

Chapter 1

The Sources and Impacts of Firm-Level Innovation in China, Japan, and the U.S.*

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Abstract: This paper employs a cross-country panel of firm-level data spanning 2010-2019 to compare firm performance across three countries: China, Japan, and the U.S. Specifically, we formulate a three-equation system that enables us to estimate and compare innovation efficiency and the impact of innovation, measured in terms of patent production, on firm-level sales and profits. We estimate the model with a seeming unrelated regression (SUR) estimator. In order to minimize indigeneity bias, we employ a five-year differencing of the data and industry-level fixed effects. The results show different degrees of innovation efficiency with the sample of Chinese firms exhibiting the least impact of R&D expenditure on patenting and the least impact of patenting on firm sales and profits. The paper also profiles the evolving concentration of patent production and holdings. As compared with Japan and the U.S., over the sample period, the data show in China a substantial reduction in firm-level patent concentration, although such a fall in concentration and redistribution of patenting activity is evident in all three economies. This change in patent concentration, particular in China, raises important questions regarding the heterogeneity of firms within the sample and the ways in which that heterogeneity is changing over time and the implications of that change for overall firm performance.

Key Words: China, patent production, firm performance, firm heterogeneity, country comparisons

* The authors very much appreciate the resource and technical support provided by Koichiro Kimura.

1. Introduction

The first two decades of the current century have witnessed a surge of innovation activity, particularly in Asia, most dramatically in China, but also in the OECD economies, including Japan and the U.S. It is not surprising that this surge has been most evident for China, given that it only promulgated its patent law in 1985, followed by a dramatic increase in R&D spending. By 2015, China's ratio of R&D to GDP surpassed two percent, enabling China's R&D intensity to rise to the range of 2-3%, comparable to that of the larger OECD economies.

Our objective in this paper is to examine both the source of a key measure of innovation, i.e., patent grants, the effectiveness of R&D in producing patent grants and the impact of patents on firm-level performance, i.e., both sales and profitability. While a substantial literature has emerged concerning patenting in China, little of it is supported by firm-level data. The paper supports three objectives:

- Identify the incidence, distribution, and concentration of innovation effort and innovation outcomes;
- Estimate the impact of innovation effort on innovation outcomes; and
- Estimate the impact of innovation outcomes on enterprise performance.

Robert Solow's seminal contribution to economic growth (1956), followed by a substantial body endogenous growth theory and application confirmed the central role of technical change as the principal driver of long-run growth and rising living standards. Whereas during the first three decades of China's economic transformation, Chinese producers were generally able to imitate and absorb readily available technologies from abroad, often without formal applications of research and development spending, during the past decade, China's continued movement toward the international technology frontier has required more formal and costly modes of innovation. Such formal applications of R&D spending have resulted in widely-publicized technology achievements, including those in renewable energy, electric vehicles, and various 5G technologies, as well as in the defense sector.

The surge in patenting both domestically and internationally has drawn substantial academic attention. Jefferson and Jiang (forthcoming) review much of this literature. While firm-level data had been available and used in some quarters prior to 2010, during the recent decade, as China has increasingly expanded its R&D and patenting, limited

amounts of firm-level data have been accessible. The research project of which this paper is a part seeks to remedy this paucity of analysis.

A key finding of this study is that like Japan and the U.S., estimates of China's patent-R&D elasticity are positive and highly robust. However, as compared with these two large OECD economies, the magnitude of the Chinese estimates is relatively small. One result that is unexpected and difficult to explain is that the impact of patent production on overall firm performance – sales and profits – appears at best to be negligible. Taking the estimates at face value, the results show that greater patent production in China's firm sector has a negative impact on firm performance.

This study raises certain questions regarding the quality and consistency of the data. We attempt to examine these. Furthermore, a time series analysis of the concentration of patenting indicates that the concentration profile differs substantially across groupings of firms; moreover, that profile is shifting as the China, substantially more so than Japan or the U.S., is exhibiting a substantial shift in patenting concentration away from its largest firms. Hence, we see not only a substantial heterogeneity of firms within the three countries, but also shifting profiles of this heterogeneity over our sample period.

2. Literature Review

Table 1 outlines 14 published papers relating to patent production; most also report the impact of patent production on some measures of firm performance. All but two papers use U.S. firms; the remaining two consist of samples from Germany and India. Most of the samples are relatively small. Only two – the Indian study and a study using Compustat data – include more than 1,000 firms. None provides country comparisons. Most use data that are single period cross sections. While the data sets may include more than one year of data, in order to accommodate a time structure involving a substantial lag of uncertain duration between R&D activity and the filing or granting of the resulting patents, the formatted data combine two or more years of the innovation input and output measures, thereby smoothing the data. Finally, a number of the papers examine the recursive nature of patent production in which the patent outcomes significantly affect measures of firm performance.

