|y_{it} - x'_{it}\beta| + \sum_{i,t:y_{it}<x'_{it}\beta} (1-\theta)|y_{it} - x'_{it}\beta| \right\} = \min_\beta \frac{1}{n}\sum_{i=1}^{n} \rho_\theta u_{\theta it} \tag{3}$$

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

$$\rho_\theta(u_{\theta it}) = \left\{ \begin{array}{ll} \theta u_{\theta it} & \text{if } u_{\theta it} \geq 0 \\ (\theta - 1)u_{\theta it} & \text{if } u_{\theta it} < 0 \end{array} \right\} \tag{4}$$

Equation (3) 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 Buchinsky (1998). More on quantile regression techniques can be found in the surveys by Buchinsky (1998) and Koenker and Hallock (2001); see also the special issue of *Empirical Economics* (Vol. 26 (3), 2001).

C Temporal disaggregation

Table 5: Quantile regression estimation of Equation (1), for the subperiod 1972-1979. The coefficient and t-statistic reported for the 10%, 25%, 50%, 75% and 90% quantiles. Coefficients significant at the 5% level appear in bold. Standard errors are obtained using 1000 bootstrap replications.

	Quantile regression				
	10%	25%	50%	75%	90%
SIC 35: Machinery & Computer Equipment (1227 obs)					
R&D stock	0.6687	**0.8309**	**1.5609**	3.9046	8.9095
	1.68	2.98	2.26	1.58	0.96
Patent stock	0.0269	-0.0032	0.0735	**0.5297**	0.6625
	0.75	-0.06	0.58	2.30	1.85
Empl	**0.0518**	0.0286	0.0149	-0.0307	**-0.1986**
	5.47	3.91	1.33	-1.16	-2.56
Empl. gr.	**0.4957**	**0.6634**	**0.9618**	**1.3874**	**2.4795**
	5.09	9.32	6.26	5.28	5.68
R^2	0.1000	0.1093	0.1166	0.1484	0.2263
SIC 36: Electric/Electronic Equipment (1096 obs)					
R&D stock	**1.0710**	**1.2800**	**2.2446**	**3.8597**	**7.3611**
	5.10	4.31	5.14	3.90	4.18
Patent stock	**0.3340**	**0.3622**	**0.6463**	**1.5941**	**2.5943**
	4.62	4.71	2.55	3.60	5.91
Empl	**0.0624**	**0.0342**	0.0118	**-0.0458**	**-0.1230**
	6.65	3.84	1.13	-2.47	-3.67
Empl. gr.	**0.3606**	**0.4411**	**0.6115**	**1.1404**	**1.9272**
	4.77	4.09	4.42	5.69	5.53
R^2	0.1243	0.1147	0.1307	0.1956	0.3040
SIC 37: Transportation Equipment (554 obs)					
R&D stock	0.2116	0.1234	-0.0516	-0.0909	**0.5005**
	1.21	0.50	-0.19	-0.19	0.62
Patent stock	**-0.1273**	**-0.1381**	-0.0785	-0.1217	**-0.2350**
	-2.52	-2.53	-1.09	-1.40	-2.07
Empl	**0.0195**	**0.0210**	0.0148	-0.0098	-0.0274
	3.40	3.63	1.85	-0.76	-1.40
Empl. gr.	**0.2994**	**0.2819**	**0.3062**	**0.4635**	**0.6327**
	5.94	5.05	3.67	3.05	3.36
R^2	0.1681	0.1348	0.0995	0.1110	0.1627
SIC 38: Measuring Instruments (763 obs)					
R&D stock	**2.3957**	**2.7354**	**3.7948**	**3.9300**	**6.2853**
	6.80	6.95	6.06	3.49	3.23
Patent stock	0.0612	0.0749	0.1738	0.4567	0.3635
	1.30	1.63	1.40	1.68	0.73
Empl	**0.0458**	0.0230	0.0269	-0.0228	**-0.2003**
	2.74	1.94	1.30	-0.61	-3.36
Empl. gr.	**0.7771**	**0.9236**	**1.4614**	**2.5180**	**3.6630**
	4.22	6.62	4.97	4.60	4.56
R^2	0.1017	0.1170	0.1348	0.1693	0.2747

Table 6: Quantile regression estimation of Equation (1), for the subperiod 1980-1989. The coefficient and t-statistic reported for the 10%, 25%, 50%, 75% and 90% quantiles. Coefficients significant at the 5% level appear in bold. Standard errors are obtained using 1000 bootstrap replications.

