Koichiro KIMURA, ed. (2021) *Impacts of Innovation on Firm Performance and Industrial Development in East Asia* (*BRC Research Report*), Bangkok: Bangkok Research Center, JETRO Bangkok.

Chapter 2

The Implications of R&D Intensity for Innovation Efficiency and Firm Performance: Comparing China, Japan, U.S.*

Zhenyu GONG† and Gary H. JEFFERSON‡

Abstract: China's innovation surge over the past two decades has clearly led to dramatic increases in innovation activity. The aggregate numbers, however, obscure critical knowledge regarding the overall returns to the surge in R&D as relates to firm-level intangible assets, including but not limited to patents and publications. Based on our prior work, this paper anticipates the possibility of a structural difference in overall returns as between China's high R&D intensity firms and low intensity R&D firms. This difference may result from advantages for the more efficient R&D systems for firms spending relatively less on R&D; alternatively, the high R&D intensity firms may acquire advantages from scale economies in patent production or value-adding spillovers for the firm. The paper employs a panel threshold regression model to identify the most robust threshold between high and low-intensity R&D firms. As anticipated, we find significant differences in the relative efficiency of high and low-intensity firms; as well as between China, Japan, and the U.S. The differential returns to patents, publications, and other forms of returns to R&D show benefits to resource reallocation across the various forms of R&D activity.

Key Words: Tobin's Q; R&D intensity; threshold model; patents; publications; China; marginal returns

---

* The authors deeply appreciate the support, comments, and suggestions offered by Dr. Koichiro Kimura as well as other members of our research group, including Dr. Hiroshi Matsui, Prof. Kazuyuki Motohashi, Mr. Shun Kaida, and Dr. Janthorn Sinthupundaja.

† zhenyugong@brandeis.edu

‡ jefferson@brandeis.edu

1. Introduction

Globally, the past two decades have witnessed witnessed a surge of innovation activity, having been most pronounced in Asia, including China and Japan. China, the focus of this paper, shows the most dramatic increase. Having reestablished its patent law in 1985, China's research and development (R&D) activity has since accelerated in relation to the growth of GDP, yielding substantial increases in the R&D to GDP ratio. This paper attempts to identify the types of firms – those high R&D intensity firms versus those with low R&D intensity – that have employed their R&D resources most efficiently, using both quantity and quality measures. The study compares the R&D performance of high and low-R&D intensive firms across industries within China; it also compares R&D intensity and performance in China with that of Japan and the US.

A key finding of our earlier research relating to innovation efficiency in China, Japan, and the U.S. is that of substantial firm heterogeneity with respect to R&D-patent efficiency as well as shifting profiles of this heterogeneity over our sample period. In particular, firms with high patent intensities show differences in their patterns of innovation, e.g., higher marginal returns to R&D versus those with little R&D and patenting. By dividing our sample into high and low R&D intensity firms, this paper attempts to identify the structural differences in R&D over the relevant sample period.

Specifically, in this paper, we test whether the marginal impact of innovation activities differs between high R&D intensity and low R&D intensity firms. Using a modeling approach similar to Hall et al. (2005), we investigate the impact of R&D intensity, patenting, publications, and other innovative activity on Tobin's Q, the ratio of a firm's total market value to the replacement value of its tangible fixed assets. By inference, the ratio measure the impact of the firm's R&D investment on the intangible assets of the firm, i.e., its intellectual property, reputation, and capabilities in the realm of technological innovation. Our approach incorporates two innovations. The first results from the fact that we do not have access to patent citations as Hall et al. do, causing us to measure the quality of the firm's patenting innovation in terms of publication production rather than citations. The second, critical difference, is that in order to identify the salient structural differences between firms with high and low R&D intensity, similar to Hansen (1999), we utilize the panel threshold regression method, which is able to identify the threshold value of firm R&D intensity that provides the best overall fit for the combined single equation estimate.

Using this method, we are able to estimate the marginal products of patenting intensity, publication intensity, and R&D intensity, controlling for patents and publications, on Tobin's Q. Where as Hall et al. use U.S. firm-level data to estimate their model for the period 1963-1995 for the U.S. economy, we use firm-level data spanning 2013-2018 for the Chinese economy, which we complement with applications to the Japanese and U.S. economies for comparative purposes. This approach enables us to make comparisions regarding the relative returns to patenting, publications, and other R&D contributions as between China, Japan, and the U.S. The approach also reveals difference in returns within each of the countries. The stricing differences in returns to R&D activity in China highlight the benefits of reallocating R&D effort across patenting, publications, and other forms of innovation enhancing R&D activity.

We anticipate that the empirical results could show an efficiency advantage in either direction. The low intensity R&D firms may exhibit greater patent production efficiency simply because they are more parsimonious in the use of their limited R&D resources. On the other hand, high R&D intensity firms may enjoy scale and scope advantages from a large and wide portfolio of patent production. We also test for the possibility that R&D spending may result in reputation, supply chains, and other intangible assets that are not captured solely by patent or publication production.

The history of patenting in China is short, but its impact is far-reaching. China enacted its first patent law in 1950, but little patenting transpired until 1985 when China reinstated its patent law. According to statistics published by the recently renamed China National Intellectual Property Administration, (CNIPA),[1] by the end of 2017, China's domestic (excluding Hong Kong, Macao, and Taiwan) invention patent ownership totaled 1.356 million, with 9.8 invention patents per 10,000 population. These figures have propelled China to first place in the world in terms of the sheer quantity of patent applications for the past seven consecutive years. As anticpated, the surge in patenting activity has been accompanied by a surge in R&D spending. While 25 years ago, in 1995, China's R&D/GDP ratio was only 0.6% in recent years, it has gown to levels comfortably in excess of 2%. This level of aggregate R&D intensity compares well with the largest of the OECD economies which also report levels in the 2-2.5% range.

Our findings will be beneficial for firm strategy and government policy. On the one hand, through our statistical results, firms can have a more detailed view of the

[1] From 1985 to 1994, China received 439,529 patent applications, of which 380,431 (86.6 percent) were domestic applications, and 59,098 (13.4 percent) were foreign applications.

relationship between various innovation activities and the market value of firms operating in their domestic economies. The results have bearing on government policy toward R&D subsidies and taxation. They also have implications for firm behavior, including the level and proportion of R&D spending, as well as its distribution over patents, publications, and other innovative activity.

The remainder of the paper is organized as follows: In Section 2, we present the literature review. Section 3 presents a theoretical context for interpreting the implications of R&D intensity. Section 4 describes and summarizes the data. Section 5 presents the model and method. Section 6 reports the empirical result. In Section 7, we summarize certain of our conclusions and discuss priorities for further research.

2. Literature Review

The literature on the relationship between R&D intensity and firm performance validates our research objective. Evidence by Ugur et al. (2015) shows an inverted-U relationship between R&D intensity and firm survival in the UK. When R&D intensity is low, R&D exhibits a positive marginal effect on firms performance and survival. However, when the R&D intensity level is too high, it requires too much investment into R&D expenditure but cannot get enough return to fulfill it, causing the firm's death. Besides, Kima (2015) and Coccia (2009) both point out an optimal level of R&D expenditure concerning firm development; at the margin, the returns to research diminish.

