

Patent Intensity and Firm Performance: Evidence from Chinese Listed Firms

Haicheng Jiang *

School of Economics and Finance, South China University of Technology, Guangzhou, China

*Corresponding Author: Haicheng Jiang

ABSTRACT

Using a large sample of approximately 2,500 listed firms in China over the past thirty years, I examine the relationship between innovation output and firm performance, as measured by return on assets (ROA). I document a significant increase in the number of patents granted to Chinese listed firms domestically. My findings indicate that patent intensity—measured as the number of patents scaled by total assets—is positively associated with future ROA, even after controlling for various patent-related covariates, as well as year and industry fixed effects. These results contribute to the existing literature on the positive impact of innovation on firm performance, which has been well-documented in Western economies such as the United States and European countries. Furthermore, I identify heterogeneities in this relationship across industries, patent types, and firm sizes. Specifically, the effect of patent intensity on subsequent ROA is more pronounced among firms in the manufacturing sector, those with a higher intensity of invention patents, and those with greater market equity. This study provides new evidence on the real effects of innovation output on firm performance in the context of China's listed firms.

KEYWORDS

Innovation output; Patent intensity; ROA

1. INTRODUCTION

Technological innovation is a key driver of modern economic growth. Numerous studies have highlighted innovation as the most critical engine of macroeconomic performance (Kogan, Papanikolaou, Seru, & Stoffman, 2017; Farre-Mensa, Hegde, & Ljungqvist, 2020). In parallel, the role of corporate innovation in financial markets has become an increasingly important topic, garnering significant attention from financial economics researchers over the past two decades (He & Tian, 2018).

The literature on innovation in financial economics primarily follows two main strands. The first focuses on the determinants of corporate innovation at both the firm and market levels. Various factors, such as entrepreneurship, ownership structure, corporate governance, institutional quality, and market liquidity, have been identified as key drivers influencing firms' incentives and ability to finance innovation. The second strand examines the impact of corporate innovation on firm performance. Empirical research suggests that innovative activities—measured by innovation input (e.g., R&D expenditure), innovation output (e.g., the number of granted patents), or innovation efficiency (e.g., the number of granted patents scaled by R&D expenditure)—serve as strong predictors of future firm performance indicators, including return on assets (ROA) and stock returns (Gu, 2005; Hsu, 2009; Chan, Chen, Hong, & Wang, 2015; Hou, Hsu, Watanabe, & Xu, 2016; Hirshleifer, Hsu, & Li, 2013, 2018).

This paper examines the impact of innovation on firm performance. To be more specific, I utilize patent data from more than 2,500 listed firms in China over the past three decades to examine the relationship between innovation and subsequent ROA. The number of granted patents, scaled by total assets, is used to measure the intensity of firms' innovative output. Building on prior studies that establish the predictive power of innovation on firm performance in the U.S. (Hsu, 2009; Hirshleifer et al., 2013, 2018), I extend this analysis by investigating a large sample of Chinese listed firms. After controlling for a wide range of firm characteristics, patent-related covariates, as well as year and industry fixed effects, I find that patent intensity is positively associated with future ROA.

Furthermore, I explore the heterogeneous effects of innovation on firm performance. To capture variations in patent intensity across industries, I disaggregate the full sample into manufacturing and non-manufacturing firms at the first-digit industry classification level and further divide non-manufacturing firms into second-digit industries, examining the impact of patent intensity on future ROA within each sub-sample. I also analyze the effects of different types of patents by distinguishing between invention patents, utility patents, and design patents, assessing their respective impacts on future ROA separately. Additionally, I investigate firm size as a moderating factor in the relationship between patent intensity and firm performance by examining this association separately for large and small firms. Overall, my findings indicate that patent intensity has a stronger predictive power for future ROA in manufacturing firms, invention patents, and larger firms.

This study closely relates to the literature examining the impact of innovation on various firm performance indicators. For instance, Griffin, Hong, and Ryou (2018) find that corporate innovation efficiency gradually enhances credit ratings, although this effect is influenced by firm-level characteristics such as downside risk, financial constraints, and sales or cash flows. Wu and Chung (2019) show that firms with greater innovation output and R&D investment are more likely to be acquired, receive unsolicited bids, and attract multiple bidders, with this effect being stronger when competition among bidders is higher, when acquiring firms operate in competitive product markets, and when technological proximity in the acquiring firms' industry is lower. Using instrumental variable regressions and a difference-in-differences approach, Hsu, Lee, Liu, and Zhang (2015) find a negative relationship between firms' default probabilities and the size of their patent portfolios. They further demonstrate that bonds issued by more innovative firms tend to have lower issuance premiums and lower realized excess returns. Similarly, Ben-Nasr, Bouslimi, and Zhong (2019) document a significant negative association between the number of patents and stock price crash risk, with this effect being more pronounced in firms with weak corporate governance and high information opacity.

The rest of the paper is organized as follows. Section 2 reviews the literature and corporate innovation in China over the last three decades, Section 3 describes the data and variable definitions, Section 4 presents the empirical results about the association between patent intensity and ROA, and finally Section 5 concludes.

2. LITERATURE REVIEW

In this section, I first discuss the impact of innovation on firm performance in the previous literature. I then introduce the achievement of corporate innovation in China over the last three decades. Finally, I summarize the previous empirical analysis and point out the research gap.

