Innovation and Initial Public Offerings (IPOs) – Evidence from China

By

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A thesis submitted in fulfilment for the degree of Doctor of Philosophy

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DECLARATION OF AUTHORSHIP

I, Lu Zhou, declare that this thesis titled, "Innovation and Initial Public Offerings (IPOs) – Evidence from China" and the work included in this thesis has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

(Signed)______________________________ Date: ____09. Oct. 2018_________

Candidate's name

DEDICATION

This thesis is dedicated to my parents, Prof. Xiaohua Zhou and Ms. Liyuan Yuan who have always encouraged, supported and helped me.

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For future, I will move forward and always remember.

ABSTRACT

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The purpose of the current study is to examine the impact of innovation information in the pre-IPO period on the Initial Public Offering (IPO) anomalies in the Chinese equity and product markets during the 2009−2016 period. This thesis constructs two indices to measure the dimensions of innovation input (R&D spending) and innovation outcome (patents) for this purpose. Three studies of the thesis respectively examine the impact of innovation of the initial public offering on the short-term performance of IPO companies, on the long-term performance IPO companies, and on the post-IPO product market feedback performance of firms. The period under the research coincides with the changes in the Chinese industrial policy that had profound impacts on the outcome of the study. Accordingly, research includes detailed analysis of government policies and how they affected the results of our investigation.

The first study focuses on the relationship between pre-IPO innovations and IPO short-term performance in the Chinese A-share market during the 2009−2016 period. Our investigation includes the extent of IPO underpricing during 2009−2014, and a new form of IPO underpricing that emerged after 2014, named “honeymoon period,” caused by changes in the reformation of the Chinese IPO market. Findings suggest that the innovation input (R&D spending) generates information asymmetry and valuation uncertainty in the market, causing shares to be more prone to IPO underpricing in the

capital market. However, for the innovation outcome in the form of patents, there exists a positive signal effect, which can significantly reduce the underpricing. In addition, the Chinese industrial policy has exaggerated the positive effects of innovation input and the negative effects of innovation outcome on the IPO short-term performance of firms before 2014. These findings suggest that China needs to improve its macroeconomic environment in order to promote its industrial policy in the IPO market more efficiently.

In the second study, we extend the previous research to investigate the impact of firms' pre-IPO innovation capital on the long-term performance of firms in the post-IPO period. This study applies Fama-French five-factor model to classify firms according to the different levels of innovation. The second part of this study also examines the impact of innovation on the IPO long-term performance by applying the OLS regression. From the perspective of innovation outcome, the number of patents has a positive impact on the post-IPO stock performance of firms. In contrast, the level of innovation input has a negative impact on the long-term performance of IPOs. Findings suggest that valuation and pricing of the two types of innovative capital significantly affect the long-term performance of firms in the IPO market.

Finally, the third study examines the role of firms' innovations in the product market and the feedback performance that firms receive through their daily operations, industry competition, and enterprise strategy in the post-IPO product market. The first part of this study utilizes the sales, profits, and capital expenditure as the proxies for the operating performance of firms in their post-IPO period to examine the impact of innovation capital on these variables in the product market. The second part investigates whether firms that have gone public in periods of higher industry innovations have become more competitive in the product market. The results show that the extent of innovation would have a significant effect on the going-public decision by firms to fund their future investments

and enhance their competitive position in the product market. Findings also suggest that firms with high levels of innovation would have better productivity and investment opportunities. Further, innovation can stimulate the firms' public finance for future investments, and thus improve their competitive position in the post-IPO periods.

Keywords: innovation, IPO market, IPO performance, product market

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THESIS BY PUBLICATION

This thesis has been prepared by the format of "thesis by publication". Chapter two through four (paper one to three) have been written and prepared as independent publications. The following publications are derived from this thesis:

Refereed Journals

Zhou, L., Sadeghi, M. The Impact of Innovation on IPO Short-term Performance – Evidence from the Chinese Markets. ***Pacific-Basin Finance Journal***, 2019, Vol 53, 208-235.

Refereed Conference

Zhou, L., Sadeghi, M., 2018. Does the Pre-IPO innovation affect the firms' Long-term performance? – Evidence from the Chinese Markets. 2018 AFAANZ Annual Conference. July 2018, Auckland, New Zealand.

Zhou, L., Sadeghi, M., 2018. Innovation and the post-IPO feedbacks in the product market – Evidence from the Chinese Markets. 6th Paris Financial Management Conference. December 2018, Paris, France.

CHAPTER 1

Introduction

1.1 Overview of the Thesis

Chinese companies have enormously benefited from the flow of capital to their country over the past four decades. China's GDP annual growth remained over 10% per year during 1978−2010. The country ranked the 8th biggest economy when it started its open-door policy in 1978. It became the second largest economy in less than four decades. However, this success story could not be sustained any longer as the growth rate started to decline after 2010. According to the Statistica report, Chinese growth rate was 6.8% in 2017 and is expected to decline to 5.8% by 2022. This suggests that, although capital plays a crucial role in the economic growth in the early stages of development when the country is undercapitalized, the marginal productivity declines over time if new investments are not accompanied by technological developments. As a result, China's "new normal" economic growth policy is based on technology transformation and generation, rather than the inflow and accumulation of capital.

In the modern global economy, innovative capital has become one of the key indicators of economic development. The formation and growth of innovation capital in a country depend on the incentives behind the individual companies' decisions to allocate resources for innovative purposes.

Theoretical background on the importance of "innovation" in generating economic development and growth is traced back to the writings of famous Austrian economist

Joseph A. Schumpeter. He saw that the driving force for development comes from the factors of production, combined with the evolutions of new technology and its commercialization. Since the publication of his book[1] in 1912, many scholars have studied or conducted empirical analyses on the role of innovations and technological advances in economic growth. They studied on the theory of economic development and considered the technological progress as an endogenous variable.

From the perspective of enterprise, investment and technological progress are the two main sources of growth over short- and long-term periods. While investment is a more essential source of growth in the early stages of economics development in a country, when companies or industries largely use unskilled labor and produce primary commodities, the role of technology in maintaining long-term growth becomes increasingly important as the marginal productivity of capital declines. Indeed, only successful R&D outcomes can generate profit and ongoing opportunities for further capital accumulation and sustainable growth. Thus, companies that achieve a dynamic optimal balance between investment spending and technological progress can survive in the long term or stay ahead of their competitors in the industry. Within an industry, innovation largely determines whether a firm can sustain its leadership position in the long term.

The purpose of a firm's technology innovation is to establish a more efficient and productive corporate operation, improve profitability, and achieve sustainable growth (Xi Jinping, 2016). However, as innovation capital is often classified as intangible assets (e.g., patents), it is hard to determine its real market value. Its value may also not be reported in the balance sheet or prospectus, causing information asymmetry for prospective

[1] The Theory of Economic Development.

investors when the company decides to go public. Information asymmetry can become more significant in the emerging economies with less transparent corporate governance and weak financial disclosure systems. Additionally, the Chinese IPO market is undergoing continuous reforms and evolutions over time with policy changes. Therefore, the information asymmetry caused by innovative capital can become an important concern for the capital market efficiency.

Although literature on IPO pricing in the financial markets is abundant, there is paucity of studies on the interaction between the IPO market and product market. Therefore, from the perspective of innovation, we divide the IPO market into three-time intervals and explore the performance of firms' innovations in the IPO market. In the first paper (Chapter 2), we investigate the effect firms' innovation on the IPO short-term performance in the Chinese market by classifying different dimensions of innovation in the pre-IPO period. In the second paper (Chapter 3), we focus on the influence of firms' innovation on the IPO long-term performance in the Chinese market by utilizing different asset pricing methods. In the third paper (Chapter 4), we extend the research from the IPO market to post-IPO product market and discuss the impact of firms' innovation on the post-IPO product market and its feedback performance in the product market.

1.2 Research Problem Statements

1.2.1 Chapter 2: The Impact of Innovation on IPO Short-term Performance – Evidence from the Chinese Markets

The first study presented in this thesis (Chapter 2) examines the impact of firms' pre-IPO innovation on their IPO short-term performance in the Chinese market. For the firm's short-term market performance, "underpricing" occurs when an IPO firm's issuing price is lower than its closing price on the first trading day, meaning that the selling price of the newly issued shares is lower than the intrinsic value. When the IPO price is too low, it simply means that the management "puts the money on the table" for the prospective investors. In other words, the IPO companies lose extra benefit they could have if the subscription price in their prospectus accurately reflected the true value of their shares.

It is widely acknowledged that the innovation capital is one of the most important assets for firms. According to an early study by Griliches (1981), investment in the innovation capital can help companies enhance their long-term returns by 200%. With the development of the market in recent years, some research has gradually emerged to explore the influence of firms' innovation on their economic decisions and activities in the capital markets. The resulting findings largely confirm that firms often decide to go public when their innovation reaches an optimal level (Pastor, Taylor and Veronesi, 2009; Bernstein, 2015). This provides the basis for our research question of how firms' innovation can affect their short-term market performance in the IPO market in China.

The phenomenon of IPO short-term underpricing has been extensively studied from different perspectives. Scholars have also conducted extensive theoretical and empirical investigations on the IPO underpricing from various angles. Studies conducted on the impact of innovation on the market performance of IPO companies are fairly recent. Their authors have used R&D expenditure or the number of patents as independent variables to examine their impacts on the IPO market performance of companies. However, in contrast to physical assets, these assets are largely intangible and contain uncertainty and risk, creating information asymmetry in the capital markets. As a result, the examination of their impacts on the IPO market performance of firms is less predictable and more complex. In many instances, the negative impact of uncertainties and information asymmetries in these capital forms offsets their positive impacts on the performance of companies in the IPO market. Therefore, the influence of various types of innovations on the IPO short-term performance of firms can be markedly different.

Moreover, majority of extant studies on the relevance of innovation to the IPO markets have been conducted in the developed countries, such as the United States. While China has recently become a country with the second largest stock market in in the world, it is still an emerging economy with a particular institutional and regulatory setting, which may not work as efficiently as in developed countries. China has also initiated the strategy of increased financial support and policies of innovation promotion. Thus, compared with the developed countries, research on Chinese market may yield different outcomes because of its distinct regulation settings.

One of the most important recent market reforms in China is the industrial policy. The effectiveness and efficiency of this policy in stimulating the innovation has been a controversial issue since its inception. This controversy also provides us with further incentives to study the role of innovation in the Chinese capital and product markets. Thus, as a part of the first paper, we also attempt to analyze the effect of industrial policy from the micro perspective of the listed firms, as well as discuss their impacts on the innovative investments in the IPO market.

The main research question in the first paper is how the level of innovation will affect firms' IPO short-term market performance. This has prompted the following sub-questions:

- Does the level of firm's pre-IPO innovation strengthen the phenomenon of IPO underpricing or reduce the extent of IPO underpricing in the Chinese IPO market?

- Since innovation input and innovation outcome create different types of information asymmetry, does this difference exert distinctly different impacts on the firm's short-term performance in the IPO market?
- How does the pre-IPO innovation affect the firm's short-term performance when under the influence of the Chinese industrial policy? Does this policy strengthen or weaken the impact of innovation in the IPO market?

1.2.2 Chapter 3: Does the Pre-IPO Innovation Affect Firms' Long-term Performance? – Evidence from the Chinese Markets

In the second study presented in Chapter 3, we investigate the effects of innovation on the post-IPO stock market performance from the long-term perspective by applying the CAPM model and Fama-French five-factor model. R&D investments have always been reported to improve firms' operating performance (Eberhart et al., 2004), create intangible assets such as patents (Kortum, 1997; Hsu, 2009), and develop new products (Cohen et al., 2013). Capital markets, however, often have problems in pricing innovation assets. Majority of investors in the Chinese capital market are retail investors. Retail investors usually have limited access to firms' information, especially the intangible capital of IPO firms in the pre-IPO period. This information asymmetry may send mixed signals to the investors, causing over- or under-reaction in the capital market. For examples, retail investors may fail to correctly evaluate a company's innovation ability, or overreact with excessive optimism towards firms' substantial patents or innovative investments. Therefore, we may categorize innovation capital according to the level of information dissemination to examine its distinct impacts on the IPO market in the long-term.

Furthermore, from the perspective of long-term market performance, we know that it is difficult for investors to make accurate judgments on the information related to intangible assets when making initial investment decisions. Such information is particularly important because it is closely related to the strategic choice of firms and the major transformation of industrial organization structure. For example, due to the budgetary constraints, market competition, and market demand, firms may not convert their patents into final products immediately after they are approved. Therefore, once the news or regulations on the development of the company's innovation prospects are publicly announced, its stock price will move accordingly. In other words, the company produces positive abnormal returns after the announcement of good news, and experiences negative abnormal returns after bad news is released. Therefore, we extend our examination of the impact of firms' innovation on the IPO market to the long-term market performance.

In summary, this study addresses the following research questions about firms' innovation in the Chinese IPO market:

- Does firms' pre-IPO innovation have a significant impact on their long-term performance in the Chinese capital market?
- How does the long-term market performance of IPO firms fluctuate according to the level of their innovation expenditure?
- Innovation input and output can generate different levels of information asymmetry in the capital markets. How does this difference influence the long-term market performance of IPO firms?

1.2.3 Chapter 4: Innovation and the Post-IPO Feedback in the Product Market – Evidence from the Chinese Markets

In the third study of this thesis, presented in Chapter 4, we utilize the IPO data from the Chinese capital market to investigate the association between pre-IPO innovation of firms and their post-IPO feedback performance in the product market. Based on the previous literature, it is widely acknowledged that an industry's technological innovations have a significant positive correlation with the volume of IPOs in that industry in the long term. Moreover, their impacts would become greater in more competitive industries (Hsu, 2014). Current study extends the literature on the firms' IPO decisions by linking *ex ante* innovations to the post-IPO feedback period in the product market. We conduct the study in two sections, pertaining to the firm's post-IPO feedback operating performance and its competitiveness in the product market, respectively.

In some industries that are undergoing technological changes, the optimal timing, pricing, and successful public offering not only depend on the individual company, but also on the competitive environment in the product market in which the firm operates. Companies that can create new technologies often face more opportunities to trade off. Start-up firms with early investments may gain more advantage in the product market. However, if a company does not have relevant technology in the product market, it is more likely to fail. These types of firms are often squeezed out of the market by their competitors which have superior technology and a stronger competitive position in the product market. Furthermore, the decision to go public contains potential risks from disclosing valuable information to the public and potential investors. This will be a major challenge for IPO firms in striking a balance between the costs and benefits of their decision. How will a new company's entry into the IPO market change its competitive position and competitiveness in the product market? What kind of feedback will the firm's innovative capital bring to the product market after its IPO? These are some of the questions we attempt to answer in this section.

Recent research suggests that companies' competitive position in the product market in the post-IPO period is highly correlated with the characteristics of their industry and the competitive position they maintain in the product market. As a result, more recent studies on IPO are no longer limited to the capital markets but also increasingly integrate with the research in the product market. In fact, the financing decision of firms to go public cannot be separated from the investment decision making in the product market, as the first decision relates to the firm's ability to cope with its competitors in the product market. Therefore, scholars are increasingly suggesting that the studies between IPO market and product market should be integrated together. For example, Spiegel and Tookes (2008) developed a model to examine the correlations between innovation, competition, and the public-versus-private financing in a company. This model revealed that firms would decide to go public only when they have superior innovations. The aim of our study on the Chinese market is to extend the existing literature in this area.

Current study specifically addresses following questions:

- Does a firm's innovation capital have a significant impact on its competitive position in the post-IPO product market? Compared with the pre-IPO period, does the firm's innovation ability strengthen or weaken its competitiveness in the product market after the IPO?
- Do the two dimensions of innovation capital (R&D and number of patents) have the same or opposite impacts on the performance and competitive position of the firms in the post-IPO product market?
- How do firms perform in the IPO market and the post-IPO product market under the Chinese regulatory settings?

1.3 Aims and Objectives

To fully explain the performance of firms' innovation in the IPO market, we examine the issue from three different perspectives. They include the short-term performance, the long-term performance as well as the feedback performance of IPO firms in the post-IPO product market. Therefore, in explaining the IPO anomalies in the emerging capital market, the aim is to help firms improve the efficiency of their resource allocation in the capital market. At the same time, we also make a comprehensive analysis on the impact of firms' innovation capability in the IPO market and product market of China. The research objectives can be divided into the following points:

(1) In the first study, we conduct a relatively detailed analysis of the relevant theories of innovation and IPO market, and illustrate the need for further research in the context of China's IPO market regulatory system. We also analyze the influence of "innovation" in China on the IPO short-term performance in general, and under the moderating effects of Chinese industrial policy. Furthermore, we extend the extant literature on the interaction between macroeconomic policy and micro-institutional mechanisms.

(2) The second study focuses on the influence of firms' innovation on their IPO long-term performance. Since China is an emerging economy in transition, its market system is still not very efficient, and the supervision mechanisms in the IPO market are constantly improving. In order to add more empirical research and augment the literature on the Chinese IPO market, we take Chinese A-share market as the research background and examine the impact and role of IPO firms' innovation ability on the stock market performance from the perspective of IPO long-term market performance. We thus not only explore the present situation of the IPO long-term market performance in the Chinese A-share market, but also discuss the empirical analysis of firms' innovation on their IPO long-term market performance.

(3) In addition to interpreting and studying on the short-term and long-term performance of IPOs, the third research objective is to analyze the effects of a firm's innovation on its feedback performance in the post-IPO product market. Drawing upon industrial economics research, we divide this study into two major parts. First, we analyze the impact of firms' innovation before the IPO on their operating performance in the post-IPO product market. Secondly, we discuss the influence of firms' innovation on their competitive position and competitiveness in the post-IPO product market to enrich the literature in this research field.

1.4 Data Collection and Methodology

(1) Research Methodology

In these three studies, we mainly adopt empirical research methodology. At the theoretical level, the analysis paradigm of general economics is utilized to demonstrate the impact of firms' innovation on the IPO market and the post-IPO product market. At the empirical level, we applied the method of cross-sectional regression, the event analysis, and the regression analysis of the Fama-French five-factor model. Our data are analyzed and managed by EXCEL VBA and STATA/MP 14.0 software.

(2) Data on IPOs and Innovations

The data from the stock market and the related financial data of the IPO firms in the capital market are mainly obtained from the CSMAR database and the RESSET database. The sample data of the listed companies from the Chinese A-share market pertains to the 2009−2016 period.

The data on the patents and R&D expenditure are collected manually from the IPO prospectus for each company. If the patent data was not reported in the prospectus, we obtained them from the official website of the State Intellectual Property Office of China (SIPO). We established two types of innovative indicators from collected data: innovation input (R&D expenditure) and innovation output (number of patents).

1.5 Key Contributions

The issues relevant to innovation have long been a hot topic in China's academic research. However, the topic of our study on the relationship between firm's innovation and IPO market is relatively unexplored. The key contributions that our study is expected to make to the current literature are presented below.

First, majority of previous studies on the relevance of innovation for the IPO market performance have been conducted in the developed countries, such as the United States, while the Chinese equity market is still an emerging economy with its own unique institutional and regulatory settings. China has also initiated the strategy of increasing financial support and incentive policies towards innovation capital to build up an innovative economy. This provides motivation for us to extend previous studies into this developing capital market.

Second, in most extant studies, researchers treated the firms' innovation capital (the R&D investment and patents) as a whole to investigate its influence on the stock markets[2]. However, Kelm et al. (1995) correctly pointed out that technological innovation is a

[2] As an example, Chin et al. (2006) examined the impact of innovation capital on the IPO performance in the Taiwan market by using the R&D expenditure and patent counts. Hirshleifer, Hsu and Li (2013) also tested the relationship between the innovation efficiency (IE), which comprised of patents and R&D, and the U.S. stock performance.

complex undertaking, which goes through the processes of start, failure or breakthrough, new technology formation, patents, promotions of the new products, etc. Investment in the research and development (R&D) is only the input to the innovative process. However, innovation input and output have their own unique features, which must be separately taken into account in research. For instance, innovation input contains a higher level of uncertainty compared to innovation outcome. Disclosure on innovation input is also highly discretionary, while the information on outcomes, such as patents, is more credible, with the endorsement of legal documents. Thus, by differentiating the two dimensions of innovation in this research, we provide a more comprehensive empirical analysis on how they influence the IPO market.

Third, in contrast to mature economies, one of the official strategic initiatives in China is to stimulate the development and growth of manufacturing through industrial policy (IP). Debate on the IP validity and efficiency in developed economies is old. Similar debates and controversies are surrounding the industrial policy in China[3]. This controversy provides further incentives for us to study the role of innovation in the Chinese capital and product markets. In our study, we not only make use of special institutional features of the Chinese economy, but also extend the investigation of the industrial policy regulations on the product market in combination with the IPO performance in the capital market.

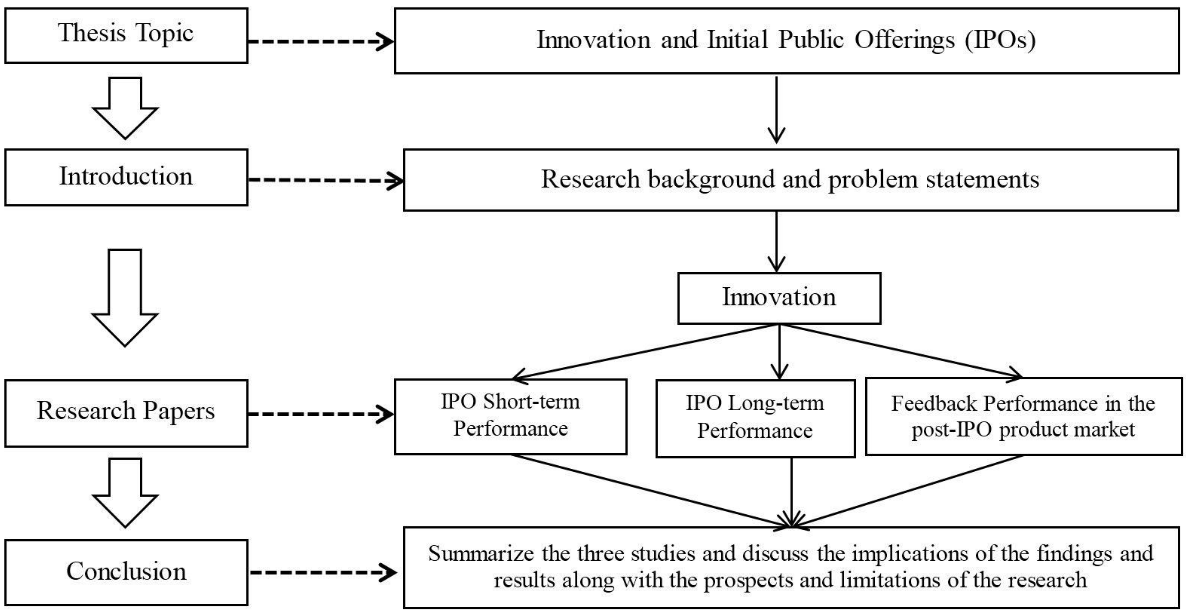
[3] For instance, Li and Zheng (2016) used the patent applications data of A-shares listed companies from 2001 to 2010 to analyze the impact of Chinese industrial policy (CIP) on corporate innovation behavior and its internal mechanisms. They found that the number of patent applications motivated by CIP increases significantly in those firms. Thus, the macroeconomic industrial policy of China, according to this study, is one of the key factors affecting the innovation in the product markets. However, Pistor et al. (2003), Chen et al. (2008), and Lin Y.F. (2014) argued that the industrial policy is a necessary tool for developing countries in order to help them to catch up with the developed economies. Still, Fan et al. (2007) and Zhang W.Y. (2016) raised their doubts about the efficiency of IP in China.

Fourth, in discussing the impact of firms' innovation on the IPO market, researchers normally investigate the IPO market short- and long-term performance. Due to the complex regulatory system of the Chinese IPO market, a new transition period between the IPO short-term and long-term performance, called the "IPO honeymoon period," has evolved, which we investigate in in this study. To the best of our knowledge, no research has been conducted on the IPO honeymoon period before. This investigation, therefore, is another key contribution of our study to the existing literature.

Lastly, this thesis constructs a bridge between product and capital markets in China. Although there are substantial studies on the product markets and stock markets in separate forms, little is known about the interaction between these two markets. We utilize the industry economics and finance theory to examine the impact of pre-IPO innovation power on a firm's IPO decision and the feedback it receives on the post-IPO period from the product market.

1.6 Structure of the Thesis

This thesis comprises of five chapters. In Chapter 2, we present paper one, in which we investigate the impact of a firm's innovation on the IPO short-term performance based on the Chinese IPO market. Chapter 3 is designated for paper two, where we examine the effects of a firm's innovation on the IPO long-term market performance in the Chinese A-share market. Chapter 4 is reserved for paper three, in which we discuss the relationship and influence between pre-IPO innovation and the firms' feedback performance in the post-IPO product market in China. Chapter 5 concludes the thesis by summarizing the main findings reported in the three papers and discussing their implications, along with the study limitations and future research prospects.



Thesis Topic
Innovation and Initial Public Offerings (IPOs)
Introduction
Research background and problem statements
Innovation
Research Papers
IPO Short-term Performance
IPO Long-term Performance
Feedback Performance in the post-IPO product market
Conclusion
Summarize the three studies and discuss the implications of the findings and results along with the prospects and limitations of the research

CHAPTER 2

The Impact of Innovation on IPO Short-term Performance – Evidence from the Chinese Markets

Abstract

Based on the regulation of the Chinese stock market, the current study explores the relationship between pre-IPO innovations with the IPO short-term performance (IPO underpricing and honeymoon period). We investigate R&D spending, characterized by information asymmetry and valuation uncertainty, which can aggravate IPO underpricing. Conversely, we found a positive signal effect for patents which may significantly reduce the extent of IPO underpricing. Therefore, public disclosure of information pertaining to innovation can help issuers to reduce their IPO costs. In conclusion, more R&D spending by IPO firms results in greater IPO underpricing, while a higher number of patents reduces the extent of IPO underpricing. Additionally, we provide extensive analysis of the industrial policy in China under which, the absolute effect of innovation input and innovation outcome on IPO underpricing were greater prior to 2014. However, considering the macroeconomic environment, the industrial policy plays an entirely different role in the Chinese capital market for IPO since 2014. Therefore, we recommend that the government makes use of industrial policy as the "visible hand" to guide the development of industry and further improves the macroeconomic environment for IPO firms.

Keywords: IPO underpricing, industrial policy, R&D, patent, information asymmetry

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Correspondence to: Lu Zhou, Department of Applied Finance, Faculty of Business and Economics, Macquarie University, NSW 2109 Australia. Email: jolly.zhou@mq.edu.au. This paper is co-authored with my supervisor Dr. Mehdi Sadeghi whose contributions accounted for 10% of the paper.

2.1 Introduction

Innovation as a key driver of the internal value chain for a company has been widely acknowledged by researchers in the capital markets. Firms raise money to invest in their research and development (R&D) activities with the aim of developing innovative products and services. In doing so, they strive to increase their market performance. Pioneering studies in this area reveal that innovation has a positive impact on the firm's value (Griliches, 1981; Pakes, 1985). For instance, Griliches (1981) used the number of patents and R&D expenditure from a sample of US companies to investigate the impact of this expenditure on the productivity of companies and found that investing in innovation can yield up to 200% return in the long term. Recent studies have attempted to shed some light on the impacts of innovation in the IPO market, with no clear finding for the role of innovation in the pricing of initial public offerings (IPOs). The results reported in the pertinent literature suggest that firms reach the apex of their innovative activities at the time of their IPOs (Bernstein, 2015). In addition, private firms often decide to go public following a breakthrough in their innovation (Pastor et al., 2009).

Extant literature has shown that highly developed financial markets stimulate innovation, as firms can gain access to more capital and cut down project evaluation costs (Brown et al., 2009; Hsu et al., 2013). However, their available evidence suggests that it is difficult to establish how innovation will ultimately impact the market value of firms. And the difficulty lies in the fact that the outcome from innovation investment is uncertain by nature, causing information asymmetry problem, thus leading to an incorrect assessment of the innovative project value. Thus, innovation capital expenditure has not been sufficient for decoding the IPO anomalies or the decisions of firms to go public despite the reliable signal it sends to the market.

As recent research indicates, to evaluate innovation capital and activities properly, market investors should use more information on the dimensions of innovation investment and R&D expenditure (Cohen et al., 2013; Hirshleifer et al., 2013). For example, Chen and Xu (2015) classified the information on the innovation activities into innovation input and innovation outcome. They argued that information from these innovation measurements may have different implications for investors. Firstly, in contrast to innovation outcomes, innovation input contains a higher level of uncertainty. Secondly, the disclosure of innovation input is highly discretionary, while the information on outcomes, such as patents, is more credible with the endorsement of legal documents. Thus, the two dimensions of information have different impacts on the IPO market.

Moreover, the majority of previous studies on the relevance of innovation for the IPO market performance have been conducted in the developed countries' markets, such as in the United States. While the Chinese equity market is now the second largest market in the world, it is still an emerging economy. Moreover, its particular institutional and regulatory settings are different from those in most of the developed countries. In addition, China has initiated the strategy of increasing financial support and incentive policies towards innovation capital to build an innovative economy. Thus, compared with mature financial systems, research on emerging market such as China is further complicated by the distinct regulation settings. This provides further motivations for us to extend previous studies into this market.

2.2 Background

Research on the stock market in different countries suggests that IPO underpricing is a worldwide phenomenon, as shown in Table 2.1. The country-level IPO underpricing overview illustrates that China has an extremely high IPO underpricing rate (Tian, 2011).

Table 2.1 Country-level First-day IPO Underpricing from 1998 to 2008

Continent	Country	Number	Mean
EUROPE	Austria	30	6.01%
	Belgium	60	10.11%
	Denmark	25	7.08%
	Finland	42	25.94%
	France	492	15.63%
	Germany	362	36.96%
	Greece	107	59.02%
	Italy	155	10.62%
	Netherlands	12	13.49%
	Norway	60	4.18%
	Poland	23	50.97%
	Portugal	8	10.65%
	Spain	20	7.95%
	Sweden	42	6.22%
	Switzerland	43	14.86%
	United Kingdom	1043	17.75%
ASIA	China	685	120.65%
	India	166	40.73%
	Indonesia	58	39.89%
	Japan	1256	58.29%
	Malaysia	307	34.04%
	Philippines	21	13.08%
	Singapore	460	26.37%
	South Korea	515	47.08%
	Thailand	141	17.35%
	Turkey	15	8.51%
NORTH AMERICA	Canada	420	47.93%
	United States	1792	33.91%
SOUTH AMERICA	Brazil	45	6.96%
	Mexico	10	7.53%
AFRICA	South Africa	7	8.85%
OCEANIA	Australia	1008	23.96%
	New Zealand	35	14.93%
TOTAL	Full Sample	9465	25.68%

Data sourced from CAPITALIQ and WIND database and collected by author.

To obtain more detailed information about the IPO underpricing in China, Table 2.2 provides the first-day abnormal returns in the Chinese A-share market from 1990 to 2016, revealing the high level of IPO underpricing of Chinese firms in the capital market. Although the yearly average first-day abnormal returns are decreasing over time, the underpricing phenomenon in Chinese A-share market still exists and the extend of new shares' underpricing phenomenon is changing with the different regulation in the Chinese market.

Table 2.2 The First-day Abnormal Returns in the Chinese A-Shares Market from 1990 to 2016

Year	N	Mean	Min	Max
1990	7	284.66%	160.00%	540.60%
1991	5	642.30%	-27.00%	1498.00%
1992	40	430.63%	0.70%	2330.00%
1993	124	292.88%	-94.00%	3550.00%
1994	110	150.18%	-96.25%	1869.00%
1995	24	95.58%	-99.02%	748.00%
1996	203	222.93%	-95.98%	4900.00%
1997	207	213.77%	-91.30%	4380.00%
1998	106	181.32%	-86.13%	3590.00%
1999	98	143.26%	7.14%	3095.00%
2000	137	150.82%	0.28%	476.77%
2001	79	132.78%	-66.00%	413.79%
2002	71	148.63%	24.78%	1356.25%
2003	67	72.03%	10.73%	227.99%
2004	100	70.14%	-9.00%	324.89%
2005	15	45.12%	2.79%	133.86%
2006	66	83.58%	0.00%	345.71%
2007	126	222.18%	32.25%	4092.00%
2008	77	114.87%	7.66%	403.54%
2009	99	74.15%	2.34%	209.73%
2010	349	41.90%	-9.91%	275.33%
2011	282	21.08%	-23.16%	198.89%
2012	155	26.55%	-26.33%	626.74%
2013	2	27.69%	-5.21%	60.58%
2014	125	43.52%	13.75%	46.19%
2015	219	44.00%	43.90%	44.16%
2016	227	44.00%	43.90%	44.09%
Total	3120	148.91%	-99.02%	4900.00%

Data are collected from RESSET database.

Some authors have used the theory of information asymmetry to study the phenomenon of IPO underpricing in the Chinese equity market. For instance, Mok and Hui (1998) first indicated that the proxies for ex-ante uncertainty signaled the pattern of A-share IPO returns from 1990 to 1993. Findings reported by Chan et al. (2004) imply that Chinese special regulation settings have amplified information asymmetry, increasing the extent of underpricing in the IPO process. Thus, due to the special regulation system in the Chinese IPO market, we first give an overview of the IPO system in this country to clarify its differences relative to the developed markets.

2.2.1 Institutional Features of Chinese IPO Auctions

The China Securities Regulatory Commission (CSRC) has highly regulated the IPO process in China. Since its establishment, this institution has implemented several reforms to improve the new share issuing system and reduce the extremely high first-day returns to make them more consistent with those in the developed countries. For example, since the establishment of China's stock market in 1990, the issuing system has changed from the initial examination approval system to one similar to the "pathway system."[4] This situation was changed later to an approval system, which is similar to the "sponsor system,"[5] and finally to the "registration system."[6] These drastic and frequent reforms are rare in the evolution of security markets in other emerging economies, or in developed

[4] The pathway system refers to the system in which the CSRC determines the number of listed shares owned by each broker, and the brokers recommend the issuers in accordance with the procedures to issue one and report another. By January 1, 2005, when the "pathway system" was abolished, a total of 318 channels were owned by 83 securities companies nationwide.

[5] The sponsor system is defined as a system in which the sponsor (broker) recommends and provides the guidance on new shares for issuers, verifies the issued documents for issuers, and assists them in establishing strict information system. The key point of the sponsor system is to clarify the responsibility of sponsor institutions and sponsor representatives and establish a responsibility investigation mechanism, which increases the content that the sponsors bear the joint liabilities in the process of issuing.

[6] In the registration system, issuers are required to provide all information about the IPO firms, especially the prospectuses. The most important feature: under the registration system, the securities issuance and examination institutions only review the registration documents in a formal way, and do not make substantive judgments on them. If the disclosure is appropriate, the securities regulatory institution cannot refuse to register on the grounds, such as the reasons that the issue prices or other conditions for the IPO firms are unfair, or the prospect of the company proposed by the issuer is not reasonable.

countries around the world. The participants in the security market have undertaken corresponding steps and necessary measures to adjust to these major reforms, affecting the operational characteristics of the market and its performance after IPO. Although trial and error changes in the Chinese issuing supervision system have resulted in a significant decline in the abnormal returns associated with IPOs, the extent of this underpricing in this country is still much higher than that found in any other country in the world.

For instance, the average underpricing rate in China during 1990−2005 was over 160%, which was the highest in the world. In 2005, the CSRC began to implement the inquiry and allotment system. As a result, the annual average IPO underpricing rate declined to 50%, increasing again in 2006, and reaching a historic peak of 193% in 2007. The underpricing rate declined to 115% in 2008 due to the Global Financial Crisis (GFC), along with the decline in the A-share index. GFC and a large number of IPOs during this period forced the CSRC to suspend the IPOs from December 2008 until June 2009. During this eight-month period, the CSRC completely abandoned window guidance of pricing. It subsequently issued *"Guiding Opinions on Further Reforming and Improving the Issuance System of New Shares"* (CSRC Announcement [2009] No. 13) as well as launched a new reform for IPO issuance system. We have used the beginning of this major market reform as the start of our sample period, during which three other important regulatory reforms for IPO pricing were implemented in 2010, 2012 and 2013, respectively.

2.2.2 Three Major Reforms of Chinese IPO Auctions in 2010, 2012 and 2013

Many factors may influence the IPO markets in China, including the administrative regulations imposed by the government. Recent regulatory changes in China aim to improve the efficiency of the IPO process, in line with the developed countries. Xu and Zhang (2015) reported nine occasions where IPOs on the China A-share market have been suspended in recent years and were reinstated again after sometimes. Two of these suspensions occurred during our sample period (July 2009−December 2016), including the longest one in the history of Chinese stock market. Period 1 covers October 2012−January 2014 (fifteen months), while Period 2 covers July 2015−November 2015 (four months). During our sample period, not only was the IPO issuing system changed, but the IPO offer market price regulation was also changed significantly, as discussed below.

In October 2010, the CSRC issued the *"Guidelines on Extending Reform of New Issue System"* (CSRC Announcement [2010] No. 26) and started the second stage of IPO system reform. With the evolution of IPO system reform, the IPO underpricing rate declined continuously.

In 2012, the CSRC issued a document titles the "*Guiding Opinions on Further Reforming the Issue System of New Shares"* (CSRC Announcement [2012] No. 10). This reform mainly aimed to strengthen information disclosure, adjust the inquiry scope and placement proportion, introduce stock issuance rules, strengthen the regulation of issuance, combat speculation, and increase the intensity of punishment for misconducts. However, this reform failed to achieve the outlined objectives. In fact, issues such as high underpricing rate, excessive raised funds, and performance deterioration persisted after the reform of 2012. Furthermore, due to the downturn in the stock market and large-scale activity of IPO self-examination and verification by the CSRC, Chinese IPOs were suspended after the last suspension of Zhejiang Shibao on November 2nd, 2012, which lasted fifteen months, the longest period in the history of A-shares.

On November 30th, 2013, the CSRC issued the "*Opinions on Further Promoting the Reform of the Issuance System of New Shares"* (CSRC Announcement [2013] No. 42), which marked the formal transition of IPO from the approval to the registration system.

The continuous evolution of the system, in a sense, has shown the gradual progress of market supervision from “government-oriented” to “market-oriented,” with no tangible achievement in the IPO reform. The abnormal returns on the initial offering day occurred irrespective of the kind of issuance system in place. However, until January 2014, CSRC rules restrained Chinese IPO first-day underpricing to 44%. This date also marked the end of the fifteen-month-long suspension and the beginning of a new period of registration issuing system.

Overall, we expect that these reforms will ultimately encourage firms to go public more prudently, improving information insemination. These discrete and substantial regulatory changes provide us with a near perfect natural experiment to examine the information content of the firms’ innovation ability and ascertain how innovative information is incorporated into asset pricing.

The present study makes a useful contribution to the existing body of literature by examining IPOs in general, and the Chinese A-share market in particular. As stated in the study of Chin et al. (2006) when examining the situation of stock market in Taiwan before 2005, we also propose that a new type of IPO underpricing in Chinese A-share market observed after 2014 is, in fact, the IPO honeymoon period. Furthermore, the introduction of industrial policy in the Chinese IPO market provides a new dimension for testing the efficiency of macroeconomic policy. The results from different periods illustrate that, prior to 2014, the Chinese IPO market was influenced by the macroeconomic environment and the innovation ability of firms, which affected industrial policy implementation. In addition, this research increases the understanding of the effects of information asymmetry theory in IPO underpricing. Specifically, our findings indicate that this theory can be applied to assess the internal value of innovative activities for firms undertaking IPOs. In other words, we demonstrate that new stock value uncertainty stems primarily from internal firm-specific factors. However, the phenomenon of IPO underpricing has rarely been investigated from the internal firm value uncertainty perspective. Therefore, based on the few existing studies on the innovation capital and IPO underpricing in developed markets (Heeley et al., 2007), in this work, we provide analysis of the relationship between two different dimensions of innovative activities of the firms and IPO underpricing in Chinese markets.

The remainder of this paper is organized as follows. In Section 3, we present the hypotheses development and relevant theoretical frameworks, while describing the data collection process, variables employed in the analyses, and research design in Section 4. In Section 5, we present the descriptive statistics results, along with the findings yielded by the main empirical regression tests and robustness tests. The last section concludes the paper by summarizing the findings reported in the preceding sections, as well as providing policy recommendations for Chinese equity markets, and suggestions for further research in this field.

2.3 Hypotheses Development and Theoretical Framework

2.3.1 Information Asymmetry and IPO Underpricing

Shares at which trading opens at the start of an IPO are deemed underpriced when the initial offer price is lower than the closing price at the end of the first day of trading, implying that the value of the shares publicly offered for the first time is lower than their real market value. If an issue offering is underpriced, the management is deemed to have "left money on the table" (Ritter, 1998) for investors to pick up; i.e., they have failed to earn extra funds that would have been obtained if the offer price better reflected the actual value of the firm. A large body of empirical evidence shows that initial public offerings are on average underpriced. The theoretical explanations of IPO underpricing put forth by scholars are typically rooted in (i) information asymmetry, (ii) institutionalism[7] and (iii) market behavior[8]. From a short-term perspective, scholars attribute IPO underpricing to asymmetric access to firm-related information, as external investors have limited information about the firms in the primary market. Thus, it is difficult for them to evaluate the true value of the shares (Carter and Manaster, 1990; Rock, 1986; Yan Gao, 2010). Others rely on the Lawsuit Avoidance Explanation[9] to elucidate the reasons behind short-term IPO underpricing. While other factors are also considered, the information asymmetry theory remains the most powerful explanation for the phenomenon of IPO underpricing (Ljungqvist, 2007).

(1) Innovation Input and IPO Underpricing

The level of R&D spending is a reliable sign of innovation activity in a company and scholars usually use this variable as a proxy for the measure of efforts to increase the innovative output in a company. However, higher R&D spending does not automatically mean success in more innovative outcomes. Innovation success depends on how managers of a company can transform the new technology to profitable commodities and services. Lev (2001) considers R&D as a high risk non-tradable property of a firm that can hardly be evaluated by the market. So, prospective IPO investors face valuation problem as they cannot rely on financial statements or prospectus to have a comprehensive view about the market value of a company. Higher R&D companies create higher level of business and financial uncertainty for investors. Aboody and Lev (2000)

[7] Due to the bespoke regulation background in China, many scholars (Liu and Xiong, 2005; Tian, 2011) claim that institutional defects are the root cause of the excessive IPO returns.

[8] In order to elucidate the development of the Chinese IPO system, Liu and Xiong (2005) drew upon the theory of behavioral finance postulates to explain the non-rational pricing in the secondary market.

[9] Tinic (1988) argued that, owing to information asymmetry between regulators, issuers, and underwriters, underpricing is an effective form of insurance for issuers and underwriters to avoid lawsuits.

asserted that insider gain is substantially higher for companies which have more intensive R&D.

It is important to note that, in the process of R&D investment, there are many uncertainties that can cause misevaluation. For example, Harri Jalonen (2012) identifies eight innovation uncertainty as a cause of misvaluation[10]. However, none of them exactly match the definition in our research. The investors' valuation uncertainty in the context of our research arises from asymmetric information between insider and outsiders of a company. This information asymmetry might be reduced or alleviated by any positive signal that IPO investors might receive, such as information about the number of patents, from a company[11]. So, valuation uncertainty, information asymmetry and signaling hypothesis concepts are complimentary to each other and provide the theoretical foundation of our study.

From the perspective of our research on Chinese market, firms with high-intensity of R&D investments may also not be considered highly innovative for two reasons: First, based on the Chinese accounting standard, firm's pre-IPO R&D investment includes the expensed R&D and capitalized R&D. In other words, the R&D investment on the firm's balance sheet also contains the expensed R&D which are not capitalized in the firm's operation (Xu et al., 2016). This exercise doesn't allow investors to get the valuable investment information from firm's pre-IPO R&D investment in the balance sheet, resulting in asymmetric information and mispricing of the new share. Second, the efficiency of R&D investment expenditure cannot be determined directly from balance sheet or prospectus of a company. Jian Zhao (2008) have pointed out that the effectiveness

[10] Including technological uncertainty, market uncertainty, regulatory/institutional uncertainty, social/political uncertainty, acceptance/legitimacy uncertainty, managerial uncertainty, timing uncertainty, and consequence uncertainty.

[11] This is also highlighted by Guo et al. (2005).

of the R&D investment is identified through firm's valuation standard system, management process and organization structure which are difficult to measure by an IPO investor. Thus, firm's R&D investment has the nature of uncertainty and can induce high level of informant deficiency in the IPO market. Based on asymmetric information theory and literature discussed above, the following hypothesis was formulated and was tested in the present study:

H_{1a}: Keeping other conditions unchanged, greater R&D expenditure of IPO firms will exacerbate the IPO underpricing.

(2) Signaling Theory of Innovation Outcome and IPO Underpricing

Technological innovation is a complex process that undergoes a series of stages, including project initiation, innovation, progress, commercialization, acquisition of patents, product launch, etc. (Kelm et al., 1995). R&D is thus the input to innovation, not the output. Firms with stronger innovation ability can adapt to the changes in the market demand, efficiently allocate the internal resources, generate new knowledge and technology, and have more patents and technical confidentiality. Patents and technical confidentiality are the important technological intangible assets of the firms. They are the direct output and product of R&D (Griliches, 1990), and can dramatically reduce the internal uncertainty pertaining to R&D activities (Lev, 2001).