A good deal of evidence shows the link between R&D and firm performance and patenting activity at the firm level. Erickson and Jacobson (1992) show that more patents enable firms to earn high profits and prevent rivals' imitation. Wang (2011) also concludes that firms that invest more in R&D enjoy higher rates of profitability than firms that do not. Thus, R&D expenditure and patenting activities have emerged as a critical factors in promoting firm competitiveness worldwide.

A number of empirical studies have been devoted to uncovering the possible underlying relationship between firm performance and specifical innovation activities, most often but not always patenting. Those relating to China tend to be ambiguous. Some find a positive relationship (Johnson and Pazderka, 1993; Long and Ravenscraft, 1993; Lee and Shim, 1995; Monte and Papagni, 2003; Connolly and Hirschey, 2005; Ho et al., 2006; Ghaffar and Khan, 2014), while other notes a negative impact (Gou et al., 2004; Lin and Chen, 2005; Lin et al., 2006; Artz et al., 2010; Pandit et al., 2011; Donelson and

Resutek, 2012). As set forth in the introduction, certain of these ambiguous results may disguise the diversity of results across firms with varying degrees of R&D intensity; hence the focus of this paper.

The literature provides a solid foundation for our method. The panel threshold regression model (PTR) is widely used in finance and development economics topics. Ibhagui (2009) uses a firm's size as a threshold variable, investigating whether R&D expenditure and capital structure affect firms' ROA and ROE. He finds that these variables' effects have varying magnitudes on firm performance, depending on firm size. Similarly, Chen and Lee (2017) apply the PTR model, studying the factors influencing firms' market value in Asia. They take corporate social responsibility as the threshold variable. Firms fall into disparate groups and conclude that CSR investment does not enhance company value until it exceeds the value transition threshold. Further, Ngundu (2017) also uses this model to examine the FDI impact on countries' GDP growth. He concludes that groups with different FDI levels determine the efficiency in using endowments.

3. Theoretical Perspective

Scotchmer (2004) provides a helpful perspetive on the implications of R&D effort. Figure 1 consists of the following variables. That figure includes the following variables:

P: the probability the research fails.
R: the revenue earned by the firm.
S: The total social benefit of the innovation, including the externality, $S > R$.
nc: Total cost = $n \times$ marginal cost.

- Possible equilibria:

n_c: profit maximization for firms, max $[(1-p^n)\,R - nc]$.
n^*: profit maximization considering externality, $\max(1-p^n)\,S - nc$.
n_e: free-entry level of R&D input, $nc = (1-p^n)\,R$.

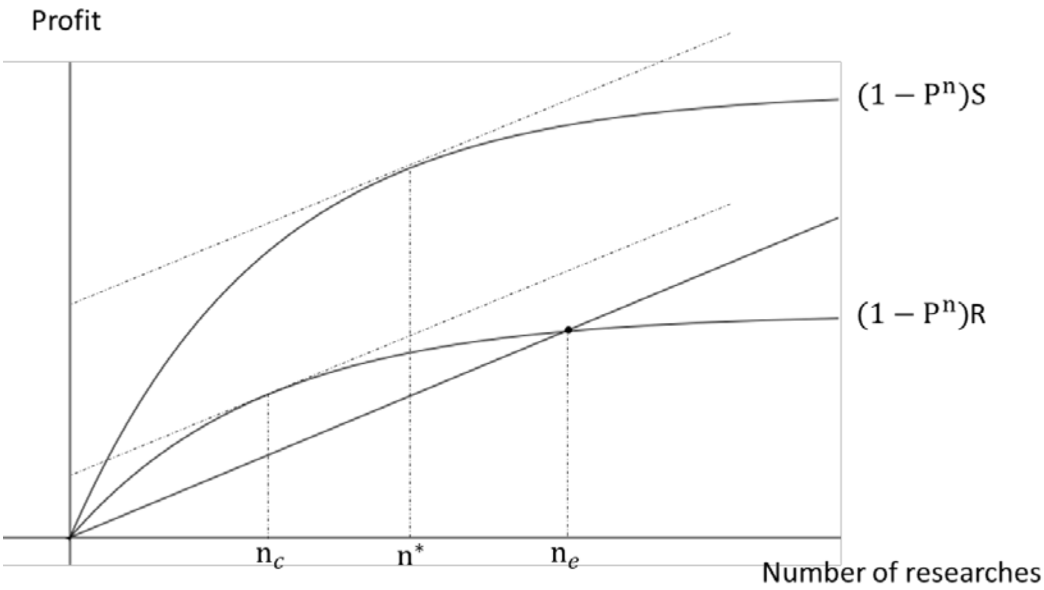
Key features and results of the theoretica perspective include:

- The increasing probability of a successful research outcome with the addition of more reseachers;

- Diminishing returns to R&D effort as additional researchers attempting to achieve a given invention engage in wasteful duplication; and
- Free entry, i.e., high R&D effort, results in the highest probability of success combined with the lowest marginal revenue due to wasteful duplication.

Hence, as shown in Figure 1, for a given invention, the addition of resarchers results in a increasing probability of success with diminishing returns to additional researchers: $MR_{nc} > MR_{n*} > MR_{ne}$.

Figure 1: Optimal Patent Design; Possible Equilibria



Source: Scotchmer (2004, p. 101)

We deduce from Figure 1 that if the returns to R&D effort for high and low R&D intensive firms are equal or higher in the high R&D intensity firm, it must be that the high R&D intensity firm is conducting multiple research projects such that there exists limited overlap or that economies of scope between the individual projects and scale economies for the overall research operation offset the duplication condition. We intend to map our results into Figure 1 as a starting point for our analysis.

4. Data Description

Our data set, obtained from Orbis, spans the period 2011 to 2018. All of the included firms are classified as "large size firms." We draw from the data set the following variables:

- Dependent variable: Tobin's Q, an indicator of firm's innovation performance, i.e., intangible asset creation
- Independent variables:
  - *R&D*/*ASSETS*, an indicator of R&D contribution.
  - *PAT*/*R&D*, an indicator of patent efficiency.
  - *PUBS*/*PAT*, an indicator of patent quality (substitutes for citations used by Hall et al.)
  - Stock measures of *R&D*, *PAT* and *PUBS*. We directly get yearly measures of the stock of patents from the database, and accumulate yearly data to get *R&D* and *PUBS*.
  - Dummies: year dummy

For the purposes of creating a balanced data set, Table 1 is constructed to show the number of firms and total number of observations that can be fashed from different time periods. The panel threshold regression model requires the use of a balanced data set. On the other hand, as a non-linear model, we are unable to use the fixed effects estimator. We are, however, able to incorporate fixed effects variables for the year observations and industry classifications.

Table 1: The Number of Observations Each Year to Achieve a Balanced Dataset, China

Period	Years	Number of Obs.	Number of firms
2011-2018	8	4848	606
2013-2018	6	8034	1339
2015-2018	4	5644	1411

Source: The authors.

As shown in the table, the maximum number of observations results from the 6-year panel spanning 2013-2018. For this reason, we select this period for our regression analysis.