2.1. Innovation and Firm Operating Performance

The exploration of the relationship between innovation and firm performance originates from Schumpeter's innovation theory, which highlights the role of new combinations and creative destruction in the survival and growth of firms, particularly in competitive industries (Schumpeter, 1934). Firms can benefit from innovation by enhancing their future performance through several key

mechanisms. First, engaging in innovative activities gradually strengthens firms' absorptive capacity, facilitating the accumulation of technical knowledge and experience (Hu, Jefferson, & Jinchang, 2005). A rich history of innovation fosters the development of high-quality, technologically advanced products, increasing firms' competitiveness and profitability. Second, innovation enhances expected profitability and productivity by reducing investment costs and enabling firms to realize potential economies of scale in production (Griffith, Harrison, & Van Reenen, 2006; Adams & Jaffe, 1996). Third, innovation allows firms to temporarily establish a monopoly position in the market, leading to higher profits (Schumpeter, 2013). Technologically advanced products attract customers while limiting direct competition, thereby granting firms a competitive advantage. However, as high profits attract new market entrants, the profitability of innovative products tends to decline over time (Lieberman & Montgomery, 1988). Although the high returns from innovation may be short-lived, firms that continuously introduce new products can sustain a series of monopoly profits, thereby improving long-term performance (Montgomery, 1995).

A substantial body of empirical research has investigated the relationship between innovation and firm operating performance. Early studies primarily measure firms' innovative activities using innovation input proxies, such as R&D expenditure, since R&D investment marks the beginning of the innovation process. Ehie and Olibe (2010) find a positive relationship between R&D investment and firm performance in both the U.S. manufacturing and service industries, after accounting for firm size and leverage. Their results further indicate that the positive impact of R&D investment was more pronounced in the manufacturing sector before 9/11, whereas the service sector became more sensitive to R&D investment in the post-9/11 period. Hou et al. (2016) provide evidence that R&D intensity has a significant positive effect on future operating profitability, based on a large sample of firms from 21 countries. Similarly, using a sample of leading Chinese electronics manufacturing firms, Gui-long, Yi, Kai-hua, and Jiang (2017) argue that R&D-based innovation constitutes a critical long-term investment for the growth and development of high-tech manufacturing firms.

However, R&D expenditure, as a measure of innovation activities, may not be the most appropriate proxy for firms' innovation intensity. Subsequent studies have explored the relationship between innovation and firm performance from the perspective of innovation output. Compared to R&D expenditure, patents and citations are preferred measures of corporate innovation because they represent the tangible outcomes of innovation investment, effectively capturing the extent to which firms utilize their R&D input (Hall, Jaffe, & Trajtenberg, 2005). Additionally, Acharya and Subramanian (2009) argue that R&D expenditure is sensitive to accounting norms, as firms may strategically choose to capitalize or expense R&D costs for financial reporting purposes. Empirical evidence further supports the use of patents and citations as indicators of firm innovation. Gu (2005), in a study of 1,330 U.S. firms, finds that changes in patents and citations are positively associated with future earnings, particularly in industries such as computing and medical equipment, where the time lag between technological progress and profit realization is relatively short. Moreover, the strength of this relationship increases over time and may persist for up to five years. Pandit, Wasley, and Zach (2011) extend this analysis by relaxing the assumption of constant marginal productivity of R&D expenditure, demonstrating a positive association between patents and firms' future operating performance. Additionally, they find that firms with a larger number of patents experience less volatile future performance. More recent studies introduce the concept of innovation efficiency, defined as innovation output relative to innovation input, as an alternative measure of firms' innovative activities. For instance, Hirshleifer et al. (2013) and Mama (2018) provide evidence that higher innovation efficiency positively influences firms' future operating performance.

On the contrary, some studies report mixed empirical findings regarding the relationship between innovation and firm performance. Using a sample of listed firms in the United States, Cui and Mak (2002) find that while R&D intensity is positively correlated with Tobin's Q, it is negatively associated with return on assets (ROA). Similarly, Vithessonthi and Racela (2016) show that although R&D intensity positively influences firm value, it is negatively correlated with operating performance

indicators such as ROA and return on sales (ROS). Their findings further indicate that, when firms are categorized based on their level of R&D intensity, ROS is negatively affected by high R&D intensity, whereas the effect is not statistically significant for firms with low R&D intensity. They emphasize that substantial R&D expenditure may have an adverse impact on short-term performance, even though it enhances competitiveness and contributes to long-term growth. Furthermore, Artz, Norman, Hatfield, and Cardinal (2010), employing a longitudinal study, examine the relationship between innovation output and firm performance. Their results suggest that patents negatively affect ROA, which they attribute to the rise of strategic patenting practices rather than genuine innovation-driven performance gains. In another study, Atalay, Anafarta, and Sarvan (2013) investigate the impact of different types of innovation on firm performance using a sample of 113 firms from the Turkish automotive supplier industry. Their findings indicate that product and process innovation positively correlate with firm performance, whereas organizational and marketing innovation exhibit no significant effects. Overall, the relationship between innovation and firm operating performance remains inconclusive, suggesting that various factors, such as firm heterogeneity and the type of innovation activity, may shape this association.

2.2. Innovation in China

China, as one of the largest emerging economies, holds a crucial position in the global business landscape. While the country has experienced rapid economic growth for more than three decades following the implementation of the reform and opening-up policy, this achievement has largely been driven by factor mobilization and technological adoption. Historically, China has served as the "world's factory," relying on cheap labor to produce low-cost, low-end products for global markets (Golder & Mitra, 2018). Between 1980 and 2000, China's export-oriented economic model fueled its rapid development, with the country's strong manufacturing sector playing a pivotal role in the global industrial supply chain. However, as labor costs have risen and the technological gap between China and advanced economies has narrowed, the sustainability of this growth model has come into question (J. Y. Lin & Treichel, 2012). Recognizing the limitations of an economy dependent on low-cost manufacturing and external technology, the Chinese government has increasingly emphasized the importance of indigenous innovation as a driver of long-term economic transformation. To this end, a series of policies have been introduced since the early 21st century to foster corporate innovation. Among these, the most influential is the Outline of the National Program for Long- and Medium-Term Scientific and Technological Development (2006–2020), promulgated in 2006. This policy marked a significant shift by elevating independent innovation to a national strategic priority, making China one of the few countries where the government explicitly mandates intellectual property targets.