Table 1: Firm-Level Studies

| Authors | Sample | Variables | Method | Findings |
|----------------------------|---|--|---|--|
| Scherer(1965) | 365 firms from the Fortune 500 list(USA) | Patents granted 1959 | Cross-section analyses | Positive relationship between patents granted and sales growth |
| | | Profits, sales growth, profit ratio (1955–1960) | Time-lag of four years between invention (1955) and patent grant (1959) | Patents granted have a positive impact on profits via sales increases |
| | | Dummy-variable per industry | Regression analyses between patents granted in 1959 (1955), and subsequent yearly success variables (1955–1960) | No impact of patents granted on the profit ratio i.e., profits as percentage of sales |
| Comanor and Scherer (1969) | 57 firms from the pharmaceutical industry | Patent applications (1952–1957) Patents granted (1955–1960) | Cross-section analyses | Positive relationship between patent applications, patents granted and sales |
| | | Sales from product innovations in the first 2 years after market introduction (1955–1960) | Time-lag of 3 years between patent applications and first commercial use | Larger influence of patent applications on sales |
| | | | Correlation analyses | |
| Griliches et al. (1991) | 340 firms USA | Successful patent applications (1970-1980) | Panel analyses fixed effect. | No influence of unexpected patent applications on the market value |
| | | Market value (1973–1980) | Unexpected patent applications as the difference between present and predicted patent applications | Present and past patent applications explain 5% of the variance in market value changes |
| | | Dummy-variable per firm | Estimation of a patent prediction function under the assumption of lagged effects of past patents and past R&D of up to three years | Present patent applications alone explain 0.1% of the variance in market value changes |
| Austin (1993, 1995) | 20 biotechnology firms USA | 550 patents granted | Event study | Positive influence of patents granted on market value |
| | | Key patents patent citations. | Weighting of patent variables by quality indicators key patents. | Stronger influence of key patents on market value |
| | | Change of relative market value during the first 2 days after the patent had been granted | | Negative influence on the market value of competing firms |
| Narin et al. (1987) | 16 firms from the pharmaceutical industry USA | Patents granted (1975–1982) | Cross-section analyses | Positive relationship between patent citations per patent granted and financial performance |
| | | Patent citations (1975–1982) | No time-lag | No relationship between the number of patents granted or of patent citations and financial performance |
| | | Patent citations per patent granted (1975–1982) | Correlation analyses | |
| | | Concentration ratio | Weighting of patent variables by quality indicators | |
| | | Aggregated measure of financial | | |
| Ernst (1995, 2001) | 50 firms from the machine-tool industry (Germany) | Patent strategies consisting of multiple patenting indicators: number of patent applications, share of | Cross-section analyses | Firms with many patents of high quality are significantly more successful with regard to all three success variables |

| | | | | |
|------------------------------|---|--|---|--|
| | | patents granted, share of valid patents, share of foreign patent applications, patent citation ratio and concentration ratio (1979–1992) | | |
| | | Sales growth, sales per employee, development of sales per employee (1984–1992) | Time-lag partly incorporated | Firms with few patents of low quality are significantly less successful with regard to all three success variables |
| | | | Various multivariate data analysis techniques | Firms with a systematic patent strategy are significantly more successful than firms with unsystematic patent activities |
| | | | Weighting of patent variables by quality indicators | |
| Chauvin and Hirschey (1993) | Roughly 1500 firms from COMPUSTAT | R&D intensity and R&D expenditure (1988-1990) | Cross-section analyses | Positive effects of advertising and R&D expenditures on the market value of the firm |
| | | Capitalized Market Value without accounting-based adjustment | No time-lag | size advantages exist in advertising and R&D activity |
| | | Intercept dummy variable interactions for industry group classification | Regression between market value, R&D and advertisement expenditure | |
| Belderbos et al. (2004) | 53 firms from Community Innovation Surveys (CIS) conducted in 1996 and 1998 (Netherlands) | Patents granted | Cross-section analyses | Cooperating firms are generally engaged in higher level innovative activities |
| | | Different R&D cooperation profiles | Correlation analyses | Supplier and competitor cooperation have a significant impact on labor productivity growth |
| | | Labour productivity and productivity in innovative sales new to the market | | |
| Erickson and Jacobson (1992) | 99 U.S. firms | R&D expenditures | Panel analyses fixed effect | Neither R&D nor advertising expenditures increase the market value of the firm more than other types of investments or expenditures. |
| | | Stock return | Instrumental variable (IV) estimation | Obtaining a comparative advantage through R&D or advertising depends crucially on the specific nature of the expenditure |
| | | Specify R&D to be influenced by concentration, current profitability, and level of debt at the beginning of the period. | Instrumental variable combined with serial correlation | |
| | | | Instrumental variable combined with serial correlation and fixed effect | |
| | | | The competitive process and isolating mechanisms | |
| Bosworth and Rogers (2001) | 60 firms from IBIS large firm database | Patents granted (1994-1996) | Least Square Dummy Variable | R&D and patent activity are positively and significantly associated with market value |
| | | Market value (1994-1996) | Fixed-effect model | Private returns to R&D in Australia are low by international standards |
| | | Expenditure on R&D Intellectual property | | |
| Miller (2006) | 806 firms in the Compustat Industry Segment data (1990) | Patents granted | Cross-section analyses | Evidence from a large sample of firms shows the positive relationship between diversification based on technological |