	Quantile regression				
	10%	25%	50%	75%	90%
SIC 35: Machinery & Computer Equipment (1867 obs)					
R&D stock	**0.6926**	**1.2636**	**1.9462**	**2.7603**	**2.9308**
	2.26	4.53	5.20	4.89	2.28
Patent stock	-0.0698	0.7984	**2.1593**	**2.6316**	**7.4409**
	-0.20	1.90	3.61	2.20	2.60
Empl	0.0150	-0.0165	**-0.0622**	**-0.1641**	**-0.3770**
	1.64	-1.75	-5.14	-7.74	-6.15
Empl. gr.	**0.4056**	**0.5794**	**1.2768**	**2.0241**	**3.4236**
	4.30	4.72	7.50	7.42	5.63
R^2	0.0498	0.0708	0.1242	0.1870	0.2588
SIC 36: Electric/Electronic Equipment (1923 obs)					
R&D stock	**0.7175**	**0.7023**	**1.2461**	**2.5867**	3.9531
	3.79	2.69	2.21	4.23	1.92
Patent stock	0.3357	0.3329	0.9680	**1.5206**	2.2131
	1.39	0.78	1.37	2.09	1.28
Empl	**0.0272**	0.0099	**-0.0269**	**-0.1437**	**-0.4379**
	3.09	1.02	-1.98	-5.89	-8.86
Empl. gr.	**0.5161**	**0.7101**	**1.0398**	**2.0501**	**3.0477**
	4.86	5.84	5.79	6.25	4.79
R^2	0.0570	0.0703	0.0961	0.1619	0.2394
SIC 37: Transportation Equipment (606 obs)					
R&D stock	**1.5712**	**1.6139**	**2.1888**	**2.5051**	0.4884
	3.16	3.74	2.97	2.81	0.38
Patent stock	**-0.5168**	-0.2372	0.3600	0.0397	-0.3901
	-2.33	-0.65	0.71	0.04	-0.16
Empl	-0.0032	-0.0069	**-0.0469**	**-0.1250**	**-0.2074**
	-0.39	-0.70	-3.32	-6.42	-7.40
Empl. gr.	**0.4350**	**0.6103**	**0.5943**	**1.0868**	**1.2270**
	4.03	4.28	3.79	4.42	4.20
R^2	0.1576	0.1133	0.1181	0.1525	0.2392
SIC 38: Measuring Instruments (1611 obs)					
R&D stock	**0.8712**	**1.2206**	**2.1414**	**5.4908**	**9.9501**
	4.88	4.31	2.89	3.02	2.60
Patent stock	0.0296	0.2998	1.1002	2.7713	7.5900
	0.16	1.09	1.66	1.95	1.71
Empl	0.0168	**-0.0273**	**-0.1115**	**-0.3154**	**-0.6791**
	1.26	-2.13	-5.38	-7.39	-8.77
Empl. gr.	**0.6336**	**1.0943**	**2.4475**	**4.5726**	**8.0319**
	4.83	6.54	9.10	8.95	6.79
R^2	0.0526	0.0631	0.1030	0.1968	0.3168

Table 7: Quantile regression estimation of Equation (1), for the subperiod 1990-1999. The coefficient and t-statistic reported for the 10%, 25%, 50%, 75% and 90% quantiles. Coefficients significant at the 5% level appear in bold. Standard errors are obtained using 1000 bootstrap replications.

	Quantile regression				
	10%	25%	50%	75%	90%
SIC 35: Machinery & Computer Equipment (1764 obs)					
R&D stock	**0.9405**	**1.3231**	**3.8535**	**7.1418**	**22.4709**
	4.21	3.64	3.44	4.61	2.13
Patent stock	1.1352	**2.2031**	**3.5108**	8.1163	9.3056
	1.83	4.91	2.46	1.88	0.87
Empl	**0.0343**	0.0017	**-0.0661**	**-0.3326**	**-0.7566**
	3.28	0.13	-2.81	-5.63	-6.28
Empl. gr.	**0.6713**	**1.1381**	**2.2139**	**5.5265**	**9.0320**
	4.55	5.98	5.88	7.70	5.02
R^2	0.0335	0.0381	0.0565	0.1100	0.1695
SIC 36: Electric/Electronic Equipment (2096 obs)					
R&D stock	0.1118	0.1151	1.5408	4.0625	**12.9043**
	0.39	0.19	1.28	1.55	2.60
Patent stock	**1.0432**	**1.7250**	**3.4654**	**6.2901**	4.7565
	4.29	3.66	2.79	3.18	1.58
Empl	**0.0875**	**0.0735**	0.0147	**-0.1320**	**-0.5567**
	6.89	5.03	0.69	-2.84	-4.81
Empl. gr.	**0.5967**	**1.1357**	**2.5314**	**4.3163**	**8.2557**
	3.81	4.82	6.35	5.42	5.41
R^2	0.0456	0.0491	0.0767	0.1342	0.2190
SIC 37: Transportation Equipment (494 obs)					
R&D stock	0.3542	0.5884	1.0562	2.2014	3.8945
	0.56	0.90	1.34	1.55	0.89
Patent stock	**2.3190**	**2.8533**	**6.2880**	9.3533	**28.2329**
	3.81	2.10	3.15	1.31	3.01
Empl	**0.0628**	0.0259	-0.0011	**-0.1408**	-0.2485
	2.99	1.52	-0.05	-3.42	-1.95
Empl. gr.	0.3245	**0.4805**	**0.9960**	**2.4410**	2.8123
	1.69	2.61	3.13	4.04	1.77
R^2	0.1183	0.1117	0.1437	0.1860	0.2727
SIC 38: Measuring Instruments (1879 obs)					
R&D stock	0.0037	0.0250	1.0427	1.4114	2.0859
	0.01	0.05	1.45	1.01	0.72
Patent stock	**0.7239**	**1.1963**	**1.6973**	**4.5741**	7.1429
	2.40	2.44	2.40	2.62	1.79
Empl	**0.1070**	**0.0695**	-0.0556	**-0.3771**	**-1.0951**
	6.29	3.96	-1.69	-4.74	-5.47
Empl. gr.	**0.5875**	**1.0828**	**2.8553**	**5.7762**	**10.7105**
	4.00	3.99	6.07	6.73	5.99
R^2	0.0404	0.0486	0.0898	0.1491	0.1946