Due to the widespread practice of patenting, the information asymmetry between the innovative companies and the investors becomes more aggravated. Investors cannot correctly evaluate the innovation ability of firms undergoing IPOs. Therefore, market urges firms to disclose more information on their innovation activities. The difficulty in measuring the R&D investments doesn't lie in the fact that firms do not disclose their relevant information (Lev, 2001). Voluntary disclosure is an important way for innovative companies to alleviate the information asymmetry and enhance the degree of transparency of information. Guo et al. (2004) found that most of the American biotechnology firms volunteer to disclose the R&D information when they go public to improve the transparency of their information. This directly helps firms to decrease the cost of raising capital and acquire higher value for their shares in the market. Thus, innovative firms that volunteer to disclose more R&D information will attract the attention of market participants more easily (Jones, 2007).

The benefits of disclosing innovation information to issuers include conveying positive signals to the market, which can help firms successfully go public, alleviation of uncertainty and information asymmetry of R&D, increased transparency of information, and a decrease in the cost of capital. Accordingly, the more patents the issuers have, the stronger the innovation ability is perceived to be. Further, the information disclosed in the prospectuses can help convey positive signals to the market, thus decreasing the magnitude of IPO underpricing.

Following the earlier discussion, we explain the relationships between patents and IPO underpricing in more detail here. A large number of studies in the field of innovative economics show that the patents reflecting the technological changes have a significant positive contribution to the value of firms (Hall et al., 2005). Heeley et al. (2007) stated that, when the connection between firms' innovative activities and value creation is transparent, innovative activities can decrease the information asymmetry during IPO. Hall et al. (2005) found that patents as a non-financial indicator contain more implied information than does R&D, which can be used by investors to assess the market value of R&D activities. During 2003−2014, the IPO prospectuses of around 99.5% of Chinese companies disclosed their patent information. Moreover, in most cases, detailed information about the patent number, types of patents and their names was disclosed (Zhang et al., 2016). Thus, investors think that firms with more granted patents have higher quality R&D and greater likelihood of superior performance (Lev, 2001). The hypothesis on the relationship between patent disclosure and the extent of IPO underpricing is thus presented as follows:

H_{2a}: Keeping the other conditions unchanged, a greater number of patents of IPO firms will reduce the extent of IPO underpricing.

2.3.2 A New Form of IPO Underpricing – IPO Honeymoon Period

The IPO process in mainland China is further affected by complexities of market intervention. The pricing is not only determined by the market forces, but also by the control of administrative power. The new CSRC regulation (CSRC Announcement [2013] No. 42) has put a ceiling of 44% underpricing of IPOs on the first day of listing of the new shares on the two major stock exchanges (Shanghai and Shenzhen) since 2014. This is in addition to the old price limit policy[12] of the 1990s for the 10% limit on the maximum daily increase after the first issuing day in the stock market. The two price limit policies mean that IPO stock price may move upward by 44% on the first day and then by no more than 10% daily from the second day of the IPO afterwards. In summary, in coordination with the two major stock exchanges, the CSRC has instituted this rule of IPO price increase limits of up to 44% on the first day and 10% afterwards to dampen market volatility.

[12] CSRC has required a daily increase or fall limit of 10% for all the stocks trading in the two major stock exchanges since 1996.

Table 2.3 Days of Up-limits in the Chinese Stock Market

Days of Up-limits	Mainboard						SME board						GEM board					
	2014		2015		2016		2014		2015		2016		2014		2015		2016	
	N	Avg rise%	N	Avg rise%	N	Avg rise%	N	Avg rise%	N	Avg rise%	N	Avg rise%	N	Avg rise%	N	Avg rise%	N	Avg rise%
1~10	1	43.49	0	0.00	0	0.00	2	34.51	2	151.27	0	0.00	2	50.84	1	242.48	0	0.00
11~20	10	65.23	11	115.45	4	88.62	12	54.62	7	112.30	1	119.55	19	71.99	6	133.30	0	0.00
21~30	25	175.77	50	207.33	44	205.44	15	190.13	24	246.57	23	247.61	22	188.77	39	254.54	16	271.78
31~40	3	246.81	23	443.25	44	434.53	1	405.94	9	480.75	14	451.01	7	328.92	19	565.59	39	494.76
41~50	3	701.04	6	771.15	10	616.22	1	294.17	5	1080.34	7	954.29	1	300.43	18	1055.47	23	746.35
51~60	1	1111.31	0	0.00	1	1969.33	0	0.00	0	0.00	0	0.00	0	0.00	4	1673.20	0	0.00
Total	43	210.35	90	293.98	103	355.78	31	137.95	47	356.06	45	417.97	51	161.28	87	544.91	78	523.21

Data sourced from RESSET database and analyzed by author.

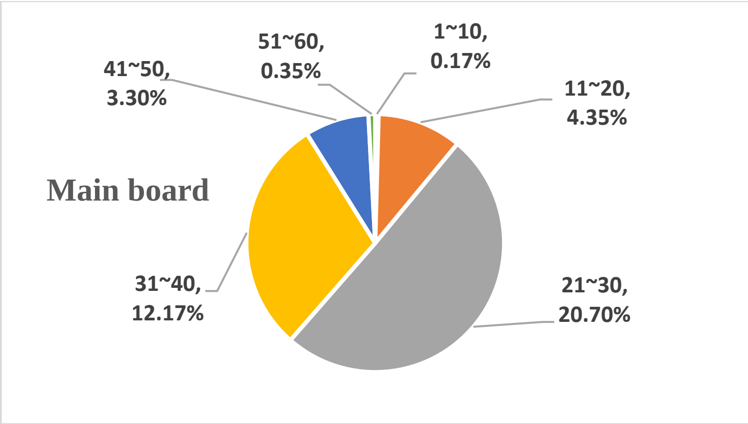

Figure 2.1 Percentage of Up-limits Days in the Main Board

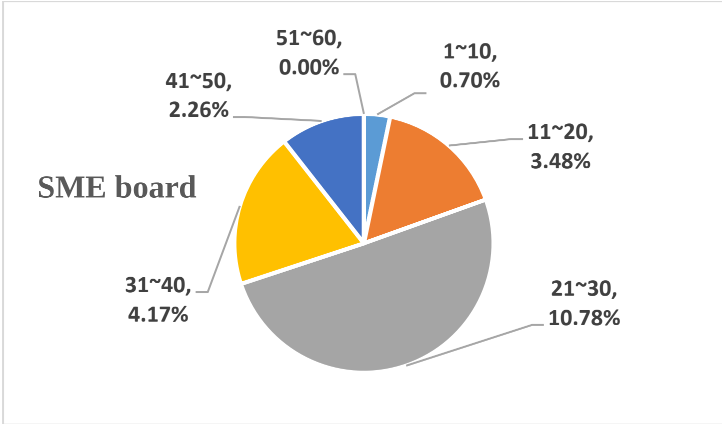

Figure 2.2 Percentage of Up-limits Days in the SME Board

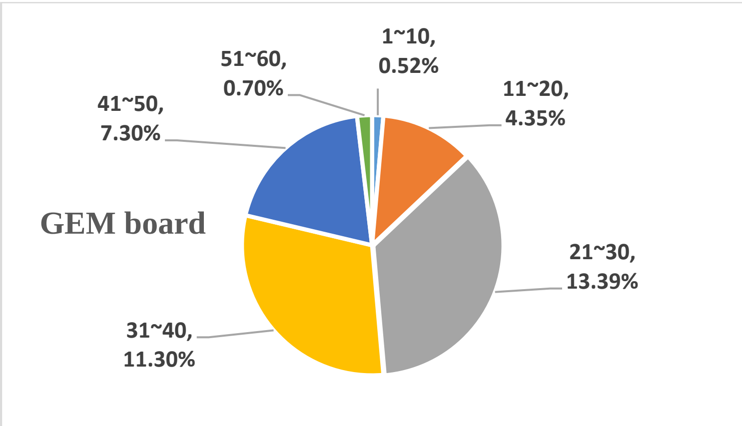

Figure 2.3 Percentage of Up-limits Days in the GEM Board

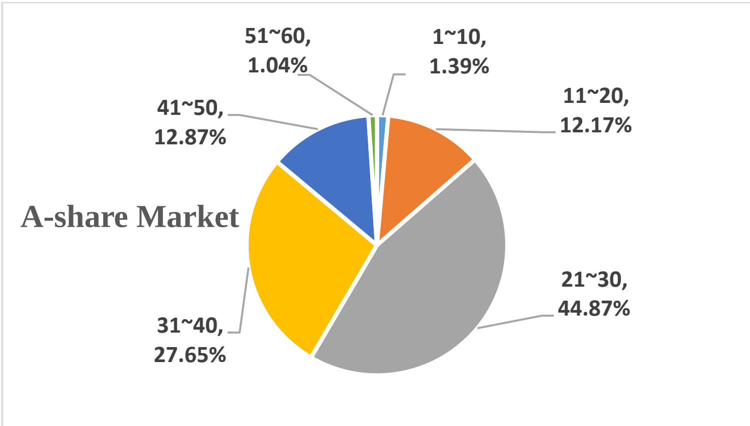

Figure 2.4 Percentage of Up-limits Days in the A-share Market

Table 2.3 contains the new shares issued from 2014 to 2016. The total number of the IPOs firms during this period is 575 which experience price up-limits, starting from the first issuing day. China Merchants Shekou Holdings Co. (001979) is the only firm that achieves the shortest two days of price up-limits after its IPO, while eight firms' reach their up-limits in less than ten days after their IPOs. The post up-limit periods for most of the IPO firms are in the range of 21~30 days, while the majority of the remaining companies reach their price up-limits between 31 to 40 days. Overall, the consecutive days of price up-limits has been a universal phenomenon for firms in the Chinese IPOs market during this study period. Figures 2.1, 2.2 and 2.3 presents the percentage (scaled by the total number of IPOs from 2014 to 2016) of up-limits days of IPOs in the three major stock exchanges in the A-share market[13]. From the pie charts, we find that two thirds of the firms from all three boards' members have around 21-40 days of price up-limits after their IPOs. However, there are more firms that their price up-limit exceeds one month in the GEM board compared with those in the other two markets. In addition, Figure 2.4 shows that 72.52% of the firms in the A-share market have 21-40 days of price up-limits after their IPOs, while 12.87% have extreme 41-50 days of price up-limits after their IPOs. We can conclude from this analysis that the new regulation of 44% up-limit has not been effective in reducing the IPO speculations on the first day, leading to a phenomenon of "fast limits" for the new IPOs. Fast-limit phenomenon occurs when few investors are willing to sell their stocks at the restricted price, leading to an insufficient number of trading. Thus, those investors who want to purchase the new stocks will not be able to do it.

[13] A-share market constitutes the main board, SME (Small and Medium-sized Enterprises) board, and GEM (Growth Enterprise Market).

The answer to the question of how the consecutive days of fast-limit phenomenon can happen requires knowledge about the stock trading norms during the price auction period in the Chinese equity mark, called "price priority" and "time priority". According to this rule, those investors who bid high can buy first, and those who lodge their trade application in the system first have the priority to trade at the same bid price. The terms for the competitive trading systems in the Chinese market are call auction[14] and the continuous auction[15]. The daily opening price for the stock is the first transaction price of the stock on that day, produced by the means of call auction. If a trade is not generated by the call auction, it will be generated by the continuous auction. Therefore, the actual trading volume during the call auction period is really limited to the one that determines the opening price of the day. The opening price may increase to the daily limit of 10% even before the continuous auction, resulting in the daily "fast limit" phenomenon which may leave the other investors out in all of the initial public offerings. While, this policy may have controlled some of the first-day abnormal returns of IPOs and dumped the new shares' speculation, Xu and Zhang (2015) point out that the newly listed stocks often induce a few successive daily limits, resulting in doubling prices of the first-day opening within 10 days after the IPOs.

Thus, the new policy actually prolonged the period of IPO underpricing, with several trading days of 10% price increase following the first day. Similar to the stock market in Taiwan[16] prior to 2005, this anomalous underpricing phenomenon is referred to as the

[14] Call auction refers to the bidding method that a centralized match is declared for a sale accepted within a period of time, and usually happens from 9:15 am-9:25 am on each trading day.

[15] Continuous auction refers to the bidding method of continuously matching the transaction declaration for all of the investors after the call auction period and happens between 9:30am-11:30am and 1:00pm-3:00pm on each trading day.

[16] The honeymoon period in Taiwan anomaly limited an increase of 7% daily stock price from the first IPO day until the prices cease to climb by 7% from the closing price of the previous day. This regulation was in force until 2005. After 2005, the security commission abolished the 7% up-limit on the first day of IPOs only.

IPO honeymoon period. Further, the two price limit policies implemented by the CSRC and two major stock exchanges prevent the IPO stock price from revealing all of the information on the initial day of the IPO offering, thus extending the honeymoon period. Taking this period into consideration, we test whether there is a correlation between a company's innovation investments (R&D spending and number of patents) and the IPO underpricing phenomenon discussed above.

Earlier studies on the honeymoon period effects on IPO underpricing in the Taiwan market allow us to extend the extant research into the Chinese A-share market with somewhat different underlying assumptions. There are two reasons to take the effects of the honeymoon period on IPOs in the Chinese stock market into consideration. First, the present approach to IPO pricing neglects the impacts of innovation capital (R&D spending and patents) and focuses on market reactions to the IPO only. However, investors' behavior may be affected by non-economic factors that ignore the underlying present value of future cash flows, reflecting the "sex appeal" of the firm or industry within which the IPO firm operates (Chin et al., 2006, p. 73). In China, retail investors who are more likely to make irrational investment decisions are the most important participants in the stock market. Second, the stabilization of the IPO market price created by the existence of what we denote as the "honeymoon" rule allows us to focus on the duration of the stock price movement to the longer-term level. Over time, after the initial market excitement prompted by the IPOs recedes, any "irrational exuberance"[17] should fade (Chin et al., 2006, p. 73). The characteristics of the "honeymoon period" in the market, thus prompt us to consider the persistence of the R&D and patent effects on the movement of stock prices post-IPO issuance. Accordingly, it is necessary to treat this

[17] Alan Greenspan, the Chairman of Federal Reserve Board, described the investor psychology and US stock market performance and activity in 1996.

period as an important transitional period for the long-term performance of stocks. This study is expected to contribute to the existing body of research by providing further evidence for the special type of IPO underpricing, which is unique to Chinese stock market.

As mentioned previously, market regulation and the honeymoon period represent another form of underpricing. The innovation capital (R&D spending and patents) also exerts different impacts on the extent of IPO underpricing. Hence, depending on the regulatory limit on the stock price movement of IPO firms after share issuance, the period of underpricing (honeymoon period) should be associated with the relative impacts of innovation capital on the extent of IPO underpricing. The corresponding hypotheses are developed as follows:

H_{1b}: *Keeping other conditions unchanged, the greater the R&D spending of IPO firms, the longer the honeymoon period will be.*

H_{2b}: *Keeping other conditions unchanged, the greater the number of patents of IPO firms, the shorter the honeymoon period will be.*

2.3.3 The Moderating Effect of Chinese Industrial Policy in IPO Market

Industrial policy in China is an instrument for the government to manage the macroeconomics of the firms and industries. The goal of the industrial policy is to help optimize the industrial structure and industrial organization, thus promoting the development of the industry as a whole. In the 1960s, Japanese scholars referred to this policy as the industrial policy, defining it as the sum of government's administrative intervention on individual industries, activities of the firms and product markets. Its aim was to support and protect targeted industries, improve the economic structure, enhance the international competitiveness and R&D activities, expand the rate of employment, and promote the balance of development of social economy and technology. Therefore, Japan may be considered as the first country in recent decades to implement an industrial policy with obvious positive effect to the innovation output. Similarly, many other developed economies, such as the United States and Australia, with the objective of free competition and optimization of resource allocation through market forces, still have their own industrial policy to promote R&D activities and encourage the innovation within firms and industries (Li, 2006; Li and Turpin, 2011).

However, in contrast to the developed countries, there has been an extensive debate on the efficiency of Chinese industrial policy. China began to implement industrial policy in the late 1980s. In the 21st century, Chinese industrial policy has significantly intervened in the microstructures of the country. Thus, as mentioned in the introduction, a large body of studies debating the feasibility of Chinese industrial policy has emerged. This has provided further motivation for us to test the efficacy of this policy in China from a different perspective.

The Chinese economic growth rate has significantly declined in the past few years. Facing this slowdown of "New Normal" economy and inspired by Japanese success, the Premier Keqiang Li proposed "innovation" to increase the marginal productivity of labor and stimulate economic growth. Yifu Lin (2002), the former World Bank vice-president, pointed out that innovation can promote the industrial and technological upgrade, as well as contribute to the development of emerging industries. This in return helps to improve the industries chain effects. Since country's innovation is based on individual firm innovation, promoting innovation at firm level results in creating a more conducive environment for economic growth in the whole country. Accordingly, it is important to study the feasibility of industrial policy from the micro perspective to help us to learn more about how it can promote firm-level innovation, upgrade industries, and thus stimulate stable growth and development in IPO markets through innovation.

A study conducted by Chen et al. (2010) examine the relationship between macro industrial policy and the micro financial institutes from the perspectives of IPOs' seasoned equity offerings (SEOs). From their detailed research, they have found that the industries under the support of industrial policy have greater growth rate in IPO financing exercise and on the number of IPO offerings than industries without the industrial policy support. Their result remains robust after controlling for the industry ROA, industry debt-to-asset ratio and the industry M/B ratio. In addition, this finding is also consistent with the results from the perspectives of SEO and bank loans, suggesting that policy-supported industries have more opportunities in SEO than the industries without any support. Their research suggests that government industrial policy plays an important role in the corporate financing behaviour. Li and Zhang (2015) also reported that firms with the support of industrial policy have a significant increase in the size and frequency of their equity financing.

Accordingly, from the perspective of the firm's R&D investment, providing subsidies and tax incentives for R&D activities in an industry and at a firm level is the most common tool of Chinese Government's industrial policy (Lu and Chen, 2004). However, the R&D investment intensity in a free market is determined by the firm's leading position in the market. In another word, a firm which has not become the industry leader will not be able to make high-intensity R&D investment. The firm's valuation standard system, management process and its organization structure is also determined by the effectiveness of the R&D investment (Jian Zhao, 2008). However, subsidies and tax incentives for firm's R&D activities can trigger high intensity R&D investment and create illusion in the IPO market about the competency of a company discussed above. In addition, due to the high uncertainty of R&D development investment outcome, investors may not have the capacity to forecast the firms' performance in the short-term IPO market. This unpredictability may even trigger greater extent of information asymmetry in the IPO market. Based on these analyses, we propose the following hypotheses on IPO underpricing:

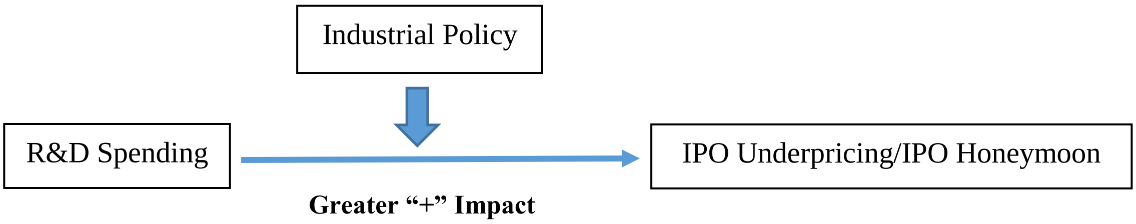

Figure 2.5 The moderating effect of industrial policy on R&D spending in IPO market.

H_{3a}: Under the industrial policy, positive impact of R&D spending on IPO underpricing will be higher.

H_{3b}: Under the industrial policy, positive impact of R&D spending on the IPO honeymoon period will be higher.

These assertions indicate that industrial policy in the forms of subsidies and tax concessions can enhance the effect of R&D spending on the IPO underpricing. In addition, for the new form of IPO underpricing that has been in place since 2014, the innovation input is also predicted to have a greater positive influence on the length of the IPO honeymoon period under the support of the industrial policy. However, in contrast to R&D spending, which is treated as input to innovation, it is hard to describe the relationships between industrial policies and patents as the outcome of innovation.

Authors of most extant literature in this field have examined the innovation behavior of firms from the perspective of innovation quality and intensity, rather than from the innovation motivation of the firms. In fact, in addition to the innovative behavior, which aims to promote technological progress and maintain competitive advantage in the industry, there also exists another type of innovation behavior, named strategic behavior. This means that firms aim to obtain the tax concessions and subsidies through governments' innovation strategy by pursuing "quantity" and "speed" of innovation (Tong et al., 2014). It is therefore essential for us to study the differences in the motivation behind innovation, as this allows us to examine the interaction between government behavior and firms' reaction in evaluating the implementation and impact of the industrial policy. Tong et al. (2014) and Li et al. (2016) found that firms stimulated by the Chinese industrial policy have an increased number of patents. This shows that the fiscal and taxation support of industrial policies makes firms more innovative with greater number of patents, therefore reinforcing the association between innovation outcome and IPO underpricing or length of IPO honeymoon period. We have defined this relationship according to the flowing figure and hypotheses:

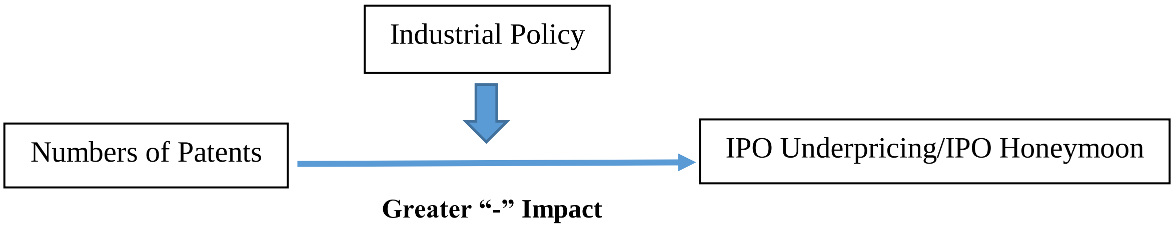

Figure 2.6 The moderate effect of industrial policy on the impact of patents on IPO market.

H_{4a}: Under the industrial policy, negative impacts of the number of patents on IPO underpricing will be greater.

H_{4b}: Under the industrial policy, negative impacts of the number of patents on the IPO honeymoon period will be greater.

2.4 Data, Variables and Research Design

China has a very poor performance in its IPO market, with extremely high first-day IPO underpricing rate compared to other countries (Yu and Tse, 2006). In the pertinent literature, this phenomenon was typically studied using the IPO data before 2012 (Lin and Tian, 2012; Chen Y. et al., 2015; Chen J. et al., 2016; Cao, 2016). However, CSRC has played an important role in the IPO market after 2012 in China. Thus, we separate our study period into two intervals to examine the association between R&D and patents of pre-IPO innovations with the extreme short-term IPO market performance. We specifically have included all IPO firms that have gone public from July 2009 to December 2016 on the A-share market of Shanghai and Shenzhen Stock Exchanges in our sample.

2.4.1 IPO Sample and Data

Our primary sample comprises 1,460 IPOs listed on the Main Board, SME Board and GEM Board between July 2009 and December 2016 in Shanghai and Shenzhen stock exchanges. We then divide this sample into two sub-periods spanning July 2009−September 2012, and January 2014−December 2016, respectively.

There are three reasons for choosing our sample in this period and dividing it into two sub-periods. First, it takes full advantage of China's first market-oriented IPO issuing reform because it covers three major reforms of Chinese IPO auctions. Second, separating this time window into two sub-periods allows us to examine the real effect of the IPO reforms in the Chinese market more accurately. The cut-off date of November 2012 takes into account the CSRC suspension of the Chinese IPO market for approximately fifteen months for regulatory transition (Cao, 2016). This transition marks the new era for the registration system of new shares, according to the CSRC Announcement 2013 No. 42. With the change in the issuing system, we expect the IPO market operations to change. Third, a new regulation imposing the 44% limit on the maximum underpricing on the first day of listing was expected to modify the first-day underpricing. However, it prolonged the time of speculation, with several trading days of high rise after the initial offering day. This urges us to use different methods to measure the IPO underpricing rate in the second sub-period to detect the predicted effects of the innovation capital on IPO underpricing rate more accurately.

2.4.2 Research Design

Table 2.2 shows the distribution of the IPO sample by the calendar year. We collected the sample data directly from the Chinese Stock Market Accounting Research (CSMAR) and RESSET databases. According to the data given in Table 2.4, 1,460 IPOs were listed on the two major stock exchanges in the Chinese A-shares market during the sample period, excluding two firms that were listed in 2013 by absorption merger.

Table 2.4 Sample Selection

Year	2009	2010	2011	2012	2013	2014	2015	2016	Total
Main board	10	28	38	26	2	43	92	103	340
SME board	59	203	114	52	0	31	45	45	549
GEM board	42	116	125	72	0	51	87	78	571
Final Sample	111	347	277	150	-	125	224	226	1460

Note: This table shows the IPOs in the Chinese A-share market from June 2009 to December 2016. Due to the IPO examination and verification of CSRC, all IPO activity was suspended in 2013. Two companies, namely Midea Group (000333) and Zheneng Electric Power (600023), were delisted through absorption merger of exchange stock. Thus, they are excluded from our sample.

Research models:

(1) For testing the hypotheses H_1 and H_2, we use the following ordinary least squares regressions for H_{1a} and H_{2a}:

$$UP_i = \beta_0 + \beta_1\ patent_i + \beta_2\ R\&D_i + \gamma_1\ control\ variables + \varepsilon_i \qquad (2.1)$$

To examine the effect of innovation on the length of the IPO honeymoon period from January 2014 to December 2016, we employ Eq. (2.2) to test the hypotheses H_{1b} and H_{2b}:

$$HM_i = \beta_0 + \beta_1\ patent_i + \beta_2\ R\&D_i + \gamma_1\ control\ variables + \varepsilon_i \qquad (2.2)$$

(2) For testing H_3 and H_4, we use the interaction terms for H_{3a} and H_{4a}:

$$UP_i = \beta_0 + \beta_1\ patent_i + \beta_2\ R\&D_i + \beta_3\ patent_i \times IP + \beta_4\ R\&D_i \times IP + \beta_5\ IP + \gamma_1\ control\ variables + \varepsilon_i \qquad (2.3)$$

(3) On the other hand, for H_{3b} and H_{4b} (IPO honeymoon period start from January 2014 to December 2016), we employ:

$$HM_i = \beta_0 + \beta_1\ patent_i + \beta_2\ R\&D_i + \beta_3\ patent_i \times IP + \beta_4\ R\&D_i \times IP + \beta_5\ IP + \gamma_1\ control\ variables + \varepsilon_i \qquad (2.4)$$

2.4.3 Dependent and Independent Variables

(1) Dependent Variables:

1) Underpricing (UP_i)

Due to the changes in the regulation period of IPO issuing system in China, we employ different calculation measures to describe the IPO underpricing rate during different time intervals.

①The first period from July 2009 to September 2012

We follow previous research and use the classic approach to calculate the level of IPO underpricing according to the following expression for the first-day return of stock "i":

$$UP_{i1} = IR_{i1} = \frac{P_{i1,t} - P_{i0}}{P_{i0}} \times 100\% = \left(\left(\frac{P_{i1,t}}{P_{i0}}\right) - 1\right) \times 100\% \qquad (2.5)$$

where the closing price of stock "i" is denoted as "$P_{i1,t}$" at the end of the first day of issue, and "P_{i0}" is the offering price.

To get a more meaningful underpricing rate, Aggarwal et al. (1993) introduced a market-adjusted formula, given below:

$$UP_{it} = IR_{i1} - M \qquad (2.6)$$

Or

$$UP_{it} = \left(\frac{\left(P_{i1,t} - P_{i0}\right)}{P_{i0}} - \frac{\left(M_t - M_{t,0}\right)}{M_{t,0}}\right) \times 100\% \qquad (2.7)$$

where "$M_{t,0}$" refers to the closing price of the market index on the day "0" which is the day before the first trading day. We apply their proposed market-adjusted IPO underpricing approach to the initial empirical test of IPO underpricing (UP1) level in our study.

②The second period from January 2014 to December 2016

This period is marked by the price limit policy in the Chinese A-share Market, for the duration of first issuing day to the IPO stock price closing day when price rise is below or equal to 10% (the maximum up-limit rate). According to Table 2.3, the maximum duration of price increase observed in our sample is 59 days. Therefore, it is not rational to calculate the IPO underpricing rate for this period according to discrete pricing expression in Eq. (2.7). According to Beatty and Ritter (1986), Chin et al. (2006), and Zhang and Liao (2011), if the closing bid price on the first day of public trading is not available for all cases in the conventional function used for IPO underpricing, we can apply a continuous price adjustment approach between primary and secondary market to capture the price changes after IPOs. Thus, our final operational measurement of underpricing in this period is defined as follows:

$$UP2 = \left(\ln\left(\frac{P_{i,t^*}}{P_{i0}}\right) - \ln\left(\frac{M_{i,t^*}}{M_{t,0}}\right)\right) \times 100\% \qquad (2.8)$$

where $P_{i,t}$ is the closing price on the t^{th} day after the initial public offering, P_{i0} is the offering price, $M_{i,t}$ is the concurrent market index at the end of trading day, $M_{t,0}$ is the market index at the offering day, and t^* is the last trading day when the IPO stock closed at a price below or equal to the maximum up-limit of 10%. We thus use the market index to obtain the market-adjusted returns of IPO firms from January 2014 to December 2016. Then, we apply continual price adjustment method given by Eq. (2.8) to calculate the market-adjusted abnormal returns on the first day of trading for the public offering of (UP2).

2) Honeymoon period (HM_i)

The IPO honeymoon period (HM_{it}) is a period during which the IPO stock price moves upward by 10% relative to the previous day's closing price. This period is terminated when the new share's closing price becomes lower than the maximum limit price of 10% relative to the previous day's closing price (Chin et al., 2006). The honeymoon period (HM_{it}) length can be calculated as follows:

$$HM_{it} = (t^* - t_0) + 1 \qquad (2.9)$$

where t^* is the last trading day when IPO stock price closes below the 10% maximum up-limit, and t_0 is the initial offering day.

(2) Independent Variables:

1) Innovation variables

①Innovation input (R&D)

According to Xu et al. (2016), innovation input is measured by research and development—R&D intensity—calculated as R&D investment scaled by total assets. We manually collected the two-year R&D investment and total assets data from the IPO prospectuses, and subsequently used two-year average R&D investment in the pre-IPO period of firms to measure the final R&D intensity.

②Innovation outcome (Patents)

As mentioned earlier, patents are an output of innovation capital in the process of firm's production (Chen and Xu, 2015). Thus, we use the number of patent applications and acquired patents stated in the IPO prospectuses in the pre-IPO period. We then apply the logarithm of numbers of patents as the index of the measurement of innovation output in our model.

2) Variable of industrial policy

To measure the Chinese industrial policy, we employed the method developed by Chen et al. (2010), Lu and Han (2013), Zhu et al. (2015) and Li and Zheng (2016). The industry development plan is included in the "The Five-Year Plan"[18] and these authors used it to measure the Chinese industrial policy. They separated the industries according to the key words of "stimulate" and "support" in the plans. Moreover, based on extant literatures, the most common method to measure the industrial policy is utilizing a dummy variable (Chen et al., 2010; Li and Zheng, 2016). The industrial policy in the later study covers the "11th Five-Year" (2006−2010), "12th Five-Year" (2011−2015), and "13th Five-Year" (2016−2020) periods proposed by the Central Committee of China. We followed their method to generate our variable for the industrial policy. First, we selected the industries which are supported by the "Five-Year Plan". According to previous studies procedures, if an industry is tagged with the two key words of the "stimulate" and

[18] "The Five-Year Plans" provide "the outline of the national five-year economic and social development of People's Republic of China." Thus, they are an important part of national long-term economic plan in China. The plans mainly focus on the development of national major construction projects, productivity distributions, national economy allocations, etc., in order to improve the national economy in the long term.

"support", we considered that industry as the policy-supported industry in our study. Second, since our sample data included the year of 2016, we extended the industrial policy to the period of "13^{th} Five-Year Plan" (2016-2020). Thus, we divide the industries and the listed firms into three groups. Two groups comprise of industries that are explicitly stimulated and supported by the industrial policy, and the other group includes the industries that are not affected by the policy (Appendix A). We employ a dummy variable with the value of IP = 1 for industries with the policy stimulation and support, and IP = 0 for industries with no support.

Additionally, to examine the correlation between innovation and IPO short-term performance under the effect of industrial policy, we allow the patents and R&D coefficients to change systematically through dummy variables that represent the correlation between industrial policy and patents and R&D spending, respectively. For instance, with three groups—two groups of the IPO firms belonging to the industries stimulated and supported by industrial policy (coded 1), otherwise does not have any policy support (coded 0)—we test the hypotheses H_3 and H_4 according to Eq. (2.3) and (2.4), respectively.

(3) Control Variables:

1) Venture capital (VC): Gompers (1996) asserted that the younger the venture-capital firms, the higher the level of IPO underpricing rate the investment firms will have. A more recent research by Salim et al. (2012) indicates that venture-capital firms with diverse features are expected to have higher IPO underpricing rates. Finally, Zhang et al. (2016) have found that the listed firms with venture capital have a relatively low and statistically insignificant IPO underpricing rate. However, debate on the relationship between venture capital and IPO underpricing is not over yet. Current paper examines the relationship between venture capital and IPO underpricing in the Chinese market. We do

so by including a dummy variable in the model. If the IPO firm has one or more venture capital firms before going public, the VC will be coded as 1, and 0 otherwise.

2) Offer Price (Price): According to Benveniste and Spindt (1989), lower IPO offer price is a compensation offered by the underwriters to well-informed investors for disclosing their information about the true value of the new shares. Huang (2005), also, suggest that the offer price of new IPO is inversely related to the IPO performance. Thus, we use the offer price of each IPO firm as another control variable in our study.

3) Trading Volume (Volume): Lowry (2003) indicated that IPO trading volume has a positive impact on the firm's demand for capital and the level of investor's sentiment. According to Baker and Wurgler (2007), firms with higher trading volume indicate that investors are more optimistic about the new issues and are more likely to trade in the market. Thus, we utilize the logarithm of IPO trading volume to control for the investor sentiment effect.

4) Size (Asset): Previous research indicates that larger firms are expected to have less information asymmetry (Barth and Kasznik, 1999). Therefore, we will use the logarithm of total assets one year before IPO to control for the size effect.

5) First-day turnover (Turnover): According to the study conducted by Loughran and Ritter (2002), there is a direct relationship between expected return and the first-day turnover. Baker and Wurgler (2007) use the turnover as one of the essential proxies for the investor sentiment in the market. Following previous studies, we consider IPO first-day turnover rate as another proxy for the investors' sentiment to control the effect of this variable in our study.

6) Lottery rate (Lottery): Li (2006) found that the IPO underpricing is negatively correlated with the lottery rate. Accordingly, the lottery rate of online issue of IPO stocks will be controlled in our study.

7) Total proceeds (Proceeds): According to Li (2006), the IPO underpricing rate is also negatively related to offering size of the issuance. We thus apply the logarithm of total proceeds (total issue volume multiplied by the issue price) to control for the IPO underpricing.

8) Age of the firm (Age): As authors of existing studies acknowledge that the age of firm plays an essential role in its organizational outcomes, especially its performance (Filatotchev and Bishop, 2002). We have measured the age of a firm from the date of its establishment to the date of its IPO.

9) Underwriter reputation (UW): Previous research indicates that underwriter reputation has an important effect on IPO underpricing (Carter and Manaster, 1990; Higgins and Gulati, 2000; Song et al., 2014). The reported findings largely indicate that firms with more prestigious underwriters during their IPOs tend to have lower IPO underpricing rate. We follow these studies and include a dummy variable in our model to measure the effect of underwriter reputation on the IPO underpricing rate. Thus, firms with at least one of the Top 10 underwriters[19] will be coded as 1, and 0 otherwise.

2.5 Results

2.5.1 Descriptive Statistics

[19] According to the CSRC report of the net income of securities firms on the underwriting and sponsoring during 2006-2016.

Table 2.5 presents the descriptive statistics for the final sample of 1,356 IPO firms.[20] The mean IPO underpricing rate during the 2009−2012 period is 0.3618, which is higher than the mean (0.2760) for the 34 countries examined by Lin and Tian (2012). Moreover, the maximum underpricing rate during 2009−2012 is 6.2491. The mean underpricing rate from 2014−2016 is 1.3740. The average IPO honeymoon period length is around 30 days, while the minimum is 10 days. Compared with the honeymoon period of the IPO market in Taiwan before 2006, the mean length of the honeymoon period in Chinese A-share market is nearly 24 days longer. In addition, the longest IPO honeymoon period of nearly two months (59 days) is noted for Haitian Precision Machinery (601882). However, compared with the maximum underpricing rates between UP1 and UP2, we find that the IPO underpricing rate after 2014 is around 3.2230, which is less than that in the period before 2014. It seems that the first-day issue price limit policy (44%) from 2014 onwards has reduced the extremely high rate of underpricing. However, it has generated a new form of IPO underpricing that extends the first-day underpricing phenomenon to a honeymoon period with a substantial increase in the average IPO underpricing rate in consecutive days.

Additionally, for the innovation capital, the average number of the innovation output (patents) is 70 counts, with 7,713 counts recorded for BYD Company (002594). In comparison to other markets, the number of patents filed by IPO firms is very high in China. For example, Heeley et al. (2007) reported that the average number of patents of US firms before IPO is about 6. According to Chin et al. (2006), the mean number of patents of IPO firms in Taiwan market is about 1. Thus, the relatively high innovation

[20] From the 1,460 firms included in the original sample, we removed firms with no prospectuses and firms without R&D investment or patents. In addition, we treat the patents as 0 only if the firm does not have patents. We finally screened out 1,356 IPO firms in our research sample. The number of IPO firms in the 2009 to 2012 sub-sample is 824, while the remaining 532 are in the 2014 to 2016 sub-sample.

output in the Chinese A-share market shows that the innovation ability of IPO firms is strong. It is also be growing due to the encouragement and support of the industrial policy.

Table 2.5 Descriptive Statistics

Variables	N	Mean	Std. Dev.	Min	Max
UP 1	824	0.3618	0.4477	-0.2022	6.2491
UP 2	532	1.3740	0.5523	0.1210	3.0261
HM	532	29.8477	9.0548	10	59
Patents	1,356	70.4204	270.4758	0	7713
(Patents+1)[1]	1,356	3.1836	1.4642	0	8.9508
R&D	1,356	0.0672	0.5883	1.93E-05	19.9749
VC	1,356	0.6851	0.4646	0	1
Price	1,356	21.8159	13.9507	1.5	148
Volume	1,356	2.55E+07	1.76E+08	1500	4.17E+09
Asset[1]	1,356	20.2798	1.0881	15.9441	29.8151
Turnover	1,356	0.4297	0.3731	0.0001	0.9592
Lottery	1,356	0.0104	0.0241	0.0001	0.6552
Proceed[1]	1,356	20.0475	0.7118	17.4714	24.0422
Age[1]	1,356	2.2355	0.6192	0	3.5553
UW	1,356	0.4565	0.4983	0	1

Note: This table presents descriptive statistics for variables used in this study, including observations (*N*), mean, standard deviation (*Std. Dev.*), minimum value (*Min*) and maximum value (*Max*). *UP 1* refers to the market-adjusted IPO underpricing ratio from 2009 to 2013. *UP 2* refers to the market-adjusted IPO underpricing ratio from 2014 to 2016. *HM* refers to the number of days from the IPO stock issue day to the last trading day when the price closes below 10% maximum up-limit price. *Patents* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *RD_1* and *RD_2*. Control variables include VC (venture capital), Price (offer price), Volume (trading volume), Asset (total assets), Turnover (first-day turnover), Lottery (lottery rate), Proceed (total proceed), Age (age of firm) and UW (underwriter reputation). [1] Logarithm.

2.5.2 Univariate Analysis

To further explore the correlations among the variables in our study, we computed Pearson correlations, which are presented in Table 2.6. The results show that the innovation outcome of patents has a statistically significant (at the 1% level) negative correlation with both IPO underpricing and the honeymoon period length from 2009 to 2016. This finding is consistent with the hypotheses H_{2a} and H_{2b}, suggesting that firms with more patents before IPO experience lesser extent of IPO underpricing and a shorter honeymoon period after the IPO. In contrast, the innovation input associated with R&D and the honeymoon period length from 2009 to 2016 are positively correlated with IPO underpricing, in line with hypotheses H_{1a} and H_{1b}. In addition, the relationship between R&D and IPO underpricing is statistically significant at the 10% level during 2009−2012 period, and at 1% level after 2013, implying that firms with greater innovation input before IPO suffer greater extent of IPO underpricing and a longer honeymoon period after IPO. In addition, the correlation between R&D and the number of patents is near zero in the table. However, R&D intensity is an innovation input and in a free market economy is theoretically linked to the number of patents which is regarded as the innovation output. The patent count is a measure of productivity and source of information for companies to make the allocation of R&D resource more efficient. As a result, the near-zero correlation, with a negative interactive trend in the relationship between the number of patents and R&D in our study, suggest that firms are getting fewer patents from their more recent R&D expenditure due to decline in the "effectiveness" or productivity of their investment in innovation.

To fully explain the correlations among innovation outcome, innovation input, IPO underpricing and IPO honeymoon period length, we further classify our IPO sample into high and low groups regarding their median R&D investment and the number of patents. The data in Panel A shows that the numbers of low-R&D firms and high-R&D firms are the same in our sample. However, in Panel B, there are 86 IPO firms which do not have any patent counts before their IPOs, indicating that some firms with R&D input may have produced the patent outcomes with a time lag. This is normal, as patents are typically granted at a later stage of the R&D process. According to the results reported in Table 2.7, the IPO underpricing rates, honeymoon period length, and stock performance of the group characterized by high R&D investment for both samples (2009−2012 and

2014−2016) outperforms those of the low R&D investment group at 10%, 1% and 1% levels of significance, respectively. In contrast, the results in Panel B show that the IPO underpricing, honeymoon period length, and stock performance of the high patents group are significantly below those of the low patents group at 5%, 1% and 5% levels of significance, respectively. These findings support hypotheses H_1 and H_2. Therefore, the level of firm's innovation ability is highly correlated with the extent of its IPO underpricing and the IPO honeymoon period length in the Chinese A-share market.

Table 2.6 Pearson Correlation of the Variables

Variables	UP 1	UP 2	HM	(Patents+1)[1]	R&D	VC	Price	Volume[1]	Asset[1]	Turnover	Lottery	Proceed[1]	Age[1]	UW
UP 1	1													
UP 2	.	1												
HM	.	0.9051***	1											
(Patents+1)[1]	-0.0962***	-0.1483***	-0.1225***	1										
R&D	0.0478*	0.1842***	0.1780***	-0.0300	1									
VC	-0.0213	0.0402	0.0301	0.0323	0.1284***	1								
Price	-0.2031***	-0.3963***	-0.3878***	0.1109***	0.1193***	-0.0086	1							
Volume[1]	0.1693***	0.6491***	0.5602***	-0.1580***	-0.1259***	-0.1127***	0.3228*	1						
Asset[1]	-0.1188***	-0.1859***	-0.1485***	0.2350***	-0.3157***	-0.0632**	-0.2154*	0.0212	1					
Turnover	0.5946***	-0.3196***	-0.3017***	-0.2104***	-0.0592**	-0.1010***	0.3119**	0.8791**	-0.2020***	1				
Lottery	-0.2369***	-0.6332***	-0.5615***	-0.0406	-0.0319	-0.0477*	0.2034*	0.2284*	0.1696***	0.0758***	1			
Proceed[1]	-0.2997***	-0.4631***	-0.4239***	0.0899***	-0.1415***	-0.0757***	0.4001*	0.4132**	0.6235***	0.1493***	0.2969***	1		
Age[1]	0.0193	0.0417	0.0381	0.0681**	-0.0086	0.0330	-0.2122	-0.3901	0.0007	-0.3441***	-0.1394***	-0.2624***	1	
UW	-0.0672*	-0.0412	-0.0239	0.0534**	-0.0058	-0.0130	0.0170	0.0450	0.1144***	0.0003	0.0049	0.1496***	-0.0463*	1

Note: This table presents the pearson correlation of the variables used in this study. *UP 1* refers to the market-adjusted IPO underpricing ratio from 2009 to 2013. *UP 2* refers to the market-adjusted IPO underpricing ratio from 2014 to 2016. *HM* refers to the number of days from the IPO stock issue day to the last trading day when the price closes below 10% maximum up-limit price. *Patents* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of RD_1 and RD_2. Control variables include *VC* (venture capital), *Price* (offer price), *Volume* (trading volume), *Asset* (total assets), *Turnover* (first-day turnover), *Lottery* (lottery rate), *Proceed* (total proceed), *Age* (age of firm) and *UW* (underwriter reputation). [1] Logarithm. ***1% significance level, **5% significance level, *10% significance level.