| | | | | |
|------------------------------|---|--|---|---|
| | | Patent citations Tobin's q | Technological diversity, multiple equations Dummy variable for status | diversity and market-based measures of performance |
| Lee et al. (2006) | 258 technology-based US-based Firms (1985-1999) | Tobin's q as market value Dummy variables for different categories Patents granted, convert both R&D/marketing spending and firm value into ratio measures | Cross-section analyses | A firm's commercialization orientation can play a more important role than R&D in the process of exploiting the value of technology assets |
| Basant and Fikkert (1996) | 4975 Indian firms (1974- 1975, 1981-1982) | Output, was constructed by deflating the value of firms' reported output using wholesale price deflators Firms' book values for physical capital were converted into net capital stocks Annual R&D expenditures, foreign technical knowledge purchased, spillover R&D emanating from other domestic firms, and so on | Multiple equations Fixed-effect model Output follows the Cobb- Douglas production function, capital/stock follows the Generalized Leontief- Linear functional form. Estimating Annual TFP | There are substantial returns to be had from increasing the levels of TP expenditures. The private returns to technology purchases are estimated to be high and statistically significant, while the private returns to firms' own R&D expenditures are somewhat lower and are often insignificant. |
| Lo et al. (2006) | 344 largest public companies in the technology sector (1996- 2001) | Three years total shareholder returns R&D spending Institutional ownership | Cross-section analyses Correlation analyses | Independent outside directors had an effect of the strength but not the form of the relationship External monitors can affect the form and the strength of the relationship between R&D spending and performance. |

Source: Prepared by the authors.

Viewed against this literature, the similar and distinctive features of our study are as follows:

- A cross-country comparison of patenting activity and impacts in three countries – China, Japan, and the U.S.
- Relatively large firm-level samples, each exceeding 2,000 firms.
- Similar to most of the studies included in Table 1, we combine multiple years to input and output measures to create a single composite measure of inputs and output, i.e. R&D and patents and patent and measures of firm performance. However, because we have access to 10 years of data, the two sub-periods of 5

years apiece enable both a considerable smoothing of the data and ability to minimize the possible endogenous effects.

- Given our three-equation model, we use a seemingly unrelated regression (SUR) estimator.

Given that our focus is primarily on China's innovation performance over the period 2010-2019, we make note of several of the Chinese patenting research highlights.

3. Patenting

China's patent office – renamed in 2018 at the China National Intellectual Property Administration – issues three types of patents. These are invention patents, utility model patents, and design patents. A Chinese invention patent is similar to a United States utility patent and protects a new technical solution relating to a product, a process, or an improvement thereof. An invention patent has a 20-year term. A Chinese utility model patent, on the other hand, covers a new technical solution relating to a product's shape, structure, or a combination thereof. A utility model patent has a 10-year term. Utility model patents are not substantively examined and are granted after formality examination, which generally takes about one to one-and-a-half years or less. In contrast, invention patents are substantively examined and can take three to five years to grant. Therefore, it is advantageous to have early issuance of a utility model patent to sue for infringement or to serve as a deterrent, in addition to or in substitution for an invention patent.

Partly due to the relatively new establishment of China's patent system, the system has experienced an evolving legal, regulatory, and policy environment.¹ It has been a widespread practice of patent applicants to obtain invention patents and utility model patents on the same inventions, although such a practice has discouraged by the courts. Therefore, some double patenting has occurred in China. This practice continued until the State Intellectual Property Office ("SIPO") amended its Patent Examination Guidelines to limit its occurrence in July 2007.

¹ <https://www.jonesday.com/en/insights/2009/01/what-does-the-third-amendment-to-chinas-patent-law-mean-to-you>

The Amendment substantially adopts the 2007 SIPO approach and stipulates that the same invention can be granted only one patent at any given time. While the same applicant can file an application for both an invention patent and a utility model patent related to the same invention on the same day, the invention patent can be granted only when the applicant declares his intention to abandon the previously granted utility model patent, if such utility model patent has not lapsed.

However, ambiguities still exist. For example, it is not clear whether the prohibition against double patenting applies only to same-invention double patenting (*i.e.*, applications with identical claims), or whether it also applies to obviousness-type double patenting (*i.e.*, applications with indistinguishable claims). Furthermore, it is not clear whether a genus claim and species claim will be considered as double patenting.

A further condition that has likely contributed to lower quality patent proliferation is the creation, particularly by lower levels of government, of patent incentive system that reward the filing or grant of patents. Studies show that this practice sometimes leads to the splitting of patents by differentiating claims that would otherwise have been integrated into a single filing into two or more patents.

4. The Data: A Statistical Overview

Table 2 shows a variety of measures for the three key variables used in this study: the patent count,² R&D expenditure, and sales revenue. Each of the measures is based on the size of the firm sample, which is largely unbalanced over the sample period 2010 to 2019. This 10-year sample period is broken into two 5-year sub-periods, 2010-2014 and 2015-2019. In the Chinese case, for example, the mean and median patent counts for the 9,373 firms during 2010-2014 are 15.87 and 9.63. This disparity underscores the extent to which patent production is concentrated in the larger firms within the sample. The skewedness in patent counts is further underscored by comparing the average patent count for the

² This study employs the total patent count for each firm – invention, utility model, and design patents. We have only recently learned that the Orbis data set from which we draw the data enables a distinction between the higher quality invention patents and the other two patent types – utility model and design patents. We hope to be able to reestimate our model, so as to distinguish the effects of the invention patents vs. other patent types.

lowest, middle, and top quintile firms. For all three countries, the patent count balloons for the top quintile of firms.