The policies implemented by the Chinese government have yielded remarkable results. In recent years, many Chinese firms have evolved from mere adopters and imitators of foreign knowledge to innovative enterprises capable of challenging the dominance of Western multinational corporations. From an innovation input perspective, China's R&D expenditure surpassed that of Japan in 2011, making it the world's second-largest spender on R&D. By 2014, China had also overtaken continental Europe in this regard (McKinsey Global Institute, 2015). From an innovation output perspective, the country has witnessed a substantial increase in patent applications, particularly following its accession to the WTO. As of 2018, China had ranked first globally in patent applications for eight consecutive years. Furthermore, the McKinsey Global Institute (2015) highlights that China has made comprehensive advancements in science and engineering across various industries. The country's well-established industrial production system, supported by a robust manufacturing sector, provides a strong foundation for corporate innovation across different industries. Additionally, China has achieved notable success in various forms of innovation, including cost innovation, manufacturing innovation, and business model innovation, over the past three decades (Williamson & Yin, 2014).

2.3. Summary

As evidenced by the aforementioned empirical studies, the majority conclude that innovation is positively correlated with firm performance, while a few suggest that the relationship remains inconclusive. However, it is important to note that most of these studies focus on firms in the United States and European countries, primarily due to the availability of firm-level innovation data. Consequently, there is a significant gap in research on the impact of innovation on firm performance in emerging economies such as China, which plays a crucial role in global economic performance and innovation. Existing studies on China are largely conducted at the industry level or limited to select firms. However, the continuous development of Chinese databases, particularly those related to patents, now offers a unique opportunity to examine the relationship between innovation and firm performance in the Chinese context. Therefore, this study aims to investigate whether the relationship between innovation capabilities and future operating performance (measured by ROA) in Chinese listed firms aligns with the patterns observed in Western companies.

3. DATA DESCRIPTION

In Section 3.1, I first outline the data sources and selection criteria for firms included in the empirical analysis. I then describe the construction of the patent variable, operating performance indicators, and other control variables. In Section 3.2, I present the descriptive statistics and the simple correlations among all key variables.

3.1. The Data and Variables

The dataset is sourced from the Chinese Stock Market and Accounting Research (CSMAR) database, which provides comprehensive firm-level and market-level financial data for all Chinese listed firms since 1990. These firms are traded on the Main-Board Market (including A-shares and B-shares on the Shenzhen and Shanghai Stock Exchanges) and the Second-Board Market (Growth Enterprises Market Board). Over the past thirty years, the database has included more than 3,000 listed firms. To ensure data reliability, I exclude firm-year observations with significant missing values in key financial variables (ROA and total assets), invalid total assets or market equity (zero or negative), instances where the earliest accounting year precedes the firm's market entry, and firms in the financial industry. Additionally, the dataset includes patent information from 1992 to 2017. After merging patent data with operating performance indicators, the final sample consists of approximately 2,500 listed firms.

The CSMAR patent database records two key timestamps for each firm-year observation: the application date and the grant date. Since patent applications may be rejected by the State Intellectual Property Office (SIPO), the grant date is a more reliable measure of a firm's innovative activities. To minimize potential look-ahead bias, I use the grant date as the effective date of each patent and count the number of patents granted to firm i in year t . Additionally, the database classifies patents into three types based on SIPO's classification: invention patents, utility patents, and design patents.

Empirical studies typically represent firm-level innovative activities through three main aspects: innovation input, innovation output, and innovation efficiency. Earlier studies primarily relied on innovation input (R&D expenditure) or innovation output (the number of patents) to examine the relationship between innovation and firm performance. A more recent study by Hirshleifer et al. (2013) introduced a different approach by focusing on innovation efficiency, which is measured as the ratio of innovation output to input.

Ideally, I would use innovation efficiency—defined as the number of patents granted scaled by R&D expenditure—to assess firms' innovative efficiency. However, data on R&D expenditure is only available from 2007, and even within this period, significant missing values exist. Due to these data

limitations, I construct patent intensity as a measure of firms' innovative activities. Following Gu (2005), patent intensity is computed as the number of patents granted scaled by total assets.

A more accurate measure of innovative activities should account not only for the number of patents but also for patent citations, as suggested by previous studies (Hall et al., 2005; Hirshleifer et al., 2013; Ben-Nasr et al., 2019). However, the CSMAR patent database does not provide firm-level patent citation data. As a result, I rely solely on the number of patents granted as a proxy for innovative activity. Thus, the key explanatory variable, patent intensity, is constructed as follows:

$$PatentIntensity = \frac{patents_{it}}{assets_{it}}$$

Where $patents_{it}$ denotes the number of patents granted to firm i in year t and $assets_{it}$ denotes total assets of firm i in year t . The patent intensity variable covers the period between 1992 and 2017.

The operating performance of listed firms is measured using Return on Assets (ROA), which serves as an indicator of how efficiently a company utilizes its assets to generate profits. ROA reflects a firm's profitability relative to its total assets, offering investors insight into how effectively the company converts its investments into net earnings. A higher ROA indicates greater profitability, as it signifies that the firm generates more income with fewer resources. In the CSMAR database, ROA is calculated using the following formula:

$$ROA_{it} = \frac{profits_{it}}{(0.5 * assets_{it} + 0.5 * assets_{it-1})}$$

Where $profits_{it}$ denotes net profits of firm i in year t , and the denominator is the average of total assets of firm i in year t and $t - 1$.