Table 2 reports the summary statistics for the key variables. Our measure of research effectiveness is Tobin's Q, a measure of the ratio of the firm's total market value to the book value of its tangible physical assets. Values of Tobin's Q > 1 indicate that the firm has acquired intangible assets, such as intellectual property, reputation, and other intangible factors, many of which are likely to be associated with the firm's research effort.

Table 2: Summary Statistics of key control variables*

Variable	Obs.	Mean	SD	Min**	Median	Max
China						
Tobin's Q	4274	1.321	1.010	0.000	1.065	4.936
Assets	4274	3.78e+06	1.87e+07	25950	7.39e+05	3.93e+08
R&D/Assets	4274	0.020	0.019	0.000	0.016	0.448
Patents/R&D	4274	0.038	0.125	0.000	0.014	3.177
Publications/Patents	4274	0.197	0.162	0.001	0.155	0.842
Japan						
Tobin's Q	5585	0.676	0.595	0.021	0.497	4.999
Assets	5585	4.84e+06	2.03e+07	8155	7.89e+05	4.74e+08
R&D/Assets	5585	0.025	0.030	0.000	0.017	0.710
Patents/R&D	5585	0.073	0.091	0.001	0.047	0.798
Publications/Patents	5585	0.107	0.074	0.000	0.091	0.444
US						
Tobin's Q	2504	1.864	1.127	0.005	1.586	4.979
Assets	2504	1.23e+07	4.44e+07	580	9.91e+05	6.57e+08
R&D/Assets	2504	0.110	0.138	0.000	0.061	0.965
Patents/R&D	2504	0.018	0.028	0.000	0.010	0.260
Publications/Patents	2504	0.124	0.128	0.000	0.086	0.750

Note: *The table and our analysis has omitted certain observations that are implausible. Specifically, we limit Tobin's Q to values ≤ 5. Also for R&D/Assets, we sorted the valuations through two steps. In order to recenter the mean, we first eliminated observations that exceeded 25x the mean; thereafter we eliminated observations that exceeded 5x the mean. ** For minimum values that are reported as 0.000, the minimum value is smaller than 0.001, but not zero, i.e., 0 < X < 0.001.

Source: The authors.

Our independent variables include the number of publications each year, R&D expenditure, total profit, sales, intangible assets, the number of patients each year, the patent portfolio value each year. The threshold variable, R&D intensity, is calculated by:

$$R\&D\ intensity = \frac{R\&D}{Assets}$$

The number of patents each year is calculated by differencing the number of stock patents each year. All other variables are directly extracted from the database. Table 2 reports the summary statistics for China, Japan and the U.S.

Table 2 shows certain maximum values that appear as outliers compared with the mean and median values shown for the same variable. Most notable, and concerning, among these is the maximum measure of R&D intensity, i.e., R&D/Assets, reported as 122.931 for a U.S. firm. This figure substantially exceeds those of 0.451 and 1.233 for the counterpart Chinese and Japanese firms. Appendix 2 reports levels of R&D intensity for five of the most R&D intensitive firms in China, Japan, and the U.S. As the Table shows, the figures for these high-intensity R&D firms are all substantially greater than those for certain of the largest and well known firms shown in the Table. Indeed, within our firm sample the top 50 high intensity R&D firms are all U.S. firms. It appears that the most R&D intensive firms are among the smaller of the large firms in our sample with respect to their accumulated physical assets. As a robustness test, we drop these outlier observations, including only those for whom R&D intensity < 1.

5. The Model

The model used for the analysis consists of several parts. The first is for the construction of the dependent variable, Tobin's Q, which measures the ratio of the firm's total market value to the replacement cost of its physical assets. The second part is the regression model, which is similar to that employed by Hall et al. (2005). Finally, in order to assess the difference in R&D performance between high and low R&D intensity forms, we employ the panel threshold regression model technique, which identifies the threshold value of our R&D intensity measure that results in the most robust estimation result when we combine estimates of the high and low R&D intensity firms in the same regression equation. We describe the relevant method for each of these elements.

5.1. The Construction of Tobin's Q Equation

We use the firm-level market value function developed by Griliches (1981). In this model, the firm's total market value (*V*) is assumed to be the combinated values of its tangible physical assets (*A*) and its intangible assets, otherwise characterized known as its knowledge assets (*K*) as shown below:

$$V_{it} = q_t(\pi_t A_{it} + \gamma_t K_{it})^\sigma \tag{1}$$

In Eq. (1), π_t and γ_t denote the shadow price of physical assets and applied knowledge assets at time *t*, respectively. The scale parameter allows for a non-constant scale effect in the market value function. Finally, q is an intercept representing the "current market valuation coefficient," e.g., differential risk and monopoly conditions, which in our empirical application, we captured by using a year dummy. All the variables are in the nominal terms. Like Griliches (1981), we impose the restriction, $\sigma = 1$ representing the standard property of constant returns of scale.

Consistent with Hall et al. (2005) we take logarithms of both sides of Eq. (1), and recombine as:

$$\log(V_{it}) = \log(q_t) + \log(\pi_t A_{it}) + \log(1 + \gamma_t K_{it}/\pi_t A_{it})$$

So that $\pi_t A_{it}$ appears in the denominator of $\gamma_t K_{it}/\pi_t A_{it}$ and as the log of $\pi_t A_{it}$. In this formation, γ_t/π_t denotes the shadow value of knowledge assets relative to the physical assets of the firm.

Considering the constant returns to scale, σ = 1, log A can be removed to the left-hand side, and the model estimated with the conventional Tobin's Q as the dependent variable. Then, we can get the estimating equation,

$$\log(Q_{it}) = \log(V_{it}/A_{it}) = \log(q_t) + \log(1 + \varphi_t K_{it}/A_{it}) + \varepsilon_{it}$$

where q represents the time dummy/fixed effect, such that Q_{it} denotes Tobin's Q, and the intercept of the model can be interpreted as an estimate of the logarithmic average of Tobin's Q for each year. φ_t measures the shadow value of applied knowledge assets relative to the physical assets that do not account for in the denominator of q. If knowledge assets make a difference to market value, then $\varphi_t > 0$.

The knowledge creation process is treated as a continuum going from R&D to patents, as shown in Hall et al. (2005). R&D reveals the commitment of a firm's resources to innovation. Patents catalog the success in generating knowledge that the firm can in principle act to appropriate and gain value. As previously explained, rather than use citations as a measure of patent quality, we use publications under the assumption that intellectual property that has been vetted in published papers, is, on average, more scientifically and technologically advanced that that which has not been similarly vetted (e.g., Harhoff et al., 1999).

There may be also be spillover benefits that result from R&D, someof which are associated with specific patents and publications, others of which accumulate from unpatented or unpublished innovation, such as technology that is appropriated by secrecy or rapid movement up the technology ladder. Reputation, intellectual and supply chain links and other intangible assets may accrue from R&D spending.