Table 2: Summary Statistics

| | | Patent count | | R&D expenditure | | Sales revenue | |
|--------|---|--------------|-------------|-----------------|-------------|---------------|------------|
| | | 2010-2014 | 2015-2019 | 2010-2014 | 2015-2019 | 2010-2014 | 2015-2019 |
| China | mean | 15.87 | 17.99 | 3,400 | 6,977 | 373,511 | 467,983 |
| | median | 9.63 | 7.96 | 510.39 | 985.99 | 38,221 | 25,407 |
| | st. dev | 174.50 | 153.14 | 36,640 | 52,154 | 5,881,207 | 5,597,704 |
| | # of firms | 9,373 | 9,373 | 9,373 | 9,373 | 9,373 | 9,373 |
| | # of year observations | 2.43 | 2.57 | 2.77 | 3.86 | 2.77 | 3.85 |
| | ratio | 48.6% | 64.3% | 55.3% | 96.5% | 55.3% | 96.4% |
| | quintiles: 1 st middle top | 5.5 | 4.5 | 255.20 | 328.13 | 26234 | 7552.54 |
| | | 10.59 | 8.81 | 672.37 | 1398.99 | 44989 | 41643 |
| 15,875 | | 10,116 | 2,128,639 | 1,847,692 | 412,664,635 | 343,353,940 | |
| Japan | mean | 240.93 | 246.43 | 58,562 | 48,422 | 2,488,421 | 2,092,278 |
| | median | 33.54 | 39 | 2454.93 | 3874.11 | 368,031 | 353,985 |
| | st. dev. | 1308.88 | 1235.722703 | 361,290 | 281,562 | 9,436,258 | 7,811,392 |
| | # of firms | 2,289 | 2,289 | 2,289 | 2,289 | 2,289 | 2,289 |
| | # of year observations | 3.44 | 3.38 | 4.80 | 5.0 | 4.80 | 5.0 |
| | ratio | 68.7% | 67.6% | 96.0% | 100% | 96.0% | 100% |
| | quintiles: 1st middle top | 11 | 10.5 | 23.24 | 1609.41 | 118,900 | 125,224 |
| | | 36.56 | 49.80 | 4,101.83 | 5,647.25 | 567,327 | 537,159 |
| 25751 | | 24552.5 | 8,814,131 | 7,633,736 | 233,119,133 | 209,911,126 | |
| US | mean | 98.75 | 106.28 | 119,942 | 165,265 | 2,599,818 | 2,638,047 |
| | median | 20.58 | 13.75 | 9347.45 | 18,015 | 79,331 | 110,912 |
| | St. dev. | 694.88 | 778.12 | 611,742 | 899,502 | 14,894,380 | 13,149,833 |
| | # of firms | 2,123 | 2,123 | 2,123 | 2,123 | 2,123 | 2,123 |
| | # of year observations | 3.04 | 3.13 | 3.93 | 4.28 | 4.13 | 4.37 |
| | ratio | 60.7% | 62.5% | 78.5% | 85.6% | 82.6% | 87.4% |
| | quintiles: 1 st middle top | 9.13 | 7.50 | 3,048.64 | 5,593.92 | 12,114 | 27,124 |
| | | 20.98 | 17.52 | 14,529 | 28,227 | 142,165 | 219,422 |
| 18,498 | | 19,333 | 9,872,000 | 19,164,092 | 420,720,800 | 243,252,321 | |

Source: Calculated by the authors.

Given that each firm-level observation used for each 5-year period is an average of the available year observations for that period, Table 2 also reports the number of year observations falling within each 5-year period for each firm. Thus, for the patent count

for China during 2010-2014, the 5-year observations used in the regression exercise are based on the average of 2.43 year observations.

For China, from the earlier to the later period, the measures of patents, R&D, and sales all increase, although the change in the three variables varies somewhat. Specifically, while the patent count and sales show modest increases – 13.5% for the former and 25.3% for the latter –

Table 2 shows R&D spending more than doubling during the sample period. The implication is that while R&D intensity rises from 0.91% in the earlier period to 1.45% in the later period, R&D productivity – patents per unit of R&D – and sales revenue decline. Clearly, these changes are not representative of the overall change in Chinese patenting. We examine this disparity below.

5. The Model and Estimation Strategy

In this section, we formulate a model that enables us to achieve the following:

- Identify the impact of innovation effort, measured as R&D expenditure, on innovation outcomes, i.e. total patent grants;
- Identify the impact of patent production on firm performance, i.e., sales revenue and profitability.

In order to identify and estimate these relationships, the model includes the following three equations:

$$\log(PAT_t) = \log(R\&D_{t-1}) + a_i + u_{it} \quad (1)$$

$$\log(R\&D_t) = \log(SALES_{t-1}) + a_i + u_{it} \quad (2)$$

$$\log(SALES_t) = \log(SALES_{t-1}) + \log(R\&D_{t-1}) + a_i + u_{it} \quad (3)$$

In the above specification, t and $t-1$ represent the two five-year periods 2010-2014 and 2015-2019. The variable a_i represents the 30 two-digit sectoral classifications as shown in Annex 1. We use the two five-year periods for several reasons. The first is that the sample is highly unbalanced. For all the full sample of 9,373 Chinese firms, each reports at least one year-observation for each of the two sub-periods. As shown in Table 2, the average number of year observations for each 5-year period ranges from a low of 2.4 to a high of 3.9. For Japan and the U.S., incidence of reporting is somewhat higher,

significantly so for Japan for which the reporting incidence for both R&D expenditure and sales revenue is 4.8 for the earlier period and 5.0 for the later period.