Table 2.7 A Univariate Analysis of High and Low Innovation Capitals on IPO Short-term Performance

Panel A: A comparative result regarding high and low R&D investments						
Variables	Group by R&D	N	Mean	High-Low	T-value	P-value
UP 1	High	412	0.3921	0.0606	1.8769	0.0609*
	Low	412	0.3315	0.0606		
UP 2	High	266	1.4790	0.2100	4.4211	0.0000***
	Low	266	1.2690	0.2100		
HM	High	266	31.3811	3.0667	3.9289	0.0001***
	Low	266	28.3144	3.0667		
Panel B: A comparative results regarding high and low logarithm of patents						
Variables	Group by (Patents+1)[1]	N	Mean	High-Low	T-value	P-value
UP 1	High	383	0.3157	-0.0862	-2.1205	0.0343**
	Low	441	0.4019	-0.0862		
UP 2	High	252	1.2801	-0.1785	-2.6451	0.0084***
	Low	280	1.4586	-0.1785		
HM	High	252	27.9801	-3.5485	-2.3070	0.0214**
	Low	280	31.5286	-3.5485		

Note: This table presents the univariate analysis of high and low innovation capitals on IPO short-term performance. *UP 1* refers to the market-adjusted IPO underpricing ratio from 2009 to 2013. *UP 2* refers to the market-adjusted IPO underpricing ratio from 2014 to 2016. *HM* refers to the number of days from the IPO stock issue day to the last trading day when the price closes below 10% maximum up-limit price. [1] Logarithm. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

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2.5.3 Empirical Analysis

(1) Innovation Ability and IPO Short-term Performance

1) Innovation input and IPO underpricing

Table 2.8 presents the impact of IPO firm's innovation ability in the pre-IPO period on the extent of the IPO underpricing when a firm goes public. Consistent with our predictions, the results yielded by Model 1 to 6 indicate that greater innovation input (R&D investment) leads to a higher extent of IPO underpricing (UP1, UP2) at the 10% and 1% significance level, respectively. These results support H_{1a}, indicating that greater capital investment into R&D by firms before their IPOs will lead to greater information asymmetry, thus triggering greater extent of IPO underpricing when they go public.

2) Innovation outcome and IPO underpricing

From the perspective of innovation outcome, Model 1 to 6 shown in Table 2.8 reveal that firms with greater innovation outcome (patents) before the IPO experience lower extent of IPO underpricing during 2009−2012 and 2014−2016 at the 10% and 1% significance level, respectively. These results are consistent with H_{2a}, suggesting that the firms that have more patents will be less affected by IPO underpricing. This finding also indicates that the innovation outcome of patents related to the innovation ability of IPO firms can send a positive signal to the market, effectively reducing the information asymmetry of the R&D investment in IPO firms, and thus reducing the extent of IPO underpricing. Consequently, issuers prefer to release the innovation outcome (e.g., number of patents and patent applications) in their IPO prospectuses before going public. This should help them to realize and evaluate the value of their firms correctly, effectively reducing the cost of going public.

3) Innovation ability and IPO honeymoon period

Results yielded by Model 7 to 9 show a positive relationship between innovation input and the IPO honeymoon period length at the 1% significance level. Hence, the greater the innovation input, the longer the honeymoon period. Different from the innovation input, the innovation outcome related to the number of patents has a negative correlation with the IPO honeymoon period length at 1% significance level, suggesting that firms with more patents before IPO experience a shorter IPO honeymoon period after IPOs. These results are consistent with hypotheses H_{2a} and H_{2b}.

4) Control variables

From the perspective of control variables, venture capital (VC) has a positive impact on the IPO underpricing. However, consistent with the findings reported by Zhang et al. (2016), it is not statistically significant at the conventional levels. The coefficient for the underwriter reputation (UW) is also positive but not statistically significant. The size of firms (Asset) has a positive influence on both the IPO underpricing rate and the honeymoon period length at the 1% significance level. The effect of total proceeds (Proceeds) on both IPO underpricing and honeymoon period length is negative and statistically significant at the 1% level. Additionally, the impacts of firm's age (Age) and firm's offer price (Price) on IPO underpricing are different in the two sample periods. First, from the perspective of the firm's age, the results yielded by Model 1 to 3 show that this variable has a positive impact on IPO underpricing during 2009—2012 at the 1% significance level. However, from 2014 to 2016, when the first-day 44% return up- limit is imposed, the age of firm does not have a significant influence on IPO underpricing and the honeymoon period length. Second, from the perspective of firm's offer price, we find that this variable does not have significant influence on the IPO underpricing during 2009—2012. For the 2014−2016 period, our findings show that the offer price has a statistically significant inverse relationship with both IPO underpricing and the honeymoon period length shown in the Model 4 to 9 at the 1% significance level. This finding suggests that the lower is the offer price of a firm, the higher is the increase in the IPOs underpricing. Furthermore, the lottery rate (Lottery) of firms shows a negative and significant effect on the IPO underpricing and honeymoon period. From the Model 4 to 9, this negative effect becomes stronger from 2014 onward at the significant level of 1%. Therefore, the higher the investors' expectations, the greater the extent of IPO underpricing is expected to be. Moreover, firm's first-day turnover rate (Turnover) and trading volume (Volume) have significantly positive impact on the IPO underpricing and honeymoon period. For firm's turnover, the results from Model 1 to 6 present a significantly positive effect on the firm's IPO underpricing during 2009 to 2016 at the 1% significant level. However, according to Model 7 to 9 the relationship between firm's first-day turnover and IPO honeymoon period after 2014 is positive, but statistically insignificant. In contrast, firm's trading volume, as another proxy for the investor sentiment, exhibit a significantly positive influence on the IPO underpricing and honeymoon period during 2009 – 2016 at the 5%, 1% and 1% significant levels, respectively.

We used variance inflation factors (VIF) to test the possible existence of multicolliniarity between independent factors. Our result suggests that all VIF coefficients of the variables in the models are less than five, and the mean VIFs are all below two for Model 1 to 9, providing evidence that the regression results are not affected by multicollinearity.

(2) Classification Analysis

To further explore the impacts of firm's innovation on the IPO short-term performance, we classify our sample firms into different groups according to the level of their innovation abilities. We utilize the 35th and 65th percentile of our total sample to classify the two innovation capitals of the IPOs into high-, middle- and low- groups, respectively. The sample firms based on R&D spending have three groups of high, middle and low. And firms based on patent counts also have three corresponding classifications of high, middle and low groups. Thus, we get nine groups of IPO firms with different levels of innovation capital to test the impact of innovation on the IPO short-term performance. Table 2.9 exhibits a cross classification influence of high, middle and low innovation capital on IPO short-term performance from 2009 to 2016. We first estimated the mean values of IPO underpricing (UP1 and UP2) and IPO honeymoon period (HM) for different groups of innovation capital. Then, calculated the T-values and P-values for the difference between the large and small number of patents and the difference between high and low R&D. Results indicate that IPO firms with high R&D intensities perform a higher degree of IPO underpricing and a longer honeymoon period than those in the middle and low R&D groups. Conversely, vertical results in Table 2.9 support the hypothesis that IPO firms with a large number of patents have a lower extent of IPO underpricing and a shorter honeymoon period than those in the medium and small number groups. In order to conduct more investigations, we further undertake a regression analysis based on the different groups of innovation capital.

Table 2.10 presents the regression results of the impact of the innovation capital on the IPO short-term performance of companies with different levels of high-R&D, middle-R&D, and low-R&D intensities from model 1 to 3. The R&D investment in the high-R&D group shows a significantly positive impact on the IPO underpricing and honeymoon period at the significant levels of 10%, 1% and 5%, respectively. However, the coefficients for the middle-R&D and low-R&D groups do not have any statistical significance at the conventional levels. This finding also supports the hypothesis that more R&D investment would cause higher level of information asymmetry, accompanied by more IPO underpricing and longer honeymoon period.

From the perspective of innovation outcome, Table 2.11 also classifies the sample firms into high-patents, middle-patents and low-patents groups. Compared with the middle-patents (Model 4 to 6) and low-patents groups (Model 7 to 9), the innovation outcome from the high-patents group (Model 1 to 3) has a significantly negative effect on the IPO underpricing and honeymoon period at the significant levels of 5%, 1% and 1%, respectively. This negative impact gradually becomes less significant as we move from Model 1 to 9, ending with insignificant effect in the low-patents group. On the other hand, the R&D investment does not have any statistically significant impact on the IPO short-term performance in the high-patents group. This impact becomes gradually significant as the level of patents decrease, supports the signal effect of this innovation outcome. Our finding suggests that firms with high level of innovation outcome send a positive signal to the market for alleviating the level of information asymmetry caused by the firm's R&D investment in the pre-IPO period. In doing so, it could thereby decrease the extent of underpricing and length of honeymoon period in the IPO market. Finally, the estimated coefficients for the control variables in both Table 2.10 and Table 2.11 show relatively similar effect compare to their corresponding counterparts in Table 2.8.

Table 2.8 Regression of Innovation Capitals on IPO Short-term Performance

VARIABLES	UP 1			UP 2			HM		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
(Patents+1)[1]	-0.0146*		-0.0160*	-0.0467***		-0.0458***	-0.6205***		-0.6056***
	(0.093)		(0.083)	(0.000)		(0.000)	(0.004)		(0.003)
R&D		0.5568*	0.6184*		3.0180***	2.9972***		51.7498***	51.4748***
		(0.098)	(0.099)		(0.000)	(0.000)		(0.000)	(0.000)
VC	0.0162	0.0128	0.0127	0.0694*	0.0389	0.0515	0.9620	0.4881	0.6543
	(0.471)	(0.569)	(0.572)	(0.058)	(0.274)	(0.143)	(0.159)	(0.461)	(0.321)
Price	0.0024	0.0025	0.0023	-0.0145***	-0.0148***	-0.0146***	-0.2333***	-0.2364***	-0.2344***
	(0.176)	(0.173)	(0.192)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volume[1]	0.1122**	0.1143**	0.1099**	0.1436***	0.1359***	0.1356***	1.7646***	1.6329***	1.6283***
	(0.035)	(0.033)	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset[1]	0.0578***	0.0582***	0.0639***	0.0296	0.0756***	0.0865***	0.6137	1.4466***	1.5896***
	(0.007)	(0.007)	(0.003)	(0.275)	(0.006)	(0.002)	(0.225)	(0.005)	(0.002)
Turnover	0.7712***	0.7764***	0.7719***	0.8894***	0.8524***	0.8926***	7.7157	7.2405	7.7709
	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.001)	(0.155)	(0.170)	(0.138)
Lottery	-0.6539*	-0.6156	-0.6649*	-23.4116***	-23.9959***	-25.1013***	-372.0535***	-386.4805***	-401.0724***
	(0.099)	(0.120)	(0.094)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Proceed[1]	-0.2269***	-0.2293***	-0.2280***	-0.1224***	-0.1695***	-0.1604***	-2.3305***	-3.1029***	-2.9832***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
Age[1]	0.0448**	0.0461**	0.0463***	-0.0588	-0.0395	-0.0368	-0.8855	-0.5434	-0.5068
	(0.012)	(0.010)	(0.009)	(0.128)	(0.294)	(0.322)	(0.219)	(0.438)	(0.467)
UW	-0.0035	-0.0051	-0.0033	0.0284	0.0218	0.0242	0.6324	0.5286	0.5605
	(0.872)	(0.813)	(0.876)	(0.385)	(0.493)	(0.439)	(0.299)	(0.371)	(0.340)
Constant	2.3346***	2.3994***	2.2883***	5.2243***	4.8079***	4.551***	90.0414***	81.8688***	78.4705***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF	1.95	1.95	1.95	1.86	1.94	1.98	1.86	1.94	1.98
Observations	824	824	824	532	532	532	532	532	532
R-squared	0.5467	0.5464	0.5482	0.5704	0.5936	0.6071	0.4540	0.4850	0.4935
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capitals on IPO short-term performance. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *UP 1* which is the IPO underpricing during 2009 to 2013. Model 4 to Model 6 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *UP 2* which is the IPO underpricing during 2014 to 2016. Model 7 to Model 9 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *HM* which is the IPO honeymoon period during 2014 to 2016. Definitions of the independent variables and control variables are presented in the Appendix B. [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

Table 2.9 The Cross Classification Analysis of High, Middle and Low Innovation Capital on IPO Short-term Performance

		Variables	High R&D	Middle R&D	Low R&D	Test between high and low R&D (High-Low)	
						T-value	P-value
Large # of patents		UP1	0.3261	0.3258	0.2928	1.9108	0.0308**
		UP2	1.5336	1.2357	1.1140	5.2182	0.0000***
		HM	30.4179	27.6854	25.9412	5.2153	0.0000***
Medium # of patents		UP1	0.3644	0.3414	0.3137	0.9051	0.1847
		UP2	1.4516	1.3579	1.2754	1.6819	0.0477**
		HM	32.8391	29.9434	27.5000	1.6923	0.0466**
Small # of patents		UP1	0.4328	0.4008	0.3860	1.0786	0.1416
		UP2	1.6270	1.5349	1.3683	3.1949	0.0048***
		HM	33.9545	32.3333	29.8947	2.8803	0.0082***
Test between large and small # of patents (High-Low)	T-value	UP1	-1.1805	-2.5338	-2.9551		
		UP2	-1.6877	-3.0858	-2.5804		
		HM	-0.9170	-3.1531	-2.5544		
	P-value	UP1	0.1196	0.0077***	0.0021***		
		UP2	0.0470**	0.0012***	0.0056***		
		HM	0.1792	0.0010***	0.0060***		

Note: This table presents the cross-classification analysis of high, middle and low innovation capital on IPO short-term performance based on the 35th and 65th percentile of the total sample. *UP1* refers to the market-adjusted IPO underpricing ratio from 2009 to 2013. *UP2* refers to the market-adjusted IPO underpricing ratio from 2014 to 2016. *HM* refers to the number of days from the IPO stock issue day to the last trading day when the price closes below 10% maximum up-limit price. All the values in the middle of the table are the mean values of the variables from different classifications of innovation capital. Values at the two sides of the table are the T-values and P-values of the variables from different groups. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

Table 2.10 Regression of Innovation Capitals on IPO Short-term Performance Grouped by Innovation Input

	High R&D			Middle R&D			Low R&D		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
VARIABLES	UP 1	UP 2	HM	UP 1	UP 2	HM	UP 1	UP 2	HM
(Patents+1)[1]	-0.0092	-0.0324*	-0.4363	-0.0134	-0.0490**	-0.7730**	-0.0112	-0.0575***	-0.8457**
	(0.500)	(0.095)	(0.256)	(0.458)	(0.020)	(0.050)	(0.524)	(0.005)	(0.016)
R&D	0.6249*	1.8479***	29.6002**	0.9056	4.1767	49.2716	0.5901	1.6043	38.5159
	(0.080)	(0.004)	(0.020)	(0.416)	(0.647)	(0.258)	(0.487)	(0.534)	(0.381)
VC	0.0119	0.0786	1.9850	-0.0272	-0.0379	-1.0846	0.0301	0.1009*	0.6927
	(0.560)	(0.218)	(0.117)	(0.534)	(0.031)	(0.348)	(0.477)	(0.080)	(0.478)
Price	-0.0058*	-0.0211***	-0.2631***	-0.0025	-0.0121**	-0.1696	-0.0019	-0.0134***	-0.3188***
	(0.062)	(0.001)	(0.001)	(0.259)	(0.031)	(0.106)	(0.368)	(0.000)	(0.000)
Volume[1]	0.1916*	0.1503***	1.4423**	0.0955	0.1069***	1.5330**	0.0899	0.1313***	1.6404***
	(0.066)	(0.000)	(0.020)	(0.321)	(0.003)	(0.022)	(0.304)	(0.000)	(0.002)
Asset[1]	0.0372	0.0359	1.0825	0.0477***	0.1525**	2.6705**	0.0424	0.0999**	1.7067**
	(0.343)	(0.462)	(0.264)	(0.001)	(0.010)	(0.017)	(0.287)	(0.029)	(0.029)
Turnover	1.2938***	0.4377	-9.4575	0.8599***	1.4043**	20.2404**	0.6854***	0.8241**	6.3587
	(0.000)	(0.518)	(0.481)	(0.000)	(0.011)	(0.049)	(0.008)	(0.037)	(0.343)
Lottery	-1.6326	-19.7893**	-330.6181*	-0.8153	-31.9993***	-483.7518***	0.7126	-31.1868***	-484.2089***
	(0.150)	(0.026)	(0.059)	(0.155)	(0.001)	(0.009)	(0.178)	(0.000)	(0.001)
Proceed[1]	0.1130	-0.1474**	-3.0455**	-0.2340**	-0.2643***	-4.1267**	-0.2795**	-0.0643	-1.2007
	(0.301)	(0.026)	(0.020)	(0.037)	(0.003)	(0.013)	(0.014)	(0.390)	(0.346)
Age[1]	0.0734***	-0.0702	-1.2077	0.0450	0.0351	0.4928	0.0472	-0.0116	0.2555
	(0.006)	(0.275)	(0.343)	(0.221)	(0.595)	(0.691)	(0.164)	(0.861)	(0.820)
UW	-0.0056	0.0566	1.6718	-0.0807*	0.0212	0.3037	0.0366	-0.0514	-1.1256
	(0.857)	(0.306)	(0.127)	(0.057)	(0.704)	(0.772)	(0.387)	(0.348)	(0.228)
Constant	1.3302**	5.5542***	90.4905***	1.9041*	5.0856***	85.6426***	3.3412***	2.4032**	41.4479**
	(0.021)	(0.000)	(0.000)	(0.069)	(0.000)	(0.000)	(0.001)	(0.014)	(0.013)
Observations	277	196	196	228	177	177	319	154	154
R-squared	0.6565	0.6339	0.4989	0.6644	0.5528	0.4349	0.5832	0.6312	0.5648
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capitals on IPO short-term performance by classifying the innovation input (R&D) into high R&D, middle R&D and low R&D groups. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the IPO short-term performance in the high-R&D groups. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the IPO short-term performance in the middle-R&D groups. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the IPO short-term performance in the low-R&D groups. Definitions of the independent variables and control variables are presented in the Appendix B. [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

Table 2.11 Regression of Innovation Capitals on IPO Short-term Performance Grouped by Innovation Outcome

	High Patents			Middle Patents			Low Patents		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
VARIABLES	UP 1	UP 2	HM	UP 1	UP 2	HM	UP 1	UP 2	HM
(Patents+1)[1]	-0.0197**	-0.0296***	-0.2879***	-0.0461	-0.0834**	-1.0526**	-0.0065	-0.0325	-0.2417
	(0.038)	(0.000)	(0.001)	(0.111)	(0.030)	(0.041)	(0.191)	(0.304)	(0.682)
R&D	0.6313	2.7535	47.9616	0.6736	4.0893*	62.0121*	0.3188	2.4891***	50.0855***
	(0.510)	(0.109)	(0.169)	(0.540)	(0.093)	(0.072)	(0.598)	(0.001)	(0.000)
VC	0.0237	0.0352	-0.1337	-0.0515	0.0174	0.4821	0.0477	0.1171*	1.6383
	(0.553)	(0.512)	(0.894)	(0.252)	(0.780)	(0.672)	(0.228)	(0.100)	(0.217)
Price	-0.0024	-0.0074**	-0.0591	-0.0025	-0.0167***	-0.2244***	-0.0025	-0.0236***	-0.5192***
	(0.473)	(0.032)	(0.375)	(0.613)	(0.000)	(0.000)	(0.660)	(0.000)	(0.008)
Volume[1]	0.0627	0.1278***	1.3445**	0.0952	0.1435***	2.4258***	0.1346	0.2027***	1.8666**
	(0.524)	(0.000)	(0.010)	(0.419)	(0.000)	(0.000)	(0.166)	(0.000)	(0.017)
Asset[1]	0.0799**	0.1735***	3.7524***	0.1244**	0.0506	0.0496	0.0076	0.0867	1.1315
	(0.021)	(0.000)	(0.000)	(0.013)	(0.404)	(0.964)	(0.855)	(0.101)	(0.252)
Turnover	0.9127***	1.0250***	7.1969	1.0238***	0.1482	1.3157	0.7089***	11.3741***	192.9267***
	(0.000)	(0.003)	(0.265)	(0.001)	(0.824)	(0.914)	(0.002)	(0.001)	(0.002)
Lottery	-1.2905	-30.2145***	-477.4201***	-1.4622	-20.8623**	-207.0242	-0.8865*	-35.0851***	-788.8705***
	(0.290)	(0.000)	(0.002)	(0.145)	(0.028)	(0.229)	(0.079)	(0.001)	(0.000)
Proceed[1]	-0.0602	-0.2825***	-5.9509***	-0.1925	-0.0155	1.2551	-0.2387**	-0.1886**	-4.2998***
	(0.619)	(0.000)	(0.000)	(0.137)	(0.873)	(0.476)	(0.018)	(0.018)	(0.004)
Age[1]	0.0190	-0.0549	-0.9561	0.0661*	-0.0325	-0.5081	0.0451	-0.0206	0.3750
	(0.521)	(0.268)	(0.305)	(0.075)	(0.670)	(0.716)	(0.151)	(0.813)	(0.818)
UW	-0.0240	-0.0181	0.4778	0.0053	0.0435	0.0074	0.0265	0.0427	0.8496
	(0.533)	(0.695)	(0.582)	(0.897)	(0.448)	(0.994)	(0.490)	(0.504)	(0.478)
Constant	2.094**	4.7386***	85.3465***	1.4904**	2.7081**	38.9112*	2.3493**	5.7362***	113.7521***
	(0.034)	(0.000)	(0.000)	(0.041)	(0.036)	(0.098)	(0.020)	(0.000)	(0.000)
Observations	226	241	241	246	168	168	352	118	118
R-squared	0.6336	0.5820	0.4633	0.5978	0.6174	0.5487	0.5924	0.7130	0.6170
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capitals on IPO short-term performance by classifying the innovation outcome (patents) into high patents, middle patents and low patents. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the IPO short-term performance in the high-patents groups. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the IPO short-term performance in the middle-patents groups. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the IPO short-term performance in the low-patents groups. Definitions of the independent variables and control variables are presented in the Appendix B. [1] Logarithm. P-value in parentheses. ***1% significance level, **5% significance level, *10% significance level.

(3) Industrial Policy

1) 2009–2013 period:

①Innovation input (R&D investment):

For examining the relationship between the microstructure of companies and industries and macro-policy of the Chinese Government, we construct nine models, as shown in Table 2.12. According to our hypotheses, we expect that the industrial policy works as a moderator in the relationship between innovation input and IPO underpricing. The first analysis is based on Model 2 and 3. The regression results yielded by these models reveal that the interaction of R&D and industrial policy is positively related to IPO underpricing for the years before 2013 at the 1% and 5% significance levels, respectively. These results support the hypothesis H_{3a}, indicating that the industrial policy in China has strengthened the positive impact of firms' innovation input (R&D investment) on the IPO underpricing during the 2009−2012 period.

We also examine our models individually. The application of Model 2 in Table 2.12 shows a significant effect of the interaction term between R&D and industrial policy at the 1% significance level. This means that the effect of R&D on the IPO underpricing rate is different for different levels of the industrial policy. As a result, for two IPO firms without the support of the industrial policy, one firm with 0.1 higher R&D intensity before IPO is expected to attain a 0.85% higher underpricing rate when it goes public than the other firm with less R&D investment. However, for two firms that benefit from the industrial policy support, a firm with 0.1 more R&D intensity before its IPO would be expected to get 18.04% higher underpricing rate when it goes public than the other one with less R&D investment. Thus, because of the interaction, the underpricing effect of R&D investment is different for IPO firms belonging to the industry benefiting from the industrial policy support compared to those that do not. In addition, the results yielded by Model 2 in Table 2.12 show that the individual coefficient for R&D is not significant, indicating that, when industrial policy does not support the firms, the effect of their R&D investment on the IPO underpricing is not significant. Therefore, the industrial policy has a moderating effect on the relationship between R&D investment and the extent of IPO underpricing. This moderating effect is further reinforced by the finding in Figure 2.7-(2), suggesting that the IPO firms with the support of industrial policy will benefit from greater positive impact of R&D investment on the IPO underpricing. The figure also perfectly depicts the statistical results reported in Table 2.12, as it shows that the industrial policy has a positive moderating effect on the relationship between R&D investment and IPO underpricing at the 1% significance level.

②Innovation outcome (Patents):

Model 1 and Model 3 show the influence of industrial policy on the relationship between innovation outcome and IPO underpricing. The interaction term of patents and industrial policy has a significant negative impact on the IPO underpricing at the 1% significance level in Model 1, and at the 5% level in Model 3. This finding supports the hypothesis H_{4a}, suggesting that the Chinese industrial policy reinforced the negative correlation between innovation outcome and the IPO underpricing in the A-share market from 2009 to 2012.

Different from Model 1 in Table 2.8, the variable of industrial policy for this model in Table 2.12 has moderated the effect of innovation outcome on IPO underpricing. This finding suggests that, without the support of industrial policy a firm with one more patent before IPO is expected to attain a 2.9% lower underpricing rate when it goes public compared to a firm with fewer patents. However, for two firms supported by the industrial policy, a firm with one more patent before its IPO is expected to get 7.1% lower underpricing rate when it goes public compared to a firm with fewer patents. Thus, the moderating effect of industrial policy has strengthened the negative influence of innovation outcome on the IPO underpricing. Figure 2.7- (1) depicts the correlation among these variables, indicating that a firm with a higher number of patents before going public achieves a lower IPO underpricing rate after going public. This negative correlation becomes greater if the IPO firm belongs to the industry under the support of industrial policy.

2) 2014–2016 period:

From Model 4 to 6 in Table 2.12, the interaction terms of industrial policy with both innovation variables show the insignificant effect on IPO underpricing, revealing that the moderating effect of industrial policy does not have a significant influence on the relationship between firm’s innovation capital and its IPO underpricing. However, the signs of the two interaction terms of industrial policy with two types of innovation variables in Model 4 to Model 6 are the same as those in Model 1 to Model 3. Based on these results, we produce Figure 2.8 to illustrate the effect of industrial policy on the relationships between innovation and IPO underpricing to obtain a more intuitive overview of their correlations. Figure 2.8 depicts similar prediction to that shown in Figure 2.7, albeit with an insignificant outcome.

The insignificant moderating effect of industrial policy also relates to the relationships between innovation capital and the IPO honeymoon period length in Model 7 to 9 for the sample period spanning 2014–2016. We also produce Figure 2.9 to illustrate the correctly predicted sign of interaction terms between industrial policy and innovation input, or innovation outcome in Model 7 to Model 9. The trend in Figure 2.9 is similar to that in Figure 2.8, suggesting that the IPO honeymoon period length is another form of IPO underpricing, which has experienced similar trends under the industrial policy after 2014. Therefore, we can conclude that industrial policy in Model 4 to Model 9 does not exert significant influence on the IPO short-term performance during this period.

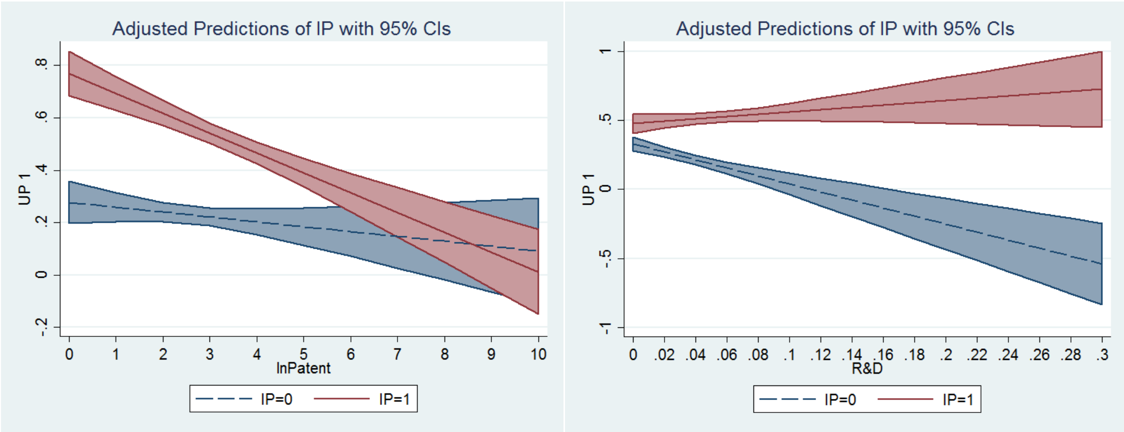
In conclusion, although the two dimensions of innovation exhibit different impacts on the IPO underpricing, the Chinese industrial policy interaction played an important role during the 2009−2012 period. From the perspective of innovation input, industrial policy has helped innovation input to increase the IPO underpricing to some extent, suggesting that this policy had unsatisfactory impacts on the short-term IPO performance. From the perspective of innovation outcome, it seems that the implementation of industrial policy had a desirable influence on reducing the short-term IPO underpricing performance. However, for the years after 2014, it is very controversial to argue whether the industrial policy was effective. In the following, we will attempt to investigate the reasons for the inefficiency of industrial policy after 2014 from the perspective of the microeconomic structure of the Chinese market.

The industrial structure of Chinese economy has changed several times in past decades, with the most recent change taking place in 2013. The Chinese National Development and Reform Commission (CNDRC) issued a new guideline for this change, replacing the old 2005 guideline. This change was deemed necessary to solve the problems of too broad industrial classification and unclear limited range for most industries. The newly reformed industrial classifications reinforced the range of industries and became much more restrictive. As a result, some of the industries that used to enjoy the incentives of industrial policy lost their support after 2013. However, this change was not coordinated with the change in the industrial structure defined by the "12th five-year-plan" implemented from 2011 to 2015. There is also no supporting evidence to show that the industrial policy would have varied with the upgrade of the new industrial structure during this period. Therefore, it is imprudent to claim that the industrial policy has been effective during this period.

Table 2.12 Regression of Innovation Capitals on IPO Short-term Performance under the Influence of Industrial Policy

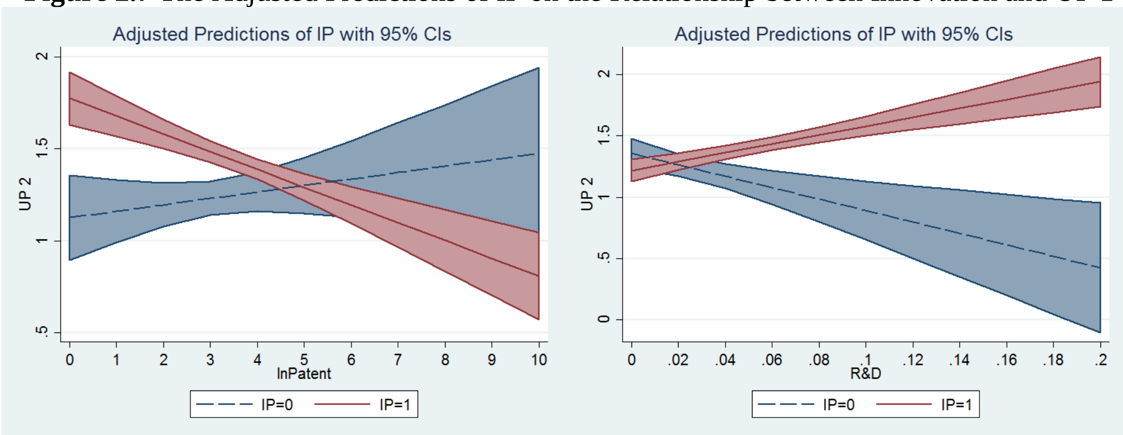
VARIABLES	UP 1			UP 2			HM		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
(Patents+1)[1]	-0.0287***		-0.0268***	-0.0496***		-0.0516***	-0.6361***		-0.6815***
	(0.001)		(0.003)	(0.000)		(0.000)	(0.008)		(0.004)
(Patents+1)[1] × IP	-0.0443***		-0.0410**	-0.0120		0.0109	-0.3027		0.1104
	(0.006)		(0.011)	(0.661)		(0.680)	(0.553)		(0.825)
R&D		0.0808	0.1186		3.2926***	3.4252***		60.1562***	61.8064***
		(0.828)	(0.748)		(0.000)	(0.000)		(0.000)	(0.000)
R&D × IP		1.8261***	1.4946**		-0.8506	-1.6706		-24.1895	-34.9812
		(0.004)	(0.017)		(0.489)	(0.174)		(0.291)	(0.130)
IP	0.1737***	0.1607***	0.1734***	0.1085***	-0.0161	-0.0007	1.6074**	-0.6071	-0.3921
	(0.000)	(0.000)	(0.000)	(0.004)	(0.707)	(0.988)	(0.023)	(0.446)	(0.626)
VC	0.0113	0.0132	0.0112	0.0652*	0.0392	0.0519	0.9017	0.5027	0.6720
	(0.594)	(0.537)	(0.598)	(0.074)	(0.271)	(0.140)	(0.185)	(0.448)	(0.309)
Price	0.0021	0.0029*	0.0026	-0.0145***	-0.0147***	-0.0145***	-0.2324***	-0.2344***	-0.2312***
	(0.216)	(0.090)	(0.124)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volume[1]	0.1090**	0.1344***	0.1278**	0.1393***	0.1354***	0.1346***	1.6920***	1.6183***	1.6055***
	(0.029)	(0.008)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset[1]	0.0620***	0.0475**	0.0603***	0.0373	0.0788***	0.0937***	0.7226	1.5388***	1.7354***
	(0.002)	(0.020)	(0.003)	(0.169)	(0.005)	(0.001)	(0.154)	(0.003)	(0.001)
Turnover	0.5197***	0.5389***	0.4961***	0.8958***	0.8572***	0.9269***	7.6229	7.3521	8.2287
	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.001)	(0.163)	(0.164)	(0.120)
Lottery	-0.7069*	-0.5564	-0.6180*	-23.1613***	-24.8551***	-26.6985***	-368.3548***	-411.7831***	-436.1714***
	(0.057)	(0.134)	(0.094)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Proceed[1]	-0.2558***	-0.2579***	-0.2618***	-0.1296***	-0.1732***	-0.1693***	-2.4262***	-3.2046***	-3.1481***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
Age[1]	0.0469***	0.0474***	0.0469***	-0.0626	-0.0394	-0.0390	-0.9347	-0.5282	-0.5222
	(0.005)	(0.005)	(0.005)	(0.103)	(0.298)	(0.294)	(0.193)	(0.453)	(0.455)
UW	-0.0036	-0.0035	-0.0023	0.0312	0.0231	0.0267	0.6846	0.5643	0.6151
	(0.857)	(0.861)	(0.910)	(0.338)	(0.468)	(0.395)	(0.261)	(0.341)	(0.298)
Constant	2.5832***	2.7911***	2.5976***	5.1060***	4.8166***	4.5842***	87.9772***	82.0585***	78.8789***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	824	824	824	532	532	532	532	532	532
R-squared	0.5793	0.5732	0.5826	0.5773	0.5940	0.6089	0.4597	0.4862	0.4958
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regression of innovation capitals on IPO short-term performance under the influence of industrial policy. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *UP 1* under the influence of industrial policy (*IP*) during 2009 to 2013. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the *UP 2* under the influence of industrial policy (*IP*) during 2014 to 2016. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the *HM* under the influence of industrial policy (*IP*) during 2014 to 2016. *(Patents+1)[1] × IP* refers to the interaction term of the firm's patent counts and the industrial policy. *R&D × IP* refers to the interaction term of the firm's R&D intensity and the industrial policy. The variable of industrial policy is measured from the Appendix A. Definitions of the other independent variables and control variables are presented in the Appendix B. [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.



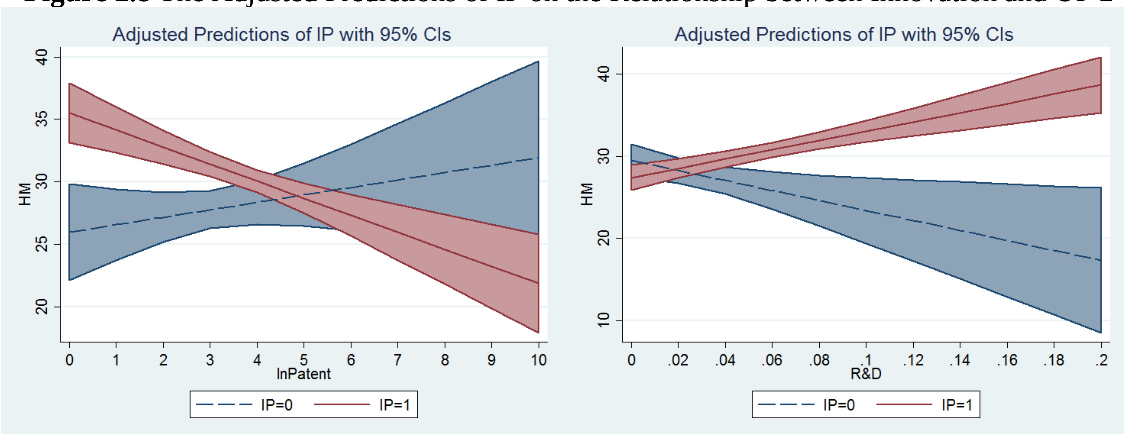
(1) (2)

Figure 2.7 The Adjusted Predictions of IP on the Relationship between Innovation and UP 1



(1) (2)

Figure 2.8 The Adjusted Predictions of IP on the Relationship between Innovation and UP 2



(1) (2)

Figure 2.9 The Adjusted Predictions of IP on the Relationship between Innovation and HM

2.5.4 Robustness Test

To test the robustness of our study, we use both the one-year period before research and development (R&D) investment intensity, and the two-year period before R&D investment intensity to proxy for the innovation variables and to re-examine the association between innovation and IPO underpricing. We defined these variables as R&D_1 for the one-year period before R&D investment intensity, and R&D_2 for the two-year period before R&D investment intensity.

The results reported in Table 2.13 show that the coefficients of R&D_1 and R&D_2 are positively related to IPO underpricing from 2009 to 2016 and the IPO honeymoon period length from 2014 to 2016. However, the coefficient of R&D_1 is not statistically significant in Model 1, and is marginally significant for R&D_2 in Model 2 at the 10% significance level. The coefficients of R&D_1 in Model 3 and Model 5 are positively related to both IPO underpricing and IPO honeymoon period length at the 1% significance level. Moreover, the coefficients for R&D_2 in Model 4 and Model 6 are also positively correlated to both IPO underpricing and IPO honeymoon period length at the 1% significance level. Since the sign and significance of the patents' coefficients under two control variables of R&D_1 and R&D_2 in Table 2.13 did not change, we conclude that the regression results in the models are stable and robust.

Table 2.13 Robustness Test

VARIABLES	UP 1		UP 2		HM	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Patents+1)[1]	-0.0153*	-0.0158*	-0.0464***	-0.0445***	-0.6140***	-0.5821***
	(0.098)	(0.087)	(0.000)	(0.000)	(0.003)	(0.005)
R&D_1	0.2887		2.8361***		48.7422***	
	(0.167)		(0.000)		(0.000)	
R&D_2		0.5355*		3.0224***		51.4546***
		(0.096)		(0.000)		(0.000)
VC	0.0150	0.0135	0.0545	0.0472	0.7053	0.5849
	(0.506)	(0.546)	(0.121)	(0.181)	(0.284)	(0.378)
Price	0.0024	0.0023	-0.0147***	-0.0143***	-0.2360***	-0.2284***
	(0.186)	(0.193)	(0.000)	(0.000)	(0.000)	(0.000)
Volume[1]	0.1110**	0.1099**	0.1360***	0.1349***	1.6336***	1.6169***
	(0.038)	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)
Asset[1]	0.0604***	0.0629***	0.0847***	0.0862***	1.5605***	1.5765***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Turnover	0.7721***	0.7725***	0.8885***	0.8934***	7.7014	7.7838
	(0.000)	(0.000)	(0.001)	(0.001)	(0.141)	(0.139)
Lottery	-0.6587*	-0.6639*	-25.1434***	-25.1533***	-401.8163***	-401.7052***
	(0.097)	(0.094)	(0.000)	(0.000)	(0.000)	(0.000)
Proceed[1]	-0.2273***	-0.2277***	-0.1579***	-0.1649***	-2.9399***	-3.0545***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age[1]	0.0456**	0.0462***	-0.0338	-0.0480	-0.4550	-0.7020
	(0.010)	(0.009)	(0.363)	(0.196)	(0.513)	(0.314)
UW	-0.0032	-0.0031	0.0231	0.0261	0.5409	0.5928
	(0.881)	(0.884)	(0.461)	(0.407)	(0.357)	(0.315)
Constant	2.3062***	2.2879***	4.5381***	4.6611***	78.2495***	80.4541***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	824	824	532	532	532	532
R-squared	0.5470	0.5477	0.6077	0.6037	0.4943	0.4893
Industry	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES

Note: This table presents the robustness test of innovation capitals on IPO short-term performance. Model 1 to Model 2 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *UP 1* during 2009 to 2013. Model 3 to Model 4 respectively test the impact of firm's innovation capitals on the *UP 2* during 2014 to 2016. Model 7 to Model 8 respectively test the impact of firm's innovation capitals on the *HM* during 2014 to 2016. *R&D_1* refers to the R&D one year before IPO/total assets one year before IPO. *R&D_2* refers to the R&D two years before IPO/total assets two years before IPO. Definitions of the other independent variables and control variables are presented in the Appendix B. [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

2.6 Conclusion

To realize the dream of becoming an innovative country, China needs a greater number of innovative and competitive companies. Innovation enhances total factor productivity (TFP) and economic growth in the medium to long term. Chinese Government has actively promoted the firms’ innovation abilities and industrial structure optimization through its industrial policy in recent years. It has also attempted to improve the efficiency of resource allocation in the stock market by implementing the IPO price limit policy. The government has been specifically concerned with the extremely high level of IPO underpricing as a potential hazard for the development of more efficient financial markets. In this paper, we studied the phenomenon of high IPO underpricing in the Chinese IPO market by examining the two dimensions of innovation ability of IPO firms from 2009 to 2016 under the influence of Chinese Government industrial and financial policies. We specifically tested the associations between the macroeconomic policy and the microeconomic institutions, i.e., testing the effect of Chinese industrial policy on the relationship between innovation and IPO underpricing and the IPO honeymoon period. Our main findings are discussed below.

First, from the perspective of innovation input, our findings suggest that research and development (R&D) investment, as the main source of information asymmetry and uncertainty, can lead to a great extent of IPO underpricing and a longer IPO honeymoon period for IPO firms. In addition, the more capital IPO firms invest in R&D before the IPO, the higher the IPO underpricing rate will be and the longer the IPO honeymoon period they will experience.

Second, from the perspective of innovation outcome, a great majority of IPO firms prefer to disclose their innovative proprietary information, especially the number of patent applications and granted patents, to signal their innovation ability to the market and make their IPOs a success. Similarly, the number of patents as a proxy for this ability can alleviate the information asymmetry and send positive signals to the market, which helps investors recognize and evaluate the firm value correctly. Thus, higher innovation outcome results in a lower IPO underpricing rate and a shorter IPO honeymoon period.

Finally, as the "visible hand" of government intervention in the market economy, the industrial policy had a profound impact on the relationship between the investment and financing of firms' innovation capital and their IPO short-term performance in the A-share market before 2014. Under the incentive of Chinese industrial policy, the positive impact of firm's pre-IPO innovation input on the IPO underpricing and IPO honeymoon period length will be greater. In addition, the industrial policy can reinforce the negative correlation between pre-IPO innovation outcome and IPO underpricing or the IPO honeymoon period length. Comparing the impacts of those two distinct dimensions of innovation capital under the industrial policy, the innovation input has greater positive impact on IPO underpricing than the innovation outcome's negative impact on IPO underpricing regarding the industrial policy before 2014. In other words, the role of industrial policy has been recognized as a relatively important macroeconomic factor in the Chinese IPO market before 2014, which has been ignored in most previous research. Furthermore, due to the new reform of industrial structures that has been in place since 2014, the results show an insignificant link between the innovation capital and IPO underpricing under the industrial policy, suggesting that the industries that used to enjoy the incentives of the policy lost their support.

The validation of industrial policy to some extent depends on the governmental executive ability. The industrial policy should be adjusted by relevant governmental departments, along with the upgrade of industrial structure. A successful and achievable industrial policy should promote efficiency of resource allocation in different industries and improve the development of product markets (Yifu Lin, 2016). However, China as an emerging market has little experience in improving the efficiency of industrial policy in the free market, thereby suggesting an immature and unsatisfactory implementation of the industrial policy within the markets. Therefore, owing to the accelerated developments of the capital markets, the controversial industrial policy in China should be carried out after careful consideration and be improved over time, thus improving the information allocation in the IPO markets. In other words, all the benefiting parties should participate in the formulation of the industrial policy. The government should formulate the industrial policy according to the different circumstances and should consider the changes in market conditions.

In conclusion, this study shows that the two dimensions (R&D and patents) of innovation ability have a significant impact on IPO underpricing. The findings also expand the interpretation and application of the information asymmetry theory on the IPO underpricing phenomenon, helping to correctly understand the formation of the IPO underpricing for the innovative firms in the emerging capital markets and the efficiency of the industrial policy in China.