Accounting for the role of patenting, our basic estimation equation is;

$$\log(Q_{it}) = \log(q_t) + \log\left(1 + \beta_1 \frac{R\&D_{it}}{A_{it}} + \beta_2 \frac{PAT_{it}}{R\&D_{it}} + \beta_3 \frac{PUBS_{it}}{PAT_{it}}\right) + \varepsilon_{it} \qquad (2)$$

Eq. (2) is nearly identical to that used by Hall et al (2005). The only differences is that we substitute the stock of publications for Hall et al.'s use of citations. The measures of *R&D*, *PAT*, and *PUBS*, as well as *A*, physical assets, are all stocks. Therefore, as do Hall et al., we expect that the use of stocks to measure the independent variables whereas *V*, the current market value is a flow variable, the stocks should not be highly sensitive to transitory shifts in the firm's market value. Hence endogeneity issues should be minimal.

5.2. Panel Threshold Regression Model

A persistent theme of this paper has been that the impact on firm performance of a unit of R&D expenditure may vary with firm characteristics, such as R&D intensity. It could be the the impact of R&D investment is dominated by sharply diminishing marginal returns, or R&D investment may accumulate surplus even as R&D intensity rises.

To determine whether firms may fall into distinct groupings, we use the dynamic panel threshold regression model by Hansen (1999). Considering a single threshold model,

$$y_{it} = \mu_i + \beta_1 X_{it} I(rdi_{it} \leq \gamma) + \beta_2 X_{it} I(rdi_{it} > \gamma) + e_{it}$$

where y_{it} denotes the dependent variable, i denotes the time-invariant fixed effect, is the threshold and the threshold variable, rdi_{it}. R&D intensity is smaller or larger than the threshold. The coefficients β_1, β_2 are 1×K vectors, and the regressor $\boldsymbol{X_{it}}$ is also a 1×K vector.

The observations are divided into disparate groups depending on whether the threshold variable is smaller or larger than the threshold. We assume that both rdi_{it} and X_{it} are time-variant, and the error term ε_{it} is independent and i.i.d. with zero mean and finite variance.

The model can be rewritten as:

$$y_{it} = \mu_i + X_{it}(rdi_{it}, \gamma)\beta + e_{it}$$

where

$$X_{it} = \begin{pmatrix} X_{it} I(rdi_{it} \leq \gamma) \\ X_{it} I(rdi_{it} > \gamma) \end{pmatrix}.$$

Given γ, the ordinary least-squares estimator of β is

$$\hat{\beta} = \{X^*(\gamma)' X^*(\gamma)\}^{-1}\{X^*(\gamma) y^*\}$$

where $X^*(\gamma)$ and y^* are within-group deviations. The residual sum of squares (RSS) is given by

$$RSS = \widehat{e^*}' \widehat{e^*}.$$

Chan (1993) and Hansen (1999) recommend the estimation of γ by least squares. This method is most comfortable to achieve by minimization of the concentrated sum of squared errors RSS. Hence the least-squares estimator of γ is

$$\hat{\gamma} = \arg\min_{\gamma} RSS(\gamma).$$

Hansen (1999) proved that $\hat{\gamma}$ is a consistent estimator for γ.

Further, we can also extend this model into multiple thresholds; for example, the double threshold model is

$$y_{it} = \mu_i + \beta_1 X_{it} I(rdi_{it} \leq \gamma_2) + \beta_2 X_{it} I(\gamma_2 \geq rdi_{it} > \gamma_1) + \beta_3 X_{it} I(rdi_{it} \leq \gamma_1) + e_{it}$$

where γ_1 and γ_2 are the thresholds that divide the observations into three groups with coefficients β_1, β_2, and β_3.

Thus, our final estimation equation will be, take single threshold model as an example,

$$\log(Q_{it}) = \log(q_t) + F_1(X_{it}) I(rdi_{it} \leq \gamma) + F_2(X_{it}) I(rdi_{it} > \gamma) + \varepsilon_{it}.$$

So that we estimate two values of each of the coefficients, one for the high R&D intensity firms; the other for the low-inensity R&D firms, (i.e., k = 2), our estimation equation is:

$$F_k(X_{it}) = \log\left(1 + \beta_{1k}\frac{R\&D_{it}}{A_{it}} + \beta_{2k}\frac{PAT_{it}}{R\&D_{it}} + \beta_{3k}\frac{PUBS_{it}}{PAT_{it}}\right), k = 1,2.$$

Further, to access their marginal impacts in this nonlinear model, we need to compute the semi-elasticity,

$$\frac{\partial \log Q}{\partial\ (R\&D/Assets)} = \hat{\beta}_{1k}\left(1 + \hat{\beta}_{1k}\frac{R\&D_{it}}{A_{it}} + \hat{\beta}_{2k}\frac{PAT_{it}}{R\&D_{it}} + \hat{\beta}_{3k}\frac{PUBS_{it}}{PAT_{it}}\right)^{-1}, k = 1, 2$$

$$\frac{\partial Q}{\partial\ (R\&D/Assets)} = \hat{\beta}_{1k}\left(1 + \hat{\beta}_{1k}\frac{R\&D_{it}}{A_{it}} + \hat{\beta}_{2k}\frac{PAT_{it}}{R\&D_{it}} + \hat{\beta}_{3k}\frac{PUBS_{it}}{PAT_{it}}\right)^{-1}\hat{Q}, k = 1, 2$$

And similarly, for Patent/R&D and Publications/Patents:

$$\frac{\partial \log Q}{\partial\ (Patents/R\&D)} = \hat{\beta}_{2k}\left(1 + \hat{\beta}_{1k}\frac{R\&D_{it}}{A_{it}} + \hat{\beta}_{2k}\frac{PAT_{it}}{R\&D_{it}} + \hat{\beta}_{3k}\frac{PUBS_{it}}{PAT_{it}}\right)^{-1}, k = 1,2$$

$$\frac{\partial \log Q}{\partial\ (Publications/Patents)} = \hat{\beta}_{3k}\left(1 + \hat{\beta}_{1k}\frac{R\&D_{it}}{A_{it}} + \hat{\beta}_{2k}\frac{PAT_{it}}{R\&D_{it}} + \hat{\beta}_{3k}\frac{PUBS_{it}}{PAT_{it}}\right)^{-1}, k = 1,2$$

6. Results

6.1. Threshold Analysis

Before we run the regression on our full model, we must identify the threshold values in our model. We test the significance of a single threshold and double threshold model to choose which model we will use. Table 3 below shows the threshold effect testing using Hansen's (1999) method. We can see that the single threshold is significant at the 95% level, while the double threshold test is not significant even at a 90% level. We also attached the 95% confidence interval for our single and double threshold model. Hence, we can conclude for China that the single threshold model is significant, whereas, for the double threshold model, the first threshold is significant, but the second threshold is not.

Table 3: Test Threshold Effects Using Hansen (1999), China

Test for a single threshold	
F statistics	102.63
P-value	0.000
Critical values 10% 5% 1%	54.1624, 65.2397, 134.1339
Test for double threshold	
F statistics	11.77
P-value	0.900
Critical values 10% 5% 1%	37.4677, 39.5504, 57.1788

Threshold estimator 95%			
Single threshold model			
	Threshold	Lower	Upper
Th-1	0.135	0.124	0.146
Double threshold model			
	Threshold	Lower	Upper
Th-21	0.135	0.124	0.146
Th-22	0.361	0.331	0.391

Source: The authors.