The first reason for the division of the data over the 2010-2019 period into two 5-year sub-periods is an attempt to capture the dynamic interaction, or time structure of the firms within our sample. Estimating the relationship between innovation – innovation inputs and output, firm size and innovation effort, and innovation outputs and firm performance – generally spans multi-year periods. This is particularly the case for our only measure of patent production, i.e., patent grants, which may materialize only several years after innovation resources, i.e., R&D spending are committed to projects that eventually yield patent grants. As reported in our literature review, a significant share of the literature in the field of patent production incorporate multi-year lags between R&D input and patent count output. Likewise, for the sales and profit equations, we anticipate a lag between patent production and firm performance. To the extent that new patents represent new products, product quality improvements, or process improvements, these are likely to materialize in the market only with a significant lag.

A second, related reason for the two 5-year segments is to minimize endogeneity bias. The greater lag between innovation input and innovation output is likely to enable a fuller assessment of innovation input-output causality, rather than the simply a correlation in which positive shocks to patent production result in commitments of greater R&D resources.

While the time dimension of our panel does not allow for shorter time horizons that would ideally enable a panel consisting of additional numbers of time-series observations for each firm, thus enabling the application of fixed effects, we do include fixed effects for industry classifications. Given our formulation of the 3-equation model of firm innovation and performance, we anticipate a degree of correlation of shocks across the equations. That is, firm-level shocks to the innovation equation may be correlated with shocks to the firm performance equations. Likewise, shocks to the sales equation are likely to be correlated with shocks to the profit equation. In order to internalize information from these shocks into the estimation procedure, thereby improving the efficiency of the estimation results, we employ a seemingly unrelated regression (SUR) estimator for each country.

6. Estimation and Results

Tables 3-5 show the estimation results for three sets of regressions – patents, sales, and profit – for China as well as, for purposes of comparison, Japan and the U.S. Each of the tables reports a p-statistic for each point estimate. The results are quite robust, for the relevant explanatory variables, each of the country three-equation models reports p-stats of 0.00. Nonetheless, between the three countries, the results show significant differences in the point estimates.

Table 3: Patent Creation, PAT_t

| | China | Japan | U.S. |
|--|-----------------|------------------|------------------|
| $R\&D_{t-1}$ | 0.286 (0.00) | 0.534 (0.00) | 0.433 (0.00) |
| intercept | 0.065 (0.81) | -1.554 (0.00) | -0.702 (0.25) |
| #observations | 9373 | 2289 | 2123 |
| Adj. Rsq. | 0.191 | 0.437 | 0.403 |
| *The numbers in parentheses are p-stats; the time period, t, spans 5 years. t-1 spans the preceding 5-year period. | | | |

Source: Estimated by the authors.

Table 4: Impact of Patenting on Sales, $SALES_t$

| | China | Japan | U.S. |
|---|------------------|-----------------|-----------------|
| $SALES_{t-1}$ | 1.298 (0.00) | 0.853 (0.00) | 0.570 (0.00) |
| PAT_{t-1} | -0.132 (0.00) | 0.053 (0.00) | 0.282 (0.00) |
| intercept | -3.991 (0.00) | 1.898 (0.00) | 4.284 (0.00) |
| #observations | 9373 | 2289 | 2123 |
| Adj. Rsq. | 0.689 | 0.955 | 0.781 |
| *The numbers in parentheses are p-stats; the time period, t, spans 5 years. t-1 spans the preceding 5-year period | | | |

Source: Estimated by the authors.

Table 5: Impact of Sales and Patents on Profit, $PROF_t$

| | China | Japan | U.S. |
|--|------------------|-----------------|-----------------|
| $SALES_{t-1}$ | 1.209 (0.01) | 0.761 (0.00) | 0.529 (0.00) |
| PAT_{t-1} | -0.114 (0.02) | 0.114 (0.00) | 0.329 (0.02) |
| intercept | -3.622 (0.37) | 1.468 (0.22) | 3.301 (0.61) |
| #observations | 9373 | 2289 | 2123 |
| Adj. Rsq. | 0.650 | 0.894 | 0.746 |
| *The numbers in parentheses are p-stats; the time period, t, spans 5 years. t-1 spans the preceding 5-year period. | | | |

Source: Estimated by the authors.

We first examine the results in Table 3 regarding the power of R&D spending to drive patent production. As expected, these results are highly robust, both for China and the other two economies. However, as shown, the estimated patent-R&D elasticity for China – 0.286 – is substantially smaller than the counterpart estimates for Japan and the U.S. The overall adjusted Rsq. measure is also substantially less. The implication is that within China, spending on R&D does not exercise as direct an impact on overall patent production as it appears to exert on patent production in Japan and the U.S. There are several possible explanations for this difference.

The first is that, because China’s total patent count includes a substantial portion of lower-quality patents – utility and design patents – as compared with Japan and the U.S. for which the proportion of such patents is rather low, we anticipate that many of the lower quality patents materialize without substantial applications of formal F&D spending. The fact that the relative intercept values show China producing more patents without applications of R&D spending as compared with Japan and the U.S. likely reflects the fact that many Chinese patents result from learning by doing and technology spillovers.