To control for potential confounding factors in the empirical analysis, several financial indicators are included as control variables. These include capital expenditure, advertising expenditure, R&D expenditure, and market equity. Additionally, firms in the CSMAR database are categorized into first-level industries, such as manufacturing, real estate, business, public utilities, and general industries. Each of these broad categories is further divided into more specific two-digit industries, with a total of 70 two-digit industries represented in the dataset.

3.2. Descriptive Statistics

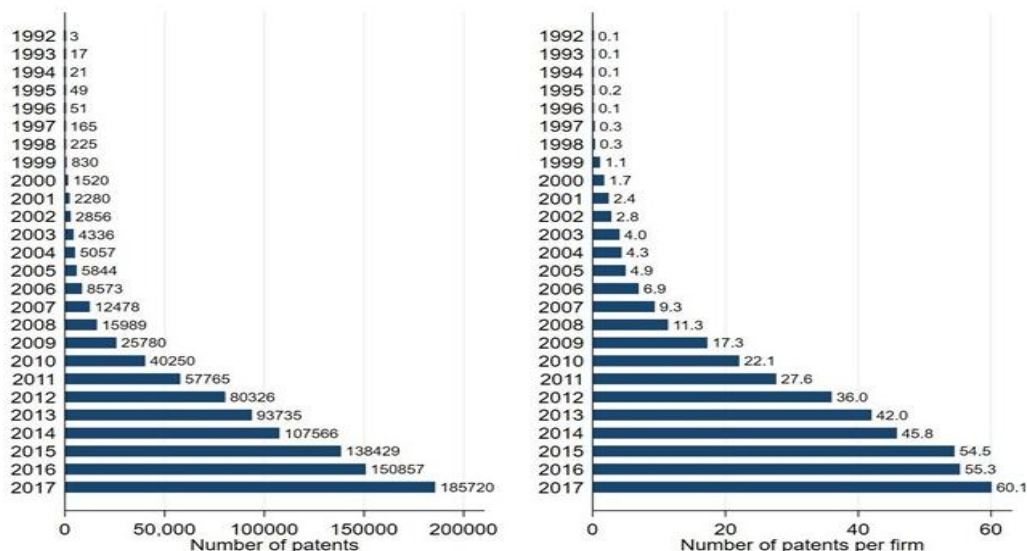


Figure 1. The trend of the number of patents in China (1992-2017)

Figure 1 illustrates the trend in the total number of patents and the number of patents per firm from 1992 to 2017. Over the past three decades, there has been a substantial increase in patent grants, with a particularly sharp rise in the most recent ten years of the sample period. For instance, the total number of patents granted to all listed firms surged from 12,478 in 2007 to 185,720 in 2017, while the average number of patents per firm increased from 9.3 to 60.1 over the same period.

Table 1 presents the number of observations, pooled mean, standard deviation, 25th percentile, median, and 75th percentile of patent intensity across first-digit and selected second-digit industries. There is significant variation in patent intensity both at the first-digit and second-digit industry levels. At the first-digit level, the manufacturing industry exhibits the highest patent intensity (0.068), whereas the real estate and business industries have the lowest values (0.0102 and 0.0108, respectively). Meanwhile, the public utility and general industries fall in the middle range, with patent intensities of 0.0351 and 0.0325, respectively. The variation in patent intensity is even more pronounced across second-digit industries. For example, agriculture and forestry record the lowest patent intensities (0.0054 and 0.0059), while other manufacturing (0.1592), furniture manufacturing (0.148), and electrical machinery and equipment manufacturing (0.1291) rank among the highest.

Table 1. Patent intensity across different industries

Industries	Obs	Mean	Std	25th percentile	Median	75th percentile
Panel A: first-digit industry						
Public Utility	4947	0.0351	0.0979	0	0.0004	0.0270
Business	2007	0.0108	0.0585	0	0	0.0040
Manufacturing	23447	0.0680	0.1986	0	0.0164	0.0739
Real Estate	2413	0.0102	0.0335	0	0	0.0060
General	1114	0.0325	0.1732	0	0	0.0196
Panel B: second-digit industry						
General machinery manufacturing	1122	0.0890	0.1351	0.0130	0.0464	0.1100
Electrical machinery and equipment manufacturing	2043	0.1291	0.3081	0.0181	0.0694	0.1560
Furniture manufacturing	84	0.1480	0.2181	0.0084	0.0555	0.1606
Pharmaceutical manufacturing	2295	0.0337	0.0646	0	0.0125	0.0397
Other manufacturing	144	0.1592	0.3359	0	0.0177	0.1311
Forestry	57	0.0059	0.0146	0	0	0
Health care industry	128	0.0153	0.0333	0	0	0.0176
Civil Engineering	711	0.0195	0.3551	0	0.0066	0.0240
Construction Industry						
Agriculture	199	0.0054	0.0153	0	0	0.0046
Art industry	37	0.0201	0.4694	0	0	0.0036

Note: This table reports patent intensity across different industries. Patent intensity is defined as the number of granted patents scaled by total assets. Panel A shows patent intensity across five industries at the first-digit industry level, while Panel B shows patent intensity of some selected industries at the second-digit industry level.

Table 2 presents the summary statistics of patent variables, ROA, and other control variables by dividing the sample into two groups. Panel A includes firm-year observations with zero patents, while Panel B consists of firm-year observations with at least one patent. The number of firm-year observations is larger in Panel B than in Panel A across ROA and various patent variables, suggesting

that more firms belong to the group with at least one patent. Based on the patent measure in year t , the average ROA in years t and $t+1$ is 0.069 and 0.071, respectively, for firms in Panel B. In contrast, for firms in Panel A, the average ROA in years t and $t+1$ is 0.067 and 0.059, respectively. These findings suggest that firms with at least one patent tend to outperform those without patents in terms of ROA in China.