D Lagged explanatory variables

Table 8: Quantile regression estimation of Equation (1), where the four main explanatory variables of interest are lagged one period. The coefficient and t-statistic reported for the 10%, 25%, 50%, 75% and 90% quantiles. Coefficients significant at the 5% level appear in bold. Standard errors are obtained using 1000 bootstrap replications.

	Quantile regression				
	10%	25%	50%	75%	90%
SIC 35: Machinery & Computer Equipment (4413 obs)					
R&D stock	**0.9210**	**1.3808**	**2.5222**	**6.6842**	**14.0740**
	6.74	4.84	5.56	4.34	4.11
Patent stock	0.0221	0.1665	**0.5241**	**0.9037**	1.0353
	0.35	1.61	3.59	2.81	1.53
Empl	**0.0254**	-0.0040	**-0.0423**	**-0.1372**	**-0.3890**
	3.89	-0.63	-4.76	-8.35	-9.47
Empl. gr.	**0.4100**	**0.5885**	**0.8956**	**1.7355**	**2.9619**
	8.89	8.11	7.91	8.72	7.14
R^2	0.0496	0.0633	0.0880	0.1317	0.2061
SIC 36: Electric/Electronic Equipment (4658 obs)					
R&D stock	0.2056	0.6202	**1.7522**	**4.2081**	**9.6937**
	0.88	1.91	4.48	4.45	5.11
Patent stock	**0.6326**	**0.5702**	**1.0242**	**2.0818**	**2.0863**
	5.02	2.90	3.95	4.01	2.19
Empl	**0.0497**	**0.0379**	-0.0054	**-0.0908**	**-0.2796**
	7.90	5.96	-0.61	-5.39	-8.82
Empl. gr.	**0.3457**	**0.4724**	**0.8373**	**1.5986**	**2.6510**
	6.43	6.58	6.94	8.68	7.99
R^2	0.0550	0.0653	0.1022	0.1729	0.2705
SIC 37: Transportation Equipment (1519 obs)					
R&D stock	**0.7920**	**0.6364**	**1.0469**	1.4228	2.5313
	2.72	2.10	3.07	1.95	1.87
Patent stock	**-0.1599**	-0.1058	-0.1306	0.0145	0.2080
	-2.35	-1.90	-1.35	0.08	0.37
Empl	**0.0204**	0.0091	-0.0099	**-0.0682**	**-0.1549**
	3.07	1.72	-1.26	-4.38	-6.19
Empl. gr.	**0.2298**	**0.2585**	**0.3696**	**0.6577**	**1.1000**
	2.71	3.60	4.35	4.75	4.72
R^2	0.1446	0.1562	0.1881	0.2314	0.2987
SIC 38: Measuring Instruments (3868 obs)					
R&D stock	0.0164	0.2114	0.6783	2.3869	5.9343
	0.05	0.43	0.93	1.64	1.84
Patent stock	0.1543	**0.5717**	**0.9705**	**2.4711**	**6.1627**
	1.52	2.84	3.03	3.26	3.25
Empl	**0.0276**	0.0098	**-0.0686**	**-0.2886**	**-0.5635**
	3.12	1.19	-4.66	-7.94	-7.76
Empl. gr.	**0.5081**	**0.8167**	**1.5351**	**3.2740**	**4.9910**
	6.47	7.41	7.95	8.81	5.59
R^2	0.0386	0.0497	0.0949	0.1708	0.2548

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