A second possible explanation for the relatively weak effect of R&D expenditure on patent production was foreshadowed by Hu and Jefferson (2009). Using a large panel of Chinese firm level data for 1995-2001, as in this study, these authors estimate the impact of R&D on patent production. They find substantially weaker elasticity estimates than those reported in Table 3. Hu and Jefferson explain that the likely reason for the low estimates is the relatively robust role that industry foreign direct investment played in promoting patenting activity. Having focused on a period nearly two decades earlier than our sample period when imitation was a far more active pathway for technology transfer

and patenting, their result was not surprising. While FDI may continue to be a stimulant to Chinese innovation, independent of R&D spending, its effect is likely to be greatly diminished. Nonetheless, whether the impact is direct or through its interaction with R&D spending, FDI is likely to continue in some sectors to be a gateway for Chinese patenting.

A third factor concerns changes in China's patent law and other special, evolving features of China's patent regulatory landscape. Such changes that alter appraisal standards, including those incorporated the patent system's China's Third Amendment could potentially weaken the input-output link in patent production.³ Such changes in the Third Amendment include the implementation of more rigorous novelty standards for both invention and design patents, limitation of double patenting, including obtaining a fast-approved lower-quality patent followed by a standard higher-end 20-year patent. Other such changes during this period include a variety of provincial and local governments instituting reward systems for patent filings and grants. One difficulty with these policy schemes, however, is that the reward systems are often transitory, subject to restructuring or outright elimination, again with hard-to-predict impacts on overall patent production. The upshot is that such changes in patent standards and the incentive system, may cause our estimates to be less efficient than they are for the more stable and uniform R&D and patent systems in Japan and the U.S.

Table 4 reports estimation results for the role of prior sales and patenting on sales. Here the differences between China and Japan and the U.S. are notable and puzzling; differences are not only statistical different with estimates of the same sign, but show results that are signed differently. First, for all three countries, as expected, sales revenue over the earlier 2010-2014 period is a robust predictor of sales volume during the recent five years. Nonetheless, the differences are striking, with the estimate for China showing at 1.30, while those reported for Japan and the U.S. are 0.85 and 0.57. The fact that China shows a result exceeding unity, more than twice that of the U.S. begs explanation. That the Chinese firms show an estimate for SALEL₋₁ likely reflects the fact, as shown in the Table 2 Summary Statistics, that from 2010-2014 to 2015-2019, average sales revenue grew by 25%. By comparison, for the Japanese sample, sales shows a substantial decline, while for the U.S, average sales revenue remains little unchanged from the early to later period.

³ <https://www.jonesday.com/en/insights/2009/01/what-does-the-third-amendment-to-chinas-patent-law-mean-to-you>

Quite likely, the difference between China and the U.S. is shown in comparisons of the means and median values of sales revenue. That China shows the coincidence of a substantial increase in the means paired with a substantial decline in median sales indicates that firms with the largest sales during 2010-2014 enjoyed the most rapid increase in sales revenue during the latter half of the sales period. For the U.S. the result is different, median sales grow faster than the mean, suggesting that smaller firms enjoyed relatively robust sales growth during the sample period. These firm size-related differences can account for the difference in the estimates of the impact of sales. This pattern is also likely to account for the similar counterpart estimates for profit.

The most surprising result for the sales and profit equations is the difference in the impact of innovation on the firm's later performance. For the U.S. and, to a lesser degree, for Japan, the results show an extremely robust, positive impact of early patenting on later sales and profit performance. In Table 2, the mean and median results for both China and the U.S. shows what appears to be a greater concentration of patenting in larger firms from the early to the later 5-year period. As firms that are the most patent productive during 2010-2014 become even more comparatively patent productive during 2015-2019, we would expect this shifting heterogeneity to impart an upward bias to estimates of the patent coefficient. While this may be the case for the U.S., reporting estimates in excess of 0.5, the contrary appears to be true for Chinese firms that report estimates of -0.11 or less.

At this point, we advance two possible, related, explanations for this set of surprising results. One possibility is that the firms with the greatest patent count in 2010-2014 tend to undertake the greatest restructuring during 2015-2019. In particular, their restructuring is outside their main product line. We know for Chinese firms that when they report their sales revenue to the National Bureau of Statistics, the accounting is solely for the firm's "principal business." Sales activities that falls outside the high-patenting firm's principal business are not included in the formal reporting of sales revenue. Related to this explanation is the possibility that China's high-volume patent producers tend to sell their patents, thereby generating revenue that falls outside their official reporting channels. These possible conditions require further exploration.