Applying the same procedure, we obtain the threshold estimations for Japan and the US. For Japan and the U.S. in Table 4, we find that, as with China, the double threshold estimates are insignificant and therefore use the single threshold estiamtes for all three economies.

Table 4. Threshold Estimation (R&D Intensity)

	Threshold Estimation		Number of Observations	
	Mean	SD	Low R&D intensity	High R&D intensity
China	0.0135	0.0011	6371	1663
Japan	0.0143	0.0008	3923	2651
US	0.0140	0.0030	2430	316

Source: The authors.

One result that stands out in Table 4 is the extreme asymmetry of the numers of low and high R&D intensity firms in the U.S. sample. Given that the threshold estimates seek to approximately balance the weighted distance of the observations form the delineating thresholds and the fact that the U.S. in Table 2 and in Appendix 2 shows a core set of firms with exceedingly high R&D intensities, i.e., high R&D/Asset ratios, it should be expected that the high R&D intensities are associated with a relatively small number of high R&D intensity firms as shown for the U.S.

We are also interested in comparisons of the threshold values for our three-countries, China, Japan, and the US. Based on the t statistics test results, we conclude tha there exists minimal difference between the three countries' thresholds. This finding is interesting and intriguing. Our finding shows that the threshold for R&D intensity is approximately 1.3%-1.5%. Whether this similar pattern is the optimal level across the wider set of economies and whether it can have an economic explanation is promising gist for further study.

Given the determination of the respective thresholds for each country we analyze the results for our full model applied to each of the three countries. We note that our estimation model includes fixed effects for not only time, but also for the industry effects. Our estimation equation includes industry dummies for six sectors: Drugs (including biology and life science), Chemicals (Chemicals, Petroleum, Rubber & Plastic), Computers and Communications, Electrical (Industrial, Electric & Electronic Machinery), Metals (Metals & Metal Products), and miscellaneous (Miscellaneous Manufacturing, low-tech industry), and interact them with the knowledge ratios. BVD sectors in our database determine the sectors.

6.2. Cross-country Comparisons

To determine whether our result is robust across countries, we apply the same nonlinear threshold regression using Japanese and US data. For purposes of comparison, we limit or period to the same 2013-2018 period for the regressions for Japan and the U.S. There are 4081 observations in Japan and 3239 observations in the US. Since we estimate our threshold based on our data set, the threshold will differ in different groups. Hence, the R&D intensity threshold is 0.143 in Japan and 0.140 in the US, respectively. As explained above, givent the singular robustness of a single threshold, the observations are distribute only across high and ow intensity firms. The results are shown in the following Table 5.

Table 5: Cross-country Comparisons, 2013-2018

Nonlinear Model with Dependent Variable: log Tobin's Q

(with year and industry fixed effects)

	(1) China	(2) Japan	(3) US
R&D intensity > threshold, high R&D intensity firms			
R&D/Assets	0.393***	0.158***	0.137***
	(12.220)	(7.751)	(8.692)
Patents/R&D	0.226***	-0.076***	-0.042***
	(10.431)	(-5.826)	(-3.517)
Publications/Patents	0.118***	0.090***	0.086***
	(5.834)	(5.997)	(6.920)
R&D intensity ≤ threshold, low R&D intensity firms			
R&D/Assets	0.238***	0.065***	0.215***
	(5.900)	(3.951)	(5.332)
Patents/R&D	0.253***	-0.036***	0.031
	(6.681)	(-2.621)	(1.139)
Publications/Patents	0.180***	0.025	-0.042
	(4.301)	(1.526)	(-1.473)

Note: Estimation method: nonlinear least squares and panel threshold regression. All equations include a complete set of year dummies and six industry dummies.

Source: The authors.

Table 5 reports the semi-elasticity coefficients obtained from estimates of Eq. (3). Column (1) is shows the estimates of our full model for China, columns (2) and (3) represents the full model estimation for Japan and the US. The Table shows that for the R&D intensive firms, all of the estimates are statistically robust at the 1% level. For the low-intensity R&D firms, whle each of the three estimated coefficients is significant at the 1% level for Japan, the publication intensity coefficient is not significant, nor are the patent and publication intensity estimates for the U.S. firm sample.

Since the model is non-linear, we cannot directly assess the impacts of the knowledge intensities on Tobin's Q. Given the large difference in the mean and median values for a number of the country variables shown for the full sample in Table 2, we compute the median values for the high intensity and low intensity R&D firms; we use these to compute the respective marginal products of the knowledge intensity measures. These are reported in the bottom panel of Table 6.

Table 6: The Marginal Product of the Knowledge Stock Intensities on Tobin's Q using the median values of each of the variables

Median Values	China	Japan	US
R&D intensity > 0.0135, high R&D intensity firms			
R&D/Assets	0.022	0.028	0.103
Patents/R&D	0.045	0.001	0.001
Publications/Patents	1.000	2.889	1.472
R&D intensity ≤ 0.0135, low R&D intensity firms			
R&D/Assets	0.029	0.005	0.007
Patents/R&D	0.006	0.003	0.001
Publications/Patents	1.000	1.724	1.077
Semi-elasticity			
R&D intensity > 0.0135, high R&D intensity firms			
$\frac{\partial \log Q}{\partial (R\&D/Assets)}$	0.263	1.280	5.051
$\frac{\partial \log Q}{\partial (Patents/R\&D)}$	0.100	0.250	0.822
$\frac{\partial \log Q}{\partial (Publications/Patents)}$	0.897	0.334	0.325
R&D intensity ≤ 0.0135, low R&D intensity firms			
$\frac{\partial \log Q}{\partial (R\&D/Assets)}$	1.469	0.849	3.350
$\frac{\partial \log Q}{\partial (Patents/R\&D)}$	1.170	0.733	1.358
$\frac{\partial \log Q}{\partial (Publications/Patents)}$	0.950	0.576	0.905
Marginal Product			
R&D intensity > 0.0135, high R&D intensity firms			
$\frac{\partial Q}{\partial (R\&D/Assets)}$	0.393	0.158	0.137

$\frac{\partial Q}{\partial\,(Patents/R\&D)}$	0.226	0.076	-0.042
$\frac{\partial Q}{\partial\,(Publications/Patents)}$	0.118	0.090	0.086
R&D intensity ≤ 0.0135, low R&D intensity firms			
$\frac{\partial Q}{\partial\,(R\&D/Assets)}$	0.238	0.065	0.215
$\frac{\partial Q}{\partial\,(Patents/R\&D)}$	0.253	0.036	0.031
$\frac{\partial Q}{\partial\,(Publications/Patents)}$	0.180	0.025	-0.042

Source: The authors.

Starting with China, we compare the within country results for the high intensity R&D firms and low-intensity R&D firms. We first note that given that $Q = V/Assets$, the coefficient estimate for $\frac{\partial Q}{\partial(R\&D/Assets)}$ shown in Table 5 can be interpreted as either the marginal product of Tobin's Q with respect to R&D intensity, or the marginal product of the firm's total market value,V, with respect to R&D expenditure, $\partial V/\partial R\&D$. In either case for the high-intensity and low-intensity R&D firms, the estimates are 0.393 and 0.238 respectively.