Table 2. Summary statistics

	Obs	Mean	Std	Min	Max
Panel A: No patent granted in year t					
One-year Forward ROA	12221	0.05915	0.06866	-0.2048	0.3454
Current ROA	12872	0.06703	0.07369	-0.2048	0.3507
Δ ROA	11976	-0.01516	0.3733	-14.34	16.24
Patents	13415	0	0	0	0
Total Asset	13415	409.3	1236	0.134	41923
Patent Intensity	13415	0	0	0	0
$\ln(1+\text{Patent Intensity})$	13415	0	0	0	0
$\ln(1+\text{CapExp/ME})$	11726	3.027	1.507	0	8.944
$\ln(1+\text{AD/ME})$	1473	1.14	1.051	0	4.526
$\ln(1+\text{RD/ME})$	1497	14.82	1.772	0	18.42
Size	13318	4.647	9.628	0.01223	332.5
Panel B: At least one patent granted in year t					
One-year Forward ROA	17770	0.07094	0.06659	-0.2047	0.3497
Current ROA	20168	0.06885	0.06539	-0.2047	0.3513
Δ ROA	18606	-0.009898	0.3032	-20.87	27.38
Patents	20513	45.86	223.9	1	13394
Total Asset	20513	1301	7068	2.461	240538
Patent Intensity	20513	0.09018	0.2168	0.00001364	12.6
$\ln(1+\text{Patent Intensity})$	20513	0.07734	0.1181	0.00001364	2.61
$\ln(1+\text{CapExp/ME})$	20387	3.192	1.239	-0.003539	7.832
$\ln(1+\text{AD/ME})$	8696	0.9902	1.074	-2.228	5.822
$\ln(1+\text{RD/ME})$	13353	15.84	1.229	0	21.42
Size	20486	11.67	57.34	0.02759	5013

Note: This table shows descriptive statistics of all the variables. The unit of observation is firm-year. The firms are sorted into two groups according to whether they have new patents granted in year t .

4. THE ASSOCIATION BETWEEN PATENT INTENSITY AND ROA

In Section 4.1, I first examine the relationship between patent intensity and future ROA using all available Chinese listed firms. In Section 4.2, I explore the heterogeneous effects of patent intensity across different industries, patent types, and firm sizes. Finally, I perform various robustness checks to confirm the positive association between patent intensity and future ROA.

4.1. Special Signs

To systematically examine the relationship between patent intensity and subsequent operating performance, I conduct pooled regressions using variations of the following econometric model:

$$\begin{aligned}
ROA_{it+1} = & \alpha_0 + \alpha_1 \ln(1 + PatentIntensity_{it}) + \alpha_2 \ln\left(1 + \frac{CapEx_{it}}{ME_{it}}\right) + \alpha_3 \ln\left(1 + \frac{AD_{it}}{ME_{it}}\right) \\
& + \alpha_4 ROA_{it} + \alpha_5 \Delta ROA_{it} + \alpha_6 \ln\left(1 + \frac{RD_{it}}{ME_{it}}\right) + IndustryDummy + YearDummy \\
& + \epsilon_{it}
\end{aligned}$$

Where ROA_{it+1} is firm i 's one-year forward return on assets in year $t+1$, the preferred measure of the future operating performance, $\ln(1 + PatentIntensity_{it})$ is the natural log of one plus patent intensity, $\ln(1 + \frac{CapEx_{it}}{ME_{it}})$ is the natural log of one plus capital expenditure to market equity, $\ln(1 + \frac{AD_{it}}{ME_{it}})$ is the natural log of one plus advertising expenditure to market equity, ΔROA_{it} is the change in ROA between year t and year $t-1$, $\ln(1 + \frac{RD_{it}}{ME_{it}})$ is the natural log of one plus R&D expenditure to market equity. Considering the significant difference of ROA across different industries and the potential unobservable industry-level time-invariant variables, the model accounts for industry fixed effects. Similarly, to alleviate the bias from external economic and political shocks to ROA in specific years, the model controls for year fixed effects as well.

Since the distribution of patent intensity is highly skewed and often zero, I use $\ln(1+PatentIntensity)$ in the regression model. Similarly, because capital expenditure, advertising expenditure, and R&D expenditure can sometimes be zero, I take the natural logarithm of one plus their value scaled by market equity. Capital expenditure and advertising expenditure are included as standard control variables when examining the relationship between innovation and firm performance (Pandit et al., 2011; Hirshleifer et al., 2013). Following Gu (2005) and Hirshleifer et al. (2013), I include ROA in year t to account for its persistence over time. Additionally, I control for the change in ROA between year t and $t - 1$ to capture mean reversion in operating performance (e.g., Fama & French, 2000; Hirshleifer et al., 2013). Given the emphasis in prior literature on the role of R&D expenditure in explaining firm performance, I include the ratio of R&D expenditure to market equity to capture its potential explanatory power. Finally, in line with common practice in financial studies, I winsorize ROA at the 1% and 99% levels to mitigate the influence of outliers. Standard errors are clustered at the second-digit industry level.