7. Patenting Concentration

We find it somewhat curious that in our data set, only the largest size firms report owning patents. Taking the reported patents on their face value, we investigate the concentration of patenting within the sample of the largest 1,000 firms. By computing these ratios, we are able to estimate changes in patent concentration over the period 2010 to 2018. The results are shown in Table 6.⁴

Table 6: Patent Concentration by Number of Firms

| Top # of firms | 5 | 10 | 25 | 100 | 500 |
|--|---------|---------|---------|---------|---------|
| China | | | | | |
| 2010 | 25,591 | 29,156 | 35,386 | 45,499 | 59,033 |
| | 39% | 45% | 54% | 70% | 90% |
| 2018 | 17,106 | 22,522 | 31,360 | 49,292 | 75,087 |
| | 20% | 26% | 36% | 56% | 86% |
| Japan | | | | | |
| 2010 | 101,066 | 165,680 | 251,966 | 379,239 | 476,845 |
| | 21% | 34% | 52% | 78% | 98% |
| 2018 | 39,451 | 57,892 | 89,004 | 149,520 | 192,862 |
| | 20% | 29% | 45% | 76% | 97% |
| U.S. | | | | | |
| 2010 | 54,976 | 73,753 | 99,039 | 131,015 | 157,988 |
| | 34% | 45% | 61% | 80% | 97% |
| 2018 | 28,477 | 40,892 | 55,170 | 73,533 | 88,355 |
| | 31% | 45% | 60% | 80% | 96% |
| *% represents patent production as a share to the total number of patents produced by the 1000 largest patent producers in the given year. | | | | | |

Source: Calculated by the authors.

For all the countries, as anticipated as the proportion of firms included in the concentration counts increases – from 10 out of 1,000 to 500 of 1,000 – the patent share increases. In 2010, China reports the highest patent concentration for its top five firms. At the other end of the distribution, for the top 500 firms, while at 90%, the concentration is high, it is less than the concentration ratios reported for Japan and the U.S.

For China, Table 6 shows a substantial decline in patent concentration from 2010 to 2018, whereas for Japan and the U.S. the concentration ratios are either stable or show

⁴ Note that in each period, i.e., 2010 and 2018, the 5, 10, 25...1000 firms may not be the same firms; they are, within their numerical group, the largest patent producers within each period.

a small decline. For all three countries, the number of patents held by the top 5 firms declines substantially from 2010 to 2018. For China, the decline persists, but diminishes, for the top 10 and top 25 firms. For the top 100 and top 500 firms, the total patent count then grows from 2010 to 2018. For both Japan and the U.S., the total patent count declines substantially over the sample period. Whereas for the U.S. the decline is consistently somewhat less than one half, for Japan the reductions lie in the range of 2.5 to 3.

Overall, the results reported in Table 6 raise important issues for our analysis. This shift in the concentration and distribution of patent productivity raises critical issues for our interpretation of the estimation results shown in Tables 3-5. That is, from the earlier to the later period, the concentration distribution of patent production is changing dramatically as between the larger and smaller firms within our sample, our results may be overlooking key structural changes within the data that are obscured by the aggregation of the data. These changes argue for a more granular examination of the data, exploring the nature of our three relationships between R&D and patenting and patenting and firm performance sub-samples or interaction effects accounting for size and industry differences.

8. Conclusion and Discussion

This study investigates the impact of innovative activity at the firm level within China. For purposes of comparison, we extend the analysis to samples of firms in Japan and the U.S. The comparisons are helpful, showing that while China shows impressive numeric comparisons with the OECD economies in relation to R&D intensity and overall patent counts, the productivity of its innovation system and the impact of that innovation, in turn, on firm performance may continue to lag behind OECD standards.

These results must be tentative. At this point, the research encounters a number of limitations resulting from limitations of or difficulty in interpreting the data on the data set made available for this study. There are two key difficulties:

- The principal difficulty is ambiguity regarding which firms are included and excluded from the data set. The fact that for China, less than 10,000 firms report data with sufficient consistency to conduct this research raises deeply serious problems with respect to selection bias. Unable to use the data set to identify selection criteria that are associated with the included and excluded firms, we are

unable to correct for the resulting selection bias associated with the omission of several million firms from the data set.

- A second problem is that of identifying patent quality. The first quality-related issue is that of distinguishing between different patent types – higher quality invention patents and lower quality utility and design patents. Furthermore, within the patent data, we are unable to identify the number of claims and citations – backward and/or forward – that serve to differentiate patent quality. With recent clarification of the data set, it appears that some of this patent quality control can be incorporated into the analysis. This should be attempted.

Nonetheless, given these limitations, this study raises important questions and possibilities. One such issue is concerning the vast heterogeneity across firms within the data set and the transitioning of this heterogeneity even over the relatively short period covered by the data. Table 6, for example, shows substantial evolution with our firm sample of R&D effort, patent production, and sales and profit outcomes by firm size. That is, the concentration of Chinese patents appears to be substantially flattening as increasingly numbers of firms acquire innovation capabilities. Key issues concern the differences across industries that are becoming more technology and patent intensive, particularly as these may relate to China so-called “pillar industries” and the priorities set forth in *China 2025*.

A final issue concerns location, the recent study by Jiang et al (2019) using USPTO patent data finds extreme geographic concentration of Chinese patents filed and granted by the U.S. patent agency. According to these authors, 66.7% of the USPTO patent grants originating from China originate from the residents of only three cities – Beijing, Shanghai, and Shenzhen – representing just 4.25% of the population. The ability of China to diffuse its innovation capabilities across a larger swath of Chinese geography and population is a key challenge to the country’s ability to achieve a deep and wide-angled set of technology frontier capabilities.

References

- Austin, D.H. (1993) “An event-study approach to measuring innovative output: the case of biotechnology,” *American Economic Review* 832: pp. 253–258.
- Austin, D.H. (1995) “The power of patents,” *Resources* 119: pp. 2–5.