The analysis of this finding is not straightforward. That is, these estimates are conditional on the controls for patent intensity and publication intensity. As such, we interpret estimates of the coefficients for $\frac{\partial Q}{\partial(R\&D/Assets)}$ as estimates of the impact of R&D intensity as the residual effect once we account for the impact of patent and publication intensity. Hence, we analyze the marginal contributions of patent and publication intensity and then return to interpret the impact of R&D intensity on Tobin's Q.

Patent Intensity: As shown in Table 6, for the R&D intensive firms, Japan and the U.S. report far lower levels of patent intensity than China. While these differences persist, they are not as large for the low R&D intensity firms. These differences may result from at least two different possibilities. First, it is possible that Japanese and U.S firms, in fact, spend more on each patent, causing the returns to Japanese and U.S. patent intensity to be closer to n^e in the Scotchmer Diagram (Figure 1), that is, close to zero, than China. Hence, the combination of high R&D intensity and low patent productivity.

An alternative possibility is that as compared with China, Japan and U.S. firms patent a smaller portion of their patentable inventions, possibly because the patent approval process is too time consuming and requires a description of the invention. Seeking to achieve first-mover status by successfully staying one or more rungs ahead of the competition, by intensifying their R&D effort and relying on secrecy methods and legal protection, Japanese and U.S. firms are able to augment the probability of earlier success, while securing secrecy, if over shorter durations. These two interpretations are not mutually exclusive; in order to retain their technological advantage, Japanese and U.S. firms may need to outspend their competition on frontier innovation. Moreover, once the technology of the first mover comes on line, the follower companies are likely to spend less per innovation as they seek to imitate, improve, and adapt the emergent technologies.

China's high Patent/R&D intensity may result from one or a combination of several issues. One notable reason is that a portion of Chinese patent approvals are utility and design patents of lower quality and shorter duration than the invention patents that are closer to high international standards. Within our data set that share appears to be small, while as much as two-thirds in some Chinese firms, the average is approximately 5%. As explained by Jiang and Jefferson (2021), other possibilities include the incentives for large patent counts spurred by subsidies and rewards for patent production provided by various levels of government. As a result of the heightened focus and return to patenting, firms sometimes convert single patents that might have condensed multiple claims into a single patent into multiple patents, each with fewer claims.

Publication Intensity: This heterogeneity of patent quality could explain why China has the highest return on publications per patent, which we use as a proxy for patent quality. Chinese firms with high publication to patent ratios also have relatively high proportions of invention patents. The importance of publication intensity is still greater for China's low-intensity R&D firms for which the lower quality patents are likely to be more prevalent.

For the high-intensity R&D firms, the returns to publications and publication intensity are relatively evenly distributed across the three countries, with small declines in their marginal returns from China to Japan to the U.S. Apart from China, the returns to publishing fall off substantially from high-intensity to low-intensity R&D firms. This is likely due to the fact that the specialization and comparative advantage of the high intensity firms lies in the area of technology development for which the returns to high quality innovation and reputation are likely to be most pronounced.

R&D Intensity: As explained about, we interpret estimates of the returns to R&D intensity as the residual return, once the contributions of patent and publication intensity are accounted for. Our estimation results indicate that an increase in R&D intensity, i.e., the ratio of R&D to fixed tangible assets, may result in the following outcomes:

- Reduce patent/R&D intensity and, as suggested by Figure 1, increase the patent productivity of R&D effort;
- Increase patenting and R&D spending in equal proportions thereby leaving the marginal product of patent intensity unchanged, with a likely increase in the spillover benefits of patenting, such as the reputation effect as well as a reduction in the marginal contribution of R&D intensity to Tobin's Q.
- Increase the overall contribution of R&D through avenues other than those that augment the steady-state stock of patents and publications, including conferences, networking, purchases of recent explansions of R&D capabilities that have not yet translated into higher patent output, and innovations for which patents are not applied or approved.
- Enhance reputation effects without increasing patent or publication intensity.

Again, we see that the returns to China's high-intensity R&D firms is more than 50% higher than their low-intensity counterparts. Across the three countries, for both high and low-intensity R&D firms, China's marginal returns to R&D intensity outpaces those for Japan and the U.S., although for low-intensity firms, the marginal returns are comparable for China and the U.S. These comparisons indicate that notwithstanding its surge in R&D spending and intensity over the recent decades, the returns to R&D, more so for China's R&D intensive firms, remains robust. Moreover, for the high intensity R&D firms, the returns to patent and publication intensity remain high. Whether constrains that the U.S. and certain other countries have imposed on some of China's most technologically advanced firms has substantially diminished their returns to research and development remains unknown. As the data accumulate for the current year and beyond, the impacts of these limits on the cross-border transfer and sale of technology will become more evident.

In the last panel of Table 7 below, we show the simple marginal products for the firm samples for each country with respect to the returns to the firm's total market value, V with respect to R&D expenditure, the patent count, and the publication count. While the relative magnitues are similar to the relative values of the returns to knowledge intensity, several of the signs and absolute values change significantly.

Table 7: The Adjusted Marginal Product of Knowledge Stocks on Market Value (the median firm)

	China	Japan	US
Adjusted Marginal Product, *year dummies deliminated*			
High R&D intensity firms			
$\frac{\partial V}{\partial (R\&D)}$	0.393	0.158	0.137
$\frac{\partial V}{\partial (Patents)}$	16,270	6,580	2,060
$\frac{\partial V}{\partial (Publications)}$	680	630	420
Low R&D intensity firms			
$\frac{\partial V}{\partial (R\&D)}$	0.238	0.065	0.215
$\frac{\partial V}{\partial (Patents)}$	178	22	41
$\frac{\partial V}{\partial (Publications)}$	168	26	37

Note: Unit: per dollar

Source: The authors.

We first note that given that Q = V/Assets, the coefficient estimate for $\frac{\partial Q}{\partial (R\&D/Assets)}$ shown in Table 5 can be interpreted as either the marginal product of Tobin's Q with respect to R&D intensity, or the marginal product of the firm's total market value with respect to R&D expenditure, ∂V/∂R&D. In either case for the high-intensity and low-intensity R&D firms, the estimates are 0.393 and 0.238 respectively.

We note several features of Table 7. The first is that while the total market value returns continue to differ substantially as between patent intensity and simple patent counts, Japan and the U.S. continue to earn positive, non-zero returns. Also while we continue to see higher returns to publications for China, the disparities as not s great as they shown for publication intensity in Table 6 above. Overall, Table 7 confirms as shown in Table 6, China continues to have possibilities for augmenting its innovation intensity and output while exhibiting returns that show well in relation to Japan and the U.S.

7. Conclusion

Combining the model of Hall et al. (2005) with an adapted measure for patent quality with Hansen's approach (1999) to separating the critical explanatory variable, R&D intensity in our case, into low and high-intensity firms and using firm-level data to compare China, Japan, and the U.S., we are able to compare the returns to Tobin's Q from three measures of R&D intensity – R&D/assets, Patents/R&D, and Publications/Patents.