4.2. Baseline Results

Table 3 presents the baseline results from the variants of the econometric model specified in Equation (4). To predict one-year forward ROA, Column (1) includes only the key explanatory variable—the log of patent intensity—along with ROA in year t , the change in ROA between year t and $t - 1$, industry fixed effects, and year fixed effects. This parsimonious model indicates a positive and statistically significant association between patent intensity and one-year forward ROA. Column (2) introduces capital expenditure as an additional control, while Column (3) further includes advertising expenditure. The model specification in Column (2) is preferred due to data limitations related to capital expenditure, advertising expenditure, and R&D expenditure. Column (3) closely follows the model specification in Equation (3) of Hirshleifer et al. (2013), which examines the relationship between innovation efficiency and firm performance (i.e., ROA and cash flows). Finally, Column (4) incorporates R&D expenditure alongside the control variables used in the previous specifications. Despite the presence of missing values in some control variables, the positive and significant relationship between patent intensity and future ROA remains robust across the last three specifications. In terms of economic significance, an increase of one standard deviation in the natural logarithm of one plus patent intensity raises subsequent ROA by 0.19%, a magnitude comparable to the coefficient estimates for patent efficiency reported in Hirshleifer et al. (2013).

Table 3. The association between patent intensity and the future ROA

	(1)	(2)	(3)	(4)
Δ ROA	-0.0144*** (0.0048)	-0.0158** (0.0064)	-0.0081* (0.0043)	-0.1006*** (0.0136)
Current ROA	0.5764*** (0.0199)	0.5771*** (0.0202)	0.6053*** (0.0199)	0.6617*** (0.0201)
$\ln(1+\text{Patent Intensity})$	0.0203*** (0.0032)	0.0191*** (0.0032)	0.0167*** (0.0033)	0.0145*** (0.0032)
$\ln(1+\text{CapExp/ME})$		-0.0017*** (0.0004)	-0.0030*** (0.0008)	-0.0029*** (0.0008)
$\ln(1+\text{AD/ME})$			0.0020*** (0.0005)	0.0020*** (0.0005)
$\ln(1+\text{RD/ME})$				0.0001 (0.0007)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
R-squared	0.3640	0.3662	0.4293	0.4733
Observations	26931	25882	7387	6265
Number of firms	2573	2573	1889	1700
Number of industries	70	70	67	63

Note: This table shows the relation between ROA and patent intensity after controlling some variables from pooled cross-section regression. The dependent variable is the one-year forward ROA. Δ ROA is the change in ROA between year t and year $t+1$. Current ROA is the return on assets in year t . $\ln(1+\text{Patent Intensity})$ denotes the natural log of one plus patent intensity. $\ln(1+\text{CapExp/ME})$ is the natural log of one plus capital expenditure scaled by year-end market equity. $\ln(1+\text{AD/ME})$ is the natural log of one plus annual advertising expenditure divided by year-end market equity. $\ln(1+\text{RD/ME})$ denotes the natural log of one plus R&D expenditure in fiscal year ending in year t divided by market equity in year t . Industry dummies are based on the CSMAR classification. Year dummies are included to alleviate the effect of economic and political shocks in some specific years. The variables have been winsorized at the 1% and 99% levels. Standard errors are clustered at the second-digit industry level and reported in parentheses. *, **, and *** denote 10%, 5%, and 1% significance level, respectively.

The coefficients of the control variables are generally consistent with the existing literature. Advertising expenditure is positively associated with one-year forward ROA, as expected. The significantly positive coefficient for ROA and the significantly negative coefficient for the change in ROA confirm both the persistence of ROA and the phenomenon of mean reversion. In contrast, capital expenditure is significantly and negatively associated with one-year forward ROA, which contrasts with findings from previous studies.

4.3. Heterogeneity and Robustness Checks

In this subsection, I examine the potential heterogeneous effects of innovation on future ROA across different industry categories, patent types, and firm sizes. To maintain consistency with the baseline results, the empirical analyses in this section use the model specification and control variables outlined in Column (3) of Table 3.

Industry-specific factors significantly influence a firm's innovative behavior, which in turn affects its innovation performance (Guan & Pang, 2017). Firms within the same industry are likely to share similarities in products, markets, technologies, and resource bases, leading them to adopt similar

strategies. In contrast, firms operating across different industries may exhibit distinct patterns of innovation and operating performance. Innovation is expected to create variations in economic performance both across industries and within firms (Breschi, Malerba, & Orsenigo, 2000; Malerba & Orsenigo, 1997). As shown in Table 1, patent intensity varies widely across industries. For instance, at the first-digit level, the patent intensity in manufacturing industries is more than twice that of other industries. Further evidence in Figure 2 demonstrates that both the total number of patents and the number of patents per firm are significantly higher in manufacturing firms compared to non-manufacturing firms. Over the past thirty years, this gap has grown larger, indicating a dramatic increase in patent grants to manufacturing firms. Manufacturing industries are typically capital-intensive, and firms in these sectors are generally better equipped with funds and technology, making them more likely to innovate (Guan & Pang, 2017). Additionally, ROA in listed firms tends to vary systematically across industries. For example, capital-intensive industries (e.g., machinery manufacturing) typically have different asset structures than labor-intensive industries (e.g., agriculture), leading to distinct patterns in ROA. Empirical studies examining the determinants of ROA should account for these industry-specific differences.