CHAPTER 3

Does the Pre-IPO Innovation Impact the Long-term Performance of Firms? – Evidence from Chinese Equity Markets

Abstract

This paper investigates how pre-IPO innovations measures (R&D investment and the number of patents) may influence the long-term performance of IPO firms in China. By employing both the Fama-French five-factor model and cross-sectional regression analysis, this research examines the long-term performance of firms in the post-IPO period categorized by different levels of innovation. From the perspective of innovation outcome, the number of patents has a positive impact on the post-IPO stock performance of examined firms. In contrast, their level of innovation input (R&D intensity) has a negative impact on the long-term performance of IPOs. Therefore, given the pervasive and constant growth of the firms' and industries' innovative capabilities in modern economies, identification of innovation as a major factor affecting IPO performance can contribute to the understanding of this economic and capital market phenomenon in the Chinese market.

Keywords: Initial Public Offering, innovation capital, long-term performance

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3.1 Introduction

In the capital markets, valuation and market performance of IPO firms within an industry varies according to their innovation level. The innovation ability of firms can also significantly affect their performance across different industries. For instance, companies in the highly innovative industries, such as information technology and biotechnology, may show superior performance in the markets because of their strong innovation capabilities. In general, scientific and technological innovations can become a very important factor in the competitiveness of enterprises over time. Firms with leading technology may develop monopolistic advantage with high growth in the capital markets. Therefore, innovation ability plays an essential role in the development of enterprises.

Innovation can influence firm value both in the primary market (IPO underpricing) and in the secondary market through price discovery process. Innovations may initially trigger higher aggregate market returns (Hsu, 2009), or even cause "bubbles" in the stock markets (Pastor and Veronesi, 2009). As a result, companies may use this phenomenon to their advantage and go public when market conditions are favorable. Additionally, innovative activities and knowledge capital would make issuing firms more attractive to investors. Therefore, firms may decide to go public to raise capital and earn greater competitive advantage over their competitors within the industry (Maksimovic and Pichler, 2001; Hsu, Reed, and Rocholl 2010; Chod and Lyandres, 2011). Lastly, innovation would imply further investment opportunities (Chemmanur and Fulghieri, 1999). Thus, innovative firms may decide to go public to enhance their future financing opportunities (Lowry, 2003).

While the existing literature has extensively covered short-term IPO events and has provided diverse reasons on how innovations can influence the market, the impacts of this phenomenon on the long-term IPO performance is less explored, especially in the Chinese capital market. The scope of many of these studies is also limited to the application of one proxy measure of the innovation ability of IPO firms or is focused on one industry. For example, Eberhart, Maxwell and Siddique (2004) and Guo, Lev and Shi (2006) only utilized R&D activities to test the long-term performance of IPOs in the U.S. market. Similarly, Guo and Zhou (2016) limited their study to the U.S. biotech industry. Chen and Xu (2015) also examined the long-term performance of IPO firms in the Chinese bio-pharmaceutical industry. Hence, the first motivation of the current study is to fill this research gap in the Chinese market and examine the long-term effect of innovation in post-IPO stock market performance in a more comprehensive way.

Second, authors of most previous studies treated the firms' innovation capital (R&D investment and number of patents) as a whole to investigate their influence in the stock markets. For instance, Chin et al. (2006) examined the impact of innovation capital on IPO performance in the Taiwanese market by using R&D expenditure and number of patents. Hirshleifer, Hsu and Li (2013) tested the effect of innovation efficiency (IE) which comprised of patents and R&D on the US stock performance. Similarly, Guo and Zhou (2016) created measurements of firms' innovation capability by employing R&D expenses, products, patents and strategic alliances in their research sample. However, Kelm et al. (1995) correctly pointed out that technological innovation is a very complex undertaking. It goes through the processes of start, failure or breakthrough, new technology formation, patents, new product promotions, etc. Thus, R&D investment is only the input to the innovative process rather than the desirable outcome. In the current study, we simultaneously examine the impacts of innovation capital on the firms' IPO long-term performance from two dimensions of input (R&D expenses) and output (number of patents) in the Chinese equity market. This is an extension of previous studies conducted by Guo, Lev and Shi (2006) and Zhang et al. (2016), who considered only one aspect of innovation capital in their research.

Third, studies on the long-term market performance of IPOs in the Chinese market have emerged relatively late (in 2000) compared to those in the developed countries. Thus, controversies and debates on the long-term performance of IPOs are not settled yet. While some researchers in this area have reported weak long-term IPO market performance (Wang and Luo, 2002; Li, Song and Wu, 2002; Du, Zhou and Yang, 2003), other studies show strong long-term performance (Wang and Zhang, 2000; Liu and Li, 2001). We thus hope that our study will shed some light on the controversy of previous findings. In examining the actual long-term IPO performance in the Chinese market, we also contribute to the existing research by applying a more comprehensive methodology and employing both CAPM and Fama-French five-factor model to compare the influence of two kinds of innovation capital on the new shares' returns in the long term.

Finally, to provide further analysis and more evidence, we apply both Fama-French five-factor model and cross-sectional regression models to examine the relationships between innovation and long-term IPO performance in the Chinese market by separating the innovation capital into three distinct levels of no, low and high sectors on a monthly basis. We thus contribute to the pertinent literature by conducting further technical analyses on the post-IPO performance of Chinese market[21]. Further, in contrast with previous literature, we conduct a comprehensive ordinary linear regression to test the impact of innovation on the long-term IPO performance from two distinct perspectives,

[21] Zhao et al. (2016), Li et al. (2017), and Song et al. (2017) have questioned the validity of the application of Fama-French multifactor models in emerging markets. However, we believe that the economy and investment environment have rapidly changed in recent years. The regulation settings of the stock market have also evolved and improved over time. Thus, we feel that the application of three-factor and five-factor models to the latest data sets is useful in providing evidence of long-term IPO performance in the Chinese market.

innovation input and innovation outcome. Results exhibit two opposed impacts of these different kinds of innovation capital of firms on the stock performance in the long term and demonstrate that the impact is variable over time.

The remainder of this paper comprises of five sections. Section 2 describes the theoretical framework and hypothesis development of this study. Section 3 is designated for the data selection and methodology, including Fama-French five-factor model. Section 4 provides the variable definitions and regression models. Section 5 shows the regression results and analyses. Section 6 summarizes the main conclusions of this study, along with its limitations as well as further research prospects.

3.2 Theoretical Framework and Hypothesis Development

3.2.1 The Long-term Performance of IPOs

A large and growing body of literature has documented the IPOs' long-term underperformance in different equity markets (Ritter, 1991; Loughran and Ritter, 1995; McGuinness, 2016). Stoll and Curley (1970) were the first to study IPO market performance from the long-term perspective. They selected 205 stocks with small capitalization from the U.S. capital market as their sample and found that newly listed stocks have experienced high short-term underpricing and long-term underperformance after IPOs. Ritter and Welch (2002) used a sample of 6,249 U.S. IPOs from 1980 to 2001 and reported a buy-and-hold return (BHR) of 22.6% for three years after the issuing date. However, they found -23.4% buy-and-hold abnormal return (BHAR) after adjusting by the market index returns. Some of the financial theories have also been developed to explain the long-term IPO underperformance, including the disagreement hypothesis[22], "Band Manager" hypothesis[23], window of opportunity hypothesis[24], and the earnings management hypothesis[25].

Findings yielded by other studies do not support the hypothesis of long-term IPO underperformance. For instance, Brav and Gompers (1997) found that the newly listed stocks did not exhibit long-term underperformance after their IPOs based on the BM (book-to-market ratio) of listed firms as reference figure and the market-weighted average return measurement. Brav, Geczy and Gompers (2000) tested the long-term performance of 4,622 listed firms from 1975 to 1992 in the U.S. stock market and found no significant support for the long-term IPO underperformance, except for small-sized IPO firms. Gompers and Lerner (2003) further employed a sample of 3,661 U.S.-listed firms from 1935 to 1972 to test their long-term performance by using the equally weighted CAR, BHAR methods, and Fama-French five-factor models. They also found no evidence of long-term IPO underperformance in the U.S. market.

Similar to the U.S. stock market, the findings of extant research on the long-term IPO performance in the Chinese equity market are controversial and can be separated into two groups. Some authors argued that Chinese market does not show signs of IPO long-term underperformance, while others found some evidence that the underperformance really exists in the Chinese market. For instance, Wang and Zhang (2000) employed a sample of 110 stocks newly listed on the Shanghai stock exchange from 1996 to 1997 to

[22] Disagreement hypothesis: Miller (1977) introduced a heterogeneous expectation model to explain the initial underpricing and long-term underperformance of new shares. His model shows that more uncertainty about the initial real value will lead to poorer long-term market performance.
[23] "Band Manager" hypothesis: The newly issuing market is a popular trend. In order to encourage investors to buy IPO shares, the investment bank will package the issues as a good "event", akin to band performance.
[24] Window of opportunity hypothesis: Investor sentiment plays an important role in corporate valuation, which in turn affects IPO activities and IPO underpricing.
[25] Earnings management hypothesis: Firms can use methods to show the unreal financial situation, operating results and cash flow to the public.

study the long-term IPO performance in the Chinese equity market. They found that returns of the newly listed shares have underperformed within the first six months following the IPOs and outperformed the market in the subsequent six months. Overall, they found no evidence of long-term IPO underperformance in the Chinese equity market. Yang and Lin (2006) used a sample of 774 A-share market from 1995 to 2006. Their empirical results show that IPOs over- rather than under-perform in the long term. These results are robust to the application of the CAPM versus Fama-French three-factor model.

In another study, Wang and Luo (2002) investigated the three-year performance of the newly listed shares in the Chinese A-share market by using 165 samples from 1997 to 1998. After eliminating the impact of IPO underpricing during the first month, their analyses of one-year returns indicated that stocks performed worse than the market. The cumulative abnormal returns in the second, and especially the third year, were also below the market returns. In addition, Li, Song and Wu (2002) studied the three-year cumulative abnormal returns of 542 listed stocks in the Shanghai and Shenzhen stock exchange from 1994 to 1997 by using the market value weighted method. Their results show an average -22.85% return in the long term. The small-cap stock performance was slightly better than that of the large-cap stocks in this study. However, as the capitalization of these firms grows, the authors noted that their performance deteriorates in the long term. Du, Zhou and Yang (2003) employed the Fama-French three-factor model to study the five-year returns of 71 IPO stocks on the Shanghai stock exchange. They found that new shares underperform for five years following the IPO. Accordingly, our aim is to extend the previous studies on the Chinese A-share market's IPO long-term performance to estimate the abnormal returns of the newly listed stocks during the 2009–2016 period. We divide the sample data into three distinct levels of innovation intensity and apply the Fama-

French five-factor model regressions to provide new evidence of this phenomenon in the Chinese IPO market.

3.2.2 The Impact of Innovation on the Long-term Performance of IPOs

From the perspective of long-term performance, previous studies suggest that the market competition of firms intensifies after their IPOs. An important source of competition intensity is core innovation, such as patents and other technological improvements. Thus, it is essential for IPO firms to measure their innovation ability and explore its impact on the long-term performance of their shares. This information can improve their operating and market performance in the post-IPO period**.** In recent years, scholars have begun to direct their attention to R&D investment and number of patents as a measure of firms' innovation ability. One strand of research in this area has specifically focused on testing the impact of innovation on the long-term IPO performance of firms (Chin et al., 2006; Chen and Xu, 2015). There are two dimensions of innovation capital for the firms, namely R&D investment (innovation input) and number of patents (innovation outcome). In the current study, we examine the impacts of both dimensions of innovation and extend the existing literature on the impacts of firm's innovation on the IPO long-term performance in China in a more comprehensive manner.

(1) The Impact of Innovation Input on the Long-term IPO Performance

Authors of previous research have acknowledged the positive impact of innovation on firms' value. Intangible assets such as innovative activities generally create riskier future profits than fixed and tangible assets. However, for any given level of risk, companies with more innovative capital are expected to generate greater returns than those on non-innovative activities (Balkin et al., 2000). Hence, companies with more tangible innovations prefer to spread the good news of their success on their R&D efforts.

Hence, investors would become increasingly aware of the real value of these companies and consequently update their evaluations.

When examining the innovation input (R&D), a majority of scholars have focused their attention on the stock market valuation of this factor as the intangible asset of the firms. For example, Chan et al. (2001) and Eberhart et al. (2004) documented that R&D may be accompanied by greater level of uncertainty and information asymmetry, causing the market to underestimate the expected profits of R&D investments. Guo, Lev and Shi (2006) used a sample of 2,696 IPOs from the U.S. market during 1980 to 1995 and found that the issuers' R&D activities are the main source of the information asymmetries, with prominent influence on the underpricing of IPOs in short-term and their long-term underperformance. However, some researchers have raised doubt about the validity of these findings. For instance, Balatbat (2006) argued that Guo, Lev and Shi's (2006) application of pre-IPO R&D activities cannot be completely considered as the capitalized assets for the firm's future value. They do not clearly distinguish between the capitalized and expensed R&D from R&D activities, but rather assume that all IPO firms rely on existing R&D spending as the source of future value[26]. This controversy can cast doubt about the positive impact of R&D activities on the long-term IPO performance, especially in emerging markets such as China.

In addition to R&D agenda, China has its own corporate governance setting, which can be different from the U.S. market. In 2006, China issued new Accounting Standards (CAS) prescribing that only the expenditures that have been used for the technical and commercial viability of sales and assets could be considered as research expenditure and

[26] Similar to the U.S., there is no requirement for the Chinese companies to disclose their R&D spending on capitalized R&D vs. expensed R&D in their prospectuses before IPOs. This can cause information asymmetry for investors. Thus, the expected future value of R&D can become uncertain and risky in the IPO market.

capitalization of development outlays. If an R&D project does not meet the requirements of the firms' board, the budget allocated for R&D should be regarded as expenditure, rather than capital, when incurred (Wang and Fan, 2014). Thus, under the new CAS, it is not compulsory for issuers to disclose R&D capitalization in the IPO prospectuses or financial balance sheets, which means that managers may choose the method of reporting their R&D activities. This greatly reduces the extent of information disclosure of IPO firms' R&D activities in their prospectuses, reducing investors' knowledge about the true value of their R&D activities, exacerbating the information asymmetry, and even leading to IPO underpricing (Barth et al., 2001; Xu and Tang, 2010; Xu, Xia and Li, 2016). Although voluntary R&D disclosure in the IPO prospectuses can make investors optimistic about the firms' stock returns, leading to more underpricing in the short term, it is doubtful that reporting R&D allocations in the prospectuses can be successfully capitalized in the firms' expected future value. Moreover, as the investors' short-term market over optimism decreases, the available information on the level of R&D activities gradually increase, whereby prices of newly listed stocks move towards their long-term true value (Window of Opportunity; Ritter, 1991). Thus, based on the aforementioned analysis, we test the following hypothesis:

H_1: The R&D expenditure is negatively associated with the long-term market performance of IPO firms.

(2) The Impact of Innovation Outcome on the Long-term IPO Performance

Different from the innovation input measurement of R&D investments, patents provide a measure of innovation output and are an important outcome of the firms' innovation process. The long-term IPO performance of firms with high R&D investments may thus be distinct from those with a rich portfolio of patents. In 1990, Griliches first indicated that patents are the most essential and straightforward measure of the quality and extent of firms' innovations as the materialized outcomes with tangible value in the intellectual property markets. Furthermore, number of patents signals the quality of the output of a company's innovative investments. According to Cohen and Lemley (2001), patents are evidence of well-managed firms at certain stages of their development, with a carved market niche. Thus, in the existing literature, number of patents has been widely acknowledged as a positive signal of favorable development of firms.

Additionally, in the IPO market, companies with a greater number of patents could be more inclined to regard IPO as a finance growth strategy, because new products or services are more likely to bring excess stock returns to firms (Chaney, Devinney and Winner, 1991). Lev and Sougiannis (1999) concluded that innovation capital has a significant positive influence on the stock returns of the firms. In another study of the UK market, Bloom and Reenen (2002) concluded that patents have a significant positive influence on company production efficiency and market value. Evidence also suggests that patents are a valid predictive indicator of future performance of IPOs, as firms with a greater number of patents often have better future market value and stock returns (Hirshleifer, Hsu and Li, 2013). In another study, Chin et al. (2006) found that companies with a greater number of patents outperform those with no or fewer patents in the stock market. Since companies with strong innovations have comparative advantage over companies with no innovations, their long-term performance will be more competitive, which is reflected in their returns (Cao et al., 2015). Meoli et al. (2012) also insisted that patents show the value of IPO firms, allowing them to attract investors for higher valuations. Even after the IPO, firms with a greater number of patents are more attractive to investors. Thus, we examine this expectation by testing the following hypothesis:

H_2: The number of patents is positively associated with the long-term market performance of IPO firms.

3.3 Data and Methodology

3.3.1 Data Selection

To test the long-term IPO performance, we utilize the commonly employed Event Study methodology with cross-sectional financial market data to examine the impact of a specific financial event on the value of firms. The basic assumption is that the impact of this event will be reflected immediately in the stock price when the market is informationally efficient, and all participants are rational. Therefore, in our study, the IPO event is expected to influence the firm's value, measured by the long-term abnormal returns in the stock price (Fama et al., 1969; Ritter, 1991)**.** Accordingly, we introduce five principal measures to examine the long-term IPO performance, according to the existing literature. These measures include buy-and-hold returns (raw returns and market-adjusted abnormal returns), monthly average returns (raw returns and market-adjusted abnormal returns), CAPM alphas, and Fama-French (2015) five-factor model. We estimate these models for 6-, 12-, 24-, 36-, 48-, and 60-month periods, starting two months after the IPO event.

The sample data selected for this study were obtained from Shenzhen and Shanghai Stock Exchanges A-share markets using the following procedures[27]. First, our sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. Our monthly stock returns and tradable market value of IPO firms are sourced from both

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[27] Our study is based on the Chinese A-share market. In the A-share market, there are few delisting companies. The average annual delisting rate of A-shares in the past 17 years is only 0.11 percent.

CSMAR database and RESSET database[28] for 96 months. The IPO of a firm is considered to be an event accompanied by IPO short-term underpricing and post-IPO market underperformance in the long term (Yu and Liang, 2004). To eliminate the effects of abnormal market behavior on the price of newly listed shares in the short-term, firms' stock returns for the first two months after the IPOs are excluded from our sample. The financial data of IPO firms include the IPO year, issuing price, book-to-market ratio (B/M) and so on.

Second, based on the previous studies[29], we construct two innovation indices to represent the input and outcome of innovation by manually collecting R&D intensity of firms and the number of patents in pre-IPO periods from their prospectuses. We removed the firms from our original sample if they did not publish prospectuses. Moreover, we divided our sample into groups based on the median values of IPO firms' innovation input and outcome, respectively. For innovation input, firms are segregated into low-R&D, high-R&D, and no-R&D groups. For innovation outcome, our subsamples include low-patent, high-patent, and no-patent groups.

3.3.2 Model Analysis

(1) Monthly Buy-and-hold Returns of Individual Stocks

The event study methodology utilized in this study to calculate the long-term abnormal return of the IPO stocks is mainly the buy-and-hold abnormal returns (BHAR). Compared with Cumulative Abnormal Return (CAR) method, Barber and Lyon (1997) believe that BHAR represents a strategy that is more consistent with investors' real investment experience. Since it was first introduced by Ritter (1991), the BHAR method

[28] Both CSMAR database and RESSET database are Chinese databases, and include data sourced from the Chinese capital market.

[29] Including Chin et al. (2006), Guo, Lev and Shi (2006), Chen and Xu (2015), and Zhang et al. (2016).

has gradually become a common methodology for measuring the long-term performance of IPO firms. Thus, following Ritter (1991), Loughran and Ritter (1995), and Brav and Gompers (1997), we first calculate the holding period return, measured as follows:

$$BHR_i = \prod_{t=1}^{T}(1 + R_{it}) \qquad (3.1)$$

where "R_{it}" refers to the raw return of firm "i" in the event month "t". The gross return is measured by the raw return from the buy-and-hold strategy from the closing market price of a stock at the end of the trading day of the subscribing month. Our holding periods include 6, 12, 24, 36, 48 and 60 months.

In order to reflect the long-term performance of the stocks in a more objective way, we employ the buy-and-hold market-adjusted return (BHAR) according to the following formula:

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + MR_i) \qquad (3.2)$$

where "R_{it}" is the raw return on firm "i" in the event month "t" and "MR_t" is the market return indicator. We select the weighted average return of all the stocks in the Chinese A-share market as the proxy for the market. We assume that, for every IPO stock in the market, there is an equally weighted possibility of purchasing and holding this share by an investor.

(2) Monthly Abnormal Returns of Sample Portfolios

Abnormal return (AR) is also one of the core measurements used to study the response to an IPO event reflected in the stock prices. It is estimated as the difference between actual stock return and the return on the market portfolio for every corresponding period. The advantage of this model is that it excludes the earnings that arise from market volatility, thus reducing estimation bias.

$$AR_{it} = R_{it} - MR_t \quad (3.3)$$

where "R_{it}" is the raw return on each firm "i" in the event month "t" and "MR_t" is the indicator of the market return. To eliminate idiosyncrasies in the measurement of particular stocks, we select the average abnormal return (AAR) for each day in the event window. This aggregates the abnormal returns for all N stocks to find the average abnormal return in each month "t". Thus, we estimate monthly average market-adjusted abnormal returns (AAR) as the equally weighted arithmetic average of the market-adjusted return for each firm "i":

$$AAR_t = \frac{1}{n}\sum_{i=1}^{n} AR_{it} \quad (3.4)$$

The AAR measures the total monthly abnormal return of the sample portfolio. The samples include three portfolios (No-, High- and Low-) grouped by a median for two different types of innovation (R&D and patents), respectively.

(3) Capital Asset Pricing Model (CAPM)

Nobel economics laureate William Sharpe introduced the capital asset pricing model (CAPM) in 1964 to analyze the uncertainty concerning the market equilibrium. We employ this model to calculate the firms' monthly excess returns (α_i) for 6-, 12-, 24-, 36-, 48- and 60-month periods after their initial public offerings, respectively.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + e_{i,t} \quad (3.5)$$

where "$R_{i,t}$—$R_{f,t}$" is the return on stock "i" in excess of the risk-free interest rate[30] at time "t" and "$R_{m,t}$—$R_{f,t}$" is the market risk premium from the value-weighted portfolio of market return at time "t", estimated as the difference between tradable market value weighted monthly return and risk-free interest rate.

[30] The risk-free rate is collected from RESSET database.

Table 3.1 The Adjusted-average Returns and Abnormal Returns of IPOs with R&D

Panel A IPO firms with no R&D					
Months	N	R(average)	AAR	BHAR	CAPM alpha
6 months	149	1.75%	-0.49%	-2.59%	0.94%
12 months	125	-1.02%	-0.19%	-6.07%	-0.15%
24 months	112	1.50%	-0.12%	-3.83%	-0.57%
36 months	85	3.36%	-0.18%	-13.45%	-1.08%
48 months	83	3.85%	-0.53%	-19.76%	-1.09%
60 months	71	5.11%	-1.76%	-35.20%	-1.29%
Panel B IPO firms with low R&D					
Months	N	R(average)	AAR	BHAR	CAPM alpha
6 months	647	-0.64%	-0.90%	-3.65%	-0.20%
12 months	589	-1.66%	-0.42%	-9.73%	-0.04%
24 months	529	0.83%	-0.12%	-12.61%	-0.92%
36 months	428	3.75%	-0.33%	-11.52%	-1.46%
48 months	412	4.55%	-1.05%	-39.02%	-1.68%
60 months	363	4.91%	-2.43%	-70.91%	-1.82%
Panel C IPO firms with high R&D					
Months	N	R(average)	AAR	BHAR	CAPM alpha
6 months	642	0.65%	-0.26%	-4.81%	0.45%
12 months	558	-1.06%	-0.87%	-10.63%	-0.09%
24 months	499	0.57%	-0.08%	-12.01%	-0.45%
36 months	405	2.04%	-1.01%	-21.18%	-1.30%
48 months	378	2.31%	-1.83%	-47.11%	-1.67%
60 months	328	2.78%	-3.61%	-100.18%	-2.44%

Note: The sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. Panel A reports the IPO firms with no R&D intensity according to the prospectuses before IPO. Panel B reports the IPO firms with low R&D intensity according to the prospectuses before IPO. Panel C reports the IPO firms with high R&D intensity according to the prospectuses before IPO. *R* refers to the monthly average raw return of IPO firms. *AAR* refers to the monthly average market-adjusted abnormal returns of IPO firms. *BHAR* refers to the buy-and-hold market-adjusted return of IPO firms. *CAPM alphas* are the intercepts estimated by running firm-specific time-series regressions of monthly firm excess returns on the Capital Asset Pricing model. These returns are computed on the basis of monthly stock returns ending 6, 12, 24, 36, 48, and 60 calendar months after the IPO and starting from the closing market price on the last trading day of the second month after IPO.

Table 3.2 The Adjusted-average Returns and Abnormal Returns of IPOs with Patents

Panel A IPO firms with no patents					
Months	N	R(average)	AAR	BHAR	CAPM alpha
6 months	179	0.41%	-0.42%	-3.29%	0.07%
12 months	155	-1.38%	-0.66%	-10.19%	-0.89%
24 months	144	0.47%	-0.49%	-10.52%	-0.46%
36 months	117	2.02%	-1.29%	-12.79%	-0.84%
48 months	113	2.68%	-1.96%	-20.08%	-1.20%
60 months	96	3.29%	-2.59%	-76.16%	-3.29%
Panel B IPO firms with low number of patents					
Months	N	R(average)	AAR	BHAR	CAPM alpha
6 months	637	1.04%	-0.52%	-4.44%	0.57%
12 months	586	-1.28%	-0.30%	-4.37%	-0.25%
24 months	540	1.57%	-0.46%	-8.51%	-0.39%
36 months	477	2.71%	-0.87%	-8.81%	-1.25%
48 months	461	3.11%	-1.31%	-18.61%	-1.98%
60 months	401	5.96%	-2.03%	-71.37%	-2.14%
Panel C IPO firms with high number of patents					
Months	N	R(average)	AAR	BHAR	CAPM alpha
6 months	622	-1.04%	-0.11%	-0.87%	-0.15%
12 months	531	0.53%	-0.16%	-2.51%	-0.19%
24 months	456	2.27%	-0.39%	-3.03%	-0.29%
36 months	324	4.44%	-0.56%	-5.91%	-0.58%
48 months	299	4.89%	-0.64%	-13.94%	-1.19%
60 months	265	6.22%	-1.05%	-36.38%	-1.51%

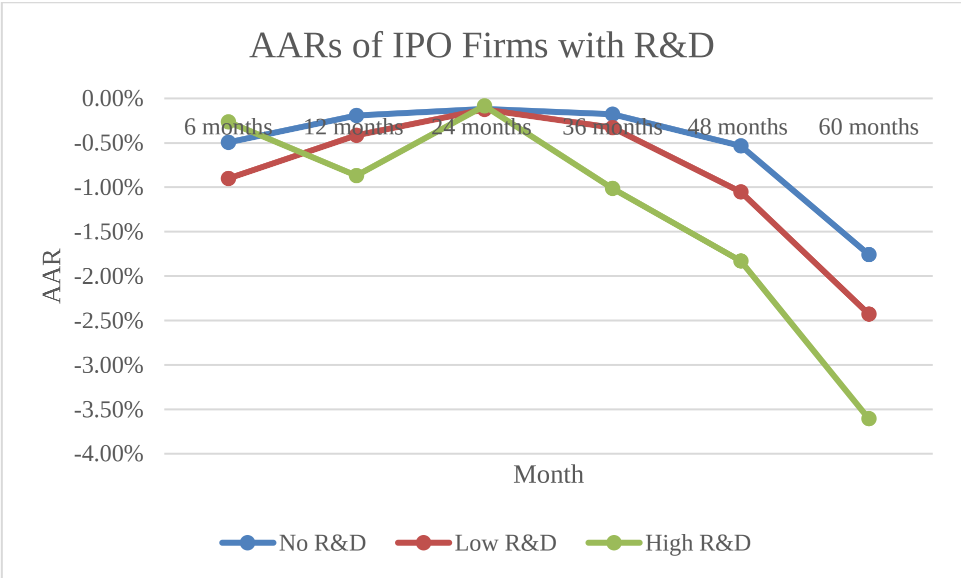
Note: The sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. Panel A reports the IPO firms with no patent according to the prospectuses before IPO. Panel B reports the IPO firms with low number of patents according to the prospectuses before IPO. Panel C reports the IPO firms with high number of patents according to the prospectuses before IPO. *R* refers to the monthly average raw return of IPO firms. *AAR* refers to the monthly average market-adjusted abnormal returns of IPO firms. *BHAR* refers to the buy-and-hold market-adjusted return of IPO firms. *CAPM alphas* are the intercepts estimated by running firm-specific time-series regressions of monthly firm excess returns on the Capital Asset Pricing model. These returns are computed on the basis of monthly stock returns ending 6, 12, 24, 36, 48, and 60 calendar months after the IPO and starting from the closing market price on the last trading day of the second month after IPO.

The preliminary findings reported in Table 3.1 show that the average monthly returns of IPO firms decrease over time. However, the average market-adjusted abnormal returns (AAR) of the IPO firms gradually decrease, starting from 6 months after the IPO event. Similar to the market-adjusted abnormal returns, the buy-and-hold market-adjusted abnormal returns (BHAR) follow a decreasing trend in the post-IPO period. The estimated CAPM alpha of each group also provides further evidence of long-term IPO underperformance in the Chinese market (across 60 months). Based on the results reported in Panel A to Panel C in Table 3.1, we also find that IPO firms with no R&D showed relatively better long-term performance in the post-IPO period than did firms with high levels of R&D.

Compared with innovation input, results in Table 3.2 suggest that IPO firms with higher level of innovation outcome (number of patents) have experienced better long-term performance after IPOs compared to the firms with no patents. Furthermore, as shown in both tables, IPO firms with either high or low level of innovation outcome outperformed the firms with a high level of innovation input. Therefore, the overall findings suggest that the two different dimensions of innovation have distinct impacts (in opposite direction) on the firms' long-term performance in their post-IPO period. On the other hand, IPO firms with higher innovation input perform worse in the market, while those with higher innovation outcome perform better in the long term.

Based on the long-term returns of IPO firms, we construct the figures of IPO firms with different groups of R&D and the number of patents. The results in both Fig. 3.1A and B show out a downward trend in the long-term average market-adjusted abnormal returns (AAR) of the firms after their IPOs. However, there is still a difference between Fig. 3.1A and B, as the slope of the high-R&D curve is steeper than the curves for the low-R&D and no-R&D groups. In contrast, Fig. 3.1B shows out a converse situation in the number of patents compared with firm's R&D, implying that the firms with a large number of patents perform a relatively better long-term market trend than those in the group of the small number of patents. Additionally, the results in Fig. 3.2 and Fig. 3.3 also provide further evidence on the BHAR and CAPM alpha of the IPO firms in support of H_1 and H_2 hypotheses.

A



B

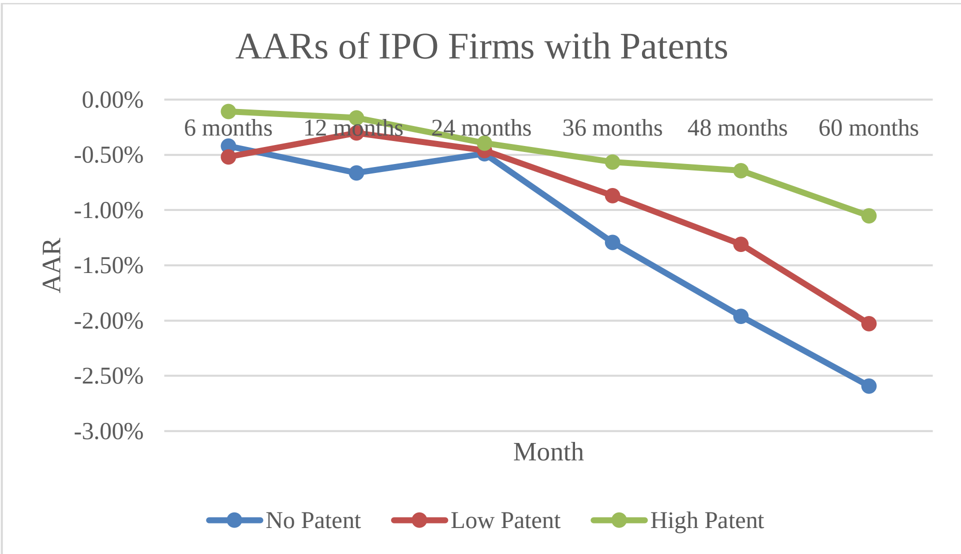
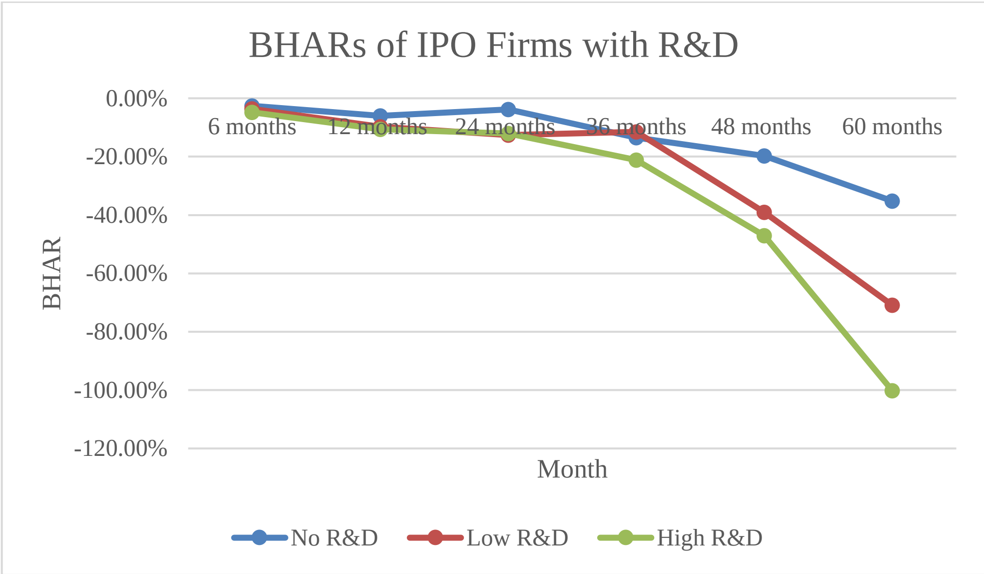


Fig. 3.1. A. AARs of IPO Firms with R&D. B. AARs of IPO Firms with Patents.

A



B

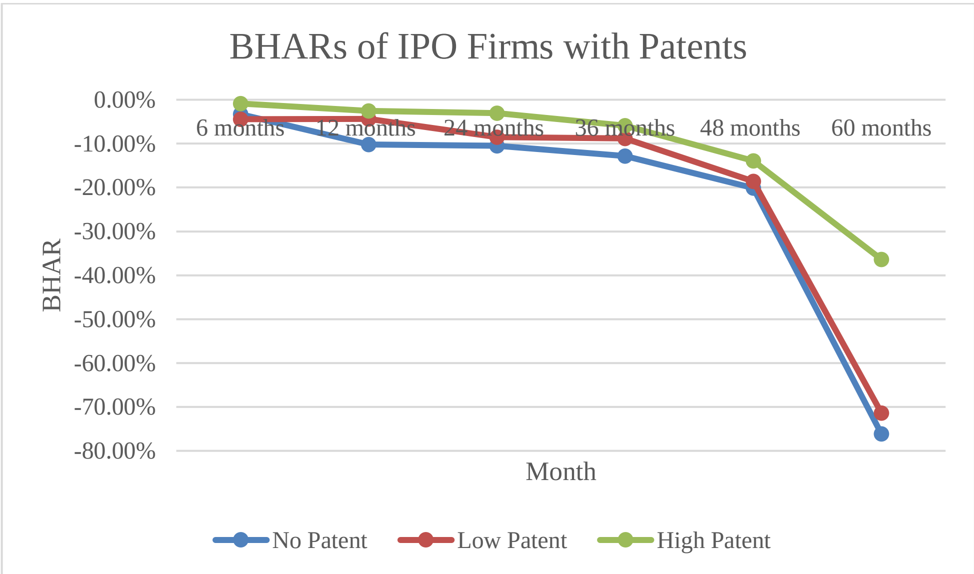
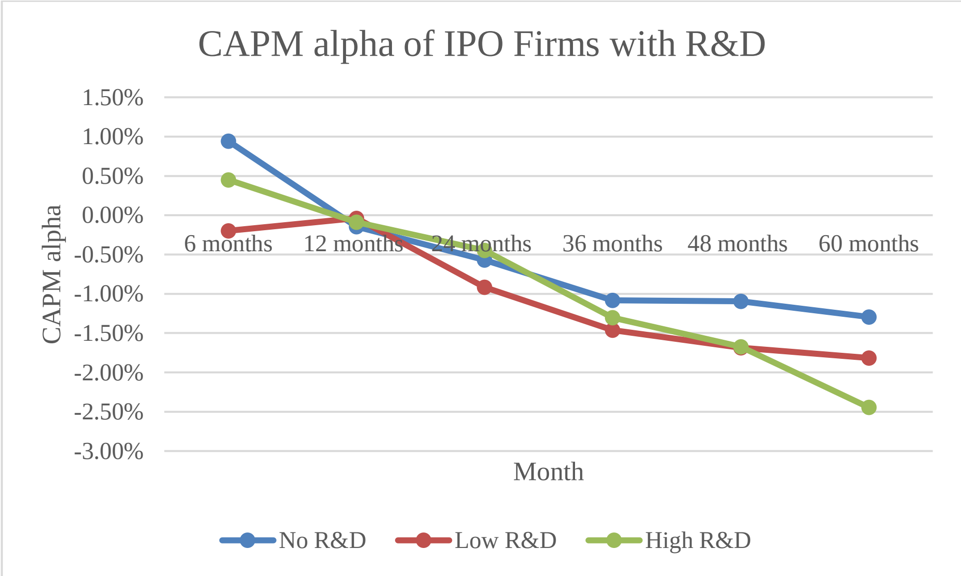


Fig. 3.2. A. BHARs of IPO Firms with R&D. B. BHARs of IPO Firms with Patents.

A



B

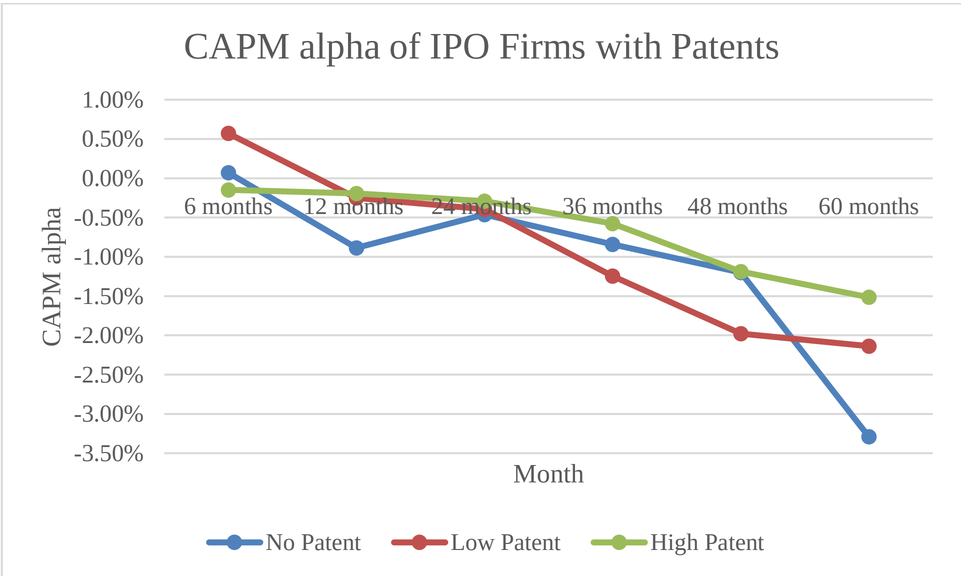


Fig. 3.3. A. CAPM alpha of IPO Firms with R&D. B. CAPM alpha of IPO Firms with Patents.

3.3.3 Fama-French Five-factor Analysis

(1) Fama-French Five-factor Model

In 1993, Fama and French put forward a three-factor model to explain the expected cross-sectional return of stocks according to the following formula:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + e_{i,t} \qquad (3.6)$$

where "$R_{i,t}$—$R_{f,t}$" refers to the return of stock "i" minus the risk-free rate at month "t"; "$R_{m,t}$—$R_{f,t}$" indicates market return minus the risk-free rate at month "t"; "SMB_t" refers to the return on a zero investment portfolio, constructed by the difference between the return on a small-sized firms' portfolio and the return on a big-sized firms' portfolio; and "HML_t" is the return on a zero investment portfolio, measured by the difference between the return on a portfolio of high book-to-market firms and the return on a portfolio of low book-to-market firms. Based on the original test of this model, Fama and French noted that small-cap stocks and stocks with high book-to-market ratios systematically experienced a higher return than other stocks in the market[31].

In 2015, Fama and French introduced an improved five-factor model. Based on the previous studies, they asserted that, in addition to the earlier three factors, profitability and investment ability also have some influence on the expected return of firms in the market. Thus, in the current study, we adopt the Fama-French five-factor model to test the abnormal return of IPO stocks grouped by the different degree of innovation ability, according to the following formula:

[31] Carhart (1997) extended the Fama-French three-factor model in his study. He introduced a fourth factor—"winners minus losers" (WML)—into the previous three-factor model. This factor is the difference between returns on one-year winners (i.e., stocks with the highest returns in the previous 12 months) and returns on one-year losers (i.e., stocks with the lowest returns in the previous 12 months). However, the four-factor model has been utilized mostly in developed markets (Czapkiewicz and Wojtowicz, 2014). As our study mainly focuses on the emerging Chinese market, we are applying the three-factor and five-factor models.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t} \quad (3.7)$$

where the two new variables are "RMW_t" and "CMA_t". The "RMW_t" is calculated as the difference between the return on robust and weak operating profitability of firms. "CMA_t" is formed by subtracting the return on conservative investment firms from that of the aggressive investment firms, which is expected to help decipher the stock returns of IPO companies (Lyandres, Sun and Zhang, 2008; Hou, Xue and Zhang, 2014; Fama and French, 2014). We will apply this model to our sample data and use the intercept of the regression to construct an indicator of risk-adjusted performance.

(2) Sample Portfolio Classification

The Fama-French (2015) five-factor model explains the average returns on different portfolios, including the factors of Size, B/M, profitability (OP), and investment (Inv). In the application of this model in our study, we collect the tradable market value of each IPO firm "i" for "$Size_{it}$". The "B/M_{it}" factor is measured by using the firm's book value at the end of "t-1" year divided by its tradable market value in the same year. Considering the difference between the accounting standards in China and the United States, we employ the "Operating profit/Total shareholders' equity" at each end of the year to reflect the annual profitability (OP_{it}) of the Chinese A-share market (Li et al., 2017). The "Inv_{it}" factor is calculated as the ratio of change in the firm's total assets from the end of "t-1" year to the end of "t-2" year by the total asset at the end of "t-2" year.

In applying the Fama-French five-factor model, we classify our sample of stocks into different groups. Following Fama and French (1993), we first classify the stocks into two main parts based on the size of the tradable market value of IPO stocks. We then classify our sample into small-cap (S) and large-cap (B) groups according to the median of the market value of the entire sample. Second, we divide the stocks into high (H), middle (M) and low (L) groups based on the 30% and 70% percentile of the book-to-market value (B/M) of sample stocks. We then cross-classify those categories into six groups, each of which becomes an asset portfolio based on the stock market value, denoted as SL, SM, SH, BL, BM, and BH, respectively.

We repeat the same procedure to constitute the factors of the operating profitability (OP) and investment style (Inv) by cross classifying the portfolios, respectively (2×3 sorts). In doing so, our sample stocks are divided into twelve groups, denoted as SR, SN, SW, BR, BN, BW, SC, SN, SA, BC, BN, and BA. Among those twelve groups, “R” represents robust profitability, “N” refers to neutral profitability, “W” represents weak profitability, “C” stands for conservative investment style, and “A” stands for aggressive investment style of a stock portfolio. We then calculate the weighted average returns of each group, as shown above, for different periods. Finally, we construct the four factors (SMB, HML, RMW and CMA) by using the differences in the returns on different stock portfolios. Table 3.3 shows the 2×3 sorts of methods used to construct the four factors.

To find more evidence on the outcome of the Fama-French five-factor model, we also provide a 2×2 classification of the sample portfolio. In the 2×2 model, our sample data are classified by the median value (50%) of the A-share market index for each factor in the model. We employ the same method of 2×3 sorts to cross-classify the B/M, OP and Inv into twelve groups, respectively. They are denoted as SH, SL, SR, SW, SC, SA, BH, BL, BR, BW, BC and BA to obtain the targeted new factors of SMB, HML, RMW and CMA. The 2×2 classification methods are also included in Table 3.3. Regarding the classification method of the calculated factors, there is another 2×2×2×2 dimensional model in the study of Fama and French (2015) to sort the entire stocks into portfolios. This model is the most complex among the three classification methods with a higher number of dimensions, smaller intersections and smaller number of shares in each group.

Considering the relatively small number of IPO firms in each group in innovation subsections, the four-dimensional model is unable to reduce the chance of small sample error in our regression. Thus, we have decided to apply the 2×3 and 2×2 classification methods in our study.