Among their findings, Hall, Jaffe, Trajtenberg (2005, p. 17) report:

> We estimate Tobin's Q "hedonic" equations on three complementary aspects of knowledge stocks: R&D "intensity" (the ratio of R&D stocks to the book value of assets), the patent yield of R&D (i.e., the ratio of patent count stocks to R&D stocks), and the average citations received by these patents (i.e., the ratio of citations to patent stocks). We find that each of these ratios has a statistically and economically significant impact on Tobin's Q. This confirms that the market values R&D inputs, values R&D output as measured by patents, and further values "high-quality" R&D output as measured by citation intensity.

With the exception of substituting "average publications" for "average citations," our conclusion for China could mimic that of Hall et al. This conclusion is somewhat more applicable to China's high intensity R&D firms than its low intensity firms.

A certain takeaway is that firms representing the two sample of large firms in China as compared with Japan and the U.S. manage their research programs strikingly differently. The Chinese firms are clearly more highly rewarded than their Japanese and U.S. counterparts for high patent intensity. Japanese and U.S. firms appear to be utilizing avenues other than patent counts to produce and secure their intellectual property. This finding may well highlight a critical shortcoming of our study. That is, that the measure of publications per patent may not be an effective proxy for patent quality. Nonetheless, regardless of difficulties associated with cross country comparisons, our within-China results yield a clear finding, which is that at the margin, the country's high-intensity R&D firms generate both higher returns to innovative activity than their counterpart low-ininsity R&D firms.

This research invites further investigation into the sources of quality differences between Chinese, Japan, and U.S. patents. Our proxy of publication intensity many not serves as a sufficiently robust measure of the value enhancing features of a given patent count. A second step concerns the need to more specifically identify certain of the measures of intangible assets that extend beyond the included measures of patents and publications. The fact that with a single exception, that of publication/patents for China's high R&D intensity firms, the returns to R&D intensity separate from patents and publication exceeds patent and publication returns, in China, Japan, and the U.S. argues for a more rigorous identification of the benefitting outputs of the R&D process.

References

Bai, J. (1997) "Estimating Multiple Breaks One at a Time," *Econometric Theory* 13: 315–352.

Bai, J., and P. Perron (1998) "Estimating and Testing Linear Models with Multiple Structural Changes," *Econometrica* 66: 47–78.

Chappell, N., and A. Jaffe (2018) "Intangible Investment and Firm Performance," *Review of Industrial Organization* 52(4): 509–559.

Chen, R. C. Y., and C.-H. Lee (2016) "The Influence of CSR on Firm Value: An application of panel smooth transition regression on Taiwan," *Applied Economics* 49(34): 3422–3434.

Coccia, M. (2009) "What Is the Optimal Rate of R&D Investment to Maximize Productivity Growth?" *Technological Forecasting and Social Change* 76(3): 433–446.

Connolly, R. A., and M. Hirschey (1988) "Market Value and Patents," *Economics Letters* 27(1): 83–87.

Fracasso, A., and G. V. Marzetti (2013) "International R&D Spillovers, Absorptive Capacity and Relative Backwardness: A panel smooth transition regression model," *International Economic Journal* 28(1): 137–160.

González, A., T. Teräsvirta, D. van Dijk, and Y Yang (2005) "Panel Smooth Transition Regression Models," SSE/EFI Working Paper Series in Economics and Finance 604, Stockholm School of Economics, revised on October 11, 2017.

Griliches, Z. (1981) "Market Value, R&D, and Patents," *Economics Letters* 7(2): 183–187.

Griliches, Z., and J. A. Hausman (1986) "Errors in Variables in Panel Data," *Journal of Econometrics* 31(1): 93–118.

Hall, B. (1993) "The Stock Market's Valuation of R&D Investment During the 1980s," *The American Economic Review* 83(2): 259–264.

Hall, B. (2000) "Innovation and Market Value." In R. Barrell, G. Mason, and M. O'Mahony, eds., *Productivity, Innovation, and Economic Performance*, New York: Cambridge University Press.

Hall, B., A. Jaffe, and Trajtenberg, M. (2005) "Market Value and Patent Citations," *RAND Journal of Economics* 36(1): 16–38.

Hansen, B. E. (1999) "Threshold Effects in Non-dynamic Panels: Estimation, testing, and inference," *Journal of Econometrics* 93(2): 345–368.

Hansen, B. E. (2000) "Sample Splitting and Threshold Estimation," *Econometrica* 68(3): 575–603.

Ibhagui, O. (2019) "Do Large Firms Benefit More from R&D Investment?" *The European Journal of Applied Economics* 16(2): 155–173.

Jiang, R. and Jefferson, G.H. (2021) "China's S&T Progress through the Lens of Patenting," *Oxford Handbook of Chinese Innovation*, ed. Xiaolan Fu.

Le, T., and A. Jaffe (2017) "The Impact of R&D Subsidy on Innovation: Evidence from New Zealand firms," *Economics of Innovation and New Technology* 26(5): 429–452.

Pakes, A. (1985) "On Patents, R&D, and the Stock Market Rate of Return," *Journal of Political Economy* 93(2): 390–409.

Rahko, J. (2014) "The Market Value of R&D, Patents, and Organizational Capital: Finnish evidence," *Economics of Innovation and New Technology* 23(4): 353–377.

Sandner, P. G., and J. Block (2011) "The Market Value of R&D, Patents, and Trademarks," *Research Policy* 40(7): 969–985.

Scotchmer, S. (2004) *Innovation and Incentives*, Cambridge: The MIT Press.

Appendix 1: Summary Table of Literature

Panel threshold regression model

Title / Author	Sample	Variables	Model	Findings
Do Large Firms Benefit More from R&D Investment? Oyakhilome Ibhagui	Nasdaq-listed companies for the period 2002 to 2017	Threshold variable: Firm size Dep var: Firm performance Control var: ROA, Tobin's Q, ROE, etc.	Panel threshold regression	R&D can have effects of varying magnitudes on firm performance, depending on firm size. When R&D weakens firm performance, the adverse effects are more pronounced for small-sized firms, but when the impact of R&D is positive, large-sized firms tend to reap most of the benefits.
Panel Smooth Transition Regression model and an application to investment under credit constraints Andres Gonzalez, Timo Terasvirtabc, & Dick van Dijk	same economic problem and data set as Hansen (1999a)	Threshold variable: Firm's debt level Dep var: Firm's investment	PSTR	Standard asymptotic theory can be used as the likelihood function in the PSTR model is a continuous function of the parameters.
Threshold effects of inflation on growth in the ASEAN-5 countries: A Panel Smooth Transition Regression approach Su Dinh Thanh	ASEAN-5 countries (Indonesia, Malaysia, the Philippines, Thailand, and Vietnam) and the period of 1980-2011	Threshold variable: Inflation Dep var: GDP growth	PSTR Two regimes	
The Influence of CSR on Firm Value: An application of panel smooth transition regression in Taiwan	Taiwan firms, 2010-2012	Threshold: corporate social responsibility (CSR) Dep var:	PSTR One break Cross effect with other control variables	We concluded that CSR investment does not enhance company value until it exceeds the value transition threshold.