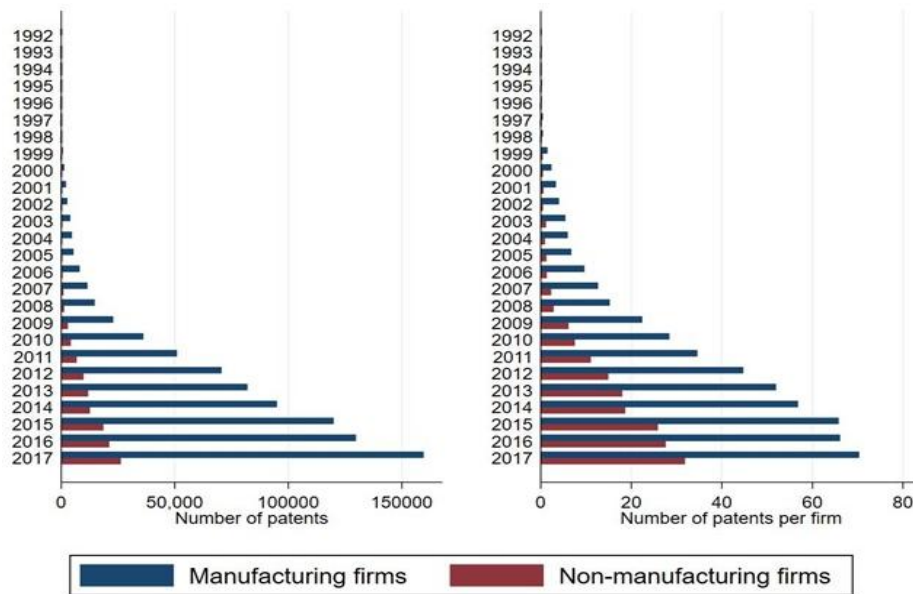


Figure 2. The trend of the number of patents across industries in China (1992-2017)

Table 4 presents the empirical results by dividing the sample into observations from different industries at the first-digit level. Columns (1) and (2) use the baseline model specification to examine the association between patent intensity and ROA for manufacturing and non-manufacturing firms separately. For the sample of 1,843 manufacturing firms across 36 second-digit industries, the relationship between patent intensity and future ROA is positive and statistically significant. In contrast, for the sample of 730 non-manufacturing firms across 34 second-digit industries, the coefficient of patent intensity remains positive but is statistically insignificant. Moreover, when the non-manufacturing industry is further divided into the public utility, business, real estate, and general industries in Columns (3) to (6), the results are mixed. The coefficient for patent intensity in the public utility and real estate industries is positive and statistically significant at least at the 5% level. However, the coefficient in the business and general industries is negative, and the economic significance is marginally small. These findings support the argument that the impact of patent intensity on subsequent firm performance, as measured by one-year forward ROA, is particularly strong in manufacturing industries. In contrast, in industries with lower levels of innovation activity, such as public utility and real estate, the impact of patent intensity is either economically or statistically insignificant. These results align with F.-J. Lin, Chen, and Lo (2014), who argue that industrial characteristics are more influential than firm characteristics in determining the long-term competitive advantages of firms in China.

Table 4. The heterogeneous association between patent intensity and the future ROA: different types of industries

	(1)	(2)	(3)	(4)	(5)	(6)
	Manufac turing	Non- manufacturing	Public Utility	Business	Real Estate	General
ln(1+Patent Intensity)	0.0196** *	0.0145	0.0169**	- 0.0055**	0.1604** *	-0.0214
	(0.0028)	(0.0128)	(0.0079)	(0.0019)	(0.0241)	(0.0129)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.3950	0.3007	0.3703	0.2486	0.2169	0.1914
Observations	17861	8021	3705	1594	1883	839
Number of firms	1843	730	401	113	136	80
Number of industries	36	34	18	5	4	7

Note: This table reports the relation between ROA and patent intensity across different types of industries. To save the space, this table only includes the results of patent intensity. The dependent variable is one-year forward ROA and ln (1+Patent Intensity) denotes the natural log of one plus patent intensity. Industry dummies are based on the CSMAR classification. Year dummies are included to alleviate the effect of economic and political shocks in some specific years. The variables have been winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the second-digit industry level. * denotes 10% significance level, ** denotes 5% significance level, and *** denotes 1% significance level, respectively.

Patents granted to listed firms at the subcategory level may have heterogeneous effects on the relationship between patent intensity and future ROA. Within China's patent system, the State Intellectual Property Office (SIPO) classifies all patents into three subcategories: invention patents, utility patents, and design patents. As shown in Figure 3, utility patents consistently represent the largest fraction of patents granted to listed firms. Another important trend is that invention patents have become increasingly significant across all types of innovation activities. Since invention patents play a crucial role in enhancing productivity, particularly in manufacturing firms (which constitute over two-thirds of the listed firms in the sample), the relationship between patent intensity and future ROA is likely to vary across the three types of patents. Therefore, I examine the impact of patent intensity on one-year forward ROA separately for invention patents, utility patents, and design patents.

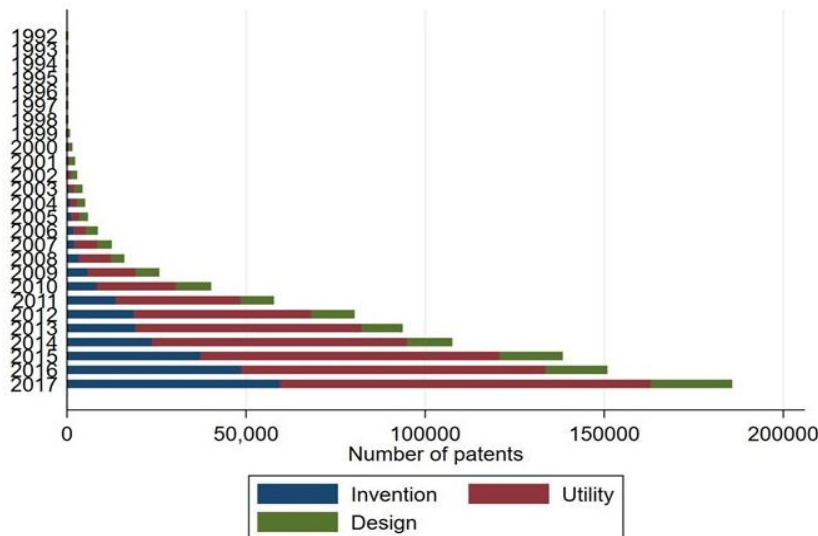


Figure 3. The trend of the number of patents across different types of patents in China (1992-2017)

Table 5 presents empirical results using invention patents, utility patents, and design patents to measure patent intensity in the first three columns. The last column incorporates all three types of patent intensity, considering the potential additive effect of patent intensity on one-year forward ROA for listed firms. The results show a strong association between invention patents and one-year forward ROA, while the patent-ROA relationship is much weaker, both economically and statistically, for utility patents and design patents. This heterogeneity is likely driven by the fact that a significant proportion of manufacturing firms, which tend to produce invention patents, are included in the sample.