Table 3.3 Construction Method for Factors

Classifications	Breakpoints	Factors and Calculations
2×3 sorts	Size: Median	$SMB_{B/M}$=(SH+SN+SL)/3 - (BH+BN+BL)/3
		SMB_{OP}=(SR+SN+SW)/3 - (BR+BN+BW)/3
		SMB_{Inv}=(SC+SN+SA)/3 - (BC+BN+BA)/3
		SMB_{Inv}=($SMB_{B/M}$+SMB_{OP}+SMB_{Inv})/3
	B/M: 30% and 70% percentile	HML=(SH+BH)/2 - (SL+BL)/2
	OP: 30% and 70% percentile	RMW=(SR+BR)/2 - (SW+BW)/2
	Inv: 30% and 70% percentile	CMA=(SC+BC)/2 - (SA+BA)/2
2×2 sorts	Size: Median	SMB=(SH+SL+SR+SW+SC+SA)/6 - (SH+SL+SR+SW+SC+SA)/6
	B/M: Median	HML=(SH+BH)/2 - (SL+BL)/2
	OP: Median	RMW=(SR+BR)/2 - (SW+BW)/2
	Inv: Median	CMA=(SC+BC)/2 - (SA+BA)/2

(3) Five-Factor Descriptive Statistics

To obtain meaningful results from the two dimensions of innovation capital, we construct portfolios with three categories of no, low and high levels of innovation input and innovation outcome. According to the results in Table 3.4, factors sorted by the two aforementioned classification methods show relatively similar results in the same level of innovation input. Panel A shows the descriptive statistics of five factors sorted by 2×3 classification method. Similar to the results for the five-factor model, Panel B shows the descriptive statistics results sorted by the 2×2 classification method.

From the perspective of innovation input, the results of the five-factor model show that the SMB is different from zero at the significance level of 1% for all portfolios. This finding is consistent with the results reported by Wang (2015) and Zhao et al. (2016), suggesting that large-cap firms do not have higher stock returns. Thus, the average stock returns of firms are negatively correlated with the firms' market capitalizations. However, the RWM coefficient is not significantly different from zero for any of the portfolios from the perspective of innovation input. This is consistent with the results reported by Cang and Yan (2005) and Zhao et al. (2016), who found that investors may not be significantly concerned about the firms' profitability. This also means that the profitability of firms may not significantly increase their value.

The coefficient for market risk premium is significant at the 10% level in the no-R&D portfolio and at the 5% level in the high-R&D portfolio group under both classification methods. For the book-to-market ratio (B/M), the HML factor is significant at the 10% level only for the high-R&D portfolio group, which means that these firms may have relatively more significant B/M effect than those with no or low R&D. Finally, the CMA factor exhibits a significant effect of investment at the 5% level in the low-R&D portfolios. The results from no-R&D and high-R&D portfolios cannot reject the null hypothesis that the average monthly returns from these portfolios are zero.

Table 3.4 Descriptive Statistics of Portfolios Sorted by No-, Low-and High-Innovation Input

Panel A: Five-Factor Descriptive Statistics by 2×3 Classification					
No-R&D	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.07	2.80	0.62	-0.16	-1.73
Std. Dev.	1.79	2.59	5.16	3.06	4.51
t-stat	1.77*	2.74***	0.29	-0.13	-0.94
Low-R&D	R_m-R_f	SMB	HML	RMW	CMA
Mean	0.61	4.24	1.50	-1.24	2.34
Std. Dev.	1.21	1.86	3.03	5.88	2.47
t-stat	1.23	5.57***	1.21	-0.51	2.32**
High-R&D	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.32	3.45	2.91	-0.11	0.07
Std. Dev.	1.35	2.12	3.75	4.55	2.64
t-stat	2.40**	3.99***	1.90*	-0.06	0.06
Panel B: Five-Factor Descriptive Statistics by 2×2 Classification					
No-R&D	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.07	3.09	0.19	-0.14	-1.85
Std. Dev.	1.79	2.81	3.35	1.62	3.95
t-stat	1.77*	2.70***	0.14	-0.21	-1.15
Low-R&D	R_m-R_f	SMB	HML	RMW	CMA
Mean	0.61	4.12	1.13	-0.36	1.22
Std. Dev.	1.21	1.86	2.19	2.22	1.68
t-stat	1.23	5.42***	1.26	-0.39	1.77*
High-R&D	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.32	3.42	1.56	-0.60	0.41
Std. Dev.	1.35	2.12	2.95	3.56	2.23
t-stat	2.40**	3.94***	1.70*	-0.41	0.45

Note: The sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. An IPO issued in the same sample year with a positive amount of R&D is then classified into a Low- or High-R&D portfolio when its *R&D* is below or above the median of the R&D intensity measure. IPOs with no R&D expenditures are assigned to a No-R&D portfolio. Panel A presents the descriptive statistics of the five factors on portfolios by 2×3 classification with zero, low and high level of R&D. Panel B presents the descriptive statistics of the five factors on portfolios by 2×2 classification with zero, low and high level of R&D. R_m—R_f indicates market return minus the risk-free rate; *SMB* refers to the return on a zero investment portfolio, constructed by the difference between the return on a small-sized firms' portfolio and the return on a big-sized firms' portfolio; *HML* is the return on a zero investment portfolio, measured by the difference between the return on a portfolio of high book-to-market firms and the return on a portfolio of low book-to-market firms; *RMW* is calculated as the difference between the return on robust and weak operating profitability of firms; And *CMA* is formed by subtracting the return on conservative investment firms from that of the aggressive investment firms. T-statistics in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

Similar to the innovation input, the five-factor descriptive statistics of innovation outcome show significant results on the 'size effect' for different IPOs portfolios at the 5% and 1% significance levels (see Table 3.5). The 'market risk premium' factor is different from zero at the 10% significance level in Panel A and Panel B of Table 3.5. For the RMW factor, the results do not show any statistical significance on these three groups of innovation outcome. This is consistent with the results for the innovation input. Additionally, the HML factors from the no-patent level, sorted by both 2×3 and 2×2 classification methods, experience 5% and 1% significance level in the low-patent portfolios, respectively. This finding implies that firms with no patents or low level of patents may have relatively more significant 'B/M effect' than the high-patent firms, which is in contrast with the findings for innovation input. Finally, the results of CMA factor from these three groups of innovation outcome in Panel B are different from zero at the significant level of 10%, and at the significant level of 5% in the no-patent portfolio in Panel A.

Although the results reported in Table 3.4 through Table 3.6 show that some of the factors sorted by different level of innovation capital are not significantly different from zero, factors may still have correlations among the other factors from a different level of innovation capital. Thus, to further explore the relationships between the factors from the perspectives of innovation input and innovation outcome, a five-factor time-series regression analysis was conducted, and the findings are discussed in the following section.

Table 3.5 Descriptive Statistics of Portfolios Sorted by No-, Low-and High-Innovation Outcome

Panel A: Five-Factor Descriptive Statistics by 2×3 Classification					
No-Patent	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.13	3.16	3.76	-1.02	3.68
Std. Dev.	1.68	3.16	4.57	3.11	4.02
t-stat	1.75*	2.45**	2.02**	-1.08	2.24**
Low-Patent	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.10	3.30	1.12	-0.33	0.95
Std. Dev.	1.61	1.32	2.41	3.12	2.35
t-stat	1.67*	6.13***	1.14	-0.26	0.99
High-Patent	R_m-R_f	SMB	HML	RMW	CMA
Mean	0.66	3.44	0.59	-0.58	1.50
Std. Dev.	0.86	1.29	3.11	6.38	3.21
t-stat	1.87*	6.55***	0.46	-0.22	1.24
Panel B: Five-Factor Descriptive Statistics by 2×2 Classification					
No-Patent	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.13	3.66	3.26	-0.95	2.22
Std. Dev.	1.68	3.42	3.48	3.14	2.84
t-stat	1.75*	2.66***	2.30**	-0.74	1.97*
Low-Patent	R_m-R_f	SMB	HML	RMW	CMA
Mean	1.10	3.52	1.74	-0.57	1.18
Std. Dev.	1.61	1.20	1.52	2.24	1.47
t-stat	1.67*	6.16***	2.80***	-0.27	1.91*
High-Patent	R_m-R_f	SMB	HML	RMW	CMA
Mean	0.66	3.37	0.19	-0.87	1.88
Std. Dev.	0.86	1.00	3.14	3.27	2.39
t-stat	1.87*	6.24***	0.15	-0.65	1.93*

Note: The sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. An IPO issued in the same sample year with a positive number of patents is then classified into a Low- or High-Patent portfolio when its *Patent* is below or above the median of the number of patents measure. IPOs with no patents are assigned to a No-Patent portfolio. Panel A presents the descriptive statistics of the five factors on portfolios by 2×3 classification with zero, low and high number of patents. Panel B presents the descriptive statistics of the five factors on portfolios by 2×2 classification with zero, low and high number of patents. R_m—R_f indicates market return minus the risk-free rate; *SMB* refers to the return on a zero investment portfolio, constructed by the difference between the return on a small-sized firms' portfolio and the return on a big-sized firms' portfolio; *HML* is the return on a zero investment portfolio, measured by the difference between the return on a portfolio of high book-to-market firms and the return on a portfolio of low book-to-market firms; *RMW* is calculated as the difference between the return on robust and weak operating profitability of firms; And *CMA* is formed by subtracting the return on conservative investment firms from that of the aggressive investment firms. T-statistics in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

(4) Five-Factor Time-Series Regressions Analysis

Following Brav et al. (2000), Eberhard et al. (2004) and Guo et al. (2006), in this section, we apply the five-factor time-series calendar regression approach to examine the long-term performance of IPO firms sorted by different levels of innovation capital. Regression estimates for the no-, low- and high-R&D subsamples and no-, low- and high-patent subsamples of IPO firms, sorted by 2×3 classification method is presented in Table 3.6. Consistent with the findings of Brav et al. (2000) and Guo et al. (2006), our results show that the intercept (excess returns) is negative and significant for some of the subsamples from the perspectives of innovation input and innovation outcome. For the innovation input, the results in Panel A suggest that the no-R&D and high-R&D portfolios have significantly negative excess monthly returns at the 10% and 5% level, respectively. No-R&D portfolio has the monthly excess return of -1.01% at the significance level of 10%, while the high-R&D portfolio has the monthly excess return of -1.41% at the significance level of 5%. These findings are consistent with the first hypothesis (H_1), suggesting that the excess returns on IPOs with R&D are lower than those of IPOs with no R&D. In contrast to innovation input, the intercept of innovation outcome in the five-factor model in Panel B shows that the estimated excess returns on IPOs with a high number of patents are higher than those of IPO firms with no patents. Thus, Panel B presents -1.05% and -1.79% for the high- and no-patent portfolios, respectively. This finding is consistent with the second hypothesis (H_2) suggesting that IPO firms with a large number of patents may have better long-term performance after their IPOs than IPO firms with no patents. Although the returns from the low-R&D and low-patent portfolios are significantly different from zero, the H_1 and H_2 hypotheses are still valid.

Additionally, to provide further evidence in support of our hypotheses, we present the results of our analysis for different levels of innovation input and innovation outcome portfolios sorted by 2×2 classification methods in Table 3.7. The estimated intercepts in this table are somewhat similar to the results in Table 3.6. The estimated coefficients for intercepts in this table are somewhat similar to the results in Table 3.6, showing that no-R&D, low-R&D, low-patent, and high-patent portfolios are not significantly different from zero. However, the coefficients for high-R&D and no-patent portfolios are -1.79% and -2.05% with the statistical significance at the 10% and 5% levels, respectively. Moreover, the estimated intercept of each portfolio in Table 3.6 and Table 3.7 indicates that Chinese firms experience IPO underperformance in the long term after their IPOs. Overall, our findings for the significant effect of IPO firms' innovation capital on the extent of their long-term underperformance are consistent with the hypotheses H_1 and H_2.

Table 3.6 Five-Factor Time-Series Regressions of Monthly Returns on Portfolios on **2×3** Classification

Panel A: Regression Analysis on Portfolios Sorted by Ratio of Innovation Input							
Coefficients	α	β	s	h	r	c	R_{adj}^2
No-R&D	-0.0101*	1.1169***	0.8722***	-0.2516**	-0.5321	-0.2459	60.35%
	(-1.76)	(4.09)	(4.36)	(-2.12)	(-1.30)	(-0.82)	
Low-R&D	-0.0067	1.2799***	0.3696**	-0.1953*	-0.2008	0.0158	59.74%
	(-0.48)	(5.57)	(2.26)	(-1.74)	(-0.91)	(1.10)	
High-R&D	-0.0141**	1.3201***	0.4669***	-0.3621**	-0.3922	-0.3893	59.19%
	(-2.55)	(5.87)	(5.10)	(-2.53)	(-0.95)	(-1.28)	
Panel B: Regression Analysis on Portfolios Sorted by Ratio of Innovation Outcome							
Coefficients	α	β	s	h	r	c	R_{adj}^2
No-Patent	-0.0179**	1.0452**	0.4187**	-0.3642**	-0.0169	-0.2008*	56.66%
	(-2.15)	(2.22)	(2.39)	(-2.17)	(-0.75)	(-1.83)	
Low-Patent	0.0028	1.2123***	0.2532**	-0.0886	-0.0406	-0.0971	56.53%
	(0.42)	(5.32)	(2.15)	(-0.91)	(-0.82)	(-1.08)	
High-Patent	-0.0105*	1.1209***	0.6766***	-0.1715	-0.084	-0.1979	57.31%
	(-1.78)	(4.84)	(3.31)	(-1.27)	(-0.95)	(-1.41)	

Note: The sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. An IPO issued in the same sample year with a positive amount of R&D (number of patents) is then classified into a Low- or High-R&D (Low- or High-Patent) portfolio when its *R&D (Patent)* is below or above the median of the R&D intensity (number of patents) measure. IPOs with no R&D (patents) are assigned to a No-R&D (No-Patent) portfolio. Panel A presents the regression results on portfolios by 2×3 classification with zero, low and high level of R&D. Panel B presents the regression results on portfolios by 2×3 classification with zero, low and high number of patents. $R_{i,t}$—$R_{f,t}$ refers to the return of stock *i* minus the risk-free rate at month *t*; $R_{m,t}$—$R_{f,t}$ indicates market return minus the risk-free rate at month *t*; *SMB* refers to the return on a zero investment portfolio, constructed by the difference between the return on a small-sized firms' portfolio and the return on a big-sized firms' portfolio; *HML* is the return on a zero investment portfolio, measured by the difference between the return on a portfolio of high book-to-market firms and the return on a portfolio of low book-to-market firms; *RMW* is calculated as the difference between the return on robust and weak operating profitability of firms; And *CMA* is formed by subtracting the return on conservative investment firms from that of the aggressive investment firms. T-statistics in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_t HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$$

Table 3.7 Five-Factor Time-Series Regressions of Monthly Returns on Portfolios on **2×2** Classification

Coefficients	α	β	s	h	r	c	R_{adj}^2
Panel A: Regression Analysis on Portfolios Sorted by Ratio of Innovation Input							
No-R&D	0.0089	1.3416***	0.7451***	-0.2013*	-0.2432	0.014	60.81%
	(1.54)	(5.72)	(2.87)	(-1.71)	(-1.07)	(0.32)	
Low-R&D	-0.0051	1.2025***	0.2496*	-0.1832	-0.2267	-0.0834	59.42%
	(-0.52)	(4.97)	(1.89)	(-1.43)	(-0.99)	(-1.47)	
High-R&D	-0.0179*	1.0111**	0.3128**	-0.2459*	0.0255	0.0164	59.27%
	(-1.87)	(2.09)	(2.04)	(-1.89)	(1.11)	(0.62)	
Panel B: Regression Analysis on Portfolios Sorted by Ratio of Innovation Outcome							
Coefficients	α	β	s	h	r	c	R_{adj}^2
No-Patent	-0.0205**	1.1039**	0.7779***	-0.2765*	0.2112	-0.3396*	56.27%
	(-2.12)	(2.33)	(4.10)	(-1.83)	(1.36)	(-1.76)	
Low-Patent	-0.0005	1.3474***	0.1908*	-0.0984	-0.0737	-0.0855	56.48%
	(-0.11)	(4.42)	(1.91)	(-1.04)	(-0.37)	(-0.70)	
High-Patent	0.008	1.1793***	0.2959**	-0.3163	-0.3316	-0.5742	57.18%
	(0.89)	(2.86)	(2.32)	(-1.25)	(-0.54)	(-1.59)	

Note: The sample includes all listed firms that went public from January 1st, 2009 to December 31st, 2016. An IPO issued in the same sample year with a positive amount of R&D (number of patents) is then classified into a Low- or High-R&D (Low- or High-Patent) portfolio when its *R&D (Patent)* is below or above the median of the R&D intensity (number of patents) measure. IPOs with no R&D (patents) are assigned to a No-R&D (No-Patent) portfolio. Panel A presents the regression results on portfolios by 2×2 classification with zero, low and high level of R&D. Panel B presents the regression results on portfolios by 2×2 classification with zero, low and high number of patents. $R_{i,t}$—$R_{f,t}$ refers to the return of stock *i* minus the risk-free rate at month *t*; $R_{m,t}$—$R_{f,t}$ indicates market return minus the risk-free rate at month *t*; *SMB* refers to the return on a zero investment portfolio, constructed by the difference between the return on a small-sized firms' portfolio and the return on a big-sized firms' portfolio; *HML* is the return on a zero investment portfolio, measured by the difference between the return on a portfolio of high book-to-market firms and the return on a portfolio of low book-to-market firms; *RMW* is calculated as the difference between the return on robust and weak operating profitability of firms; And *CMA* is formed by subtracting the return on conservative investment firms from that of the aggressive investment firms. T-statistics in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_t HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$$

3.4 Impact of the Innovation Ability of Firms on their Post-IPO Abnormal Returns

3.4.1 Regression Model

According to the results reported in the preceding section, we have calculated the buy-and-hold abnormal return (BHAR) of our samples from the third month after the firms' IPOs. To examine the regression impact of pre-IPO innovation ability on the post-IPO market performance of these firms, we construct the following regression model to analyze the relationship between the innovation outcome or input and the long-term market returns of IPO firms:

$$LT_i = a_0 + a_1 R\&D_i + a_2 Patent_i + a_3 lnMV_i + a_4 UM_i + a_5 Lot_i + a_6 IssPrice_i + a_7 lnAsset_i + a_8 VC_i + a_9 lnProceed_i + a_{10} lnAge_i + a_{11} Year_i + a_{12} Ind_i + \varepsilon_i \quad (3.8)$$

where "LT_i" is the dependent variable, denoting the long-term performance of the post-IPO market returns of the firms. Two independent variables in the function are noteworthy—innovation input, which is the intensity of research and development investment ($R\&D_i$), and number of patents ($Patent_i$) as the innovation outcome. The control variables included in the model are market value ($lnMV_i$), underwriter reputation (UW_i), lottery rate (Lot_i), issuing price ($IssPrice_i$), firm size ($lnAsset_i$), venture capital backing (VC_i), IPO volume ($lnProceed_i$), age of firms ($lnAge_i$), initial public offering year ($Year_i$) and the industry of IPO firms (Ind_i). More detailed descriptions of the model are given below.

3.4.2 Variable Definitions

(1) Dependent Variables

The long-term performance measure used for the IPO firms is the buy-and-hold returns, which are adjusted by market returns in Section 3 (BHAR). Based on the analyses reported in the previous section, the dependent variable of buy-and-hold returns is measured from two months after the IPO firm's public offering to avoid the influence of IPO short-term underpricing[32] and market sentiment.

We estimate BHAR for the long-term market performance of IPO firms for the following periods: one-year (12 months), two-year (24 months), three-year (36 months),

[32] According to Zhou and Sadeghi (2019), the short-term performance of Chinese IPO shares can extend to maximum 59 days after their stock exchange listing.

four-year (48 months), and five-year (60 months). LT_{i1}, LT_{i2}, LT_{i3}, LT_{i4}, and LT_{i5} denote long-term stock return performance of LT_i from the first to the fifth year of the firm "i" since its initial public offerings, respectively. From 1,460 firms included in the original sample, dated from January 2009 to December 2016, we removed firms with no prospectuses and firms without R&D investment or patents. In addition, we denote the patents as 0 only if the firm has none.

(2) Independent Variables

We collected the data on innovation from the 1,451 firms' IPO prospectuses manually. Following Chin et al. (2006) and Chen and Xu (2015), we employ R&D and number of patents to demonstrate innovation in our study. For innovation input, we employ R&D intensity to depict the pre-IPO innovation input by using the R&D expenditure scaled by the total assets of the firms two years before IPOs, respectively. For the innovation outcome, we apply number of patents as the pre-IPO innovation output collected from firms' prospectuses.

(3) Control Variables

1) Firm age (lnAge): According to Filatotchev and Bishop (2002), age of the firm has a significant influence on the firm's performance in the market. Firm age is calculated from its foundation to the IPO year.

2) Firm size (lnAsset): The size effect has been acknowledged in the existing studies. Barth and Kasznik (1999) pointed out that larger firms have less information asymmetry in the markets. We apply the logarithm of the firm's total assets one year before IPO as a control variable.

3) Total proceeds (lnProceed): We use the logarithm of total proceeds as the product of the issuing price with the total issue volume of each IPO firm as another control variable in our study (Li, 2006).

4) Lottery rate (Lot): According to Li (2006), lottery rate is one of the important variables in the research of IPO phenomenon. Thus, we use the lottery rate of offline issue of IPO stocks for the control of this variable.

5) Underwriter reputation (UW): A substantial body of literature suggests that underwriter reputation has a significant impact on the IPO markets. Carter et al. (1998) found that firms with prestigious underwriters have a better market performance three years after their IPOs. We employ a dummy variable to control for underwriter reputation of each IPO firm. Thus, firms with at least one of the top 10 underwriters will be coded as 1, and 0 otherwise.

6) Venture capital (VC): Previous studies suggest that venture-backed IPO firms outperform the non-venture-backed firms (Brav and Gompers, 1997; Jiang et al., 2014). Hence, we include a dummy variable in the model with a value of 1 if the IPO firm has one or more venture capital firms before going public, and 0 otherwise.

7) Issuing price (IssPrice): According to Huang (2005), the issuing price of a new IPO is inversely related to the long-term IPO performance. Thus, we use the issuing price of each IPO firm as another control variable in our study.

8) Market value (lnMV): Following Huang (2005) and Zhang and Zhang (2017), we include the logarithm of IPO firm's market value on the first trading day as an independent variable in our study. The stock market is a fluctuating market, and the stock market price is constantly fluctuating. Thus, the marker value in the model can control

the market fluctuate in the study. We estimate the value of this variable as the closing price of the first trading day multiplied by the share of outstanding common stocks.

3.5 Regression Analysis

3.5.1 Descriptive Statistics

Table 3.8 summarizes the descriptive statistics for independent, dependent and control variables, estimated using STATA 14. For the buy-and-hold market-adjusted returns, we find that the mean values of the BHARs gradually decline from 12 months to 60 months after the IPOs. The mean value of BHAR for 60 months after IPOs is 69.48%, with 762 observed IPO firms during that period. For the innovation outcome (Patent), the average number of patents in our sample is 75, which is higher than the average number for most of the developing and some of the developed countries (Chin et al., 2006; Heeley et al., 2007). The maximum number of patents in one IPO firm is 7,713, belonging to BYD Company (002594). Compared with the innovation outcome, the innovation input (R&D) of firms has a very high mean value of 0.0684. The maximum value of R&D intensity is around 19 for two years before IPOs. Thus, the relatively high levels of innovation input and output indicate that the innovation abilities of IPO firms are strong in the Chinese IPO market.

Table 3.8 Descriptive Statistics

Variables	N	Mean	Std. Dev.	Min	Max
12M-BHAR	1,272	-0.0854	0.4326	-1.5764	8.2416
24M-BHAR	1,140	-0.0501	0.6355	-2.5097	6.3568
36M-BHAR	918	-0.0849	1.1875	-4.4620	10.5574
48M-BHAR	873	-0.1739	1.7473	-5.5002	13.7014
60M-BHAR	762	-0.6948	1.8024	-4.4434	19.8175
Patent	1,271	75.1298	278.7461	1	7713
R&D_1	1,302	0.0711	0.6374	3.9E-05	20.7642
R&D_2	1,302	0.0658	0.5653	0	19.1856
R&D	1,302	0.0684	0.6003	1.9E-05	19.9749
R&Dpp	1,329	18.1942	14.1272	0.1600	93.5800
lnAge	1,451	2.2351	0.6194	0	3.5835
lnAsset	1,451	20.3753	1.2346	15.9441	29.8151
lnProceed	1,451	20.0876	0.7485	17.4714	24.1264
Lot	1,451	0.0105	0.0243	0.0001	0.6552
UW	1,451	0.4590	0.4985	0	1
VC	1,451	0.6809	0.4663	0	1
IssPrice	1,451	21.5589	13.8767	1.5	148
lnMV	1,451	21.1562	0.7676	19.2541	24.7967

Note: This table presents descriptive statistics for variables used in our study, including observations (*N*), mean, standard deviation (*Std. Dev.*), the minimum value (*Min*) and the maximum value (*Max*). *12M-BHAR, 24M-BHAR, 36M-BHAR, 48-BHAR*, and *60M-BHAR* refer to the buy-and-hold market-adjusted returns of IPO firms for the following periods: one-year, two-year, three-year, four-year, and five-year, respectively. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *lnAge* (age of firm), *lnAsset* (total assets), *lnProceed* (total proceed), *Lot* (lottery rate), *UW* (underwriter reputation), *VC* (venture capital), *IssPrice* (issuing price), and *lnMV* (market value).

To further explore the correlations between variables, we have estimated the Pearson statistics presented in Table 3.9. Our results show that the innovation input (research and development) is negatively correlated with the first three years' BHAR after the firms' IPOs. This correlation becomes statistically insignificant after this period. Therefore, the results of the association between innovation input and BHAR for the first three-year post-IPO performance are consistent with the previous analysis in the valuation of hypothesis H_1. Meanwhile, the innovation outcome (patents) is positively correlated with the long-term IPO performance, becoming statistically significant in the third year after the IPOs. This pattern is consistent with the hypothesis H_2 and the notion that an increase in pre-IPO innovation outcomes of the firms is correlated with their superior long-term performance after IPO.

We further observe a significantly negative correlation between total assets and long-term IPO performance. There is also a significantly negative correlation between total proceeds and the BHAR of the firms for consecutive 60 months. On the other hand, the market values of IPO firms are significantly and positively correlated with the BHAR, especially for the first three-year in the post-IPO period. However, the Pearson correlation only aims to test pairwise associations between variables. Therefore, to provide evidence of independent variables' effect on the dependent variable, we provide the details of empirical regression analysis in the following section.

Table 3.9 Pearson Correlation of the Variables

Variables	12M-BHAR	24M-BHAR	36M-BHAR	48M-BHAR	60M-BHAR	ln(Patents+1)	R&D	lnAge	lnAsset	lnProceed	Lot	UW	VC	IssPrice	lnMV
12M-BHAR	1														
24M-BHAR	0.6669***	1													
36M-BHAR	0.4285***	0.7203***	1												
48M-BHAR	0.2462***	0.4614***	0.6987***	1											
60M-BHAR	0.2273***	0.3168***	0.5103***	0.7405***	1										
ln(Patents+1)	0.0288	0.0493	0.1058***	0.1807***	0.1727***	1									
R&D	-0.0981**	-0.1367***	-0.0856**	0.0062	0.0357	-0.0122	1								
lnAge	-0.0126	-0.0136	-0.0169	-0.0049	-0.0085	0.0635**	-0.0074	1							
lnAsset	-0.1201***	-0.1539***	-0.1462***	-0.2147***	-0.1816***	0.2851***	-0.3281***	0.0444*	1						
lnProceed	-0.0680**	-0.0726**	-0.1131***	-0.1731***	-0.1929***	0.1389***	-0.1426***	-0.2142***	0.6598***	1					
Lot	0.0136	0.0125	-0.0536	-0.1145***	-0.0705*	-0.0524*	-0.0315	-0.1234***	0.1450***	0.2783***	1				
UW	-0.0300	-0.0020	-0.0219	-0.0367	-0.0819**	0.0768***	-0.0079	-0.0440*	0.1284***	0.1558***	0.0021	1			
VC	0.0102	0.0111	0.0056	0.0246	-0.0057	0.0203	0.1309***	0.0443*	-0.0373	-0.0624**	-0.0586**	-0.0163	1		
IssPrice	0.0456	0.0866***	0.0333	0.0276	-0.0537	-0.1294***	0.1182***	-0.2085***	-0.2371***	0.3361***	0.1958***	0.0126	-0.0126	1	
lnMV	0.1224***	0.1001***	0.1367***	0.0086	0.0047	0.1967***	0.0155	0.0440	0.6251***	0.5697***	0.1109***	0.1226***	0.0551**	-0.0347	1

Note: This table presents the Pearson correlation of the variables used in this study. *12M-BHAR, 24M-BHAR, 36M-BHAR, 48-BHAR*, and *60M-BHAR* refer to the buy-and-hold market-adjusted returns of IPO firms for the following periods: one-year, two-year, three-year, four-year, and five-year, respectively. *ln(Patent+1)* refers to the logarithm of the number of patents of IPO firms applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *lnAge* (age of firm), *lnAsset* (total assets), *lnProceed* (total proceed), *Lot* (lottery rate), *UW* (underwriter reputation), *VC* (venture capital), *IssPrice* (issuing price), and *lnMV* (market value). ***1% significance level, **5% significance level, *10% significance level.

3.5.2 Empirical Analysis

(1) Innovation input

In this section, we fully investigate the impact of innovation on the IPO long-term performance from three distinct perspectives in the Chinese IPO market. First, we provide extensive regression analysis of the innovation input on the buy-and-hold market-adjusted returns for 12, 24, 36, 48, and 60 months after the IPO in Table 3.10. The results yielded by Model 1 to Model 3 show a negative impact of R&D intensity on the 12-month, 24-month and 36-month BHAR at the significance levels of 1%, 1% and 5%, respectively. Overall, the statistical results of Model 1 to Model 3 show that higher innovation input of the firms before IPOs may result in less long-term underperformance in the post-IPO period. This is consistent with the analysis of hypothesis (H_1) discussed in the previous section.

However, the estimated coefficients for innovation input in Model 4 and Model 5 gradually turn from negative to positive, starting at 48 months after the IPO. This intriguing finding provides evidence that research and development activities may have some significant positive long-term impacts on the stock market. However, due to the high risk and uncertainty in the R&D outcome, it has an unstable impact on the firms' future market performance and value (Pakes, 1985). Our finding is consistent with the results reported by Penman and Zhang (2002), who found that the impact of innovation input on the long-term performance of firms after IPOs gradually turns from significantly negative to insignificantly positive. Hence, the influence of R&D intensity on the firms' performance has the characteristics of cumulative and lag effects in the process of production.

Further, total assets are negatively correlated with the BHAR for 12-, 24-, 36-, 48-, and 60-month periods at the significance level of 1%, 1%, 1%, 5% and 10%, respectively. This implies that the firms with higher total assets before IPOs may have worse long-term performance after their IPOs. Similar to the total assets, the total proceeds of IPO firms also experience a negative relationship with the buy-and-hold abnormal adjusted returns after their IPOs at the significance level of 1% for consecutive five years. In contrast, the relationship between market value of the long-term IPO returns and the dependent variable is positive and statistically significant at the 1% level for consecutive five years. As a result, firms with a higher market value have better IPO performance in the long term.

Table 3.10 Regression of the Innovation Input on BHAR for 12, 24, 36, 48, 60 Months after IPO

	Model 1	Model 2	Model 3	Model 4	Model 5
VARIABLES	12M-BHAR	24M-BHAR	36M-BHAR	48M-BHAR	60M-BHAR
R&D	-1.353***	-1.613***	-2.629**	1.189	1.828
	(0.004)	(0.002)	(0.025)	(0.625)	(0.416)
lnAge	-0.0156	0.00627	-0.0298	0.0144	-0.0436
	(0.504)	(0.798)	(0.574)	(0.890)	(0.650)
lnAsset	-0.120***	-0.135***	-0.233***	-0.298**	-0.223*
	(0.000)	(0.000)	(0.000)	(0.012)	(0.055)
lnProceed	-0.121***	-0.293***	-0.597***	-0.731***	-0.745***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Lot	0.186	-0.0639	-0.873	-3.183	0.124
	(0.740)	(0.911)	(0.457)	(0.165)	(0.953)
UW	-0.0310	-0.00570	-0.0418	-0.0643	-0.124
	(0.232)	(0.838)	(0.508)	(0.608)	(0.301)
VC	-0.0227	-0.0433	-0.130*	-0.163	-0.259**
	(0.408)	(0.147)	(0.054)	(0.221)	(0.041)
IssPrice	-0.000855	-0.000157	-0.00249	-0.00598	-0.00993*
	(0.519)	(0.908)	(0.393)	(0.309)	(0.070)
lnMV	0.333***	0.539***	0.987***	0.942***	0.823***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.244***	-3.086***	-4.485***	-0.141	0.939
	(0.000)	(0.000)	(0.001)	(0.956)	(0.699)
Mean VIF	1.83	1.83	1.92	2.04	2.16
Observations	1,147	1,028	833	790	691
R-squared	0.207	0.423	0.398	0.236	0.234
Industry	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation input on IPO long-term performance. Model 1 to 5 respectively test the impact of firm's innovation input (*R&D*) on its BHAR returns which are the buy-and-hold market-adjusted returns of firm for 12, 24, 36, 48, and 60 months after its IPO. Definitions of the independent variables and control variables are presented in the Appendix C. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

(2) Innovation outcome

Table 3.11 reveals the impact of innovation outcome (patents) on the 12-month, 24-month, 36-month, 48-month and 60-month BHAR in the post-IPO period. Compared with the impact of innovation input, innovation outcome shows a relatively stable positive influence on the IPO long-term performance, especially starting 36 months after the event. Unlike research and development, the variable of *ln(Patent+1)* shows no evidence of significant effect in the application of Model 1. However, Model 2 to Model 5 reveal positive relationships at the significance level of 10%, 5%, 5% and 1%, respectively. Accordingly, we can conclude that the direct association between innovation outcome and the long-term performance of firms continuously increases and becomes statistically more significant over time. These findings provide strong support for hypothesis H_2, indicating that having a larger number of patents before the IPO can help firms reduce the extent of their long-term IPO underperformance in the post-IPO period.

According to the control variables in Table 3.11 and similar to Table 3.10, total assets show a negative significant relationship with the long-term performance of firms for one to five years after their IPOs at the significance level of 1%, 1%, 1%, 1% and 10%, respectively. The relationship between total proceeds of firms and the buy-and-hold returns for the 60-month period after their IPOs is negative at the significance level of 1%. Moreover, for the market value of firms, the result shows that the relationship between firms' market value and the buy-and-hold adjusted abnormal returns is positive at the significance level of 1% for five years after the IPO. Finally, the venture-backed IPO firms experience a worse long-term performance in the market for two, three and five years after their IPOs at the significance level of 10%.

Table 3.11 Regression of the Innovation Outcome on BHAR for 12, 24, 36, 48, 60 Months after IPO

	Model 1	Model 2	Model 3	Model 4	Model 5
VARIABLES	12M-BHAR	24M-BHAR	36M-BHAR	48M-BHAR	60M-BHAR
ln(Patents+1)	0.00675	0.0294*	0.0532**	0.131**	0.164***
	(0.597)	(0.078)	(0.049)	(0.013)	(0.004)
lnAge	0.00142	0.0113	-0.0121	-0.0140	-0.0531
	(0.952)	(0.709)	(0.851)	(0.877)	(0.577)
lnAsset	-0.113***	-0.145***	-0.285***	-0.299***	-0.192*
	(0.000)	(0.000)	(0.000)	(0.003)	(0.082)
lnProceed	-0.105***	-0.323***	-0.582***	-0.685***	-0.905***
	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
Lot	0.274	0.494	-0.244	-2.561	0.625
	(0.611)	(0.464)	(0.858)	(0.180)	(0.752)
UW	-0.0255	-0.0132	-0.0788	-0.117	-0.165
	(0.328)	(0.702)	(0.310)	(0.289)	(0.166)
VC	-0.0116	-0.0689*	-0.158*	-0.152	-0.222*
	(0.676)	(0.061)	(0.056)	(0.189)	(0.078)
IssPrice	-0.00110	-0.000595	-0.00426	-0.00402	-0.00701
	(0.419)	(0.730)	(0.243)	(0.435)	(0.202)
lnMV	0.301***	0.589***	1.021***	0.822***	0.766***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.105***	-3.341***	-4.536***	1.231	4.218*
	(0.000)	(0.000)	(0.006)	(0.592)	(0.089)
Mean VIF	1.86	1.87	1.95	1.97	2.09
Observations	1,117	996	801	760	666
R-squared	0.194	0.371	0.334	0.260	0.237
Industry	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation outcome (*number of patents*) on IPO long-term performance. Model 1 to 5 respectively test the impact of firm's innovation outcome on its BHAR returns which are the buy-and-hold market-adjusted returns of firm for 12, 24, 36, 48, and 60 months after its IPO. Definitions of the independent variables and control variables are presented in the Appendix C. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

(3) Innovation capital

To investigate the joint effect of innovation input and innovation outcome in the IPO market, we combine the R&D and patents in the regression analysis in Table 3.12. The statistical results from innovation input and innovation outcome are consistent with the results reported in Table 3.10 and Table 3.11. When combined with the effect of innovation outcome, innovation input also exhibits a significantly negative impact on the long-term stock performance for 36 months after IPOs. This effect becomes slightly positive in the following months. In addition, the negative impact of patents on the firm's long-term performance extends from one year to five years after its IPO. In looking at the innovation outcome, we also found that the coefficients of this variable in Model 1 to Model 5 continuously increase over time. Hence, number of patents as the evidence of innovation outcome before IPOs can help increase the firms' market value following their initial public offerings in the capital market. We therefore conclude that, in contrast to innovation input, number of patents before IPOs can increase investors' optimism about firms' long-term performance in post-IPO period. For the control variables, the results of total assets, total proceeds and total market value of IPO firms are consistent with those reported in Table 3.10 and Table 3.11, reconfirming the stability of our findings. Additionally, the mean-variance inflation factors (VIF) of coefficients (which remains < 2) reported in Table 3.10 through Table 3.12 suggest that our regression results are not affected by multicollinearity.

Table 3.12 Regression of the Innovation Capital on BHAR for 12, 24, 36, 48, 60 Months after IPO

	Model 1	Model 2	Model 3	Model 4	Model 5
VARIABLES	12M-BHAR	24M-BHAR	36M-BHAR	48M-BHAR	60M-BHAR
R&D	-1.726***	-1.897***	-2.369**	-1.017	0.918
	(0.001)	(0.004)	(0.036)	(0.643)	(0.689)
ln(Patents+1)	0.0117	0.0363**	0.0388**	0.137**	0.156***
	(0.381)	(0.037)	(0.047)	(0.012)	(0.007)
lnAge	-0.00475	0.00543	-0.0225	0.00383	-0.0356
	(0.844)	(0.860)	(0.673)	(0.967)	(0.712)
lnAsset	-0.129***	-0.160***	-0.265***	-0.322***	-0.207*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.074)
lnProceed	-0.104**	-0.335***	-0.553***	-0.677***	-0.893***
	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)
Lot	0.248	0.339	-0.716	-2.647	0.458
	(0.664)	(0.634)	(0.542)	(0.190)	(0.826)
UW	-0.0297	-0.0194	-0.0508	-0.0981	-0.134
	(0.270)	(0.583)	(0.431)	(0.384)	(0.271)
VC	-0.00988	-0.0592	-0.137**	-0.134	-0.242*
	(0.728)	(0.116)	(0.047)	(0.258)	(0.058)
IssPrice	-0.000978	-0.000325	-0.00283	-0.00521	-0.00825
	(0.485)	(0.854)	(0.347)	(0.321)	(0.138)
lnMV	0.317***	0.606***	0.958***	0.834***	0.799***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.090***	-3.104***	-4.135***	1.250	3.575
	(0.000)	(0.000)	(0.002)	(0.594)	(0.155)
Mean VIF	1.82	1.82	1.87	1.88	1.98
Observations	1,071	956	772	733	643
R-squared	0.198	0.368	0.378	0.264	0.244
Industry	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capital (*R&D and number of patents*) on IPO long-term performance. Model 1 to 5 respectively test the impact of firm's innovation capital on its BHAR returns which are the buy-and-hold market-adjusted returns of firm for 12, 24, 36, 48, and 60 months after its IPO. Definitions of the independent variables and control variables are presented in the Appendix C. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

(4) Further Tests on Three Different Boards in the Chinese A-share Market

The Chinese A-share market is consisted with different exchange market platforms, i.e., the SME board, ChiNext board and Main board[33]. Thus, we set our sample IPO firms into three different exchange boards in order to find out the differential effects across mainland China's exchange market platforms. And this helps to get a clearer analysis on the impact of the firm's innovation on the post-IPO long-term performance from different exchange market boards. Thus, we undertake additional regressions on the IPO firms in identifying and distinguishing the impacts over the three platforms. The regressions in Table 3.13, Table 3.14 and Table 3.15 provide further explanations on our findings from different dimensions.

Results from these three major boards help to offer more evidence on our hypothesis. More interestingly, Table 3.13 examines the impact of innovation on the post-IPO long-term market performance of firms from the SME board, Table 3.14 tests the IPO firms in the ChiNext board, and Table 3.15 shows out the regression results of the firms in the Main board. Results from Table 3.13 have relatively more significant impact of innovation capital on the long-term market performance of firms. Compared with the results from the ChiNext board (Table 3.14) and Main board (Table 3.15), firms from SME board show out more significant impact of the innovation capital in the IPO market. We investigate that the Main board firm's innovation input shows a negative and significant impact only on the 24-month and 36-month BHAR of firm after IPO. From the perspective of innovation outcome, the number of patents have a positive and significant impact on the firms' post-IPO market performance and this impact becomes more and more significant over time after firm's IPO. Findings are consistent with our

[33] The Chinese A-share market are consisted with the Main board, SME (Small and Medium-sized Enterprises) board, and ChiNext (Growth Enterprise Market) board.

hypotheses and the results are hold in different exchange market platforms, i.e., SME, ChiNext and Main boards.

Table 3.13 Regression of the Innovation Capital on BHAR for 12, 24, 36, 48, 60 Months after IPO in the SME Board

	12M-BHAR			24M-BHAR			36M-BHAR			48M-BHAR			60M-BHAR		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
ln(Patents+1)	0.0372		0.0393	0.0827*		0.0921*	0.1019*		0.1041*	0.1334*		0.1157*	0.2045**		0.2015**
	(0.173)		(0.187)	(0.098)		(0.095)	(0.087)		(0.080)	(0.056)		(0.068)	(0.035)		(0.040)
R&D		-1.6160***	-1.6701***		-2.0213**	-1.5162*		-4.7243**	-4.1516*		-2.1376	-2.9281		0.0658	-1.0274
		(0.007)	(0.005)		(0.012)	(0.094)		(0.011)	(0.066)		(0.189)	(0.190)		(0.284)	(0.266)
lnAge	0.0310	0.0175	0.0315	0.0528	0.0356	0.0541	0.0301	0.0086	0.0124	0.0510	0.0106	0.0538	-0.0505	-0.0815	-0.0308
	(0.197)	(0.473)	(0.204)	(0.143)	(0.282)	(0.148)	(0.718)	(0.904)	(0.887)	(0.689)	(0.929)	(0.685)	(0.701)	(0.533)	(0.826)
lnAsset	-0.0947***	-0.1074***	-0.1049***	-0.1715***	-0.2045***	-0.1865***	-0.4011***	-0.4023***	-0.4278***	-0.6418***	-0.5915***	-0.6788***	-0.3427**	-0.3455**	-0.3993**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.027)	(0.015)
lnProceed	-0.0861*	-0.0856*	-0.0826*	-0.1758**	-0.1501**	-0.1562**	-0.3672**	-0.4026***	-0.3675**	-0.5400**	-0.5694**	-0.5366**	-1.5608***	-1.4618***	-1.5912***
	(0.058)	(0.062)	(0.077)	(0.011)	(0.019)	(0.029)	(0.024)	(0.004)	(0.030)	(0.029)	(0.016)	(0.036)	(0.000)	(0.000)	(0.000)
Lot	0.1188	-0.0303	0.0343	-0.0034	-0.2901	-0.2607	-0.4482	-0.6195	-0.7892	-2.9126	-3.9241*	-3.5121	0.4241	-0.6574	0.0500
	(0.784)	(0.947)	(0.939)	(0.996)	(0.630)	(0.698)	(0.755)	(0.622)	(0.604)	(0.181)	(0.063)	(0.125)	(0.846)	(0.769)	(0.983)
UW	-0.0093	-0.0292	-0.0146	0.0028	-0.0004	0.0061	-0.1512	-0.1312	-0.1560	-0.2512	-0.2231	-0.2403	-0.2047	-0.1621	-0.1722
	(0.742)	(0.317)	(0.620)	(0.948)	(0.992)	(0.892)	(0.133)	(0.131)	(0.140)	(0.102)	(0.127)	(0.134)	(0.201)	(0.316)	(0.316)
VC	0.0061	-0.0027	0.0135	-0.0358	-0.0279	-0.0295	-0.0954	-0.0724	-0.0837	-0.0812	-0.0509	-0.0682	-0.3072*	-0.3205*	-0.3647**
	(0.830)	(0.928)	(0.648)	(0.407)	(0.486)	(0.510)	(0.345)	(0.406)	(0.426)	(0.601)	(0.730)	(0.671)	(0.061)	(0.053)	(0.036)
IssPrice	-0.0013	-0.0021	-0.0019	-0.0012	-0.0022	-0.0020	-0.0022	-0.0027	-0.0027	-0.0001	0.0002	-0.0020	0.0098	0.0069	0.0058
	(0.415)	(0.207)	(0.235)	(0.595)	(0.319)	(0.414)	(0.674)	(0.551)	(0.625)	(0.987)	(0.984)	(0.815)	(0.242)	(0.418)	(0.510)
lnMV	0.2476***	0.2617***	0.2578***	0.4848***	0.4975***	0.4953***	0.8983***	0.9173***	0.9356***	0.7180***	0.7633***	0.7630***	0.7720***	0.8535***	0.9642***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.7273**	-2.0967***	-2.0171***	-3.5799***	-3.7051***	-3.9320***	-5.5502**	-3.5255*	-4.1074**	7.0493*	7.6320**	7.7985*	21.7418***	17.2713***	18.7183***
	(0.020)	(0.006)	(0.009)	(0.001)	(0.000)	(0.001)	(0.030)	(0.054)	(0.020)	(0.070)	(0.049)	(0.052)	(0.000)	(0.000)	(0.000)
Observations	460	455	430	434	431	408	396	395	375	380	381	361	335	337	319
R-squared	0.3657	0.3665	0.3659	0.4482	0.4685	0.4401	0.3383	0.3909	0.3351	0.2818	0.2908	0.2898	0.3654	0.3498	0.3690
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capital (R&D and number of patents) on IPO long-term performance. Model 1 to 15 test the impact of firms' innovation capital on their buy-and-hold market-adjusted returns (BHAR) of the firm for 12, 24, 36, 48, and 60 months after their IPO, respectively. All of the IPO firms are from the SME board in the A-share market. Definitions of the independent variables and control variables are presented in Appendix C. P-value in parentheses. ∗∗∗ represents 1% significance level, ∗∗ represents 5% significance level, ∗ represents 10% significance level.