- Basant, R., and B. Fikkert (1996) "The Effects of R&D, Foreign Technology Purchase, and Domestic and International Spillovers on Productivity in Indian Firms," *The Review of Economics and Statistics* 78(2): pp. 187 - 199.
- Belderbos, R., M. Carreeb, and B. Lokshinb (2004) "Cooperative R&D and firm performance," *Research Policy* 33: pp. 1477-1492.
- Bosworth, D., and M. Rogers (2001) "Market Value, R&D and Intellectual Property: An Empirical Analysis of Large Australian Firms," *The Economics Record* 77(239): pp. 323 - 337.
- Chauvin, K.W., and M. Hirschey (1993) "Advertising, R&D Expenditures and the Market Value of the Firm," *Financial Management* 22(4): pp. 128 - 140.
- Comanor, W.S., and F.M. Scherer (1969) "Patent statistics as a measure of technical change," *Journal of Political Economy* 77: pp. 392-398.
- Erickson, G., and R. Jacobson (1992) "Gaining comparative advantage through discretionary," *Management Science* 38(9): pp. 1264-1279.
- Ernst, H. (1995) "Patenting strategies in the German mechanical engineering industry and their relationship to firm performance," *Technovation* 154: pp. 225-240.
- Ernst, H. (1997) "The use of patent data for technological forecasting: the diffusion of CNC-technology in the machine tool industry," *Small Business Economics* 94: pp. 361-381.
- Griliches, Z., B.H. Hall, and A. Pakes (1991) "R&D, patents, and market value revisited: is there a second technological opportunity related factor?" *Economics of Innovation and New Technology* 1: pp. 183-201.
- Hu, A. G.Z, and G. H. Jefferson (2009) "A great wall of patents: What is behind China's recent patent explosion?" *Journal of Development Economics* 90(1): pp. 57 - 68.
- Jefferson, G. H., and R. Jiang (forthcoming) "China's S&T Progress through the Lens of Patenting," *The Oxford Handbook of China Innovation*, Oxford: Oxford University Press.
- Jiang, R., G. H. Jefferson, and H. Shi (2019) "Measuring China's International Technology Catchup," *Journal of Contemporary China*, published online, Oct. 2019, <https://www.tandfonline.com/doi/abs/10.1080/10670564.2019.1677362>
- Lin, B.W., Y.K. Lee, and S.C. Hung (2006) "R&D intensity and commercialization orientation effects on financial performance," *Journal of Business Research* 59: pp. 679-685.

Kimura, Koichiro, ed. (2020) *Innovation in East Asia (BRC Research Report)*, Bangkok: Bangkok Research Center, JETRO Bangkok/IDE-JETRO.

Lo, S.A., B. Walters, and M. Kroll (2006) “The moderating effects of external monitors on the relationship between R&D spending and firm performance,” *Journal of Business Research* 59: pp. 278–287.

Maltza, E., W.E. Souderb, and A. Kumar (2001) “Influencing R&D/marketing integration and the use of market information by R&D managers: intended and unintended effects of managerial actions,” *Journal of Business Research* 52(1): pp. 69 – 82.

Miller, D.J. (2006) “Technological diversity, related diversification and firm performance,” *Strategic Management Journal* 27: pp. 601–619.

Narin, F., E. Noma, and R. Perry (1987) “Patents as indicators of corporate technological strength,” *Research Policy* 16: pp. 143–155.

Scherer, F.M. (1965) “Corporate inventive output, profits and growth,” *The Journal of Political Economy* 733: pp. 290–297.

Annex 1: List of Included Classifications & # of Firms

| Classifications | China | Japan | U.S. |
|--|-------|-------|------|
| Agriculture, Horticulture & Livestock | 144 | 20 | 2 |
| Banking, Insurance & Financial Services | 10 | 26 | 17 |
| Biotechnology and Life Sciences | 43 | 18 | 200 |
| Business Services | 751 | 848 | 86 |
| Chemicals, Petroleum, Rubber & Plastic | 1332 | 673 | 453 |
| Communications | 364 | 110 | 108 |
| Computer Hardware | 78 | 19 | 41 |
| Computer Software | 246 | 210 | 99 |
| Construction | 110 | 1145 | 7 |
| Food & Tobacco Manufacturing | 273 | 261 | 39 |
| Industrial, Electric & Electronic Machinery | 2404 | 1792 | 708 |
| Leather, Stone, Clay & Glass products | 213 | 164 | 10 |
| Media & Broadcasting | 448 | 82 | 25 |
| Metals & Metal Products | 525 | 594 | 54 |
| Mining & Extraction | 119 | 16 | 46 |
| Miscellaneous Manufacturing | 389 | 118 | 17 |
| Printing & Publishing | 49 | 105 | 6 |
| Property Services | 31 | 192 | 3 |
| Public Administration, Education, Health Social Services | 79 | 72 | 24 |
| Retail | 188 | 361 | 18 |
| Textiles & Clothing Manufacturing | 208 | 134 | 11 |
| Transport Manufacturing | 378 | 210 | 72 |
| Transport, Freight & Storage | 115 | 141 | 7 |
| Travel, Personal & Leisure | 52 | 240 | 13 |
| Utilities | 209 | 39 | 17 |
| Waste Management & Treatment | 33 | 69 | 5 |
| Wholesale | 992 | 1897 | 29 |
| Wood, Furniture & Paper Manufacturing | 161 | 307 | 23 |

Source: Calculated by the authors.