Table 5. The heterogeneous association between patent intensity and the future ROA: different types of patents

	(1)	(2)	(3)	(4)
	invention patent	utility patent	design patent	All
ln(1+invention Patent Intensity)	0.0367*** (0.0135)			0.0280* (0.0141)
ln(1+utility Patent Intensity)		0.0232*** (0.0057)		0.0188*** (0.0071)
ln(1+design Patent Intensity)			0.0137** (0.0068)	0.0063 (0.0070)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
R-squared	0.3659	0.3660	0.3657	0.3662
Observations	25882	25882	25882	25882
Number of firms	2573	2573	2573	2573
Number of industries	70	70	70	70

Note: This table reports the relation between ROA and patent intensity across different types of patents. To save the space, this table only includes the coefficient of patent intensity. The dependent variable is one-year forward ROA and $\ln(1+\text{Patent Intensity})$ denotes the natural log of one plus patent intensity. Industry dummies are based on the CSMAR classification. Year dummies are included to alleviate the effect of economic and political shocks in some specific years. The variables have been winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the second-digit industry level. * denotes 10% significance level, ** denotes 5% significance level, and ***denotes 1% significance level, respectively.

Firm size, as a key characteristic of a firm, has been used to examine its heterogeneous effect on the relationship between innovation and firm value. Due to the advantages or disadvantages of economies or diseconomies of scale, firm size can have an opposing effect on the link between innovation and firm value (Connolly & Hirschey, 2005). Specifically, small firms are more likely to face diseconomies of scale, which weakens the impact of innovation on firm value. In contrast, large firms benefit from economies of scale, amplifying the effect of innovation on firm value. The theoretical influence of firm size on the market-value effect of innovation is mixed. However, empirical studies generally confirm the positive impact of firm size on the relationship between innovation and firm value (Connolly & Hirschey, 2005; Pindado, De Queiroz, & De La Torre, 2010). While previous studies have primarily focused on firms in developed countries such as the US and European nations, whether the heterogeneous size effect exists in China remains an open question that warrants further investigation.

Table 6 presents empirical results examining the relationship between patent intensity and ROA by dividing the full sample into two subgroups: large firms and small firms. To determine firm size, I use market equity and calculate the cutoff point, grouping firms with firm-year observations larger than the overall median value of market equity as large firms (1,809 observations) and firms with

firm-year observations smaller than the overall median value as small firms (762 observations). Column (1) illustrates the impact of patent intensity on subsequent ROA for large firms, while Column (2) examines the same relationship for small firms. As expected, the impact of patent intensity on one-year forward ROA is stronger in large firms and weaker in small firms. The final column explores this heterogeneous effect by including firm size, measured by the natural log of market equity, and its interaction with patent intensity. The results confirm the positive influence of firm size on the relationship between patent intensity and firm value, revealing a statistically significant size effect between large and small firms (the coefficient of the interaction term is statistically significant at the 1% level). These findings are consistent with Hung and Wang (2012) and Chun, Chung, and Bang (2015), who suggest that firm size has significant impacts on the efficiency of innovative activities, based on studies of manufacturing firms in Taiwan and South Korea.

Table 6. The heterogeneous association between patent intensity and the future ROA: size effect

	(1)	(2)	(3)
	> Median	< Median	interaction effect
ln(1+Patent Intensity)	0.0178*** (0.0031)	0.0136** (0.0056)	0.0102** (0.0043)
ln(size)			0.0044*** (0.0006)
ln(1+Patent Intensity)* ln(size)			0.0081*** (0.0024)
Year dummy	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes
R-squared	0.4962	0.2419	0.4210
Observations	15971	9141	25112
Number of firms	1809	762	2571
Number of industries	66	64	70

Note: This table shows the association between ROA and patent intensity across different sizes of firms as well as the interaction effect of size and patent intensity. Large firms are defined as firms that have market equity higher than the median, while small firms are firms that have market equity lower than the median. Ln (1+Patent Intensity) denotes the natural log of one plus patent intensity in year t. Ln (Size) is the natural log of market equity in year t. Ln (1+Patent Intensity)*ln (size) denotes the interaction between patent intensity and firm size. Year dummies are included to alleviate the effect of economic and political shocks in some specific years. Industry dummies are based on the CSMAR classification. The variables are winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the second-digit industry level. *, **, and *** denote 10%, 5%, and 1% significance level, respectively.

5. CONCLUSION

In this paper, I investigate whether innovation activities, as measured by patent intensity, impact firm performance. Using data from approximately 2,500 Chinese listed firms over the past three decades, I find that firms with higher patent intensity exhibit better operating performance, as indicated by ROA. The empirical results remain robust even after accounting for additional controls that could influence innovation activities and through various robustness checks. Furthermore, I provide evidence that the positive relationship between patent intensity and ROA is particularly pronounced in manufacturing firms, for firms holding invention patents, and for larger firms.

The results support the conjecture that patent intensity has a significant positive impact on subsequent firm performance, not only in developed countries but also in China, a developing country that has experienced a surge in patent applications and grants in recent decades. An important policy implication is that firms in developing countries could enhance their performance by fostering innovation activities.

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