Table 3.14 Regression of the Innovation Capital on BHAR for 12, 24, 36, 48, 60 Months after IPO in the ChiNext Board

	12M-BHAR			24M-BHAR			36M-BHAR			48M-BHAR			60M-BHAR		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
ln(Patents+1)	0.0104		0.0097	0.0595*		0.0703*	0.0888*		0.0929*	0.0918*		0.1139*	0.1218**		0.1784**
	(0.191)		(0.155)	(0.096)		(0.051)	(0.088)		(0.078)	(0.071)		(0.061)	(0.041)		(0.027)
R&D		-2.1874**	-3.0150***		-1.1835*	-2.4142**		-1.1777	-1.5774*		4.0403	5.8469		4.7712	5.7626
		(0.011)	(0.001)		(0.052)	(0.032)		(0.111)	(0.082)		(0.254)	(0.177)		(0.200)	(0.227)
lnAge	-0.0134	-0.0311	-0.0255	-0.0719	-0.0189	-0.0763	-0.1111	-0.0950	-0.1130	-0.0425	0.0336	-0.0148	-0.0294	0.0266	-0.1980
	(0.793)	(0.517)	(0.614)	(0.219)	(0.651)	(0.189)	(0.348)	(0.287)	(0.343)	(0.831)	(0.840)	(0.941)	(0.864)	(0.877)	(0.356)
lnAsset	-0.1755**	-0.2287***	-0.2216***	-0.0354	-0.0887	-0.0645	-0.2655	-0.1844	-0.2913	0.1188	0.0813	0.2073	-0.2761	-0.3354	-0.2100
	(0.012)	(0.001)	(0.002)	(0.660)	(0.138)	(0.427)	(0.134)	(0.180)	(0.110)	(0.694)	(0.759)	(0.508)	(0.307)	(0.238)	(0.546)
lnProceed	-0.1418	-0.1287	-0.1355	-0.7137***	-0.5058***	-0.7092***	-1.2457***	-1.1764***	-1.2360***	-1.8218***	-1.7230***	-1.8573***	-1.1578***	-0.9267**	-1.4145***
	(0.197)	(0.208)	(0.213)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.025)	(0.007)
Lot	1.3300	1.8620	1.9348	3.8788	2.2637	4.5955*	-0.5556	-2.8465	-0.1710	-15.0778*	-12.0489*	-15.1919*	-1.3126	-2.3253	-1.7973
	(0.567)	(0.402)	(0.403)	(0.134)	(0.230)	(0.075)	(0.914)	(0.469)	(0.974)	(0.079)	(0.098)	(0.079)	(0.866)	(0.770)	(0.854)
UW	-0.0346	-0.0262	-0.0367	-0.0465	-0.0110	-0.0573	-0.0355	0.0123	-0.0422	-0.0856	0.0338	-0.0866	-0.2284	-0.2116	-0.0775
	(0.540)	(0.620)	(0.512)	(0.484)	(0.817)	(0.387)	(0.801)	(0.907)	(0.766)	(0.722)	(0.866)	(0.719)	(0.299)	(0.334)	(0.778)
VC	-0.0028	-0.0166	0.0076	-0.0957	-0.0098	-0.0718	-0.1600	-0.0971	-0.1475	-0.3364	-0.3323	-0.3415	-0.1716	-0.1731	-0.1734
	(0.967)	(0.788)	(0.908)	(0.220)	(0.860)	(0.356)	(0.344)	(0.444)	(0.390)	(0.233)	(0.157)	(0.230)	(0.495)	(0.493)	(0.584)
IssPrice	-0.0010	-0.0018	-0.0009	0.0019	0.0007	0.0019	-0.0001	0.0043	-0.0001	0.0146	0.0138	0.0128	-0.0008	-0.0055	-0.0059
	(0.754)	(0.550)	(0.787)	(0.611)	(0.777)	(0.611)	(0.989)	(0.448)	(0.987)	(0.261)	(0.193)	(0.324)	(0.942)	(0.628)	(0.685)
lnMV	0.3605***	0.4136***	0.3940***	0.7733***	0.6308***	0.7855***	1.3820***	1.2074***	1.3914***	1.3706***	1.1419***	1.3127***	0.8675***	0.8749***	1.2283***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.4046	-1.6428	-1.2614	-1.4101	-1.6008	-1.1236	0.8453	1.3797	0.9931	4.2875	7.5533	4.2563	8.4908	4.8765	5.0630
	(0.368)	(0.258)	(0.415)	(0.437)	(0.214)	(0.533)	(0.826)	(0.633)	(0.798)	(0.509)	(0.164)	(0.513)	(0.137)	(0.395)	(0.478)
Observations	451	486	449	396	429	394	331	359	329	311	336	309	270	289	268
R-squared	0.1744	0.2105	0.1961	0.4514	0.5315	0.4576	0.4354	0.5169	0.4356	0.2996	0.3344	0.3079	0.2519	0.2588	0.2342
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capital (R&D and number of patents) on IPO long-term performance. Model 1 to 15 test the impact of firms' innovation capital on their buy-and-hold market-adjusted returns (BHAR) of the firm for 12, 24, 36, 48, and 60 months after their IPO, respectively. All of the IPO firms are from the ChiNext board in the A-share market. Definitions of the independent variables and control variables are presented in Appendix C. P-value in parentheses. *** represents 1% significance level, ** represents 5% significance level, * represents 10% significance level.

Table 3.15 Regression of the Innovation Capital on BHAR for 12, 24, 36, 48, 60 Months after IPO in the Main Board

	12M-BHAR			24M-BHAR			36M-BHAR			48M-BHAR			60M-BHAR		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
ln(Patents+1)	0.0348		0.0316	0.0644		0.0755*	0.0928*		0.1137*	0.1247*		0.1692*	0.2243**		0.2921**
	(0.218)		(0.293)	(0.135)		(0.094)	(0.095)		(0.094)	(0.089)		(0.080)	(0.043)		(0.035)
R&D		-0.4550	-1.1269		-1.6372*	-0.4133		-6.4071*	-6.3360*		5.7501	7.0790		-1.8934	2.9840
		(0.112)	(0.107)		(0.086)	(0.129)		(0.054)	(0.051)		(0.293)	(0.200)		(0.832)	(0.733)
lnAge	-0.0646	-0.0569	-0.0571	0.0318	-0.0073	0.0321	0.1120	0.1215	0.1217	0.0774	0.0851	0.1105	-0.1901	-0.2002	-0.1423
	(0.288)	(0.342)	(0.352)	(0.713)	(0.923)	(0.716)	(0.554)	(0.464)	(0.503)	(0.620)	(0.552)	(0.463)	(0.487)	(0.454)	(0.605)
lnAsset	-0.1252***	-0.0722*	-0.1241**	-0.1353*	-0.0596	-0.1421*	-0.0944	0.1749	-0.0510	-0.0534	0.1180	-0.0028	0.0667	0.3594	0.0979
	(0.010)	(0.086)	(0.014)	(0.063)	(0.268)	(0.062)	(0.639)	(0.251)	(0.791)	(0.748)	(0.433)	(0.986)	(0.805)	(0.180)	(0.718)
lnProceed	-0.1147	-0.1526**	-0.0987	-0.2430**	-0.3378***	-0.2804**	-0.0886	-0.3589	-0.0634	-0.3763	-0.5900**	-0.3918	-0.4205	-0.7275	-0.4584
	(0.107)	(0.026)	(0.191)	(0.016)	(0.000)	(0.011)	(0.799)	(0.215)	(0.849)	(0.199)	(0.032)	(0.163)	(0.379)	(0.132)	(0.340)
Lot	0.4960	0.5579	0.3192	0.8283	1.1668	1.0127	-0.0294	-0.8956	-2.6015	4.9673	5.6041*	3.2952	-3.5295	1.8640	-4.9360
	(0.765)	(0.705)	(0.850)	(0.730)	(0.522)	(0.681)	(0.995)	(0.797)	(0.567)	(0.201)	(0.070)	(0.384)	(0.526)	(0.683)	(0.393)
UW	0.0041	0.0047	-0.0101	0.0398	0.0482	0.0213	0.1240	0.1957	0.0245	0.0877	0.0706	0.0083	-0.1871	-0.0289	-0.2432
	(0.939)	(0.929)	(0.854)	(0.619)	(0.491)	(0.800)	(0.623)	(0.347)	(0.920)	(0.674)	(0.699)	(0.967)	(0.571)	(0.925)	(0.465)
VC	-0.0412	-0.0375	-0.0492	-0.1420	-0.1173	-0.1350	-0.2210	-0.0350	0.0305	-0.0804	0.0169	0.1429	0.0916	-0.0255	0.3310
	(0.473)	(0.525)	(0.413)	(0.105)	(0.136)	(0.142)	(0.357)	(0.883)	(0.906)	(0.683)	(0.935)	(0.504)	(0.766)	(0.940)	(0.354)
IssPrice	-0.0015	0.0008	-0.0017	8.97e-05	0.0062	0.0019	-0.0061	-0.0025	-0.0089	0.0026	0.0059	0.0014	-0.0075	-0.0024	-0.0071
	(0.687)	(0.806)	(0.655)	(0.986)	(0.144)	(0.726)	(0.551)	(0.779)	(0.365)	(0.759)	(0.449)	(0.866)	(0.566)	(0.855)	(0.588)
lnMV	0.2055***	0.2074***	0.2153***	0.4551***	0.3619***	0.4871***	0.4724*	0.4530*	0.4792*	0.5265**	0.5716***	0.5618**	0.3275**	0.2169*	0.4064**
	(0.008)	(0.007)	(0.007)	(0.000)	(0.000)	(0.000)	(0.085)	(0.064)	(0.069)	(0.023)	(0.009)	(0.013)	(0.013)	(0.084)	(0.015)
Constant	1.3560	0.2155	0.1131	-1.5742	-0.0055	-1.7926	-7.3394	-7.4530	-10.4886**	-3.9462	-3.8163	-4.8875	-0.8287	2.2303	-2.8520
	(0.409)	(0.885)	(0.944)	(0.503)	(0.998)	(0.451)	(0.193)	(0.122)	(0.044)	(0.411)	(0.356)	(0.264)	(0.910)	(0.744)	(0.707)
Observations	206	206	192	166	168	154	74	79	68	69	73	63	61	65	56
R-squared	0.4489	0.4412	0.4475	0.5566	0.5695	0.5510	0.8091	0.8224	0.8410	0.8135	0.8087	0.8352	0.8368	0.7994	0.8505
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of innovation capital (R&D and number of patents) on IPO long-term performance. Model 1 to 15 test the impact of firms' innovation capital on their buy-and-hold market-adjusted returns (BHAR) of the firm for 12, 24, 36, 48, and 60 months after their IPO, respectively. All of the IPO firms are from the Main board in the A-share market. Definitions of the independent variables and control variables are presented in Appendix C. P-value in parentheses. *** represents 1% significance level, ** represents 5% significance level, * represents 10% significance level.

3.5.3 Endogeneity Test

As we stated before, the disclosure on innovation input is highly discretionary, while the information on outcomes, such as patents, is more credible with the endorsement of legal documents. These two constructs are the main independent variables employed in our study, yet the innovation input is highly discretionary (Zhou and Sadeghi, 2019), in other words, endogenous. Thus, in this section, we apply the instrumental variable method to deal with the endogenous issue of the innovation input. We utilize the ratio of the R&D personnel to the total number of the staffs as the instrumental variable to do the 2SLS regression in this section. This instrumental variable can influence the R&D investment of the firms in the pre-IPO period, however, it cannot directly impact the firm's IPO short-term performance. The R&D personnel ratio as an exogeneous variable can be suitable for the conditions to be the instrumental variable in the study. R&D personnel ratio is from the firm's prospectus in the pre-IPO period and this data is manually collected from the IPO prospectuses.

Since there are many factors influencing the firm's innovation, in order to prevent the estimation deviation caused by the omitted variables, we add the instrumental variable in the function (3.8) to do the 2SLS regression. Thus, the model can be shown as below:

$$R\&D_i = \beta_0 + \beta_1 R\&Dpp_i + \beta_2 Patent_i + \beta_3 Control_i + \varepsilon_i \qquad (3.9)$$

$$LT_i = \gamma_0 + \gamma_1 R\&D_i + \gamma_2 Patent_i + \gamma_3 Control_i + \varepsilon_i \qquad (3.10)$$

Different from the OLS model in function (3.8), we add the instrumental variable of R&D personnel ratio in the 2SLS model. The function (3.9) shows out the first stage of the regression for utilizing the instrumental variable. And function (3.10) is the second stage of the 2SLS regression. The control variables in the first stage in the function (3.9) are the same in the function (3.10).

We first did the endogenous test on the R&D intensity to verify if it has the endogeneity. The OLS estimation is superior to the IV estimation if the R&D intensity does not have the endogeneity, otherwise, the IV estimation is better. The endogenous test requires the use of instrumental variables, which is essentially to compare the systematic difference between the estimated results of the ordinary least squares regression and the instrumental variables, which is the Hausman test. We apply the Hausman test on the instrumental variable of the R&D personnel ratio in the models. And all of the results of the long-term performance show out the Hausman tests on the average statistical chi-square value is 26.85 and rejects the null hypothesis at the significant level of 1%. This result indicates that the R&D intensity is indeed endogenous. Thus, we utilize the IV estimation method in this section in order to get a more convincing result.

Table 3.16 shows out the results of 2SLS regression with the instrumental variable at the first stage. The first-stage result shows out that the instrumental variable is effective in the model. The first-stage F statistics in Table 3.16 are all above 3.10. This finding can provide the evidence to reject the null hypothesis of "the weak instrumental variable" in our model, thus the R&D personnel ratio is not the weak instrumental variable. In order to support our finding, we also did tests on the weak instrumental variable to get the Shea's partial R square. The results from the models are all above 20% in the table that support the alternative hypothesis. Thus, the R&D personnel ratio is not a weak instrumental variable. Table 3.17 shows out the results from the second stage of the 2SLS regression. The R&D intensity still exhibits a significant impact on the firm's BHARs after IPOs. Compared with the results in Table 3.10 and 3.12, the coefficients of R&D intensity in Table 3.17 are relatively bigger than those in the Table 3.10 and 3.12. It indicates that the OLS regression underestimates the impact of the R&D intensity on the firm's IPO long-term performance. The impact of the control variables in the Table 3.17 is consistent with the variables in the Table 3.12. In addition, we also investigate that the innovation input turns from a significant negative impact to a significant and positive impact on the firm's post-IPO market performance in Table 3.17. From the fourth year since firm's IPO, the pre-IPO innovation input turns out to be a significant positive impact on the firm's BHAR and this positive impact becomes greater in the fifth year since IPO. The 2SLS regression with the instrumental variable strengthens the positive impact of the R&D intensity on the firm's post-IPO performance and make it more significant start from the fourth year since its IPO. This result also supports our finding that the firm's pre-IPO innovation input has the characteristics of lag and commutativity effect in the post-IPO period. Therefore, after controlling the endogeneity issue of the innovation input in our model, the results from the 2SLS regression with the instrumental variable also provides the evidence to explain our hypotheses.

Table 3.16 2SLS Regression for Instrumental Variable at the First Stage

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
VARIABLES	R&D	R&D	R&D	R&D	R&D	R&D	R&D	R&D	R&D	R&D
R&Dpp	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0010***	0.0010***	0.0011***	0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Patents+1)		0.0021**		0.0024*		0.0023*		0.0022**		0.0021*
		(0.041)		(0.059)		(0.064)		(0.045)		(0.053)
lnAge	-0.0020	-0.0029**	-0.0015	-0.0022	-0.0020	-0.0025*	-0.0021	-0.0029*	-0.0022	-0.0029*
	(0.150)	(0.041)	(0.278)	(0.114)	(0.182)	(0.093)	(0.160)	(0.060)	(0.186)	(0.079)
lnAsset	-0.0076***	-0.0078***	-0.0076***	-0.0075***	-0.0076***	-0.0072***	-0.0080***	-0.0078***	-0.0078***	-0.0076***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnProceed	-0.0032*	-0.0036*	-0.0027*	-0.0031**	-0.0017	-0.0023	-0.0043**	-0.0048**	-0.0033*	-0.0034*
	(0.083)	(0.087)	(0.084)	(0.044)	(0.143)	(0.123)	(0.046)	(0.040)	(0.081)	(0.093)
Lot	0.0183	0.0259	0.0203	0.0248	0.0247	0.0264	0.0206	0.0273	0.0067	0.0143
	(0.347)	(0.189)	(0.314)	(0.217)	(0.277)	(0.225)	(0.365)	(0.244)	(0.696)	(0.421)
UW	0.0001	-0.0002	-0.0004	-0.0002	-0.0005	-0.0008	0.0006	-0.0002	-0.0003	-0.0011
	(0.950)	(0.905)	(0.984)	(0.899)	(0.779)	(0.680)	(0.742)	(0.900)	(0.890)	(0.604)
VC	0.0052***	0.0043**	0.0058***	0.0048***	0.0075***	0.0064***	0.0070***	0.0060***	0.0070***	0.0063***
	(0.001)	(0.011)	(0.001)	(0.007)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)
IssPrice	0.0021*	0.0022*	0.0021**	0.0028**	0.0019*	0.0019*	0.0020**	0.0022**	0.0021*	0.0021*
	(0.089)	(0.082)	(0.047)	(0.035)	(0.062)	(0.063)	(0.048)	(0.047)	(0.087)	(0.079)
lnMV	0.0076***	0.0071***	0.0071***	0.0065***	0.0056***	0.0050**	0.0038*	0.0039*	0.0030	0.0038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.023)	(0.068)	(0.080)	(0.222)	(0.154)
Constant	0.0800***	0.0951***	0.0797***	0.0928***	0.0896***	0.1019***	0.0948***	0.1071***	0.0873**	0.0999**
	(0.005)	(0.002)	(0.005)	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.016)	(0.013)
Observations	1,117	1,050	999	936	808	767	754	716	672	629
R-squared	0.3627	0.3535	0.3448	0.3264	0.3646	0.3448	0.3510	0.3353	0.3499	0.3370
F-stat (first-stage)	40.42***	34.98***	34.20***	28.91***	31.61***	26.62***	29.98***	24.92***	26.87***	22.73***
Shea's R_p^2	0.2214	0.2247	0.2028	0.2012	0.2178	0.2183	0.2042	0.2065	0.2105	0.2109

Note: This table presents the 2SLS regressions with the instrumental variable (*R&D personnel ratio*) at the first stage. Model 1 and 2 are the first-stage regression on the 12M-BHAR of IPO firms. Model 3 and 4 are the first-stage regression on the 24M-BHAR of IPO firms. Model 5 and 6 are the first-stage regression on the 36M-BHAR of IPO firms. Model 7 and 8 are the first-stage regression on the 48M-BHAR of IPO firms. Model 9 and 10 are the first-stage regression on the 60M-BHAR of IPO firms. Definitions of the independent variables and control variables are presented in Appendix C. P-value in parentheses. ∗∗∗ represents 1% significance level, ∗∗ represents 5% significance level, and ∗ represents 10% significance level.

Table 3.17 2SLS Regression for Instrumental Variable at the Second Stage

	12M-BHAR		24M-BHAR		36M-BHAR		48M-BHAR		60M-BHAR	
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
R&D	-1.6993***	-2.0090***	-1.9449**	-1.9121**	-1.8092*	-1.9967**	1.2327*	1.7743*	2.0011**	2.0530**
	(0.001)	(0.003)	(0.028)	(0.031)	(0.077)	(0.035)	(0.083)	(0.084)	(0.031)	(0.023)
ln(Patents+1)		0.0358		0.0512*		0.0860*		0.1461**		0.1692***
		(0.115)		(0.089)		(0.071)		(0.034)		(0.003)
lnAge	-0.0191	-0.0135	-0.0175	-0.0184	-0.0539	-0.0526	-0.0321	-0.0318	-0.1105	-0.1198
	(0.242)	(0.422)	(0.466)	(0.440)	(0.326)	(0.338)	(0.704)	(0.716)	(0.383)	(0.344)
lnAsset	-0.1443***	-0.1394***	-0.1889***	-0.1712***	-0.1955*	-0.2237**	-0.2011**	-0.2397*	-0.0775*	-0.0307**
	(0.001)	(0.003)	(0.000)	(0.000)	(0.065)	(0.035)	(0.026)	(0.068)	(0.081)	(0.013)
lnProceed	-0.0121***	-0.0162**	-0.0586*	-0.0669**	-0.3607**	-0.3299**	-0.5204**	-0.4977**	-0.7162***	-0.8641***
	(0.009)	(0.025)	(0.086)	(0.015)	(0.016)	(0.029)	(0.013)	(0.022)	(0.004)	(0.000)
Lot	0.7456	0.7281	1.4125	1.3625	-0.3557	-0.3923	-3.8565**	-4.0134**	-0.4708	-0.4041
	(0.218)	(0.236)	(0.247)	(0.279)	(0.674)	(0.642)	(0.018)	(0.027)	(0.715)	(0.736)
UW	-0.0400	-0.0357	-0.0169	-0.0189	-0.0911	-0.1048	-0.0989	-0.1604	-0.1477	-0.1213
	(0.113)	(0.174)	(0.664)	(0.616)	(0.286)	(0.225)	(0.434)	(0.207)	(0.298)	(0.377)
VC	-0.0250	-0.0049	-0.0731	-0.0557	-0.2492***	-0.2546***	-0.2462*	-0.2415*	-0.3906***	-0.4053***
	(0.297)	(0.826)	(0.136)	(0.143)	(0.006)	(0.007)	(0.067)	(0.080)	(0.005)	(0.005)
IssPrice	-0.0017	-0.0013	-0.0022	-0.0011	-0.0047	-0.0042	-0.0046	-0.0045	-0.0131**	-0.0105*
	(0.118)	(0.232)	(0.284)	(0.540)	(0.215)	(0.286)	(0.352)	(0.388)	(0.032)	(0.094)
lnMV	0.2232***	0.2156***	0.3211***	0.2993***	0.6158***	0.6277***	0.6102***	0.5889***	0.7652***	0.7275***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	-1.5128***	-1.3608**	-1.8226**	-1.5658**	-1.7886**	-2.0579**	1.2123**	1.8419**	-0.9396*	1.7509*
	(0.008)	(0.016)	(0.046)	(0.040)	(0.040)	(0.021)	(0.048)	(0.045)	(0.077)	(0.063)
Observations	1,117	1,050	999	936	808	767	754	716	672	629
R-squared	0.1930	0.1852	0.1901	0.1839	0.1722	0.1769	0.1699	0.1658	0.1634	0.1613
Wald chi2	29.63***	27.40***	52.42***	62.09***	59.65***	53.76***	76.56***	84.09***	61.86***	64.60***

Note: This table presents the 2SLS regressions with the instrumental variable (*R&D personnel ratio*) at the second stage. Model 1 to 10 which show out the results of the second-stage regression are followed by the models at the first stage in Table 13, respectively. The models test the impact of firms' innovation capital on their buy-and-hold market-adjusted returns (BHAR) for 12, 24, 36, 48, and 60 months after their IPO with the instrumental variable which is the R&D personnel ratio. Definitions of the independent variables and control variables are presented in Appendix C. P-value in parentheses. ∗∗∗ represents 1% significance level, ∗∗ represents 5% significance level, ∗ represents 10% significance level.

3.5.4 Robustness Test

To further examine the stability of the models, we utilize R&D intensity for one year and two years before IPOs as additional proxies for innovation in the model for robustness testing. R&D_1 is defined as the research and development expenditure of the firms one year before their IPOs, and R&D_2 is defined as the research and development expenditure of the firms two years before their IPOs. Accordingly, we test the research and development intensity together with the number of patents in Model 1 through Model 10. To test the associations of the innovation capital and the 12-month, 24-month, 36-month, 48-month and 60-month buy-and-hold adjusted abnormal returns for the IPO firms. The results reported in Table 3.18 show that the coefficients of R&D_1 are negatively related to firms' long-term performance for two consecutive years in the post-IPO period at the significance level of 1%. The coefficients of R&D_2 also indicate a negative correlation with the long-term performance of IPOs for 12, 24 and 36 months after the IPOs at the significance level of 1%, 1%, and 10%, respectively. These coefficients, however, gradually increase after 36 months and eventually become positive. This is consistent with the findings in Table 3.10, Table 3.11, Table 3.12 and Table 3.17. Thus, they are not driven by outliers or nonlinear relationships.

Table 3.13 Robustness Tests

	12M-BHAR		24M-BHAR		36M-BHAR		48M-BHAR		60M-BHAR	
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
R&D_1	-1.584***		-1.851***		-1.809		-1.140		2.001	
	(0.001)		(0.005)		(0.135)		(0.608)		(0.388)	
R&D_2		-1.639***		-1.672***		-2.260*		-0.794		-0.0909
		(0.001)		(0.007)		(0.062)		(0.695)		(0.966)
ln(Patents+1)	0.0117	0.0113	0.0365**	0.0360**	0.0387**	0.0389**	0.138**	0.137**	0.154***	0.158***
	(0.383)	(0.400)	(0.036)	(0.039)	(0.029)	(0.027)	(0.011)	(0.012)	(0.008)	(0.006)
lnAge	-0.00533	-0.00261	0.00436	0.00711	-0.0223	-0.0230	0.00280	0.00496	-0.0311	-0.0391
	(0.825)	(0.914)	(0.888)	(0.817)	(0.677)	(0.667)	(0.976)	(0.957)	(0.747)	(0.686)
lnAsset	-0.127***	-0.129***	-0.159***	-0.160***	-0.259***	-0.263***	-0.323***	-0.321***	-0.198*	-0.217*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.087)	(0.061)
lnProceed	-0.105**	-0.103**	-0.336***	-0.334***	-0.556***	-0.554***	-0.677***	-0.677***	-0.894***	-0.892***
	(0.013)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lot	0.242	0.253	0.332	0.345	-0.728	-0.724	-2.651	-2.644	0.471	0.442
	(0.672)	(0.659)	(0.641)	(0.629)	(0.535)	(0.537)	(0.189)	(0.191)	(0.821)	(0.832)
UW	-0.0295	-0.0299	-0.0190	-0.0194	-0.0510	-0.0513	-0.0985	-0.0975	-0.133	-0.135
	(0.272)	(0.266)	(0.590)	(0.584)	(0.429)	(0.426)	(0.383)	(0.387)	(0.275)	(0.266)
VC	-0.0114	-0.00943	-0.0606	-0.0589	-0.140**	-0.138**	-0.135	-0.135	-0.244*	-0.239*
	(0.690)	(0.740)	(0.108)	(0.118)	(0.041)	(0.045)	(0.257)	(0.257)	(0.055)	(0.061)
IssPrice	-0.000928	-0.00106	-0.000237	-0.000443	-0.00272	-0.00275	-0.00514	-0.00528	-0.00850	-0.00810
	(0.508)	(0.449)	(0.893)	(0.801)	(0.368)	(0.363)	(0.328)	(0.315)	(0.127)	(0.145)
lnMV	0.316***	0.316***	0.605***	0.604***	0.954***	0.957***	0.835***	0.833***	0.793***	0.805***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.089***	-2.112***	-3.093***	-3.130***	-4.129***	-4.122***	1.266	1.233	3.499	3.629
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.590)	(0.599)	(0.164)	(0.149)
Observations	1,071	1,071	956	956	772	772	733	733	643	643
R-squared	0.197	0.197	0.368	0.368	0.376	0.378	0.264	0.264	0.245	0.244
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the robustness regressions of innovation capital (*R&D and number of patents*) on IPO long-term performance. Model 1 to 10 respectively test the impact of firm's innovation capital on its BHAR returns which are the buy-and-hold market-adjusted returns of firm for 12, 24, 36, 48, and 60 months after its IPO. Definitions of the independent variables and control variables are presented in the Appendix C. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

3.6 Conclusion

The objective of the current research was to investigate the impact of innovation capital on the long-term IPO performance. While a wide range of literature provides ample evidence on the long-term IPO underperformance in different countries, accompanied by a myriad of theoretical explanations, the impact of innovation capital as a credible market signal of a firm's value in the post-IPO period has received little attention. Still, the majority of the existing studies have been limited to the U.S. market. Our study extends this inquiry into the Chinese equity market with different institutional and regulatory settings. Accordingly, we examined the influence of innovation capital from two different dimensions of innovation input and innovation outcome on the long-term IPO performance. In contrast to the developed world, the stock performance of firms in the Chinese IPO market exhibits longer-term underperformance, extending to nearly five years after the firm's IPO. Therefore, our study contributes to the current literature on this topic and enhances our understanding of IPO long-term performance in emerging markets.

According to most existing studies, the intangible assets resulting from firms' innovation efforts and their outcomes are information asymmetric. The controversy over the realized potential benefits of the innovation capital efforts makes a market valuation of relevant companies uncertain and investors' perceived valuation unclear. In this study, we aimed to establish whether the two dimensions of innovation capital, consisting of R&D expenditure or patents, constitute a source of value to both the IPO firm and the investors.

The results presented in this paper suggest that the innovation input as R&D expenditure exerts a significantly negative impact on the long-term stock performance of IPOs, especially for the first 12 to 24 months after the IPOs. This finding is consistent with our hypothesis that firms with greater R&D expenditure experience more severe long-term underperformance after their IPOs than those firms with no or low R&D expenditure. We additionally found that accounting regulations pertaining to the research and development funds in the Chinese market that deal with capitalized R&D and expensed R&D could differently affect our findings. For instance, the pre-IPO expensed R&D funds show lagging and cumulative characteristics in the Chinese IPO market. This finding is supported by further statistical analysis indicating that the impact of firm's pre-IPO R&D investment on the long-term stock performance gradually turns from negative to positive over the period of five years after their IPOs. Different from innovation input, IPO firms with a greater number of patents outperform those companies with fewer patents, although their declining long-term performance is pervasive.

These findings imply that most investors recognize or perceive the value of R&D fund disclosure in the IPO firms' prospectuses as an off-balance sheet intangible asset of these companies. As a result, uncertainty and instability of R&D expenditure as the innovation input at the beginning of the innovation activities of firms can raise the risk of investment for investors in the emerging markets. Over time, however, part of the innovation input may gradually become capitalized in the process of production, revealing the market value of IPO firms in the long term. Further, these findings also imply that investors are willing to attribute potential development value to patent stocks held by corporations. Consequently, they are a more reliable source of the innovation outcome and can signal the information to the public more clearly. In summary, innovation input and innovation outcome can bring distinctly different impacts on the aftermarket stock performance of IPOs in the long term. However, in general, the pre-IPO innovation capital in the IPO prospectus, consisting of both R&D investment and number of patents, provides essential and relevant information for IPO investors.

CHAPTER 4

Innovation and the Post-IPO Feedback in the Product Market—Evidence from the Chinese Markets

Abstract

Innovation plays a pivotal role in the sustainable development, industry competition and enterprise strategy of companies. Companies usually promote innovation process through spending on research and development. However, at certain stage in their lifecycle, their business structure as a private firm constrains their investment financing, urging them to go public. The purpose of the present study is to examine the impact of pre-IPO innovation expenditure on firms' post-IPO product market performance in the Chinese market. In the first part of our study, we test the impact of innovation expenditure on the operating performance of firms in their post-IPO period. In the second part, we investigate whether firms that have gone public in periods of higher industry innovations have become more competitive in the product market. Our findings suggest that the number of patents (as the innovation output of the firm) and the R&D intensity (as the innovation input of firms) have completely different impacts on the firms' feedback performance in the product market. The impact of firms' patents on the market shares and competitive position of firms in the post-IPO product market is positive. However, due to the

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uncertainty and instability of R&D input in the firms' operations, R&D expenditure before the IPOs has an inverse relationship with the operational performance of the firms in the product market in the post-IPO period.

Keywords: innovation; IPO market; product market; market performance

4.1 Introduction

Innovation plays a pivotal role in the sustainable development and growth of companies. Companies promote innovation through structural measures, such as their spending on research and development. However, to finance their further growth and development, they have to go public at a certain stage in their lifecycle. Hsu (2009) perceives successful technological innovation as one of the main driving forces behind firms' decision to go public to finance their expansion. Innovation can also bring more uncertainty to the firms' products market, impacting their competitive position compared with their rivals within their industry (Maksimovic and Pichler, 2001; Chod and Lyandres, 2011). This work attempts to demonstrate the impact of firms' innovation on their IPO decision by examining their performance in the post-IPO period in their product market and their competitive position compared with their rivals in the industry. This is expected to link the companies' pre-IPO innovation capabilities with the post-IPO product market. The sample data is collected from Chinese equity and product markets.

In recent years, scholars have shown increasing interest in the examination of a theoretical link between financial markets and industrial organization. The examination of how product market affects the stock market performance has become one of the focal points of pertinent academic research. For example, Irvine and Pontiff (2009) studied the impact of product market competition on the volatility of stock heterogeneity. Tookes (2008) examined the influence of product market competition on the stock turnover rate; Peress (2010) investigated the effect of product market competition on the information content of stock returns; Kale and Loon (2011) studied the effect of product market competition on the liquidity in stock market. Chemmanur, He and Nandy (2010) empirically investigated how the characteristics of product market (total factor productivity [TFP], sales growth, market share, industry competition, capital intensity, and cash flow risk) influence firms' IPO decisions. They found that firms typically choose to go public when their productivity reached to the peaks, noting that dynamic changes in total factor productivity (TFP) and sales growth rate also present an inverted U-shaped development pattern during IPO period. Additionally, sales, capital expenditure and other variables in describing firms' performance continue to increase annually following their IPOs. Scholars have also previously attempted to show the theoretical link between industrial economics and other features of financial markets, such as IPOs. Present study contributes to the current literature by examining the link between IPO market and product market in the Chinese economy. While there is a large body of existing literature on the effect of the IPO decision of firms on their post-IPO operating performance (e.g., financial indicators), few scholars have examined this issue from the perspective of IPO market impact on the industry economics. In specific terms, we utilize the industry economics and finance theory to examine the impact of firms' pre-IPO innovation power on their IPO decisions and the feedback they receive in the post-IPO period from the product market.

Second, to further analyze the feedback performance of firms in the post-IPO product market, we divide our study into two parts, respectively focusing on the firms' operating performance in the product market after IPOs and on their competitiveness in the post-IPO product market. From the IPO perspective, previous research about the impact of this phenomenon on firms' competitiveness in the product market has been separated into the "contagion effect" raised by Foster in 1981, and the "competition effect" proposed by Jorion and Zhang in 2007. The decision of firms to go public depends on the costs and benefits of their decision in the product market. In this sense, the benefit of going public for firms is to improve their competitiveness in the product market, while their cost arises from the disclosure of their proprietary information to the public (Jong et al., 2012).

However, from another point of view, those disclosed costs also include important elements of innovation capital that warrant development of these firms. The innovative capital has the characteristics of high confidentiality and information asymmetry. Some strands of existing literatures state that voluntary disclosure of information on innovation capital or innovation ability can send positive signals to the market when a company decides to go public. This helps market investors to accurately understand and assess the value of the company and reduce the phenomenon of IPO underpricing in the market (Xu, Xia and Li, 2016). However, from a different perspective, very few authors have analyzed and empirically tested whether the existence of innovative capital has any impact on firm competitiveness in the post-IPO product market. According to the recent works by Maksimovic and Pichler (2001), Spiegel and Tookes (2008), and Hsu (2014), innovation capital would affect the competitive environment of the firms and thus their decisions to go public. Meanwhile, Hsu (2014) utilized the number of industry-level patents as the industry technology innovation index and found that his findings are consistent with the investment opportunity hypothesis. This hypothesis points out that higher productivity and better investment opportunities are the product of high-tech innovation. Thus, companies that need more investment funds may decide to go public to raise capital. Accordingly, innovation level would play an important role in deciding to go public for firms to fund future investments in order to improve their competitiveness in the product market. However, Kelm et al. (1995) pointed out that technological innovation is a very complex process. Companies may experience a multiplex of project starting, success or failure, new technology generation, patent acquisition, the birth of new products, and so on. Thus, the initial investment input of innovation contains many risks and uncertainties for a company which do not exist in the patent acquisition. Therefore, as the second contribution, we divide the pre-IPO innovation capital into the innovation input (R&D

intensity) and innovation outcome (number of patents). We then explore whether the impacts of two different dimensions of innovation capital on the performance and competitive position of firms in the post-IPO product market are the same or different.

Third, China as an emerging economy has its own unique social complexities and distinct regulation settings in the capital markets compared to the developed countries. From a macro perspective, the regulation of Chinese IPO capital market has rapidly changed over time. This market environment provides a unique laboratory to explore the recent developments in this emerging economy. From the perspective of micro institutions, this country has also started to implement the new China Accounting Standard rules (CAS) in 2006. Under these new rules, firms' innovation capital, especially the research and development investment with the characteristics of uncertainty and instability, may have different impact on their performance in the product market. Therefore, in order to fill the gap in the extant research, we explore the rules and regulations of the Chinese market to analyze and discuss this issue.

This paper will be presented in five sections, whereby the next one pertains to the feedback impact of the firm's innovation on the post-IPO product market. The second section is followed by post-IPO product market operating performance and post-IPO product market competitiveness. The third section is designated for data selection, variable definitions and methodology. The fourth section presents the empirical results, analysis and robustness test findings. The conclusion and discussion are given in the fifth section.

4.2 Innovations and Post-IPO Feedback in Product Markets

According to Jain and Kini (1999), going public is one of the most crucial decisions in the life of a firm. Chemmanur and Fulghieri (1999) and Maksimovic and Pilcher (2001) asserted that the decision to go public can benefit the firms with the lower cost of financing in the equity market. In more recent studies, Chod and Lyandres (2010) and Chemmanur and He (2011) stipulated that going public also helps a company to improve its competitive position in the product market at the expense of its rivals that have remained private. This benefits the shareholders of IPO companies in the product market with more ability to diversify their risk with greater variability in idiosyncratic profit compared to the private companies (Shah and Thakor, 1988). This also allows IPO firms to explore more aggressive strategies in the product market compared to their counterparts in the private equity market. As a result, it is important for us to study the correlation between the *ex-ante* innovation and the product characteristics of a firm in the post-IPO market.

Spiegel and Tookes (2008) developed a model to examine the correlations between innovation, competition, and the public-versus-private financing decision in the product market. According to this model, firms may decide to go public only when they have superior innovations. Furthermore, Clementi (2002) showed that companies decide to go public because of positive and stable productivity shocks that raise their operating costs in a suboptimal period, leading to an optimal operation after the IPO. Thus, the author suggested that companies characterized by a relatively higher productivity, output growth, and demand for more capital expenditures prefer to go public. Chemmanur, He and Nandy (2010) found that private firms' total factor productivity (TFP)—as one of the significant characteristics of product market—closely and essentially affects their chances of going public, thereby increasing capital expenditure and enhancing their performance measures after the IPO. Furthermore, Hsu (2014) found that firms which are in the period of greater industry-wide technological innovations are more likely to go public. These companies also enjoy greater stock returns, higher sales growth, and accelerated general capital and R&D expenditure in the post-IPO period.

Consequently, according to the extant literature, we can hypothesize that during the periods of high technological innovations accompanied by increase in productivity and greater investment opportunities, companies are more likely to go public to raise capital. This in turn can also improve their competitive position in the product market. As a part of our study, we separately investigate two issues. In the first section, we study the influence of *ex ante* innovations on the aftermarket performance in the product market. In the second section, we test the relationship between *ex ante* innovations and the competitiveness of IPO firms in the product market.

4.2.1 Innovations and Post-IPO Operating Performance in Product Markets

(1) Innovation output (Patents)

Extant studies indicate that underperformance of firms after their IPOs in the equity market is a universal phenomenon. For instance, Jain and Kini (1994), Coakley (2005) and Farinos (2007) used samples of listed firms from the United States, Great Britain and Spain to show their declining operating performance in the post-IPO period. Similar results have also been reported for emerging economies, such as Malaysia, China, and Hong Kong by Ahmad (2011), Wang (2005) and Wong (2012), respectively. However, this underperformance may be less pronounced for more innovative firms. Spiegel and Tookes (2008) examined the correlation among innovation, IPO decision and firms' performance. Under a dynamic competitive environment, firms would like to go public when they have achieved certain level of technological innovations. Thereby, firms aiming to improve their competitive positions in the product market have a better performance afterwards relative to others (Wilbon, 2003). Further, Hsu (2014) pointed out that industry-level patenting has a positive and significant impact on firms' stock value, operating performance, investment extent, and even survival ability after their IPOs. These findings are consistent with the investment opportunity hypothesis, which implies that periods of *ex ante* technological innovations lead to improved productivity and investment opportunities. Therefore, companies that go public to secure capital in order to accommodate their future investment, automatically improve their aftermarket performance (Lowry, 2003). In addition, the author concluded that firms that go public during the time of greater level of technological innovations could enjoy higher stock returns, as well as develop more rapid post-IPO sales, capital expenditure and R&D investments, and benefit more from their post-IPO survival.

However, the impacts of innovation on the aftermarket performance of firms in the emerging markets have not been adequately addressed in pertinent research. Therefore, we first test the relationships between innovation and aftermarket operating performance of firms in the product markets. We extend previous studies by distinguishing between two forms of company innovation capital, i.e., innovation input and innovation output. We then investigate the impacts of these two innovative capital forms on the aftermarket performance of firms in the IPO market. In the following section, we examine the impact of the pre-IPO innovation outcome (number of patents) on the firms' performance in the post-IPO period according to the investment opportunity hypothesis but forth by Hsu (2014). Following Chemmanur et al. (2009) and Tang (2015), we then combine the innovation measures with product market competition proxies, such as sales, profits, and capital expenditure, in order to measure the operating performance of firms in the post-IPO period. Followings are our testable hypotheses relevant to this section.

H_{1a}: The level of pre-IPO innovation outcome has a positive impact on the sales of IPO firms.

H_{2a}: The level of pre-IPO innovation outcome has a positive impact on the profit of IPO firms.

H_{3a}: The level of pre-IPO innovation outcome has a positive impact on the capital expenditures of IPO firms.

(2) Innovation input (R&D intensity)

Different from the innovation output (number of patents), firm's innovation input (R&D activity) has a high degree of uncertainty and information asymmetry (Aboody and Lev, 2000). This may allow companies to carry more risk in the capital expenditure and operating processes, resulting in a series of unpredictable economic consequences. Chan et al. (2001) pointed out that firms characterized by high R&D intensity have low historical returns and their shares show signs of mispricing. The authors also highlighted the ways of reducing the information asymmetry of the research and development input. Many scholars believe that R&D investment capitalization provides a solution to this issue. For example, Zhao (2002) studied the relative value of R&D in the French, British, German and US markets and suggested that separation of capitalized R&D and expensed R&D would provide sufficient information to disclose the success of R&D activities of a company. He asserted that these two forms of R&D funds have different impacts on the enterprise's future performance. Cazavan-Jeny and Jeanjean (2006) examined the data from the French market to conclude that the cost of research and development may have both successful and unsuccessful outcomes. As a result, the impacts of R&D investment on the company's performance can be negative or positive, depending on the relative size of the proportion of successful or unsuccessful projects in the total value of R&D. In some developed countries, such as the United States and Germany, companies' research and development expenditures must be included in the Profit and Loss Statements. However, in countries that adopted the International Financial Reporting Standards (IFRS) in the capital market in 2005, such as the UK, R&D can contain the cost of both unsuccessful projects (expenses which are unlikely to bring future economic benefits to the company) and successful projects. Only capitalized percentage of successful projects' expenditure is thus expected to have positive impacts on the market value of a company. Tsoligkas and Tsalavoutas's (2011) findings confirm this hypothesis, indicating that capitalized R&D investment is positively related to the firm's market value, suggesting that markets will treat such projects as successful and of future economic benefit. Conversely, expensed research and development investment is negatively correlated with the firm's market value.