Roger C. Y. Chen & Chen-Hsun Lee		Firm performance/ market value		
Foreign Direcet Investment, Human Capital and Economic Growth in Africa: A Panel Threshold Regression Approach Marvelous Ngundu	Sub-Sahara Africa 2002-2013	Threshold: FDI from China, the US, EU scored in years Dep var: GDP per capita	PSTR, with extra nonlinear component	Our findings reveal that Africa is short of quality human capital stock required to absorb advanced knowledge embodied in FDI from both its traditional and emerging investors
Electricity Demand Elasticities and Temperature: Evidence from panel smooth transition regression with the instrumental variable approach Chien-Chiang Lee & Yi-Bin Chiu	24 OECD countries from the period 1978–2004	Threshold variable: lagged variables, including log-transformed per capita real GDP at t-1 Dep var: log-transformed per capita electricity consumption	Panel smooth threshold regression	Evidence of a U-shaped relationship between electricity consumption and temperature

Evidence that inverted-U relationship or at least a decreasing margin benefit between R&D intensity and firm performance/patent/survival

Inverted-U Relationship between R&D Intensity and Survival: Evidence on scale and complementarity effects in UK data Mehmet Ugur, Eshref Trushinb, & Edna Solomon	37,930 of R&D-active UK firms over 1998–2012	age, size, productivity, relative growth, R&D intensity	Schumpeterian models of competition, innovation, and growth, Survival model, Machine learning model	The relationship between R&D intensity and firm survival follows an inverted-U pattern that reflects diminishing scale effects. R&D intensity and market concentration are complements in that R&D-active firms have longer survival time if they are in more concentrated industries.
What Is the Optimal Rate of		Employment rate,	productivity growth=f(GER	The econometric analysis shows that

R&D Investment to Maximize Productivity Growth? Mario Coccia		GDP per capita, GRED	D) is a concave function downwards. Panel regression, fixed effect 2SLS	more than 65 percent of productivity growth variance is due to its dependence on gross domestic expenditure on R&D expressed as a percentage of GDP(GERD). The research shows that the GERD range between 2.3 percent and 2.6 percent maximizes the long-run impact on productivity growth.
Evidence on the Optimal Level of Research & Development (R&D) Expenses for KOSPI-listed Firms in the Domestic Capital Market Hanjin Kima	firms listed on the KOSPI stock market, 2010-2015	Indep var: R&D, ROA, etc. Dep var: Stock price		Three explanatory variables, such as R&D expenses of the prior fiscal year, profitability, and Tobin's Q, showed statistically pronounced effects to account for the level of R&D spending.
The Optimal Rate of R&D Expenditurs in GDP – Between Theory and practice Steliana Sandu	Some Euro countries, 2007-2015		Case study, Input-output study	The characteristics of different countries determine the optimal rate of r&d.
Optimal Financing for R&D-intensive Firms Richard T. Thakor & Andrew W. Lo		Initial R&D, cash flow, risk shield, etc. adverse selection and moral hazard	Stochastic financial model BS formula risk-averse function pricing options	A firm may use a limited amount of debt if it has pledgeable assets in place. The analysis highlights the potential benet of an intermediation-assisted coordinating mechanism between investors and RMS

Source: The authors.

Appendix 2: Top 5 Firms in R&D Intensity

Top 5 R&D intensity firms

	R&D intensity (R&D/Assets; 5-year average)
China	
CANSINO BIOLOGICS INC.	90.58569
SHANGHAI HENLIUS BIOTECH, INC.	49.23622
VISIONOX TECHNOLOGY INC.	1.261864
GETTOPACOUSTIC COMPANY LIMITED	1.007977
VENUS MEDTECH (HANGZHOU) INC.	.8533481
Japan	
MEDRX CO LTD	116.7699
HEALIOS K.K	38.11973
NANOCARRIER CO LTD	19.21855
ONCOTHERAPY SCIENCE INC	13.87876
3-D MATRIX LTD	12.3468
US	
CATALYST BIOSCIENCES, INC.	3579
CLOVIS ONCOLOGY, INC.	3219.603
MANNKIND CORPORATION	2900.629
PARATEK PHARMACEUTICALS, INC.	2877.931
IMMUNE PHARMACEUTICALS INC	2820

Note: Top 50 are all US firms.

Source: The authors.

Other notable firms

APPLE INC.	0.0505204
ALPHABET INC.	0.163784
TESLA, INC.	0.6629741
SONY CORPORATION	0.0577596
THK CO LTD	0.0257945
HONDA MOTOR CO LTD	0.0567193
PINTEREST, INC.	0.3329162
ZOOM CORPORATION	0.1172597

Source: The authors.

Appendix 3: Additional Regression Results (Showing results for individual industries)

Full Regression Result, Adding Industry Effects, 2013-2018

Nonlinear Model with Dependent Variable: log Tobin's Q

	(1) China	(2) Japan	(3) US	(4) Three Countries
R&D intensity > threshold, high R&D intensity firms				
R&D/Assets	0.329***	0.307***	0.295***	0.349***
	(20.599)	(19.384)	(11.632)	(39.002)
Patents/R&D	0.125***	0.060***	0.048***	0.053***
	(13.511)	(5.262)	(3.115)	(7.953)
Publications/Patents	0.112***	0.080***	0.019	-0.006
	0.329***	0.307***	0.295***	0.349***
Business	0.056	-0.009	0.957***	0.212***
	(0.961)	(-0.086)	(7.707)	(4.140)
Chemicals	0.341***	0.161***	0.133***	0.218***
	(11.781)	(2.956)	(3.029)	(9.205)
Computers	0.255***	-0.110*	0.679***	0.259***
	(6.250)	(-1.771)	(8.302)	(7.830)
Electrical	0.134***	0.225***	0.229***	0.220***
	(5.507)	(4.818)	(5.762)	(10.838)
Drugs	0.346***	-0.185	0.386***	0.292***
	(3.847)	(-0.800)	(2.869)	(3.765)
Miscellaneous	0.266	-0.004	0.885***	0.226***
	(1.213)	(-0.059)	(5.686)	(3.816)
R&D intensity ≤ threshold, low R&D intensity firms				
R&D/Assets	0.258***	0.168***	0.037**	0.116***
	(11.256)	(3.632)	(2.241)	(8.140)
Patents/R&D	0.207***	0.145***	0.015	0.080***
	(9.929)	(6.058)	(1.180)	(6.862)
Publications/Patents	0.168***	0.114***	0.010	0.026**
	(7.623)	(4.123)	(0.656)	(2.024)
Business	0.062	-0.258	0.684***	0.354***
	(0.493)	(-1.027)	(9.331)	(4.848)
Chemicals	0.263***	-0.061	0.108	0.341***
	(4.153)	(-0.472)	(1.468)	(7.220)
Computers	0.756***	0.067	1.095***	0.843***
	(4.624)	(0.276)	(14.627)	(10.371)
Electrical	0.092	-0.272**	0.140***	0.101**
	(1.243)	(-2.351)	(2.842)	(2.191)
Drugs	0.868**	-0.881***	1.124***	0.627***
	(2.567)	(-3.432)	(5.636)	(3.626)
Miscellaneous	0.000	0.000	0.132	-0.040
	(.)	(.)	(0.335)	(-0.075)

Note: Estimation method: nonlinear least squares and panel threshold regression. All equations include a complete set of year dummies.

Source: The authors.