In 2006, Chinese government issued a new Accounting Standards (CAS) for companies. Under the CAS N. 6, it is not mandatory for Chinese firms to report capitalized R&D, as proprietary reporting methods are permitted. A study by Wang and Fan (2014) suggests that different R&D investment reporting methods could affect the market value of Chinese listed companies differently. They also found that R&D investment capitalization is positively correlated with the stock price of a company, while expensed R&D expenditure is negatively correlated with stock prices. This suggests that the positive and negative impact of the R&D on the firm's aftermarket performance depends on the extent of the success or failure of its innovative projects. In other words, to the extent that companies can report their capitalized R&D expenditures as some form of asset in their balance sheets, they may expect higher stock prices and returns than when they are reported as expenses in their profit and loss statements. Therefore, disclosure of the R&D spending in the firms' pre-IPO prospectus cannot warrant a positive response from prospective investors due to the inherent uncertainty and unpredictability of their expenditure outcome. This in turn may send a negative signal to the prospective investors in the market. Therefore, for the innovation input (R&D), we introduce the following hypotheses:

H_{1b}: The level of pre-IPO innovation input has a negative impact on the sales of IPO firms.

H_{2b}: The level of pre-IPO innovation input has a negative impact on the profit of IPO firms.

H_{3b}: The level of pre-IPO innovation input has a negative impact on the capital expenditure of IPO firms.

4.2.2 Innovation and Post-IPO Competitiveness in Product Markets

The decision to "go public" has been documented to be one of the most important events in the life of a company. This big event not only provides the investors and market with investment opportunities, but also paves the way for firms to raise their necessary finance in the equity market. In the more recent literature, scholars have confirmed that going public helps companies to access public capital for the first time in their lifecycle, and thus outperform their rivals in the product market (Chemmanur, He and Nandy, 2010). In order to extend the study and investigate the relative firms' feedback performance in the product market, we have extended our research question into the relationship between firms' *ex ante* innovation ability and their post-IPO competitive position in the product market.

According to the "Deep Pocket Theory"[34], after IPOs, firms have greater advantages in capital than their competitors in the same industry. IPO firms often adopt various product market competition strategies (aggressive price war, increase production, increased promotion, etc.) to gain superior positions in the product market over their rivals in the industry, or even force them out of the market. Chemmanur, He and Nandy's (2009) study indicates that going public as the first pathway for firms to enter the public capital market in their lifecycle has significant implications for their product market performance as well because product market is the primary avenue for demonstrating real performance. Furthermore, in an efficient market, the commodity market determines physical capital allocation. It is also interconnected to the capital market. Thus, another objective of this study is to bridge the research gap on the relationship between capital and physical markets.

Although market performance of companies around their IPOs has been extensively studied, the impacts of firms' innovation on their competitive position around IPOs in the product markets is poorly investigated. According to Schumpeter's 1912 hypothesis of the "creative destruction" in the industries' competitiveness, innovations can produce greater (rational or irrational) prospects of an industry valuation, leading to extra entries and investments. This point is also highlighted by Reinganum (1989) and Hoberg and Phillips (2009), who suggested that innovations can encourage more companies to go public when an industry is more competitive. However, literature on the post-IPO competitiveness of firms is scarce.

[34] "Deep Pocket Theory" first raised by Telser in 1966 suggests that, in an uncompleted capital market, some firms with more a fragile financial structure face stronger financing constraint compared with their rivals. Consequently, competitors with abundant financial strength can afford to pursue strategies based on reducing prices, expanding their output, etc., to attain a higher market share at the cost of firms with fragile financial structure, even ousting them from the market.

Some recent studies in which the impact of IPOs on the product market competition was investigated include the work of Maksimovic and Pichler (2001), who posited that a higher IPO issue price can help companies to enhance their competitive position in the product market, increase their market value, and elevate the trust level of their customers, suppliers, banks, and other investors in the product market. Similarly, Stoughton, Wong and Zechner (2001) attempted to theorize the motivation behind IPOs in the product market. According to their view, firms prefer to acquire independent certification on the quality of their products from the public, which can improve their competitive position in the product market. In their model, the consumers can identify the quality of the products through the share price movement in the capital market, helping firms to raise more capital. Thus, firms can gain competitive advantage through IPOs. Chod and Lyandres (2009) pointed out that IPOs help firms spread their heterogeneous risks in the capital markets. Therefore, listed firms tend to take riskier marketing strategies than non-listed firms in order to improve their competitive position in the industry. Based on the previous arguments, we propose the following hypotheses:

H_4: The higher intensity of pre-IPO innovation has a positive impact on the relative market share (RMS) of IPO firms in the product market.

H_5: The higher intensity of pre-IPO innovation has a positive impact on the absolute market share (AMS) of IPO firms in the product market.

4.3 Data, Variables and Methodology

4.3.1 Data Selection

The economic indicators of the listed companies selected for this study were sourced from CSMAR and RESSET databases, and the sample period ranges from January 2009 to December 2016. We selected all listed companies in the A-share market from the stock exchanges of Shanghai and Shenzhen and screened the samples without the ST (Special Treatment) and PT (Particular Transfer) companies. After screening out companies with missing data or no prospectus, 1,451[35] listed companies that went public between January 2009 and December 2016 remained. In order to reduce the influence and interference of short-term IPO underpricing and post-IPO market investor sentiment on the companies' financial indicators, we started our sample data from two months after firms' IPOs. We collected the pre-IPO innovation data from each firm's prospectus and the official website of the Chinese national intellectual property department. All data were screened, sorted and analyzed using EXCEL VBA and STATA 14, and were processed by 1% Winsorize.

4.3.2 Regression Model

According to the previous studies, we used STATA 14 to test the general least-squares regression (OLS) model in order to analyze the feedback effect of pre-IPO innovation capital on the post-IPO product market. We separate this study into two parts including five models:

(1) Firm's innovation capital and the post-IPO product market operation performance

$$Sales_{i,t} = a_0 + a_1 R\&D_i + a_2 lnPatent_i + a_3 lnAge_i + a_4 lnAsset_i + a_5 IssPrice_i + a_6 TobinQ_i + a_7 Leverage_i + a_8 UM_i + a_9 VC_i + a_{10} Year_i + a_{11} Ind_i + \varepsilon_i \quad (4.1)$$

$$Profit_{i,t} = a_0 + a_1 R\&D_i + a_2 lnPatent_i + a_3 lnAge_i + a_4 lnAsset_i + a_5 IssPrice_i + a_6 TobinQ_i + a_7 Leverage_i + a_8 UM_i + a_9 VC_i + a_{10} Year_i + a_{11} Ind_i + \varepsilon_i \quad (4.2)$$

$$Capex_{i,t} = a_0 + a_1 R\&D_i + a_2 lnPatent_i + a_3 lnAge_i + a_4 lnAsset_i + a_5 IssPrice_i + a_6 TobinQ_i + a_7 Leverage_i + a_8 UM_i + a_9 VC_i + a_{10} Year_i + a_{11} Ind_i + \varepsilon_i \quad (4.3)$$

(2) Firm's innovation capital and the competitiveness of post-IPO product market

$$RMS_{i,t} = a_0 + a_1 R\&D_i + a_2 lnPatent_i + a_3 lnAge_i + a_4 lnAsset_i + a_5 IssPrice_i + a_6 TobinQ_i + a_7 Leverage_i + a_8 UM_i + a_9 VC_i + a_{10} Year_i + a_{11} Ind_i + \varepsilon_i \quad (4.4)$$

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[35] Our study is based on the Chinese A-share market. In the A-share market, there are few delisting companies. The average annual delisting rate of A-shares in the past 17 years is only 0.11 percent.

$$AMS_{i,t} = a_0 + a_1 R\&D_i + a_2 lnPatent_i + a_3 lnAge_i + a_4 lnAsset_i + a_5 IssPrice_i + a_6 TobinQ_i + a_7 Leverage_i + a_8 UM_i + a_9 VC_i + a_{10} Year_i + a_{11} Ind_i + \varepsilon_i \quad (4.5)$$

For innovation capital, innovation input is the R&D intensity (*R&D*), which is the research and development intensity of the firms before IPOs. Innovation outcome is the number of patents (*Patent*), which is the logarithm of numbers of patent counts before firms' respective IPOs. For the operating performance of the firms in the product market, we use following variables: *Sales* measured as the logarithm of firms' sales after IPOs; *Profit* which is the logarithm of firms' profit after IPOs; and *Capex* which is the logarithm of firms' capital expenditures after IPOs. The other included control variables are: firm's age (*lnAge*), firm's size (*lnAsset*), issuing price (*IssPrice*), Tobin's Q (*TobinQ*), firm's leverage (*Leverage*), underwriter's reputation (*UW*), venture capital (*VC*), IPO year (*Year*), and the industry of the firms (*Ind*). These variables will be discussed in the following section.

4.3.3 Variables

(1) Dependent Variables

1) Post-IPO Operating Performance in Product Markets

We first test the influence of innovations on firms' post-IPO operating performance in the product market. If companies decide to go public when their affiliated industry provides incremental investment opportunities, they should also have a comparative advantage in the product market after the IPO. We follow Chemmanur, He and Nandy's (2009) method when conducting the empirical tests by employing sales, profits and capital expenditure to represent product market characteristics in the first empirical part of this study.

First, we follow Campello (2003) to define annual sales as:

$$Sales_{i,t} = lnS_{i,t} = \ln Sales_{i,t} \quad (4.6)$$

These firm's financial indicators (sales, profits, and capital expenditures) extend from the beginning of IPO to five years after, as the major measures of operating performance.

Second, we utilize five-year annual profits in the post-IPO period as another measure of the operating performance of a firm in the product market.

$$Profit_{i,t} = lnP_{i,t} = \ln Profit_{i,t} \quad (4.7)$$

Third, following Hsu (2014), we use capital expenditure as the third dependent variable to represent the firms' operating performance. Meanwhile, in order to reduce the overlap and collinearity of the data, we subtract R&D investment expenditure from the total capital expenditure:

$$Capex_{i,t} = lnC_{i,t} = \ln Capex_{i,t} \quad (4.8)$$

2) Post-IPO Competitiveness in Product Markets

The second objective of this study is to test the IPO firms' competitiveness in the product market. According to Venkatraman and Prescott (1990), company's market share is a strong predictor of corporate profitability. Greve (1999), Tanriverd and Lee (2008), and Song and Li (2013), among others, have used market share to indirectly measure the performance and competitiveness of the firms in the product market using the following methods:

① Absolute market share (AMS): In the same product market (i.e., the same industry), it is the percentage of the company's sales products or services (sales) to the total sales in the product market.

$$AMS_{i,t} = \frac{IPO\ firm's\ sales_{i,t}}{The\ sum\ of\ all\ the\ listed\ competitors'\ sales\ within\ the\ same\ industry_{t}} \times 100\% \quad (4.9)$$

② Relative market share (RMS) (Anderson and Zeithaml, 1984): Defined as the percentage of the company's sales of commodities and services to the corresponding total sales of the first three competitors in the same product market.

$$RMS_{i,t} = \frac{IPO\ firm's\ sales_{i,t}}{The\ sum\ of\ the\ Top\ 3\ listed\ competitors'\ sales\ within\ the\ same\ industry_{\ t}} \times 100\% \quad (4.10)$$

(2) Independent Variables

1) Innovation input (R&D):

Innovation input, i.e., R&D investment, was collected from the prospectuses of the listed IPO firms from January 2009 to December 2016 in the A-share market. We screened out 1,451 listed companies and manually extracted their disclosed R&D investments from their prospectuses. The innovation input comprises of: (1) *R&D* intensity expressed as the average ratio of the R&D investment before the IPO to the total corresponding assets during the same period; (2) *R&D_1*, which represents the R&D intensity as the ratio of the R&D investment one year before the IPO to the total corresponding assets during the same period; and (3) *R&D_2* that represents the average value of the R&D intensity two years before firm's IPO.

2) Innovation outcome (Patents):

Innovation output, i.e., number of patents, was also manually collected from the listed firms' prospectuses, including invention, utility models and design patents. Meanwhile, we also merged and proofread the number of patents of listed companies through the official website of the national intellectual property department of China.

(3) Control Variables

1) Firm age (lnAge): According to Filatotchev and Bishop (2002), the age of the firm has a significant influence on the firm's performance in the market. Firm age is calculated from its foundation to the IPO year. The logarithm of the IPO year minus the year of the firm's formation, plus one.

2) Firm size (lnAsset): The size effect has been acknowledged in the existing studies. Barth and Kasznik (1999) pointed out that larger firms have less information asymmetry in the markets. We apply the logarithm of the firm's total assets one year before IPO as a control variable.

3) Tobin's Q (TobinQ): Tobin's Q value is actually the stock market's estimate of the ratio of the value of a firm's assets to the cost of producing those assets. A high Q value means a high rate of return on investment in the industry. At this time, the market value of stocks issued by firms is greater than the replacement cost of capital, and firms have a strong incentive to enter the capital market to realize arbitrage. Thus, we add Tobin's Q to control this effect of firms, which is the ratio of the market value to book value of the IPO firm in any given year.

4) Leverage (Leverage): The leverage is calculated as the ratio of the total debt to the total assets of the IPO firm in any given year. Leverage ratio is an indicator to measure the liability risk of a company, which reflects the repayment ability of the company from the other side. We add this variable to control the firm-level effect in the model.

5) Issuing price (IssPrice): According to Purnanandam and Swaminathan (2004), their study showed that ‘‘overvalued’’ IPOs have high first-day returns but experience low long-run risk-adjusted returns. And they added the price to find that the overvalued IPOs have lower profitability, higher accruals, and higher analyst growth. Thus, we add the

issuing price of the new shares as one of the control variables to test our model and the impacts in the regression.

6) Underwriter Reputation (UW): A substantial body of the literature suggests that underwriter reputation has a significant impact on the IPO markets. Carter et al. (1998) found that firms with prestigious underwriters have a better market performance three years after their IPOs. We employ a dummy variable to control for underwriter reputation of each IPO firm. Thus, firms with at least one of the top 10 underwriters will be coded as 1, and 0 otherwise.

7) Venture Capital (VC): Previous studies suggest that venture-backed IPO firms outperform the non-venture-backed firms (Brav and Gompers, 1997). Hence, we include a dummy variable in the model with a value of 1 if the IPO firm has one or more venture capital firms before going public, and 0 otherwise.

8) IPO year (Year): Dummy variable. The IPO year of firms.

9) Industry (IND): Dummy variable indicating a firm's affiliation to an industry.

4.4 Results

4.4.1 Descriptive Statistics

The descriptive statistics of the main and the control variables are shown in Table 4.1. We have collected and sorted the logarithm values of the firms' sales (*Sales*), profits (*Profit*) and capital expenditures (*Capex*) in the first, second, third, fourth and fifth year after the IPOs, respectively. Results in Table 4.1 show that the average values of these three classic financial performance indicators have increased with the elapse of time for five years after the IPOs. The percentages of absolute market share (AMS) and relative market share (RMS) are also calculated. A comparison of these variables shows that the average value of the relative market share in the five years after the IPOs is in the 1.3−1.6% range, while the average absolute market share variation is in the 0.6–0.8% range during the same period. The minimum values of the relative market share and the absolute market share are nearly 0, while the maximum value ranges are between 83% and 86%[36]. In addition, from the perspective of enterprise innovation capital, the three values of R&D intensity, namely R&D_1, R&D_2, and the average value of R&D, are 0.0711, 0.0658, and 0.0684, respectively. The minimum values of these variables are approximately 0, while their maximum value is around 20[37]. At the same time, the average value of the innovative output (number of patents) of Chinese listed companies is about 75, while the maximum value is 7,713[38]. When the value of innovation input (R&D intensity) or innovation output (number of patents) is considered, compared with other developed countries, China has stayed ahead in terms of the innovation capital and innovation ability of its listed companies. Our findings may suggest that China is gradually getting closer to its aim of becoming "an innovative country" according to the President Xi Jinping's desire.

[36] Belonging to China Chemical (601117).
[37] Belonging to Kang Hong Pharmaceutical (002773).
[38] Held by BYD Company (002594).

Table 4.1 Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Sales_1yr	1,441	2.46E+09	1.47E+10	7.53E+07	2.96E+11
Sales_2yr	1,216	3.08E+09	1.99E+10	6.59E+07	3.78E+11
Sales_3yr	999	3.97E+09	2.59E+10	7.51E+07	4.91E+11
Sales_4yr	875	4.79E+09	3.09E+10	5.90E+07	5.72E+11
Sales_5yr	874	5.41E+09	3.49E+10	6.92E+06	6.82E+11
Profit_1yr	1,441	3.52E+08	3.35E+09	-3.25E+08	1.19E+11
Profit_2yr	1,216	3.91E+08	4.67E+09	-1.15E+09	1.57E+11
Profit_3yr	999	4.73E+08	6.10E+09	-1.97E+09	1.87E+11
Profit_4yr	875	5.39E+08	7.39E+09	-8.29E+09	2.12E+11
Profit_5yr	874	6.32E+08	8.08E+09	-3.24E+09	2.31E+11
Capex_1yr	1,216	2.37E+08	1.29E+09	1.18E+05	2.66E+10
Capex_2yr	999	3.05E+08	1.39E+09	1.48E+06	2.51E+10
Capex_3yr	875	3.81E+08	2.04E+09	9.91E+05	4.28E+10
Capex_4yr	874	3.85E+08	2.41E+09	1.07E+06	5.20E+10
Capex_5yr	727	3.74E+08	1.99E+09	2.08E+05	4.14E+10
RMS_1yr	1,411	1.3129	5.8235	0.0119	84.9101
RMS_2yr	1,190	1.4280	6.3342	0.0050	83.0871
RMS_3yr	987	1.4598	5.9133	0.0069	84.3815
RMS_4yr	880	1.6365	6.7825	0.0060	85.3931
RMS_5yr	876	1.4834	5.3262	0.0022	86.2365
AMS_1yr	1,411	0.6849	4.8411	0.0017	78.0843
AMS_2yr	1,190	0.7553	5.2719	0.0008	75.8188
AMS_3yr	987	0.7485	4.6617	0.0014	74.6460
AMS_4yr	880	0.8515	5.4083	0.0009	75.8713
AMS_5yr	876	0.6489	3.7582	0.0003	74.3130
Patent[1]	1,271	75.1298	278.7461	1	7713
R&D_1	1,302	0.0711	0.6374	3.86E-05	20.7642
R&D_2	1,302	0.0658	0.5653	0	19.1856
R&D	1,302	0.0684	0.6003	1.93E-05	19.9749
Age[1]	1,451	2.2351	0.6194	0	3.5835
Asset[1]	1,451	20.3753	1.2346	15.9441	29.8151
IssPrice	1,451	21.5589	13.8767	1.5	148
TobinQ	1,451	3.7654	2.6070	0.0084	30.3950
Leverage	1,451	0.2517	0.1759	0.0110	0.9475
UW	1,451	0.4590	0.4985	0	1
VC	1,451	0.6809	0.4663	0	1

Note: This table presents descriptive statistics for variables used in this study, including observations (N), mean, standard deviation (Std. Dev.), minimum value (Min) and maximum value (Max). *Sales_1yr* to *Sales_5yr* refer to the firm's sales extending from the beginning of its IPO to five years after, respectively. *Profit_1yr* to *Profit_5yr* refer to the firm's profits extending from the beginning of its IPO to five years after, respectively. *Capex_1yr* to *Capex_5yr* refer to the firm's capital expenditures extending from the beginning of its IPO to five years after, respectively. *RMS_1yr* to *RMS_5yr* refer to the firm's relative market shares extending from the beginning of its IPO to five years after, respectively. *AMS_1yr* to *AMS_5yr* refer to the firm's absolute market shares extending from the beginning of its IPO to five years after, respectively. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm.

4.4.2 Empirical Regression

(1) Innovations and Firm’s Operating Performance in the Post-IPO Product Market

1) The impact of innovation capital on the firm’s sales in the post-IPO product market

According to the results shown in Table 4.2 and the innovation output, the pre-IPO patent number has a positive impact on firm's sales in the product market in the post-IPO period, according to the relevant coefficients of Model 1, 4, 7, 10 and 13. These coefficients are all significant at the 1% level. These results also illustrate that the higher the innovative output of a firm before the IPO, the higher its sales in product market would be over the five years following the IPO. This implies that the investors may have shown a favorable investment response towards the firm’s number of patents, leading to a positive impact on the firm’s post-IPO sales performance in the product market. This finding is consistent with the hypothesis H_{1a}. Moreover, from the perspective of innovation input, the coefficients of R&D in Model 2, 5, 8, 11 and 14 are all negative and statistically significant at the 1% level. The pre-IPO innovation input (R&D intensity) is inversely related to the firm’s performance in the product market after its IPO. This means that the greater the R&D investment before the IPO, the fewer sales in the post-IPO product market will be expected, extending up to five years after the IPO. The level of uncertainty and instability of investment in R&D in the pre-IPO period has a negative impact on the success of innovation projects or innovation activities, making the results in Table 4.2 consistent with the hypothesis H_{1b}. Furthermore, we combined the variables of innovation input and outcome in Model 3, 6, 9, 12 and 15, and found similar impacts of the innovation capital on the firm’s aftermarket sales performance as those yielded by the individual models.

For other control variables, the age of listed companies has a negative but insignificant impact on the company's sales in the product market. This negative correlation lasts for five years after the firm's IPO. The longer the company is established, the fewer sales it is expected to have in the product market over the five years following its IPO. In contrast, the size of the firm in this model shows a positive impact on the firm's post-IPO sales, which is significant at the 1% level and lasts for five years after the IPO. This positive impact indicates that the larger a firm is, the more sales it is expected to have in the post-IPO product market. Furthermore, the issue price also has a significant positive impact on the sales of the company in the product market. This positive impact is significant at the 1% level for five years after the IPO. Meanwhile, the coefficients for the underwriter reputation in our regression analysis are positive but not statistically significant at the conventional levels. Conversely, the coefficients for the venture capital are positive and marginally significant in some years at the conventional levels. In addition, both the Tobin Q and leverage ratio of listed companies have positive and significant impacts on the sales of listed companies in the first year after the IPO. However, there is a minor difference between these two variables in that the firm's leverage ratio has a sustained positive effect on sales following the IPO, which weakens in the fifth year, while the statistical significance of the firm's Tobin Q gradually increases from the 10% level to 1% over time.

Table 4.2 The Impact of Innovation Capital on the Firms' Sales for Five Years after IPOs

VARIABLES	Sales_1yr			Sales_2yr			Sales_3yr			Sales_4yr			Sales_5yr		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Patent[1]	0.0314**		0.0341***	0.0481***		0.0520***	0.0628***		0.0661***	0.0719***		0.0841***	0.0699***		0.0808***
	(0.015)		(0.008)	(0.001)		(0.001)	(0.001)		(0.000)	(0.001)		(0.000)	(0.009)		(0.003)
R&D		-1.8446***	-1.7503***		-1.7405***	-1.7063***		-1.7164***	-1.5965***		-4.4599***	-4.3159***		-4.1873***	-4.0505***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Age[1]	-0.0333	-0.0269	-0.0357	-0.0275	-0.0228	-0.0283	-0.0467	-0.0422	-0.0452	-0.0343	-0.0404	-0.0423	-0.0238	-0.0285	-0.0267
	(0.153)	(0.250)	(0.118)	(0.311)	(0.400)	(0.292)	(0.145)	(0.187)	(0.156)	(0.363)	(0.279)	(0.258)	(0.600)	(0.523)	(0.556)
Asset[1]	0.9122***	0.9233***	0.9098***	0.8638***	0.8808***	0.8616***	0.8246***	0.8390***	0.8169***	0.7762***	0.7915***	0.7583***	0.7581***	0.7759***	0.7436***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	0.0067***	0.0070***	0.0071***	0.0066***	0.0067***	0.0069***	0.0068***	0.0068***	0.0071***	0.0056***	0.0058***	0.0062***	0.0047**	0.0046**	0.0052**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.0026)	(0.023)	(0.014)
TobinQ	0.0166*	0.0120*	0.0176*	0.0184**	0.0149*	0.0193**	0.0350***	0.0291**	0.0352***	0.0501**	0.0586***	0.0607***	0.0673***	0.0744***	0.0765***
	(0.062)	(0.086)	(0.075)	(0.028)	(0.078)	(0.021)	(0.006)	(0.022)	(0.006)	(0.012)	(0.003)	(0.002)	(0.005)	(0.001)	(0.002)
Leverage	0.4916***	0.6397***	0.4931***	0.7182***	0.8399***	0.7150***	0.7800***	0.8792***	0.7859***	0.9083***	0.7404***	0.7898***	0.6994**	0.5053*	0.5661*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.014)	(0.077)	(0.053)
UW	0.0242	0.0154	0.0238	0.0307	0.0211	0.0276	0.0595	0.0614	0.0585	0.0456	0.0584	0.0439	0.0047	0.0272	0.0053
	(0.377)	(0.576)	(0.377)	(0.336)	(0.507)	(0.386)	(0.125)	(0.111)	(0.130)	(0.331)	(0.202)	(0.346)	(0.933)	(0.619)	(0.925)
VC	0.0133	0.0102	0.0239	0.0547	0.0235	0.0657*	0.0602	0.0200	0.0691*	0.0858*	0.0779	0.1050**	0.0777	0.0751	0.0954
	(0.647)	(0.724)	(0.402)	(0.107)	(0.485)	(0.051)	(0.141)	(0.624)	(0.090)	(0.082)	(0.108)	(0.032)	(0.189)	(0.196)	(0.109)
Constant	1.1744***	1.1350**	1.2599***	2.2316***	2.2196***	2.3148***	3.3510***	3.4586***	3.5456***	4.0800***	4.3448***	4.5020***	4.4560***	4.6703***	4.8059***
	(0.008)	(0.012)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF	1.28	1.30	1.27	1.28	1.30	1.27	1.30	1.32	1.28	1.32	1.37	1.32	1.32	1.37	1.32
Observations	956	989	921	956	989	921	863	896	832	750	783	726	749	782	725
R-squared	0.8719	0.8679	0.8752	0.8287	0.8235	0.8302	0.7802	0.7704	0.7806	0.7219	0.7144	0.7246	0.6231	0.6169	0.6198
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of the impact of innovation capitals on the firms' sales for five years after IPOs. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *Sales_1yr* which is the firm's sales one year after its IPO. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the *Sales_2yr* which is the firm's sales two years after its IPO. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the *Sales_3yr* which is the firm's sales three years after its IPO. Model 10 to Model 12 respectively test the impact of firm's innovation capitals on the *Sales_4yr* which is the firm's sales four years after its IPO. Model 13 to Model 15 respectively test the impact of firm's innovation capitals on the *Sales_5yr* which is the firm's sales five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

2) The impact of innovation capital on the firm's profits in the post-IPO product market

When exploring the firm's operating performance in the post-IPO product market, we also take the firm's profit as a reference index. Therefore, fifteen models in Table 4.3 pertain to the impact of firm's innovation capital on its profit performance in the post-IPO product market. First, from the perspective of innovation output (number of patents), the coefficients related to the firms' patents from Model 1, 4, 7, 10 and 13 are all positive, and are significantly correlated with the firms' profits at the level of 10%, 10%, 1%, 1% and 5% for five years after the IPOs, respectively. This finding is in full conformity with the hypothesis H_{2a}, indicating that the higher the number of patents obtained before firms going public, the more profit they will make in the post-IPO period in the product market. From the positive impacts of the number of patents both on the firms' sales in Table 4.2 and on the firms' profits in Table 4.3, we can conclude that firms' number of patents before the IPO can lead to their superior performance in the product market in the post-IPO period. Thus, the number of patents as the innovative output of a firm can convey positive signals to the market. In addition, from the perspective of innovation input (R&D intensity), the intensity of R&D input is consistent with the hypothesis H_{2b}. From Model 2, 5, 8, 11 and 14, the coefficients of R&D are all negative, and statistically significant at the 1%, 5%, 1%, 1% and 5% levels, respectively. As a result, the greater the intensity of R&D investment before a firm's IPO, the less profit will be generated in the post-IPO product market. For the firms' sales, the uncertainty of R&D investment leads to a negative impact of firms' innovation input on their operating performance after their IPOs. Additionally, after combining innovation input and outcome in Model 3, 6, 9, 12 and 15 in Table 4.3, we still find similar results, suggesting that our findings are robust and stable.

Further, in contrast to the results related to firms' sales reported in Table 4.3, the firms' age does not have significant negative impact on their profits in the post-IPO period, except in the first year, which is significant at the 5% level. Meanwhile, the firms' leverage ratio has a negative impact on their profits at the significance level of 1% from the first year onward after their IPOs. Finally, similar to the coefficient signs in Table 4.2, the size, issuing price and Tobin Q of the listed companies exert a positive effect on the firms' profit performance at the significance level of 1% in the post-IPO period.

Table 4.3 The Impact of Innovation Capital on the Firms' Profits for Five Years after IPOs

VARIABLES	Profit_1yr			Profit_2yr			Profit_3yr			Profit_4yr			Profit_5yr		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Patent[1]	0.0264*		0.0257*	0.0403*		0.0492*	0.1184***		0.1181***	0.1233***		0.1311***	0.1149**		0.1178**
	(0.091)		(0.090)	(0.091)		(0.059)	(0.000)		(0.001)	(0.005)		(0.003)	(0.012)		(0.013)
R&D		-0.7887***	-1.0400***		-0.8673**	-0.9347***		-0.8920***	-0.9015***		-4.4358***	-4.4632**		-2.3652**	-2.2591**
		(0.000)	(0.008)		(0.047)	(0.009)		(0.000)	(0.004)		(0.009)	(0.011)		(0.023)	(0.016)
Age[1]	-0.0644**	-0.0518*	-0.0666**	0.0166	0.0232	0.0193	0.0588	0.0483	0.0545	0.0474	0.0495	0.0356	-0.0022	-0.0255	-0.0076
	(0.022)	(0.066)	(0.019)	(0.713)	(0.601)	(0.674)	(0.323)	(0.413)	(0.365)	(0.529)	(0.510)	(0.641)	(0.978)	(0.741)	(0.924)
Asset[1]	0.8657***	0.8677***	0.8561***	0.8473***	0.8503***	0.8292***	0.8687***	0.9183***	0.8704***	0.7585***	0.8138***	0.7540***	0.7025***	0.7623***	0.7095***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	0.0159***	0.0165***	0.0162***	0.0176***	0.0186***	0.0177***	0.0195***	0.0178***	0.0191***	0.0141***	0.0147***	0.0142***	0.0127***	0.0123***	0.0130***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
TobinQ	0.0492***	0.0456***	0.0516***	0.0745***	0.0693***	0.0756***	0.1021***	0.1007***	0.1010***	0.1460***	0.1502***	0.1583***	0.1301***	0.1286***	0.1378***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Leverage	-1.5668***	-1.4182***	-1.5180***	-1.3857***	-1.3184***	-1.3243***	-1.3873***	-1.3775***	-1.3503***	-1.0283**	-1.4116***	-1.1327**	-1.2880***	-1.4964***	-1.3771***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.028)	(0.003)	(0.019)	(0.009)	(0.003)	(0.008)
UW	0.0564*	0.0539	0.0523	0.1152**	0.0969*	0.1154**	0.1840**	0.1752**	0.1750**	0.0361	0.0204	0.0185	0.1173	0.1106	0.1225
	(0.088)	(0.103)	(0.120)	(0.031)	(0.065)	(0.035)	(0.011)	(0.014)	(0.017)	(0.697)	(0.824)	(0.844)	(0.225)	(0.240)	(0.214)
VC	-0.0131	-0.0261	-0.0092	0.0559	0.0331	0.0608	-0.0656	-0.1148	-0.0742	0.1514	0.1620*	0.1636*	0.0729	0.0329	0.0598
	(0.708)	(0.455)	(0.000)	(0.323)	(0.550)	(0.291)	(0.382)	(0.123)	(0.331)	(0.119)	(0.093)	(0.097)	(0.472)	(0.740)	(0.564)
Constant	0.5030**	0.6318**	0.7141*	0.6553*	0.9431*	1.0019*	0.4746*	1.1130**	0.4507*	1.3171**	0.4894*	1.4901**	2.0643***	1.2537***	1.9803***
	(0.043)	(0.045)	(0.095)	(0.053)	(0.076)	(0.063)	(0.075)	(0.039)	(0.073)	(0.046)	(0.057)	(0.032)	(0.006)	(0.004)	(0.003)
Mean VIF	1.28	1.30	1.26	1.28	1.31	1.27	1.30	1.32	1.27	1.32	1.37	1.31	1.32	1.38	1.32
Observations	953	986	918	921	954	889	807	837	778	676	708	654	664	692	641
R-squared	0.7429	0.7543	0.7412	0.5530	0.5709	0.5497	0.4803	0.4927	0.4758	0.3625	0.3851	0.3666	0.3304	0.3754	0.3309
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of the impact of innovation capitals on the firms' profits for five years after IPOs. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *Profit_1yr* which is the firm's profits one year after its IPO. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the *Profit_2yr* which is the firm's profits two years after its IPO. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the *Profit_3yr* which is the firm's profits three years after its IPO. Model 10 to Model 12 respectively test the impact of firm's innovation capitals on the *Profit_4yr* which is the firm's profits four years after its IPO. Model 13 to Model 15 respectively test the impact of firm's innovation capitals on the *Profit_5yr* which is the firm's profits five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

3) The impact of innovation capital on the firms' total capital expenditure in the post-IPO product market

Table 4.4 shows the impact of firm's innovative capital on the overall capital expenditure in the product market after the IPO. In order to reduce the collinearity, we modified the post-IPO capital expenditure data by eliminating the R&D expenditure from each corresponding observation. From the perspective of the pre-IPO innovation output (number of patents), our results show that the number of patents in Model 1, 4, 7, 10 and 13 has a significant positive effect on the firm's capital expenditure in the post-IPO product market. The coefficient for this variable is highly significant at the 10%, 5%, 5%, 1% and 1% level over five years after the IPO, respectively. This finding is consistent with the hypothesis H_{3a}. However, the coefficient for the pre-IPO R&D input effect on the firm's capital expenditure in the post-IPO product market is negative in Model 2, 5, 8, 11 and 14 and is statistically significant at the 1%, 1%, 10%, 10% and 5% level, respectively. Consistent with the hypothesis $H_{3b,}$ we also obtained similar results from the application of Model 3, 6, 9, 12 and 15, implying that firms with greater innovation input before the IPO have lower capital expenditure in their post-IPO product market. Capital expenditure is generally a forward-looking decision in order to expand or upgrade the asset base of a company. It can be used for a variety of reasons, including purchasing fixed assets, financing new projects, or spending on takeovers. In this sense, capital expenditure has a lasting impact on the future growth of a company. In summary, the pre-IPO R&D expenditure cannot fully bring firms with future capitalization assets in the post-IPO product market. This finding supports our hypothesis that pre-IPO R&D's uncertainty and risk can negatively affect capital expenditure in the post-IPO period.

In addition, the age of the company has a negative impact on its capital expenditure after the IPO, and this effect is significant at the level of 1% and 5% in the first and second year following the IPO, respectively. The impact of the firm's size and issuing price on its capital expenditure is significant and positive at the 1% and 5% level for the five years following the IPO event. The coefficient for leverage ratio of listed companies is also positive and statistically significant at the 1% level in the first year after the IPO. The coefficient for Tobin Q is positive in the model and is significant at the conventional statistical levels, but gradually becomes less significant over time. The coefficient for the reputation of the main underwriter variable when firms go public is positive but statistically insignificant at the conventional levels. Moreover, similar to the results shown in Table 4.2 and Table 4.3, the impact of the venture capital before the IPO on the firm's operating performance in the post-IPO product market is not statistically significant at the conventional levels. Finally, we utilized the variance inflation factor VIF test to check the collinearity of each model and variable. The estimated Mean VIF numbers for each model in Table 4.2, Table 4.3 and Table 4.4 are all less than 1.40, and the VIF for all the variables is below 5, indicating that there is no multi-collinearity in our research models.

Table 4.4 The Impact of Innovation Capital on the Firms' Capital Expenditures for Five Years after IPOs

VARIABLES	Capex_1yr			Capex_2yr			Capex_3yr			Capex_4yr			Capex_5yr		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Patent[1]	0.0347*		0.0229*	0.0594**		0.0442**	0.0650**		0.0579*	0.1006***		0.0902**	0.1221***		0.1045**
	(0.056)		(0.065)	(0.029)		(0.013)	(0.037)		(0.069)	(0.006)		(0.015)	(0.005)		(0.020)
R&D		-0.6290***	-0.5236**		-0.7044***	-0.6202**		-0.4404*	-0.6562**		-0.6061*	-0.6070*		-1.4256**	-1.6006**
		(0.000)	(0.032)		(0.000)	(0.033)		(0.073)	(0.055)		(0.061)	(0.096)		(0.039)	(0.047)
Age[1]	-0.2080***	-0.1854***	-0.2012***	-0.1315***	-0.1118**	-0.1201**	-0.0731	-0.0695	-0.0703	-0.1331**	-0.1171*	-0.1300**	-0.1505**	-0.1347*	-0.1500**
	(0.000)	(0.001)	(0.000)	(0.006)	(0.019)	(0.014)	(0.168)	(0.189)	(0.190)	(0.031)	(0.053)	(0.038)	(0.037)	(0.062)	(0.041)
Asset[1]	0.6747***	0.7093***	0.6895***	0.6240***	0.6680***	0.6416***	0.7183***	0.7531***	0.7179***	0.7219***	0.7620***	0.7195***	0.6913***	0.7313***	0.7039***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	0.0100***	0.0085***	0.0092***	0.0059***	0.0050**	0.0052**	0.0061**	0.0059**	0.0055**	0.0072**	0.0059**	0.0061**	0.0085***	0.0083**	0.0081**
	(0.000)	(0.001)	(0.000)	(0.006)	(0.019)	(0.019)	(0.012)	(0.014)	(0.026)	(0.012)	(0.032)	(0.036)	(0.010)	(0.011)	(0.017)
TobinQ	0.0421**	0.0361**	0.0448***	0.0402**	0.0329*	0.0410**	0.0463*	0.0488*	0.0533*	0.0660**	0.0522*	0.0648*	0.0568	0.0762**	0.0762*
	(0.014)	(0.034)	(0.010)	(0.036)	(0.080)	(0.035)	(0.097)	(0.078)	(0.062)	(0.042)	(0.100)	(0.051)	(0.135)	(0.045)	(0.053)
Leverage	1.3081***	1.1240***	1.2216***	0.3322	0.1469	0.1940	-0.1540	-0.3315	-0.2357	-0.4025	-0.6545*	-0.5406	-0.2751	-0.2766	-0.4176
	(0.000)	(0.000)	(0.000)	(0.229)	(0.596)	(0.495)	(0.644)	(0.328)	(0.494)	(0.300)	(0.092)	(0.178)	(0.561)	(0.568)	(0.395)
UW	0.0824	0.0777	0.0827	0.0543	0.0814	0.0770	-0.0055	0.0198	0.0112	0.1278*	0.1547**	0.1409*	0.0520	0.1275	0.0800
	(0.202)	(0.228)	(0.208)	(0.351)	(0.154)	(0.193)	(0.933)	(0.761)	(0.866)	(0.095)	(0.038)	(0.070)	(0.578)	(0.170)	(0.400)
VC	-0.0899	-0.0557	-0.0735	0.0102	0.0064	0.0126	0.1315*	0.1239*	0.1361*	0.0529	0.0513	0.0635	0.0663	0.1018	0.0898
	(0.190)	(0.413)	(0.291)	(0.868)	(0.916)	(0.840)	(0.058)	(0.072)	(0.052)	(0.511)	(0.514)	(0.437)	(0.497)	(0.297)	(0.367)
Constant	3.9110***	3.4786***	3.6610***	5.5009***	4.8522***	5.1964***	5.1211***	4.2727***	5.1347***	4.1782***	3.7051***	4.2745***	4.2767***	3.7169**	4.0023***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.004)	(0.011)	(0.008)
Mean VIF	1.28	1.30	1.27	1.30	1.32	1.28	1.32	1.37	1.32	1.32	1.37	1.32	1.32	1.37	1.32
Observations	956	989	921	863	896	832	750	783	726	749	782	725	626	652	606
R-squared	0.5303	0.5301	0.5258	0.5183	0.5223	0.5062	0.5176	0.5126	0.5123	0.4354	0.4343	0.4250	0.4023	0.4011	0.4021
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of the impact of innovation capitals on the firms' capital expenditures for five years after IPOs. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *Capex_1yr* which is the firm's capital expenditures one year after its IPO. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the *Capex_2yr* which is the firm's capital expenditures two years after its IPO. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the *Capex_3yr* which is the firm's capital expenditures three years after its IPO. Model 10 to Model 12 respectively test the impact of firm's innovation capitals on the *Capex_4yr* which is the firm's capital expenditures four years after its IPO. Model 13 to Model 15 respectively test the impact of firm's innovation capitals on the *Capex_5yr* which is the firm's capital expenditures five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

(2) Innovations and Firm’s Competitiveness in the Post-IPO Product Market

1) The impact of innovation capital on the firm’s relative market share in the post-IPO product market

In this part, we discuss the influence of the pre-IPO innovation capital on the firm's competitiveness in the post-IPO product market. First, we take relative market share as the dependent variable of a firm’s competitiveness to examine the influence of the innovation capital, i.e., innovation output (number of patents) and innovation input (R&D intensity), on the relative market share in the product market for five years after the IPO. Interestingly, it can be seen that both firm’s pre-IPO innovation input and outcome have positive impacts on the relative market share in the post-IPO product market for Model 1−15 in Table 4.5. Consistent with the hypothesis H_4, this finding implies that the higher the level of innovation capital of a firm before its IPO, the greater its competitiveness in the post-IPO product market will be. However, from the combined perspective of innovation output (number of patents) and innovation input (R&D intensity), we can see that the innovation output impact on the relative market share of the firm in the product market is significant at the 5% level. On the other hand, the coefficient for innovation input is positive, but does not have any statistical significance at the conventional levels. Overall, these findings are consistent with our hypothesis when these two variables are combined in Model 3, 6, 9, 12 and 15.

Table 4.5 also shows the influence of other control variables on the relative market share of the firm. The firm's age, size, issuing price and leverage ratio have a significant impact on the relative market share in the post-IPO product market. Our findings show that, as the companies become older, they are more likely to maintain their competitive position in the product market. This negative correlation is statistically significant at the 1% level, and gradually become less significant over time in the post-IPO period. The coefficient for firm's size is positive and statistically significant at the level of 1% over the 5-years post-IPO period, showing that a larger company would maintain a higher competitive position in the product market than a smaller one. Furthermore, both issuing price and leverage ratio show a negative influence on firm competitiveness in the product market at the 10% significance level. Thus, firms with a higher issuing price and leverage ratio are less competitive in their post-IPO product market.

Table 4.5 Innovations and Post-IPO Relative Market Shares of Firms in the Product Market

VARIABLES	RMS_1yr			RMS_2yr			RMS_3yr			RMS_4yr			RMS_5yr		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Patent[1]	0.2265**		0.2512**	0.2480**		0.2700**	0.2583**		0.2805**	0.3086*		0.3624**	0.2754*		0.3032**
	(0.041)		(0.029)	(0.027)		(0.021)	(0.037)		(0.028)	(0.052)		(0.028)	(0.054)		(0.040)
R&D		1.2648	0.9191		1.2515	1.0421		1.3553	1.0931		4.7978	3.9898		3.7726	2.5514
		(0.109)	(0.771)		(0.117)	(0.877)		(0.103)	(0.723)		(0.531)	(0.531)		(0.484)	(0.655)
Age[1]	-0.5115**	-0.6948***	-0.5314***	-0.5652***	-0.6588**	-0.5872***	-0.4602**	-0.6528**	-0.4753**	-0.3664	-0.6170*	-0.3903	-0.4503*	-0.4359*	-0.4406*
	(0.010)	(0.008)	(0.009)	(0.005)	(0.015)	(0.004)	(0.037)	(0.025)	(0.034)	(0.176)	(0.066)	(0.158)	(0.065)	(0.066)	(0.076)
Asset[1]	1.5269***	1.5389***	1.4794***	1.5661***	1.6075***	1.5177***	1.6150***	1.6954***	1.6065***	1.8339***	1.8950***	1.7913***	1.8064***	1.8964***	1.7783***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	-0.0109*	-0.0174*	-0.0121*	-0.0139*	-0.0211*	-0.0153*	-0.0103*	-0.0174*	-0.0117*	-0.0154*	-0.0139*	-0.0155*	-0.0124*	-0.0123*	-0.0138*
	(0.074)	(0.091)	(0.095)	(0.082)	(0.087)	(0.084)	(0.099)	(0.080)	(0.077)	(0.066)	(0.056)	(0.063)	(0.056)	(0.053)	(0.060)
TobinQ	-0.0263	-0.0389	-0.0188	-0.0263	-0.0390	-0.0172	-0.1006	-0.1334	-0.0949	-0.0187	-0.1030	0.0211	-0.1693	-0.1616	-0.1611
	(0.669)	(0.630)	(0.766)	(0.678)	(0.650)	(0.791)	(0.253)	(0.247)	(0.289)	(0.896)	(0.558)	(0.886)	(0.186)	(0.193)	(0.224)
Leverage	-1.4203*	-1.9133*	-1.6565**	-0.9403*	-1.0672*	-1.1945*	-1.6953*	-2.2961*	-1.9807**	-2.1813*	-3.5754*	-2.8553*	-2.0698*	-2.5369*	-2.4097*
	(0.091)	(0.083)	(0.040)	(0.094)	(0.078)	(0.095)	(0.079)	(0.075)	(0.030)	(0.071)	(0.097)	(0.079)	(0.078)	(0.096)	(0.083)
UW	0.0752	0.3100	0.0643	0.1548	0.2756	0.1265	0.0806	0.2917	0.0576	0.1585	0.5234	0.1456	0.1196	0.1482	0.1156
	(0.748)	(0.309)	(0.789)	(0.515)	(0.388)	(0.603)	(0.762)	(0.404)	(0.832)	(0.637)	(0.205)	(0.672)	(0.693)	(0.611)	(0.709)
VC	0.0392	0.1358	0.0651	0.0650	0.0766	0.0931	0.0377	0.0613	0.0473	-0.1932	-0.0901	-0.1493	0.0042	-0.0520	0.0209
	(0.875)	(0.673)	(0.798)	(0.796)	(0.821)	(0.718)	(0.892)	(0.868)	(0.869)	(0.585)	(0.836)	(0.680)	(0.989)	(0.866)	(0.949)
Constant	-26.9802***	-21.5842***	-26.0873***	-27.7046***	-22.9314***	-26.7627***	-27.4434***	-20.2419***	-27.2916***	-32.4929***	-24.6680***	-31.7796***	-31.0338***	-31.1557***	-30.6511***
	(0.000)	(0.000)	(3.930)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF	1.28	1.30	1.27	1.28	1.30	1.27	1.30	1.32	1.28	1.32	1.37	1.32	1.32	1.37	1.32
Observations	956	989	921	945	978	911	846	879	815	750	783	726	746	779	722
R-squared	0.3912	0.3180	0.3512	0.4337	0.3328	0.3848	0.4054	0.3451	0.3848	0.3744	0.3286	0.3506	0.4136	0.3934	0.3866
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of the impact of innovation capitals on the firms' relative market shares for five years after IPOs. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *RMS_1yr* which is the firm's relative market shares one year after its IPO. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the *RMS_2yr* which is the firm's relative market shares two years after its IPO. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the *RMS_3yr* which is the firm's relative market shares three years after its IPO. Model 10 to Model 12 respectively test the impact of firm's innovation capitals on the *RMS_4yr* which is the firm's relative market shares four years after its IPO. Model 13 to Model 15 respectively test the impact of firm's innovation capitals on the *RMS_5yr* which is the firm's relative market shares five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ***1% significance level, **5% significance level, *10% significance level.

2) The impact of innovation capital on the firm's absolute market share in the post-IPO product market

Besides relative market share, in this study, we also adopted absolute market share as a variable to comprehensively investigate firms' competitive position in the post-IPO product market. This test serves as another essential measure of firms' market share and confirms how robust our previous findings are. The results shown in Table 4.6 indicate that the greater the innovation input and outcome before the IPO, the more competitive the firm in the post-IPO product market is with respect to its market share. This finding is consistent with the hypothesis H_5. Moreover, if we distinguish between different forms of innovative capital, we can argue that, from the perspective of the innovation output, there is a direct relationship between the number of patents in the pre-IPO period and the firms' competitiveness in the post-IPO product market. This relationship lasts from the first year to the fifth year and the relevant coefficients are significant at the 10% or 5% level in Model 1, 4, 7, 10 and 13, presented in Table 4.6. Secondly, from the perspective of innovation input, results in Table 4.6 show that the coefficients of R&D input intensity are positive but are not statistically significant at the conventional levels. Similar to the results pertaining to the relative market share in Table 4.5, the firm's innovation output has a more significant positive impact on its competitiveness (absolute market share) in the post-IPO product market, which also confirms the robustness of the results. The insignificant impact of the innovation input on the firm's competitiveness in the product market may arise from the uncertainty of its outcome and lags in the firm's operations. In other words, the pre-IPO innovation input (R&D expenditure) may fail to generate adequate market capitalization to improve the competitive position of the firms in the post-IPO product market.

In addition, the influence of other control variables on the firm's absolute market share in the product market shows the same impact as that on the relative market share in the product market. The firm's age has a negative correlation to the absolute market share in the post-IPO product market and lasts for three years, at the significance level of 5%, 5% and 10%, respectively. This negative impact gradually decreases over time. Firm's size also exerts a positive influence on the firm's absolute market share for five years after the IPO, at the significance level of 1%. The issuing price of IPO exhibits a negative impact on the absolute market share and is significant at the 10% level in the post-IPO period for five years. However, the firm's leverage ratio has a negative but insignificant correlation with the absolute market share in the product market. The firm's Tobin Q has a significantly negative effect in the absolute market share for five years after the IPO at the significance level of 10%. Finally, all models and variables reported in Table 4.5 and Table 4.6 have passed the VIF test for the multi-collinearity, with the Mean VIFs less than 1.40 and VIFs below 5.

Table 4.6 Innovations and Post-IPO Absolute Market Shares of Firms in the Product Market

VARIABLES	AMS_1yr			AMS_2yr			AMS_3yr			AMS_4yr			AMS_5yr		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Patent[1]	0.0904*		0.0956*	0.1277**		0.1262*	0.1394**		0.1311*	0.1711*		0.1801*	0.1294*		0.1261*
	(0.094)		(0.087)	(0.049)		(0.072)	(0.036)		(0.077)	(0.055)		(0.052)	(0.064)		(0.054)
R&D		0.8989	1.1892		0.7024	0.9538		0.9432	1.4230		3.8085	3.1424		4.2893	3.6347
		(0.296)	(0.590)		(0.319)	(0.673)		(0.299)	(0.544)		(0.293)	(0.814)		(0.276)	(0.387)
Age[1]	-0.3178**	-0.5031**	-0.3311**	-0.3122**	-0.4277*	-0.3269**	-0.2639	-0.4612*	-0.2791	-0.1925	-0.4486	-0.2104	-0.2719	-0.2786	-0.2720
	(0.041)	(0.027)	(0.037)	(0.050)	(0.074)	(0.045)	(0.113)	(0.065)	(0.101)	(0.348)	(0.114)	(0.318)	(0.126)	(0.107)	(0.136)
Asset[1]	0.7756***	0.7322***	0.7751***	0.7905***	0.7862***	0.8078***	0.8145***	0.8041***	0.8441***	0.9536***	0.9178***	0.9685***	0.8921***	0.9559***	0.9137***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	-0.0101*	-0.0143*	-0.0199*	-0.0129*	-0.0174*	-0.0129*	-0.0106*	-0.0148*	-0.0108*	-0.0167*	-0.0119*	-0.0160*	-0.0112*	-0.0105*	-0.0113*
	(0.055)	(0.064)	(0.072)	(0.076)	(0.098)	(0.084)	(0.087)	(0.085)	(0.060)	(0.080)	(0.058)	(0.067)	(0.071)	(0.083)	(0.078)
TobinQ	-0.1336*	-0.1395*	-0.1277*	-0.1344*	-0.1388*	-0.1264*	-0.1005*	-0.1026*	-0.0894*	-0.0950*	-0.0930*	-0.1286*	-0.1755*	-0.1555*	-0.1612*
	(0.083)	(0.075)	(0.076)	(0.091)	(0.061)	(0.061)	(0.091)	(0.082)	(0.089)	(0.076)	(0.061)	(0.079)	(0.061)	(0.086)	(0.097)
Leverage	-1.2084	-1.4127	-1.2036	-0.8647	-0.7144	-0.8841	-1.4601	-1.6095	-1.4633	-1.8900	-2.4300	-2.0542	-1.7460	-1.7670	-1.7135
	(0.153)	(0.260)	(0.171)	(0.321)	(0.590)	(0.329)	(0.126)	(0.269)	(0.141)	(0.143)	(0.181)	(0.129)	(0.120)	(0.111)	(0.145)
UW	0.0779	0.3098	0.0651	0.1232	0.2510	0.1063	0.0708	0.2588	0.0523	0.1424	0.4560	0.1291	0.0963	0.1055	0.0876
	(0.669)	(0.244)	(0.729)	(0.512)	(0.373)	(0.583)	(0.725)	(0.389)	(0.800)	(0.576)	(0.191)	(0.622)	(0.663)	(0.620)	(0.700)
VC	0.0406	0.1618	0.0307	0.0645	0.1103	0.0572	0.0583	0.1334	0.0321	-0.1314	0.0202	-0.1349	-0.0046	-0.0672	-0.0248
	(0.834)	(0.565)	(0.877)	(0.745)	(0.711)	(0.780)	(0.782)	(0.674)	(0.882)	(0.623)	(0.956)	(0.624)	(0.984)	(0.765)	(0.917)
Constant	-12.9477***	-9.3493**	-12.9934***	-13.4015***	-10.9729**	-13.7717***	-13.2435***	-9.6118**	-13.8445***	-16.3299***	-12.6118**	-16.7645***	-14.3292***	-14.7770***	-14.9359***
	(0.000)	(0.032)	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)	(0.050)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF	1.28	1.30	1.27	1.28	1.30	1.27	1.30	1.32	1.28	1.32	1.37	1.32	1.32	1.37	1.32
Observations	956	989	921	945	978	911	846	879	815	750	783	726	746	779	722
R-squared	0.2972	0.2681	0.2712	0.3269	0.2796	0.3157	0.3419	0.2978	0.3426	0.3023	0.2827	0.3010	0.3258	0.3296	0.3252
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents regressions of the impact of innovation capitals on the firms' absolute market shares for five years after IPOs. Model 1 to Model 3 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *AMS_1yr* which is the firm's absolute market shares one year after its IPO. Model 4 to Model 6 respectively test the impact of firm's innovation capitals on the *AMS_2yr* which is the firm's absolute market shares two years after its IPO. Model 7 to Model 9 respectively test the impact of firm's innovation capitals on the *AMS_3yr* which is the firm's absolute market shares three years after its IPO. Model 10 to Model 12 respectively test the impact of firm's innovation capitals on the *AMS_4yr* which is the firm's absolute market shares four years after its IPO. Model 13 to Model 15 respectively test the impact of firm's innovation capitals on the *AMS_5yr* which is the firm's absolute market shares five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D* is the average of R&D intensity of *R&D_1* and *R&D_2*. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

4.4.3 Robustness Test

In order to ensure that our results are reliable, we have conducted a robustness test and will discuss the findings below. First, we take the innovation input (R&D intensity) with the firm's R&D input intensity one year and two years before IPO as the independent variables to conduct a robust regression test. The results shown in Table 4.7, Table 4.8 and Table 4.9 indicate that our findings are consistent with the previous results, regardless of the length of firm's R&D input before IPO used in the test. Models presented in Table 4.7 examine the impact of both innovation input and outcome on the sales of firms in the post-IPO product market. The results show that the greater the R&D input intensity in the year preceding the IPO, the lower the firm's sales in the product market after the IPO will be expected. This impact is significant at the 1% level and lasts for five years after the IPO. In Table 4.8, we examine the impact of R&D input intensity in two years prior to IPOs on the firms' profit performance. The results show that both one year's and the two year's pre-IPO R&D input intensities have significant negative impacts on the firm's profit. This finding is consistent with the result as shown in previous tables and supports our hypothesis. In Table 4.9, we examine the impact of innovation capital on capital expenditure in the same way. Interestingly, the intensity of R&D input in both one year and two years before the IPO has a negative impact on the firm's capital expenditure in the post-IPO product market. However, the negative correlation coefficients are not statistically significant for the first two years after the firms go public. In the first two years after their IPOs, firms' innovation outcome exhibits positive but insignificant impact on their capital expenditure performance. Over time, the impact of R&D input intensity and number of patents on the firm's performance in the product market becomes more significant. Therefore, our findings also show that the innovation input of the firm's

R&D investment has a cumulative and lag effect on the operations and processes of the firms (Pemman and Zhang, 2002). Overall, the findings reported in Table 4.7 through Table 4.9 show that our earlier results are robust and stable.

Table 4.7 Robustness Test on the Relationship between Innovation Capital and Firm's Sales

VARIABLES	Sales_1yr		Sales_2yr		Sales_3yr		Sales_4yr		Sales_5yr	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Patent[1]	0.0342***	0.0339***	0.0521***	0.0518***	0.0663***	0.0659***	0.0853***	0.0820***	0.0820***	0.0788***
	(0.008)	(0.009)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)
R&D_1	-1.8811***		-1.7624***		-1.6441***		-4.8422***		-4.5628***	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
R&D_2		-1.5041***		-1.5300***		-1.4345***		-3.2042***		-2.9950***
		(0.000)		(0.000)		(0.001)		(0.000)		(0.001)
Age[1]	-0.0371	-0.0343	-0.0295	-0.0270	-0.0462	-0.0440	-0.0468	-0.0370	-0.0310	-0.0216
	(0.103)	(0.134)	(0.273)	(0.315)	(0.147)	(0.167)	(0.210)	(0.325)	(0.495)	(0.634)
Asset[1]	0.9095***	0.9103***	0.8615***	0.8620***	0.8167***	0.8173***	0.7567***	0.7604***	0.7421***	0.7456***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	0.0072***	0.0069***	0.0069***	0.0068***	0.0072***	0.0070***	0.0066***	0.0059***	0.0055***	0.0049**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.009)	(0.021)
TobinQ	0.0079	0.0074	0.0193**	0.0190**	0.0351***	0.0350***	0.0611***	0.0574***	0.0769***	0.0733***
	(0.263)	(0.301)	(0.021)	(0.023)	(0.006)	(0.006)	(0.000)	(0.004)	(0.001)	(0.003)
Leverage	0.4936***	0.4961***	0.7170***	0.7163***	0.7892***	0.7863***	0.7875***	0.8142***	0.5635*	0.5894**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.053)	(0.044)
UW	0.0239	0.0241	0.0277	0.0277	0.0586	0.0588	0.0431	0.0453	0.0046	0.0067
	(0.375)	(0.374)	(0.383)	(0.385)	(0.129)	(0.128)	(0.353)	(0.332)	(0.935)	(0.906)
VC	0.0232	0.0237	0.0647*	0.0659*	0.0684*	0.0690*	0.1036**	0.1027**	0.0942	0.0932
	(0.414)	(0.407)	(0.055)	(0.051)	(0.093)	(0.091)	(0.034)	(0.037)	(0.112)	(0.118)
Constant	1.2740***	1.2395***	2.3236***	2.2988***	3.5590***	3.5286***	4.5700***	4.4265***	4.8702***	4.7348***
	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	921	921	921	921	832	832	726	726	725	725
R-squared	0.8758	0.8744	0.8304	0.8297	0.7807	0.7802	0.7259	0.7219	0.6209	0.6175
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the robust regressions of the impact of innovation capitals on the firms' sales for five years after IPOs. Model 1 to Model 2 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *Sales_1yr* which is the firm's sales one year after its IPO. Model 3 to Model 4 respectively test the impact of firm's innovation capitals on the *Sales_2yr* which is the firm's sales two years after its IPO. Model 5 to Model 6 respectively test the impact of firm's innovation capitals on the *Sales_3yr* which is the firm's sales three years after its IPO. Model 7 to Model 8 respectively test the impact of firm's innovation capitals on the *Sales_4yr* which is the firm's sales four years after its IPO. Model 9 to Model 10 respectively test the impact of firm's innovation capitals on the *Sales_5yr* which is the firm's sales five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D_1* represents firm's R&D intensity one year before IPO. *R&D_2* represents firm's R&D intensity two year before IPO. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

Table 4.8 Robustness Test on the Relationship between Innovation Capital and Firm's Profits

VARIABLES	Profit_1yr		Profit_2yr		Profit_3yr		Profit_4yr		Profit_5yr	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Patent[1]	0.0258*	0.0255*	0.0493*	0.0490*	0.1182***	0.1181***	0.1337***	0.1282***	0.1187**	0.1164**
	(0.098)	(0.099)	(0.058)	(0.060)	(0.001)	(0.001)	(0.003)	(0.004)	(0.012)	(0.014)
R&D_1	-1.1702***		-1.0108*		-0.9958*		-4.9887***		-2.3824*	
	(0.003)		(0.094)		(0.071)		(0.007)		(0.088)	
R&D_2		-0.8474**		-0.7985*		-0.8993*		-3.2855**		-1.7827*
		(0.024)		(0.095)		(0.078)		(0.031)		(0.087)
Age[1]	-0.0675**	-0.0657**	0.0185	0.0200	0.0537	0.0550	0.0302	0.0414	-0.0096	-0.0048
	(0.017)	(0.021)	(0.687)	(0.662)	(0.372)	(0.361)	(0.692)	(0.586)	(0.905)	(0.952)
Asset[1]	0.8558***	0.8566***	0.8291***	0.8295***	0.8702***	0.8705***	0.7518***	0.7567***	0.7085***	0.7110***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	0.0162***	0.0161***	0.0178***	0.0177***	0.0192***	0.0191***	0.0146***	0.0139***	0.0131***	0.0128***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
TobinQ	0.0518***	0.0512***	0.0757***	0.0754***	0.1014***	0.1005***	0.1600***	0.1543***	0.1378***	0.1362***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Leverage	-1.5189***	-1.5148***	-1.3240***	-1.3227***	-1.3539***	-1.3451***	-1.1292**	-1.1104**	-1.3720***	-1.3700***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.022)	(0.008)	(0.008)
UW	0.0522	0.0525	0.1153**	0.1156**	0.1744**	0.1756**	0.0165	0.0205	0.1217	0.1231
	(0.120)	(0.119)	(0.035)	(0.034)	(0.018)	(0.017)	(0.860)	(0.827)	(0.217)	(0.211)
VC	-0.0095	-0.0096	0.0605	0.0607	-0.0732	-0.0754	0.1618*	0.1620	0.0583	0.0593
	(0.790)	(0.788)	(0.293)	(0.293)	(0.337)	(0.324)	(0.100)	(0.100)	(0.573)	(0.568)
Constant	0.7272*	0.6985*	1.0089*	0.9918*	0.4422*	0.4563*	1.5643**	1.4111*	2.0170*	1.9387*
	(0.087)	(0.096)	(0.090)	(0.088)	(0.088)	(0.080)	(0.049)	(0.078)	(0.074)	(0.083)
Observations	918	918	889	889	778	778	654	654	641	641
R-squared	0.7417	0.7406	0.5500	0.5494	0.4761	0.4757	0.3675	0.3647	0.3309	0.3307
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the robust regressions of the impact of innovation capitals on the firms' profits for five years after IPOs. Model 1 to Model 2 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *Profit_1yr* which is the firm's profits one year after its IPO. Model 3 to Model 4 respectively test the impact of firm's innovation capitals on the *Profit_2yr* which is the firm's profits two years after its IPO. Model 5 to Model 6 respectively test the impact of firm's innovation capitals on the *Profit_3yr* which is the firm's profits three years after its IPO. Model 7 to Model 8 respectively test the impact of firm's innovation capitals on the *Profit_4yr* which is the firm's profits four years after its IPO. Model 9 to Model 10 respectively test the impact of firm's innovation capitals on the *Profit_5yr* which is the firm's profits five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D_1* represents firm's R&D intensity one year before IPO. *R&D_2* represents firm's R&D intensity two year before IPO. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ***1% significance level, **5% significance level, *10% significance level.

Table 4.9 Robustness Test on the Relationship between Innovation Capital and Firm's Capital Expenditures

VARIABLES	Capex_1yr		Capex_2yr		Capex_3yr		Capex_4yr		Capex_5yr	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Patent[1]	0.0228	0.0229	0.0442	0.0441	0.0589*	0.0571*	0.0917**	0.0892**	0.1062**	0.1028**
	(0.466)	(0.464)	(0.112)	(0.113)	(0.065	(0.073)	(0.014)	(0.016)	(0.018)	(0.022)
R&D_1	-0.3222		-0.4275		-0.8844*		-0.8133*		-2.3240*	
	(0.679)		(0.531)		(0.084)		(0.083)		(0.099)	
R&D_2		-0.4821		-0.3822		-0.6881*		-0.5533*		-1.8500*
		(0.511)		(0.551)		(0.086)		(0.092)		(0.096)
Age[1]	-0.2013***	-0.2011***	-0.1203**	-0.1200**	-0.0726	-0.0687	-0.1330**	-0.1282**	-0.1531**	-0.1466**
	(0.000)	(0.000)	(0.014)	(0.014)	(0.176)	(0.199)	(0.034)	(0.040)	(0.037)	(0.045)
Asset[1]	0.6900***	0.6894***	0.6416***	0.6417***	0.7170***	0.7186***	0.7182***	0.7202***	0.7021***	0.7060***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IssPrice	0.0092***	0.0092***	0.0052**	0.0052**	0.0057**	0.0054**	0.0062**	0.0060**	0.0083**	0.0079**
	(0.000)	(0.000)	(0.019)	(0.020)	(0.022)	(0.028)	(0.032)	(0.037)	(0.014)	(0.019)
TobinQ	0.0446***	0.0449***	0.0409**	0.0409**	0.0550*	0.0515*	0.0678**	0.0624*	0.0783**	0.0734*
	(0.010)	(0.009)	(0.035)	(0.035)	(0.054)	(0.071)	(0.041)	(0.060)	(0.046)	(0.062)
Leverage	1.2250***	1.2193***	0.1950	0.1940	-0.2482	-0.2222	-0.5630	-0.5230	-0.4350	-0.3993
	(0.000)	(0.000)	(0.492)	(0.495)	(0.471)	(0.519)	(0.161)	(0.193)	(0.376)	(0.416)
UW	0.0829	0.0825	0.0770	0.0770	0.0105	0.0118	0.1398*	0.1415*	0.0798	0.0807
	(0.207)	(0.209)	(0.192)	(0.192)	(0.874)	(0.859)	(0.072)	(0.069)	(0.402)	(0.397)
VC	-0.0742	-0.0728	0.0124	0.0126	0.1374**	0.1343*	0.0664	0.0609	0.0911	0.0874
	(0.286)	(0.295)	(0.842)	(0.840)	(0.050)	(0.056)	(0.416)	(0.456)	(0.359)	(0.380)
Constant	3.6551***	3.6631***	5.2000***	5.1920***	5.1672***	5.1141***	4.3152***	4.2578***	4.0601***	3.9566***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.007)	(0.008)
Observations	921	921	832	832	726	726	725	725	606	606
R-squared	0.5258	0.5259	0.5062	0.5062	0.5127	0.5121	0.4253	0.4252	0.4029	0.4015
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the robust regressions of the impact of innovation capitals on the firms' capital expenditures for five years after IPOs. Model 1 to Model 2 respectively test the impact of firm's innovation capitals (innovation input and innovation outcome) on the *Capex_1yr* which is the firm's capital expenditures one year after its IPO. Model 3 to Model 4 respectively test the impact of firm's innovation capitals on the *Capex_2yr* which is the firm's capital expenditures two years after its IPO. Model 5 to Model 6 respectively test the impact of firm's innovation capitals on the *Capex_3yr* which is the firm's capital expenditures three years after its IPO. Model 7 to Model 8 respectively test the impact of firm's innovation capitals on the *Capex_4yr* which is the firm's capital expenditures four years after its IPO. Model 9 to Model 10 respectively test the impact of firm's innovation capitals on the *Capex_5yr* which is the firm's capital expenditures five years after its IPO. *Patent* refers to the number of patents applied for and acquired before IPO. *R&D_1* represents firm's R&D intensity one year before IPO. *R&D_2* represents firm's R&D intensity two year before IPO. Control variables include *Age* (age of firm), *Asset* (total assets), *IssPrice* (issuing price), *TobinQ* (ratio of the market value to book value), *Leverage* (ratio of total debt to total asset), *UW* (underwriter reputation), and *VC* (venture capital). [1] Logarithm. P-value in parentheses. ∗∗∗1% significance level, ∗∗5% significance level, ∗10% significance level.

4.5 Conclusion

In this work, we investigated the impact of the Chinese firms' pre-IPO innovation capital on their post-IPO product market feedback performance. We applied two measures of innovation, i.e., innovation input (R&D intensity), and innovation output (number of patents) in the pre-IPO period, to examine their influence on the firms' performance in the post-IPO period in the product market. Our sample consisted of the price data for the listed firms in the Chinese A-share market between January 2009 and December 2016. We simultaneously collected and collated the innovation capital data manually from the IPO prospectuses for the same period. We also collected the financial data from the CSMAR and RESSET databases. Our final sample consisted of 1,451 observations for each variable from all IPO firms. We carried out empirical research and analyses by utilizing EXCEL VBA and STATA 14 software. In order to conduct a comprehensive exploration and analysis, we extended previous studies by dividing the feedback performance of the firms in the product market in the post-IPO period into two parts, namely firms' operating performance and competitiveness.

First, based on the previous studies, we measured the firm's innovation capital via two different information dimensions to examine their impact on the firm's feedback performance in the product market. We found that the number of patents as the output of the firm's innovation capital, and the R&D intensity as the innovation input of firms, have completely different impacts on the firm's feedback performance in the product market. The greater the innovation output (number of patents) of a firm before the IPO, the better the operating performance (sales, profit and capital expenditure) it would have in the product market after the IPO. However, from the perspective of innovation input, we found that, due to the uncertainty and instability of R&D in the firm's operation, the greater the R&D input before the IPO, the worse the firm's operation performance will be in the product market after its IPO. Moreover, the significant negative impact of the R&D on firm's capital expenditures in the post-IPO period suggests that firm's R&D has a certain characteristic of cumulatively, usually with lags. Our study contributes to the existing literature by extending the measurement and analysis of the innovation capital, and by filling the research gaps in the previous studies where the number of patents was used as the only measurement standard for the firms' innovation ability.

Current research is also distinguished from previous studies because of combining the industrial economics and financial market theories to examine the impact of the firm's pre-IPO innovation capital on its post-IPO competitiveness in the product market. We utilized both relative market share and absolute market share of the firms in the post-IPO product market to measure their competitiveness in the product market. Our findings indicate that the size of the innovation capital will directly affect the competitive position of the firms in the product market after the IPO. The more the innovation capital before the IPO a company possesses, the greater its relative market share and absolute market share in the post-IPO product market will be. In other words, firms with more positive innovation outcome (number of patents) before the IPO will enjoy stronger competitiveness and gain higher competitive position in the product market. These findings also support the investment opportunity hypothesis. Under the effect of innovation capital, companies are more likely to go public in order to improve their productivity and investment opportunities in the product market. In short, firms with greater innovation ability can improve their competitiveness in the product market. Thus, most companies tend to choose to go public during their high innovation period.

Finally, by using the Chinese market data in our investigations, we provide valuable research evidence on emerging economies. As an innovative emerging economy, China still has many restrictions and constraints on its capital markets compared to the developed countries. From a micro perspective, the innovation capital is the key to the listed companies' economic development. In order to meet the international standards, Chinese government newly issued a Chinese Accounting Standard (CAS) in 2006 to reform the management and reporting of financial indices in the financial markets. However, for the intangible capital, there are different forms of R&D input, namely expensed R&D and capitalized R&D. We found that the impact of the firm's pre-IPO expensed R&D on its post-IPO performance in the product market is not positive. This result confirms that R&D investment that occurred in the early stage of the innovation activities and projects would not necessarily make the firm's innovation activities and projects successful. This means that the pre-IPO R&D investment cannot be fully converted into the capitalized R&D input and assets in the balance sheet. Therefore, based on the previous research, this study extends the empirical evidence on the relationship between the IPO market and the product market. We also expect that the theoretical model we developed in the study will be explored and extended further by other researchers.

CHAPTER 5

Conclusion

China has experienced tremendous social and economic changes over the past four decades. With a carefully engineered open door policy and sustained high growth rate, the country has become the second largest economy in the world in less than four decades. The financial system has also grown and has experienced profound changes in parallel with the rest of the economies during the same period. This environment provides a fertile ground for research in many areas of economics and finance, including initial public offerings (IPOs). Academics have widely researched the relationship between pre-IPO features of companies and their post-IPO performance from different perspectives, including the capital structure, insiders' ownership of shares, and innovations in the developed countries. However, these areas of research are not adequately explored in the emerging economies.

The aim of this thesis was thus to extend the existing literature on the impacts of innovation capital and expenditure on the post-IPO market performance of the firms in the Chinese equity market. Although the relationship between innovation input and its outcome has been extensively studied, the impacts of innovations on the post-IPO performance of Chinese firms has not been explored yet. In contrast to the developed countries, such as the United States, market operation in China is not very efficient in resource allocation. Government has also implemented a variety of regulations to influence the allocation of resources in the market. For instance, depending on their ownership by the Chinese or foreign citizens, public equities in China are divided into the

A shares and B shares, respectively. Current study explores the influence of companies' "innovation" in the pre-IPO period on their post-IPO performance in the A-share market. Stating from the perspective of information theory, we analyzed the impact of innovation information dissemination on the IPO short-term market performance, IPO long-term market performance, and on the feedback of market performance during the post IPO period.

5.1 Chapter 2: The Impact of Innovation on IPO Short-term Performance – Evidence from the Chinese Markets

Chapter 2 presents our findings on the short-term post-IPO market performance of Chinese A shares during 2009–2016. We conducted our study using two measures of innovation, i.e., R&D expenditure and number of patents. From the perspective of information dissemination, our findings also explain how the disclosure of innovation information affects the IPO market performance of new shares in the short-term. Resource allocation in the markets in China is highly influenced by the government's industrial policy. As a result, our results are combined with the impact of this policy. Our findings are summarized below.

First, to the best of our knowledge, the short-term underpricing of shares in the Chinese IPO market is the highest in the world.

Second, the two forms of firms' innovation capital have opposite effect on their short-term performance in the IPO market. The more capital the IPO firms invest in R&D before their IPOs, the higher the IPO underpricing and the longer the IPO honeymoon period are expected to be. In contrast, information on a higher number of patents in the market reduces the information asymmetry for prospective investors and helps them evaluate firms correctly. Thus, higher innovation outcome results in a lower IPO underpricing rate and a shorter IPO honeymoon period.

Third, in our research, we identified a new form of IPO underpricing called "honeymoon period" located somewhere between the short-term and long-term intervals. It arises from changes in the government regulation after 2014. Findings from the impact of firms' innovation capital on their IPO honeymoon periods are very similar to the results from the IPO short-term underpricing.

Finally, we examined the correlation between firms' innovation ability and their IPO market performance from the perspective of industrial policy. This policy is an important tool for regulating the market. Therefore, it can significantly influence the market behavior of both companies and their industries. Our findings indicate that, under the incentive of Chinese industrial policy, the positive impact of firms' pre-IPO innovation input on the IPO underpricing and the IPO honeymoon period length will be greater. In addition, the industrial policy can reinforce the negative correlation between pre-IPO innovation outcome and IPO underpricing or the IPO honeymoon period length. However, after the reform of the industrial structure in 2014, industrial policy has failed to exert a significant impact on the firms' performance in the IPO market. These results have triggered the introspection on the effective implementation of industrial policies in the Chinese market.

5.2 Chapter 3: Does the Pre-IPO Innovation Affect the Firms' Long-term Performance? – Evidence from the Chinese Markets

The objective of the current research was to investigate the impact of the innovation capital on the IPO long-term performance. While a wide range of literature provides ample evidence on the IPO long-term underperformance in different countries, the impact of innovation capital on the market value of firms in the post-IPO period has received little attention. Majority of existing studies have also been limited to the U.S. and a few other developed countries. Our second study extends this inquiry into the Chinese equity market with its unique institutional and regulatory settings. We examined the influence of innovation capital (using the dimensions of innovation input and innovation outcome) on the IPO long-term performance. In contrast to the developed countries, the stock performance of firms in the Chinese IPO market exhibits a longer-term underperformance, extending to nearly five years after the event.

Starting from R&D expenditure as the innovation input, we have found that this variable is negatively correlated with the IPO long-term market performance, extending to three years after the IPOs. However, the influence of R&D expenditure on firms' long-term performance gradually changes from negative to positive three years after the IPOs. This finding suggests that a firm's R&D has a cumulative and lagging effect in the process of firm's operation. Unlike the innovation input, the relationship between innovation output (patents) and the long-term market performance of IPO companies becomes significantly positive in the second year after the IPO. Our findings also confirm that a firm's innovative capital before the IPO has a dynamic effect on its market performance over time. Therefore, the market valuation and pricing of the two types of innovative capital will affect the long-term performance of firms in the IPO market in different forms.

This difference arises from the accounting regulation of the research and development funds in the Chinese market, which deals with capitalized R&D and expensed R&D differently. Most investors recognize or perceive value of R&D fund disclosures in the IPO firms' prospectus as risky off-balance sheet intangible assets of these companies. As a result, uncertainty and instability of R&D expenditure as the innovation input can increase the investment risk for investors in the market. However, part of the innovation input may be capitalized over time, revealing the market value of IPO firms in the long term. Further, these findings also imply that investors attribute potential development value of patent stocks which are held by corporations. The more reliable source of the innovation outcome can convey the quality of firms more clearly.

5.3 Chapter 4: Innovation and the Post-IPO Feedback in the Product Market – Evidence from the Chinese Markets

The third study's aim was to construct a bridge between product and capital markets in China. Although there is a substantial research on the product market and stock market in separate forms, the interaction between these two markets has not been extensively studied, especially in the Chinese markets. Inspired by Chemmanur, He and Nandy (2010), the third study extends the empirical evidence on the role of innovations in IPO and product markets in China. We utilized three indicators—sales, profits, and the capital expenditure—as proxies for the performance of firms in the product market after their IPOs. Our findings show that the more innovative output (patents) a firm has before the IPO, the better it performs (in terms of sales, profit, and capital expenditure) in the post-IPO product market. However, from the perspective of innovation input, we found that, due to the uncertainty and instability of R&D investment, the more R&D investment the firms have before their IPOs, the worse their operating performance in the product market is expected to be in the post-IPO period. This result provides useful information for market investors to make more informed decisions. It also helps IPO companies to be more efficient in the allocation of their investment resources to R&D initiatives.

From the perspective of industrial economics, we examined the impact of firms' pre-IPO innovative capital on their competitiveness in the post-IPO product market. We used the relative and absolute market share of the companies in the post-IPO product market to measure their competitive position in the post-IPO product market. Our findings show that the greater the innovation capital before a firm's IPO, the greater its relative market share and absolute market share in the product market are expected after the IPO. In other words, companies with higher innovation achievement before IPOs enjoy stronger competitive status in the product market after their IPOs. These findings also support the investment opportunity hypothesis, implying that firms' high innovation capabilities before IPOs can increase their competitiveness in the product market after the IPOs. Thus, most companies tend to go public during high levels of innovation, when they expect to increase their future market share and competitive position in the product market.

Finally, by utilizing Chinese market data in our study, we provide further research evidence on emerging financial markets. China still has many restrictions and constraints on its capital market compared to the developed countries. At the micro level, innovation capital plays a decisive role in the economic development of listed companies. In line with the new Chinese Accounting Standards, our findings confirm that R&D spending in the early stages of innovation activities will not necessarily generate successful outcomes. This means that the pre-IPO R&D investment is not fully converted into the capitalized R&D in the market.

5.4 Study Implications and Limitations, and Possible Future Research Avenues

In the current study, we examined the influence of firms' innovations on their IPO short-term market performance, IPO long-term market performance, and market feedback performance in the post-IPO product market under the influence of the industrial policy and reforms of the Chinese IPO market. We expect that our comprehensive study will provide a valuable foundation for future research in this area. Further studies may be conducted from the following perspectives:

First, our study includes all of the companies in all industrial sectors in the A-share market. However, each industry (such as, IT, biochemistry, materials, etc.) has its own unique features with respect to the level and complexity of innovation. Thus, it would be interesting to apply the methodology used in the current research to individual industries and tease out the effects of their unique innovative features on post-IPO capital and product markets. For instance, some high-tech industries such as IT may have higher innovation outputs and present better aftermarket performance for the IPO firms in the capital market. Classification of IPO firms into different markets according to their trading board, including the main board, SME board, GEM board, etc., is also another extension of the current research. For example, IPO firms from the GEM board are supposed to have higher level of innovation input, which can affect the research outcomes. Finally, segregating data according to different industry classifications or markets may also provide a better perspective about the impact of firms' innovation on the market. In addition, more studies will be conducted to differentiate the industries. For example, the hi-tech, bio-tech, chemistry etc. Future studies can use the data from different industries to test the impacts of innovation in the distinct exchange stock markets.

Second, the three studies in this thesis are based on the capital market in China with its own unique economy size, regulations, the phase of economic development, and the level of innovation. However, there are other emerging economies and markets with different characteristics and regulation systems. Good candidates are other “BRICS” countries, namely Brazil, Russia, India, and South Africa. As a comparative study, the three research topics in this thesis can be extended to these economies to investigate whether our findings for China are robust.

Finally, we have found and defined a new IPO market phenomenon between the short-term and long-term IPO periods in China after 2014, i.e. “IPO honeymoon period.” The characteristics of the “honeymoon period” in the market show the persistence of the innovation effects on the movement of stock prices in the post-IPO market. This period is considered as an important transitional period towards the long-term performance of stocks. This study is the first to provide evidence on this type of IPO underpricing, as most of the Chinese IPO market studies and data are limited to the pre-2014 period. Therefore, another potential extension of the current study is to make a more comprehensive investigation of the IPO honeymoon period as more data becomes available in the future.

Appendix

Appendix A 11th Five-year Plan, 12th Five-year Plan, and 13th Five-year Plan and Industry Classification of Firms

INDUSTRY	11th Five-year Plan (2006-2010)		12th Five-year Plan (2011-2015)		13th Five-year Plan (2016-2020)	
	Stimulate	Support	Stimulate	Support	Stimulate	Support
A01 Agriculture	1	1	1	1		1
A03 Forestry	1	1	1	1		
A05 Animal Husbandry	1	1	1	1		
A07 Fishery	1	1	1	1		
A09 Agriculture, Forestry, Husbandry, and Fishery Services	1	1	1	1		
B01 Coal Mining			1			
B03 Oil and Gas Recovery			1		1	
B07 Nonferrous Metal Mining			1		1	
B08 Ferrous Metal Mining			1		1	
B10 Non-metal Mining			1			
B50 Mining Service			1			
C01 Food Processing	1				1	
C25 Oil Processing and Coking			1		1	
C26 Chemical Material and Product	1				1	
C51 Electronic Components Manufacturing	1	1	1		1	
C55 Household Electronic Appliance Manufacturing			1			
C57 Other Electronic Equipment Manufacturing			1		1	
C59 Electronic Equipment Repairing			1			
C65 Ferrous Metal Smelting and Extrusion			1			
C67 Nonferrous Metal Smelting and Extrusion	1		1			
C69 Metal Manufacturing			1			
C07 Machinery, Equipment, Instrument			1		1	
C71 Ordinary Machinery Manufacturing			1			
C73 Special Equipment Manufacturing	1		1	1	1	1
C75 Transportation Equipment Manufacturing	1		1		1	
C76 Electrical Machinery and Equipment Manufacturing	1		1		1	
C78 Instrumentation and Cultural, Office Machinery Manufacturing			1		1	
C08 Medicine, Biological Products			1		1	
C81 Pharmaceutical Manufacturing	1		1			1
C85 Biological Products	1	1	1		1	1
D01 Electricity, Steam, Hot Water Production and Supply	1		1	1		
D03 Gas Production and Supply	1		1	1		
D05 Tap Water Production and Supply			1			
F01 Railway Transportation	1	1	1	1	1	1
F03 Highway Transportation	1	1	1	1		

F05 Pipeline Transportation	1	1				
F07 Water Transportation	1	1	1	1	1	
F09 Air Transportation	1	1	1		1	
F11 Auxiliary Transportation	1	1			1	1
F19 Other Transportation	1	1			1	
G81 Communication and Relevant Equipment Manufacturing	1	1	1		1	1
G83 Computer and Relevant Equipment Manufacturing			1		1	1
G85 Communication Service	1	1	1	1	1	1
G87 Computer Application Service	1	1	1		1	1
I01 Bank			1	1		
I11 Insurance			1	1		
I21 Securities and Futures			1	1		
I31 Financial Trust			1	1		1
I41 Fund			1	1		1
I99 Other Financial Sectors			1	1	1	
J01 Real Estate Development and Operation	1					
K01 Public Facility Service	1		1			
K10 Mail Service			1			
K20 Profession and Research Service			1			1
K30 Catering			1			
K32 Hotel			1			
K34 Tourism	1		1	1		
K36 Entertainment Service			1			
K37 Health Care and Nursing Service			1			
K99 Other Social Service			1			
L10 Radio, Television and Film			1		1	1
L20 Information Communication Service			1		1	1
L71 Lease Service			1			

Note: The industry classifications are followed by the “Industry Classification Standard Guidance” (3-level codes).

Appendix B Definition of Variables

Type	Name	Symbol	Definition
Dependent Variables	IPO Underpricing	$UP1_{it}$ (2009-2013)	The market-adjusted IPO underpricing ratio.
		$UP2_{it}$ (2014-2016)	The market-adjusted IPO underpricing ratio.
	Honeymoon Period Length	HM_{it} (2014-2016)	Number of days from the IPO stock issue day to the last trading day when the price closes below 10% maximum up-limit price.
Independent Variables	Innovation Input	R&D_1	R&D one year before IPO/total assets one year before IPO.
		R&D_2	R&D two years before IPO/total assets two years before IPO.
		R&D	The average of R&D intensity of R&D_1 and R&D_2.
	Innovation outcome	Patents	Number of patents applied for and acquired before IPO.
		(Patents+1)	The logarithm of the number of patents.
	Industrial Policy	IP	Dummy variable. If the firm belongs to the industry which is under the support of the industrial policy, IP = 1, and IP = 0 otherwise.
Control Variables	Venture Capital	VC	Dummy variable. It indicates whether the IPO is backed by at least one venture capital firm.
	Offer Price	Price	The offer price of each new issue during IPO.
	Trading Volume	Volume	The logarithm of trading volume of each new issue during its IPO.
	Size	Asset	The logarithm of total assets one year before the IPO.
	First-day Turnover	Turnover	First-day turnover rate of IPO firms.
	Lottery Rate	Lottery	The lottery rate of online issue of IPO stocks.
	Total proceeds	Proceed	The logarithm of total proceeds (total issue volume* issue price) in IPO.
	Age of firm	Age	The logarithm of the number of years that IPO firms have been in operation.
	Underwriter Reputation	UW	Dummy variable. The underwriter reputation, which indicates the top ten underwriters regarding the ranking of net income of securities firms on their underwriting and sponsoring reported by the CSRC from 2006 to 2016.
	Industry	Industry	Dummy variable.
	IPO Year	Year	Dummy variable. The year of IPO. When to go public may affect the extent of IPO underpricing and the length of the honeymoon period.

Appendix C Definition of Variables

Type	Name	Symbol	Definitions
Dependent variables	IPO Long-term Performance	$LT_{it(1, 2, 3, 4, 5)}$	The buy-and-hold market-adjusted abnormal returns calculated by the monthly returns for 12, 24, 36, 48, 60 months (1, 2, 3, 4, 5 years) respectively started from two months after IPOs (see section 3).
Independent Variables	Innovation Input	R&D_1(2)	The research and development expenditures scaled by the total assets one year (two years) before the IPO year in the firms' prospectuses.
		R&D	The average R&D intensity of R&D_1 and R&D_2.
	Innovation Outcome	Patent	Number of patents acquired and applications before firms' IPOs.
Instrumental Variable	R&D Personnel Ratio	R&Dpp	The ratio of the R&D staffs to the total staffs of the firm in the prospectuses before firm's IPO.
Control Variables	Firm Age	lnAge	The logarithm of the number of years of IPO firms.
	Firm Size	lnAsset	The logarithm of total assets one year before IPO.
	Total Proceeds	lnProceed	The logarithm of total proceeds (issuing price*total issue volume).
	Lottery Rate	Lot	The lot-winning rate of online issue of IPO stocks.
	Underwriter Reputation	UW	Dummy variable. The underwriter reputation, which indicates the top ten underwriters regarding the ranking of net income of securities firms on their underwriting and sponsoring reported by the CSRC from 2006 to 2016.
	Venture Capital	VC	Dummy variable. It indicates whether the IPO is backed by at least one venture capital firm.
	Issuing Price	IssPrice	The issuing price of IPO firm.
	Market Value	lnMV	The logarithm of market value at the first trading day (the closing price at the first trading day * shares of outstanding common stocks).
	Industry	Industry	Dummy variable.
	IPO Year	Year	Dummy variable. The year of IPO.

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